2020

Development of Integrated Water Resources Planning Model for Dublin using WEAP21

Mohammed Yassin
Technological University Dublin

Development of Integrated Water Resources Planning Model for Dublin using WEAP21

by

Mohammed Yassin MSc, BSc

Lead Supervisor:

Dr. Ahmed Elssidig Nasr, Technological University Dublin

Advisory Supervisor:

Prof. Aidan Duffy, Technological University Dublin

THESIS

Submitted in partial fulfilment of the requirements for the Degree of Doctor of Philosophy

College of Engineering and Built Environment, Technological University Dublin, 2019

ABSTRACT

Population growth, urbanisation, and climate change are predicted to impose huge pressure on water resource systems of many cities around the world including Dublin. Integrated water resources management is seen as a viable approach to address these challenges. This approach examines the water resources system in a more interconnected manner, focusing on reducing water demands, reducing reliance on fresh water supplies, reducing discharges into receiving water bodies, and creating water supply assets from storm water and wastewater. The role of mathematical modelling in designing an integrated water resources management plan is paramount as it provides a tool whereby performances of alternative water management plans can be predicted and evaluated under future scenarios of population growth, urban development and climate. There is a lack of an integrated water resources management model for Dublin that integrates the main components of the water resources system including water supply sources, sectoral water uses, wastewater disposal, urban runoff and associated infrastructure. Previous models also did not consider water management options such as rainwater harvesting, greywater reuse, and groundwater recharge - which are important for the implementation of an integrated water resources management approach. Moreover, integration of uncertainty analysis into water resources modelling helps understand associated uncertainties and hence reduce them.

The main aim of this thesis is to develop an integrated water resources management model for Dublin using the water evaluation and planning software WEAP21, and to demonstrate the use of the developed model for assessing the impacts of number of water management scenarios on the existing water system under future scenarios of population growth and urban development. The thesis also aims to extend the capability of WEAP21 software to perform uncertainty analysis, and to investigate uncertainties in flow predictions due to parameter estimation, forcing input and model structure.

An integrated water resources management model for Dublin is developed in WEAP21 by integrating water supply catchments, sectoral water uses, water supply and wastewater infrastructure. The model has been calibrated and validated using water-use data, climatic and hydrological data in the Liffey and Dublin Bay catchment. The capability of WEAP21 software for estimating uncertainty in model output has been extended by coupling the software with the statistical parameter optimisation tool (SPOTPY) and stochastic climate models such as the generalised linear model (GLM) framework and stochastic climate library (SCL). Using this framework, uncertainties in flow predictions of a case study sub-catchment (Ryewater) due to parameter estimation and forcing data have been investigated. To assess the effects of model structure on flow predictions of Ryewater, simulation results of WEAP21 have been compared with simulation results from another software HBV-light. Finally, the use of the developed model has been demonstrated by simulating and assessing four water management scenarios for Dublin under most likely socio-economic growth and urban development projections. The management scenarios are: (i) baseline which represents status quo of the water resources system in Dublin (ii) increasing supply as estimated by the proposed new water supply scheme for the Eastern and Midlands Region (iii) intensified leakage management through improving infrastructure and recovering

leakage to offset growing water demands and (iv) total water management which focuses on reducing water demands and increasing the reuse of storm water. The efficiency of each of these scenarios has been evaluated based on hydrologic performance and supply reliability, urban runoff and groundwater recharge.

Simulation results indicate that the developed model reproduced natural and managed flows of the Liffey and Dublin Bay catchment during the simulation period (2012-2017). A retrospective analysis of the historic period 1980-2011 has shown that predictions of flows of un-managed catchments by the model are more accurate than predictions of flows of managed catchments. This is mainly due to the absence of measurements of inflows to reservoirs which are located downstream of the managed catchments. These measurements are also important for detailed representation of reservior operations that are in place. Hence, the accuracy of the model, in particular for predicting flows of managed catchments, can be improved once measurements of reservoir inflows become available.

Using the generalised likelihood uncertainty estimation method, the extended capability of WEAP21 has reduced uncertainty in parameters of Ryewater model by 30-70%. This extension can be applied by WEAP21 users to reduce parameter uncertainty and to condition model predications, providing an alternative approach to the manual and automatic calibration methods that are available by WEAP21. Simulation results from both modelling software (WEAP21 and HBV-light) indicate that the HBV-light model is superior to the WEAP21 model at representing flows of Ryewater sub-catchment during the simulation period. This result highlights that model structure and resolution of forcing data have strong impacts on the accuracy of flow predictions. The investigation of uncertainties in flow predictions of Ryewater, from both models, has shown that forcing data have greater effects on model output compared to the effects of parameter estimation. The effects of rainfall forcing on model outputs are greater compared to the effects of temperature data.

Therefore, it is suggested that future investments focus on collection and better conditioning of rainfall data and flow data (in particular for managed catchments). This in turn will ensure model results are within realistic bounds, and hence enabling a more robust water resources management model for decision-making in the catchment.

Results from modelling the four water management scenarios showed that total water management scenario is the only one that results in a reduced pressure on existing fresh water supplies and reduced storm water discharges into receiving water bodies compared to the other three management scenarios. Hence, integrating total water management options such as rainwater harvesting, greywater reuse, artificial groundwater recharge and sustainable urban drainage systems into the management plan of water resources in Dublin can produce tangible benefits over traditional practices in terms of lowering supplies from freshwater resources and increasing recharge of groundwater. The findings of this work can provide substantial platform on which to build further research to support the design and implementation of an integrated water resources management strategy in the Dublin Region.

.

DECLARATION

I certify that this thesis which I now submit for the examination for the award of Doctor of Philosophy is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

This thesis was prepared according to the regulations for graduate study by research of the Dublin Institute of Technology and has not been submitted in whole or in part for another award in any other third level institution.

The work reported on in this thesis confirms to the principles and requirements of the DIT's guidelines for ethics in research.

DIT has permission to keep, lend or copy this thesis on whole or in part, on condition that any such use of the material of the thesis be duly acknowledged.

Mohammed Yassin

June 2019

ACKNOWLEDGEMENT

In the name of ALLAH, the Entirely Merciful, the Especially Merciful.

We raise in degrees whom We will, but over every possessor of knowledge is one [more] knowing. [12:76] The Noble Quran.

“My Lord, increase me in knowledge.”

First and foremost, all praises to ALLAH (SWT) who bestowed upon me guidance, knowledge, strength and patience to carry out and complete this PhD thesis. This research project could not have been achieved without his blessing.

I would like to thank my supervisor Dr. Ahmed Naser for his guidance, support, time and efforts throughout the development of this research project.

I must thank TU Dublin for the award of the funding which enabled me to undertake this research project. Without this financial support, I would not have been able to pursue my PhD and fulfil my dream.

My sincere thanks also goes to the Head of Research for Engineering, Dr. Marek Rebow for his continued support and guidance in relation to my postgraduate affairs.

I also want to express my gratitude to my colleges in the department Stephen, Gianni, Antenello, and Sean for sharing their experience with me and for the valuable advice they offered me on different aspects. Thank you, you all made me feel home.

Special thanks to my family: my parents, my brother and sisters and my parents-in-law for their prayers and support throughout my PhD journey.

Last but not least, I would like to thank my wife, Ola, for her endless support and patience, through the difficult times of my PhD journey. No words can ever be strong enough to express my gratitude to her for her unconditional support.

LIST OF ABBREVIATIONS

AFW	Accounted for Water
CFRAM	Catchment Flood Risk Assessment and Management
CSL	Customer Side Leakage
CSO	Central Statistics Office
DD	Dodder
DEHLG	Department of Environmental and Local Government
DI	Distribution Input
DUWSiM	Dynamic Urban Water Simualtion Model
DWC	Deep Water Capacity
EPA	Environmental Protection Agency
GAP	Genetic Algorithm and Powell
GCMs	Global Climate Models
GDSDS	Greater Dublin Strategic Drainage Study
GDWSSS	Greater Dublin Water Supply Strategic Study
GIS	Geographic Information System
GLM	Generalised Linear Model
GLUE	Generalised Likelihood Uncertainty Estimation
GSI	Geological Survey of Ireland
HEP	Hydrological Estimate Point
HUs	Housing Units
ICBMs	Integrated Component Based Models
ILM	Intensified Leakage Management
IMS	Integrated Modelling System
IUWM	Integrated Urban Water Management
IUWSMs	Integrated Urban Water System Models
IWRM	Integrated Water Resources Management
LL	Lower Liffey
LP	Linear Programming
ML	Middle Liffey
NAM	Nedbør–Afstrømnings-Model
NSE	Nash Sutcliffe Efficiency
OD	Ordnance Datum
OPW	Office of Public Work
PPOCC	Permanent Occupied Properties
PBIAS	Percent BIAS
PE	Population Equivalent
PTFs	PedoTransfer Functions
RRF	Runoff Resistance Factor
RSR	Root Mean Square Error to the Standard Deviation Ratio
RW	Ryewater
SCL	Stochastic Climate Library
SDR	Standard Deviation Ratio of simulated and observed data
SEA	Strategic Environment Assessment
SELL	Sustainable Economic Level of Leakage
SMART	Soil Moisture Accounting and Routing for Transport
SPOTPY	Statistical Parameter Optimisation Tool Python
SMARG	Soil Moisture Accounting and Routing with Groundwater model
SuDS	Sustainable Urban Drainage System

SWC	Soil Water Capacity
S1	First Order Sensitivity Index
TSL	Total Sensitivity Index
TWM	Total Water Management
UFW	Unaccounted for Water
UL	Upper Liffey
WEAP21	Water Evaluation and Planning software
WFD	Water Framework Directive
WSA	Water Supply Area
WSP	Water Supply Project

TABLE OF CONTENTS

ABSTRACT ii
DECLARATION iv
ACKNOWLEDGEMENT v
LIST OF ABBREVIATIONS vi
TABLE OF CONTENTS viii
LIST OF FIGURES xiii
LIST OF TABLES xviii
Chapter 1 INTRODUCTION 1
1.1 Background 1
1.2 Problem definition 3
1.3 Overall aim 7
1.4 Research objectives 8
1.5 Research methodology 9
1.6 Report outline 9
Chapter 2 LITERATURE REVIEW 12
2.1 Introduction 12
2.2 Integration in urban water resources modelling 13
2.3 Hydrology and water management models 17
2.4 WEAP case studies 26
2.5 Uncertainty of water resources management models 30
2.6 Conclusion 32
Chapter 3 WEAP21 MODEL DESCRIPTION 33
3.1 Introduction 33
3.2 Hydrology component of WEAP21 33
3.3 Surface water and groundwater interaction 36
3.4 Surface water quality 38
3.5 Demand-management component 39
3.6 Conclusion 44
Chapter 4 DATA COLLECTION 45
4.1 Introduction 45

4.2 Data pre-processing 48

Chapter 5 DEVELOPMENT OF WEAP21 MODEL FOR DUBLIN 53

5.1 Introduction.. 53

5.2 Model configuration and parameterisation 53

5.2.1 WEAP21-Dublin catchments 53

5.2.2 Climate data 55

5.2.3 Land-use parameters 62

5.2.4 Water uses data 66

5.2.5 Infrastructure data 78

Chapter 6 APPLICATION OF WEAP21 MODEL FOR DUBLIN 82

6.1 WEAP-Dublin model schematic 82

6.2 Model calibration and validation 83

6.2.1 Quality check and processing of flow data 84

6.2.2 Strategy for model calibration and validation 85

6.2.3 Calibration and validation results of UL and RW sub-catchments 90

6.2.4 Validation results of LL, RW and DD sub-catchments 95

6.2.5 Validation results of Water uses 98

6.3 Conclusion 100

Chapter 7 UNCERTAINTY OF WEAP21 FLOW PREDICTIONS 103

7.1 Introduction.. 103

7.2 Parameter uncertainty analysis for the WEAP21 model 104

7.3 Hydrograph simulations due to uncertainties in WEAP21 parameters 110

7.4 Global sensitivity analysis 112

7.5 Separate models for the dry and wet seasons 117

7.6 Analysis of precipitation and flow data 119

7.7 Stochastic climate modelling 121

7.7.1 Rainfall sequences using the Spatial GLM framework 121

7.7.2 Rainfall sequences using the stochastic climate library (SCL) 126

7.7.3 Temperature sequences using the stochastic climate library (SCL) 130

7.7.4 Flow simulations by combining parameter sets and stochastic climate data (temperature and rainfall) 133

7.7 HBV-light modelling of Ryewater sub-catchment 134

7.8 Conclusion 143

Chapter 8 WATER MANAGEMENT SCENARIOS 147
8.1 Potential water supply options 147
8.2 Parteen Basin water supply option 148
8.3 Development of water management scenarios 150
8.4 WEAP-Dublin model for future simulations 152
8.5 Water demand projections 154
8.5.1 Domestic water uses projections 155
8.5.2 Non-domestic water uses projections 157
8.6 Projected leakage and losses 158
8.6.1 Projected customer side leakage (CSL) 158
8.6.2 Projected distribution leakage 158
8.7 Peak demands, strategic headroom and outages 159
8.7.1 Peak water demands 159
8.7.2 Headroom and outage 159
8.8 Projected capacities of existing sources 160
8.9 New source of supply (Parteen Basin/Shannon) 161
8.10 Greywater reuse systems 162
8.11 Storm water management 163
8.11.1 Rainfall harvesting 164
8.11.2 Centralised groundwater recharge 166
8.11.3 Decentralised groundwater recharge 167
8.11.3 Simplistic groundwater modelling 168
8.11.4 Traditional storm water system 168
8.12 Rainfall and storm water routing 169
Urban catchment parametrisation 172
Chapter 9 EVALUATION OF WATER MANAGEMENT SCENARIOS 178
9.1 Water balance and supply reliability 179
9.1.1 Water demand 179
9.1.2 Water supply 181
9.1.3 Water supply deficit 184
9.1.4 Water supply from rainwater harvesting 186
9.2 Urban runoff generation 188

9.3 Groundwater storage 192

Chapter 10 CONCLUSION 194

10.1 Contributions........ 194

10.2 Study limitations 201

10.3 Directions for future research 202

REFERENCES........ 205

Appendix A.1: Information on Liffey reservoirs operations provided through personal communication with ESB 214

Appendix B.1: Formal Data Request to Irish Water........ 215

Appendix B.2: Formal Data Request to ESB........ 216

Appendix C.1: Data status table for rainfall stations located within or close to the Liffey and Dublin bay catchment. 218

Appendix C.2: Area weighted monthly time series rainfall data for each river sub-basin used to drive the WEAP-Dublin model........ 219

Appendix C.3: Monthly average temperature and wind speed as applied for each river sub-basin in the WEAP-Dublin model 221

Appendix D.1: Estimated number of households per each supply zone, based on analysis of census data 222

Appendix D.2 : Volume-elevation curve for Phollaphuca reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)........ 223

Appendix D.3 : Volume-elevation curve for Golden Falls reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)........ 224

Appendix D.4 : Volume-elevation curve for Lexilip reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)........ 225

Appendix E.1: Python code linking the water evaluation and planning software (WEAP21) with the statistical parameter optimisation tool (SPOTPY) for parameter uncertainty analysis**.** 226

Appendix E.2: Calculation of first order and total order sensitivity indices of the Sobol's method for parameters of the WEAP21 model of Ryewater using SALib python library ..234

Appendix E.3: R code for fitting spatial GLM model for Ryewater sub-catchment to simulate multiple rainfall sequences 241

Appendix E.4: Python code for generating an ensemble of simulated flows for Ryewater catchment using WEAP21 modelling software by combining rainfall sequences produced from the GLM with the best performing parameter sets of the Latin Hyper Cube sampling. 245

Appendix E.5: Python code for generating an ensemble of simulated flows for Ryewater sub-catchment by combining the behavioural models of WEAP21 from the Latin Hyper Cube sampling algorithms, stochastic rainfall sequences from the SCL software, and stochastic temperature sequences from the SCL software........ 247

Appendix E.6: Python code for running HBV-light multiple times using different parameter sets, changing daily simulations into monthly simulations, and generating ensemble of simulated flows for the catchment 250

Appendix F.1 Historic rainfall data used for the urban catchment to run the model for future simulations. 252

Appendix F.2 Automating the calculation of surface areas and rainfall routing parameters as time series input for the WEAP-Dublin model to run future simulations (2016-2050). 257

LIST OF PUBLICATIONS 258

LIST OF EMPLOYABILITY SKILLS AND DISCIPLINE SPECIFIC SKILL TRAINING 259

LIST OF FIGURES

Figure 1. 1 Project population growth in Dublin Region under different planning scenarios 4

Figure 1. 2 Workflow diagram of the current research 12

Figure 2. 1 'Four Degrees of Integration' Typology for IUWM models 16

Figure 2. 2 Score matrix for different water resources modelling packages based on their capabilities in representing hydrology and water demand management sides of the water resources system 25

Figure 2. 3 Locations of river basins where WEAP21 were / has been applied 26

Figure 3. 1 Schematic of WEAP21 conceptual water balance model 34

Figure 3. 2 Schematic of conceptual groundwater model in WEAP21 and associated parameters 37

Figure 3. 3 Reservoir storage zones in WEAP21 used in describing reservoir operation rules 41

Figure 4. 1 Timeseries rainfall data for station no. 5323 "Naas (C.B.S)" for the period 2012-2017. 50

Figure 4. 2 Timeseries rainfall data for station no. 8423 "Naas (Osberstown)" for the period 2012-2017. 50

Figure 4. 3 Timeseries rainfall data for station no. 9323 "SALLINS" for the period 2012-2017. 50

Figure 4. 4 Monthly mean streamflow (in cms) of Liffey river at Phollaphuca 09032 against total monthly rainfall data (in mm) of nearby / contributing weather stations. 51

Figure 5. 1 The Liffey and Dublin bay catchment overlaying WFD river sub-basins, with locations of active gauges, major infrastructure and rivers. 54

Figure 5. 2 The Liffey and Dublin bay catchment disaggregated into representative sub-catchments, each symbolised with a unique colour. 55

Figure 5. 3 Average annual rainfall (mm) within the Liffey and Dublin bay catchment, estimated based rainfall values from Met Éireann rainfall gauges during the period 2012-2017. 56

Figure 5. 4 Final network of weather and rainfall stations used to generate monthly rainfall time-series data for river sub-basins 57

Figure 5. 5 Thiessen polygons (red lines) constructed from the rainfall point stations and overlaying river sub-basins. 60

Figure 5. 6 Intersection of thiessen polygons with river sub-basins. Each of intersect polygons derived from this process is symbolised by a unique colour 60

Figure 5. 7 Area-weighted monthly rainfall time series for river sub-basin ML2, as populated in the WEAP-Dublin model for the period 2012-2015. 61

Figure 5. 8 CORINE land covers grouped into seven major categories within the Liffey and Dublin bay catchment 64

Figure 5. 9 Fractional area of each land cover and soil combination within river sub-basin UL1, provided as percent of the area 65

Figure 5. 10 Locations of existing water supply schemes for the Dublin Region WSA. 67

Figure 5. 11 Dublin Region water supply. 68

Figure 5. 12 Water supply zones within the Dublin Region WSA characterised based on the supply source(s). 68

Figure 5. 13 Locations of UWWT plants of the Dublin region WSA, with respect to the Liffey and Dublin bay catchment. 77

Figure 6. 1 A schematic of the WEAP-Dublin model.. 83

Figure 6. 2 Monthly mean streamflow (in cms) of Liffey river at Phollaphuca 09032 against total monthly rainfall data (in mm) of nearby / contributing weather stations. 85

Figure 6. 3 Screenshot of WEAP scenario explorer used to aid sensitivity analysis and calibration 87

Figure 6. 4 Diagram illustrating calibration and validation of the model 89

Figure 6. 5 Simulated and observed streamflow volumes of river liffey at the following gauge locations; Phollaphuca 09032, Golden Falls 09007 and Lexilip station 09022. 92

Figure 6. 6 Monthly mean streamflow (in cms) of Ryewater river at Lexilip 09001 against total monthly rainfall data (in mm) of nearby / contributing weather stations. 93

Figure 6. 7 Simulated and observed streamflow for (i) Liffey at Pollaphuca 09032 (ii) Ryewater at Lexilip 09001 during the period 1980-2011 94

Figure 6. 8 Simulated inflows to Phollaphuca reservoir in the UL sub-catchment by WEAP21 model during the period 1980-2015.. 94

Figure 6. 9 Simulated and observed streamflow / estimate flows for (i) Liffey at Lexilip 09022 (ii) Liffey at HEP located at the confluence with Cammock river (iii) Dodder at HEP located just before its confluence with the Liffey.. 96

Figure 6. 10 Simulated and observed flow hydrographs of (i) Liffey river at Liffey river at Lexilip st. 09022 (iii) and (iv) Dodder at HEP. 97

Figure 6. 11 Simulated inflows to Lexilip reservoir by WEAP21 during the period 1980-2015 98

Figure 6. 12 Demands for drinking water in the Dublin region for year 2012 99

Figure 6. 13 WEAP estimates of average annual water supply to each zone in Mm^3 100

Figure 7. 1 Framework linking SPOTPY and WEAP21 for assessing parameter ucertainty........ 105

Figure 7. 2 Parameter interactions and posterior parameter distributions for the behavioural model runs from the initial GLUE analysis. 107

Figure 7. 3 Correlation of NSE values with (1) logNSE values, (2) PBIAS values and (3) RSR values for the behaviour for the 250 behavioural models of Ryewater catchment. 108

Figure 7. 4 NSE and LogNSE values for best 100 models for predicting peak flows and 100 best models for predicting low flows 109

Figure 7. 5 Results of 10,000 ensemble simulated flows of Ryewater at Lexilip flow gauging station during the period 1978-2013, generated from WEAP21 model of Ryewater sub-catchment using all Latin Hyper Cube sampling algorithm........ 110

Figure 7. 6 Results of 250 ensemble simulated flows of Ryewater at Lexilip flow gauging station during the period 1978-2013 generated from the WEAP21 model of Ryewater sub-catchment using the behavioural parameter sets from the Latin Hyper Cube sampling algorithm. 111

Figure 7. 7 Results of ensemble simulated streamflow of Ryewater at Lexilip flow gauging station during the period 1978 -2013 generated from the WEAP21 model of Ryewater catchment using the best 100 performing parameter sets of the (a) NSE, (b) LogNSE, (c) PBIAS and (d) RSR groups. 112

Figure 7. 8 Long-term average values of first order sensitivity indices (S1) and total order sensitivity indices (TSI) for all parameters of Ryewater sub-catchment produced from analyzing the variance output of the model during the period 1980-2013........ 114

Figure 7. 9 Correlations of TSI indices with monthly precipitation data across all parameters of the WEAP21 model of Ryewater catchment. 116

Figure 7. 10 Correlations of TSI indices with monthly average temperature data across all parameters for the WEAP21 model of Ryewater sub- catchment. 117

Figure 7. 11 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging in the dry season (April – September) generated from the best 100 WEAP21 models of Ryewater for the dry season. 119

Figure 7. 12 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging in the dry season (October – March) generated from the best 100 WEAP21 models of Ryewater for the wet season 119

Figure 7. 13 Monthly precipitation and flows volumes of Rye water during the year 1994 120

Figure 7. 14 Simulated and observed flows of Ryewater at Lexilip flow gauging station during the year 1994 as produced by WEAP21 model 120

Figure 7. 15 Quantile-Quantile plot of standardised error under the fitted intensity model 124

Figure 7. 16 Simulated distributions of annual time series of mean seasonal rainfall (coloured bands) along with envelope obtained from 39 imputations of rainfall observations for the Ryewater sub-catchment (black). 125

Figure 7. 17 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 rainfall time series from the spatial GLM framework with the best 100 performing parameter sets from the Latin Hyper Cube sampling based on NSE. 126

Figure 7. 18 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combing the 100 rainfall time series from the spatial GLM framework with the best 100 performing parameter sets based on LogNSE.. 126

Figure 7. 19 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated rainfall data for Ryewater sub-catchment during the period 1980-2013 produced by SCL against corresponding distribution of observed rainfall data. 127

Figure 7. 20 Scatter and whisker plots for means of different statistics in the stochastic rainfall data generated by SCL and corresponding statistics in the observed rainfall data. 129

Figure 7. 21 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 rainfall time series from the

SCL and the best 100 performing parameter sets from the Latin Hyper sampling based on NSE. 130

Figure 7. 22 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated temperature data for Ryewater catchment during the period 1980-2013 produced by SCL against corresponding distribution of observed data. 131

Figure 7. 23 Scatter and whisker plots for means of different statistics in the stochastic temperature data generated by SCL and corresponding statistics in the observed rainfall data 133

Figure 7. 24 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 temperature time series from the SCL with the best 100 performing parameter sets from the Latin Hyper sampling based on NSE 133

Figure 7. 25 Results of 100,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 from all possible combinations of stochastic rainfall data, stochastic temperature data, and the 10 best performing parameter sets for the NSE criterion.. 134

Figure 7. 26 Schematic diagram for the model structure of HBV light (Seibert 2005) 135

Figure 7. 27 Simulated (red) and observed (blue) daily flows of Ryewater at Lexilip flow gauging station during the period 1980-2005 (calibration period), produced by the HBV-light model. 137

Figure 7. 28 Simulated (red) and observed (blue) daily flows of Ryewater at Lexilip flow gauging station during the period 2006-2013 (validation period), produced by the HBV-light model 137

Figure 7. 29 Observed and simulated monthly flow hydrographs of Ryewater at Lexilip flow gauging station during the period 1980-2013, based on the best HBV-light model of Ryewater catchment. 138

Figure 7. 30 NSE and LogNSE evaluation results of best 100 simulations of HBV-light (blue) and WEAP21 (red). 138

Figure 7. 31 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light using parameter sets produced from the GAP optimisation process. 139

Figure 7. 32 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily rainfall data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data. 140

Figure 7. 33 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily temperature data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data. 140

Figure 7. 34 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily evaporation data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data. 141

Figure 7. 35 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light using stochastic climate data from the SCL library .. 142

Figure 7. 36 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light model by combining the 100 stochastic rainfall data from the SCL and the 100 parameter sets produced from the GAP optimisation. 142

Figure 7. 37 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light model by combining the 100 stochastic temperature data from the SCL and the 100 parameter sets produced from the GAP optimisation 143

Figure 8. 1 Potential water supply options to meet future water needs of Dublin and surrounding areas……………………………………………………………..............148

Figure 8. 2 Schematic illustrating proposed development of water supply at Parteen Basin 149

Figure 8. 3 Adjusted schematic WEAP-Dublin model used for future simulations. 153

Figure 8. 4 Population projections for the Dublin Region WSA 2011 – 2050 for different planning scenarios. 155

Figure 8. 5 A schematic diagram showing routing pathways of rainfall volumes as programmed in WEAP-Dublin 170

Figure 8. 6 Calculation algorithm used to derive input parameters for urban catchment in the WEAP-Dublin model during the simulation period.. 175

Figure 8. 7 Projections of surface areas for pervious, impervious and decentralised recharge facilities 176

Figure 8. 8 Change in Rainfall Adjustemnt Factor $RF_{(Adj)}$ over the planning horizon 176

Figure 8. 9 Fractions of Infiltration (%Inf) and Runoff (%RO) of monthly rainfall volumes, used in WEAP-Dublin to route rainfall into either infiltration or runoff 177

Figure 9. 1 Monthly water demands for the Dublin Region WSA during the period 2012 – 2050, as predicted by WEAP-Dublin for all scenarios.. 163

Figure 9. 2 Average annual water demand under all water management scenarios, and potential impacts of associated assumptions in terms of conservation and reuse. 180

Figure 9. 3 Mix of water supplies under the baseline scenario for the period 2012 – 2050, as simulated in the WEAP-Dublin model on annual basis. 181

Figure 9. 4 Mix of water supplies under Scenario 2 (Increase supply) for the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis....................................... 182

Figure 9. 5 Mix of water supplies under Scenario 3 (Intensified leakage management) during the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis........... 182

Figure 9. 6 Mix of water supplies under scenario 4 (Total water management) during the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis. 183

Figure 9. 7 Average annual water supplies from existing sources for (1) baseline, (2) Increase supply, (3) Intensified leakage management and (4) Total water management in (2020-2035) and (2036-2050), and reductions in these supplies relative to baseline. 184

Figure 9. 8 Monthly water supply deficits in the Dublin Region WSA (% of water supply requirements) for all scenarios along the period 2020 – 2050, as simulated by the WEAP-Dublin model. 185

Figure 9. 9 Box plots for projected water supply deficits in Dublin Region WSA (2020 – 2050) for all alternatives: Baseline, Increase supply, Intensified leakage management and Total water management – expressed as % of water supply... 186

Figure 9. 10 Annual time-series 2012 – 2050 for (a) rainfall in the urban catchment (in mm) as derived from respective rainfall stations and (b) supplies from rainfall harvesting systems as simulated by WEAP-Dublin under scenario 4 (total water management)....................... 187

Figure 9. 11 Monthly average (a) supplies from rainwater harvesting for decades 2021–2030, 2031–2040 and 2041–2050, as simulated by the WEAP-Dublin model under scenario 4 (total water management), and (b) adjusted rainfall depths for the decades 2021–2030, 2031–2040 and 2041–2050 which corresponds to the climatic conditions of the historic period 1982-2012. 188

Figure 9. 12 "Simulated" urban runoff in the Dublin Region WSA for the period 2020 – 2050, for scenarios 1-baseline, 2-increase supply and 3-intensified leakage management and for scenario 4-total water management. 189

Figure 9. 13 Upper and lower bounds of monthly urban runoff in the Dublin Region WSA for the period 2020 - 2050 under scenarios 1, 2 & 3 and scenario 4 – with monthly average urban runoff for scenarios 1,2, & 3 and scenarios 4 190

Figure 9. 14 Upper and lower bounds of urban runoff amounts in the Dublin Region 2013-2050 for scenario 4 and for all other scenarios as result of considering different urban growth scenarios. 192

Figure 9. 15 Upper and lower bounds of urban runoff under all water management scenarios including a scenario where SuDS facilities are not implemented. 192

Figure 9. 16 Cumulative increase in groundwater storage during the simulation period 2020 – 2050 under scenarios 1 – 3 and scenario 4. 193

LIST OF TABLES

Table 2.1 Classification of models based on their domains as either hydrologic or management, with potential uses and limitations. 20

Table 2.2 A comparison of water resources modelling packages in terms of representing hydrology, water demand management, wastewater and storm water and other programming features 25

Table 3. 1 Description of parameters used within the hydrology modules of WEAP21....... 35

Table 3. 2 Description of parameters used within the water management module of WEAP21 40

Table 3. 3 Parameters used in modelling reservoir operations and hydropower generation in WEAP21 42

Table 3. 4 List of data required to run the model 43

Table 4. 1 Summary of datasets collected to develop water resources planning model for Dublin using WEAP21 47

Table 5. 1 Stations with one missing record and their neighbouring stations 59

Table 5. 2 Estimation of area-weighed monthly rainfall, with the estimation of rainfall for river sub-basin “ML2” in January 2012 provided as an example. 61

Table 5. 3 Initial values of hydrological parameters for land cover – soil combinations within sub-catchment UL, as applied in the WEAP-Dublin model. 65

Table 5. 4 Outline of water supply schemes for the Dublin region and associated deployable capacity, categorised into major and supplementing schemes 69

Table 5. 5 Domestic level of activity characterised by county for each supply zone based on CSO census data 2011. 70

Table 5. 6 Estimated annual growth rates by county as derived from CSO preliminary results - census data 2016.. 71

Table 5. 7 Non-domestic level of activity characterised by county for each water supply zone, based on CORINE land cover 2012. 71

Table 5. 8 Estimated water usage rates for non-domestic activities given by county. 72

Table 5. 9 Summary of water demand components for each supply zone, calculated to parametrise demand sites in the WEAP-Dublin model............ 74

Table 5. 10 Summary of return flow routes from demand sites as represented and parametrised in the WEAP-Dublin model 78

Table 5. 11 Main control levels for Liffey reservoirs 80

Table 5. 12 Hydropower characteristics for Liffey reservoirs 80

Table 6. 1 Gauges used for calibration and validation of WEAP-Dunlin model, and associated owners... 84

Table 6. 2 Final set of calibrated parameters for the WEAP-Dublin model major sub-catchments... 90

Table 6. 3 Average annual water supply input for each zone as simulated in WEAP-Dublin.. 99

Table 7. 1 Prior uniform distributions and assumed ranges for parameters as used in the initial GLUE analysis for the WEAP21 model of Ryewater sub-catchment..................................... 106

Table 7. 2 Posterior distributions for parameters of Ryewater sub-catchment model resulting from the initial GLUE analysis and reductions in ranges relative to the prior distributions. 107

Table 7. 3 Mean and standard deviation for first order sensitivity indices (S1) and total order sensitivity indices (TSI) for all parameters of Ryewater sub-catchment period resulted from 35 year simulation period (1980-2013)... 114

Table 7. 4 Final rainfall model structure for the GLM framework applied to the Ryewater sub-catchment 123

Table 7. 5 Acceptable tolerance levels for differences in statistics used in assessing the quality of SCL models 128

Table 7. 6 Calibrated parameter set for the HBV-light of Ryewater catchment. 136

Table 8. 1 Options and settings for the baseline and water management scenarios as configured in the WEAP model. 152

Table 8. 2 Population projections for Dublin Region WSA during the period 2011–2050 for each planning scenario 155

Table 8. 3 Projected per capita consumption in l/c/d under scenario 2 (Most likely growth) 157

Table 8. 4 Projected per capita consumption in l/c/d under scenario 2 (Most likely growth) 157

Table 8. 5 Projected non-domestic water demands for the Dublin Region WSA 2011–2050 in Mm^3/yr. 157

Table 8. 6 Projected UFW for Dublin Region WSA expressed in volumetric levels and % of DI (in accordance to Irish Water Leakage Target policy)... 158

Table 8. 7 Allowance for peak demands in the Dublin Region WSA 2021 - 2050 159

Table 8. 8 Allowance for headroom and outage for the Dublin Region WSA 2021-2050. 160

Table 8. 9 Deployable output / production capacity of existing water treatment plants in Ml/d. 161

Table 8. 10 Water production requirement from a new source 162

Table 8. 11 Estimated reuse parameter to represent greywater reuse application in the Dublin Region WSA (under Scenario 4) 163

Table 8. 12 Projected number of buildings to incorporate rainwater harvesting system and the corresponding total rooftop area in the Dublin Region WSA during th period 2021 – 2050. 165

Table 8. 13 Urban land-use in the Dublin Region in 2013 and projections to 2026 for the Stagnation, Delayed adjustment and Recovery... 173

Table 9. 1 Statistical summary of predicted water supply deficits 2020 -2050, showing number of deficit episodes, minimum, maximum and quartiles for each scenario – expressed as % of water supply requirement.. 185

Chapter 1 INTRODUCTION

1.1 Background

Management of water resources has become increasingly complex due to pressing issues such as population growth, urbanisation, climate change and stricter regulatory requirements. The traditional paradigm for water management is no longer adequate to address such evolving challenges. In response, a new paradigm of integrated water resources management (IWRM) has emerged, which incorporates principles of sustainability and promotes a more holistic view of water resources system. In contrast to the traditional paradigm, IWRM aligns development of water, land-use and other related resources to maximise economic and social benefits, whilst preserving sustainability of the vital ecosystem (GWP 2012). Important features of IWRM include: (i) reduced reliance on fresh water supply sources; (ii) reduced discharges to receiving water bodies (iii) increased water recycling and reuse; (iv) matching water quality to end-use demands including natural ecosystems; and (v) recognising alternative water sources. Whilst the traditional paradigm separates water into three distinct sectors (i.e. drinking water, wastewater and storm water), IWRM places a great emphasis on the interrelationships between these components and views them as interconnected parts of an overall system. In other words, IWRM views all water as resource which undergoes a cycle, and therefore can be managed in a fully integrated manner (Rodrigo et al. 2012, GWP 2012). Hence, IWRM advocates a shift toward multi-purpose and multi-benefit projects to address challenges facing the water resources.

In light of the IWRM paradigm, a wide spectrum of alternative management options for water supply, wastewater and storm water management have evolved. For instance, demand management options include leakage control, water conservation campaigns, water metering and charging, and promoting the use of water-efficient devices (Butler and Memon 2006). On the other hand, urban runoff management has moved from solely focusing on volume control to a multi-disciplinary approach, with drainage solutions that address water quality, quantity, biodiversity and ecological flows, and amenity in an integrated manner i.e. sustainable urban drainage systems (SuDS) in Ireland (DDC 2005a) and in the UK (CIRIA 2015), low impact developments in the USA and Canada, or water sensitive urban design in Australia (Lloyd 2001) and New Zealand (https://www.landcareresearch.co.nz/). Such drainage solutions attempt to mimic the behaviour of natural environment and ecological processes, and promote a decentralised approach by placing greater emphasis on on-site collection, treatment and utilisation of water (Karamouz et al. 2010). Developing a sustainable water management strategy requires water managers to increasingly incorporate such alternative options alongside with existing centralised large-scale systems, which are likely to continue to dominate in many regions for the next few decades (Karamouz et al. 2010, Brown et al. 2009). Such strategy requires adequate scientific understanding of environmental pressures and anthropogenic drivers, and the associated impacts on the hydrological cycle (Marsalek et al. 2006). Also, the integration of decentralised options with existing centralised systems produces complex interactions which need to be carefully assessed (Sitzenfrei et al. 2013; Urich et al. 2013).

Computer-based models for water resources planning and management play a crucial role in the search for sustainable solutions. In a planning framework, such model of the system is the central analytical tool whereby the performances for a variety of water management alternatives are quantified and evaluated against development objectives (Loucks et al. 2005; Bach et al. 2014; Mitchell et al. 2007; Diaz-Granados et al. 2009). Recent developments in the field of water resources management modelling have led to software tools which incorporate principles of IWRM and seamlessly integrate the supply and demand sides of the equation in one single platform; for example, the Water Evaluation and Planning software WEAP21 (Yates et al. 2005) and Source Integrated Modelling System IMS (Welsh et al. 2013). In such models, infrastructure and demand components can be nested within underlying hydrologic processes, making them well suited to study dynamic changes within the water system i.e. changes in term of climate, land-use, water use patterns, or policy and technological conditions (Yates et al. 2009, Young et al. 2009, Yates et al. 2013a).

1.2 Problem definition

Against this background, the Dublin region, which is important to the Irish economy, faces a number of challenges in term of its water resources management. The region approximately requires 550 Ml/d of water to meet the demand of approximately 1.60 million people and hosted industries. Approximately 85% of the water is supplied from the Liffey and Dublin Bay catchment, in particular from major Liffey schemes at Phollaphuca and Lexilip reservoirs (DCC 2010a, Irish water 2015a, Irish water 2015b). The supply requirement is projected to increase to 850 Ml/d by 2050 primarily due to expected population growth, migration and industry growth. Figure 1.1 projected population growth in the Dublin Region under different planning scenarios during the period 2011 – 2050, suggesting a potential increase in population up to 2.2 million people. Research studies and public consultations suggest that existing water sources and infrastructure for the region have insufficient capacity and inadequate resilience to meet future needs in a sustainable manner. It is evident that the existing water supply system is under pressure to meet current needs, and already a number of significant outages occurred in Dublin over the past six years (Irish Water 2016a).

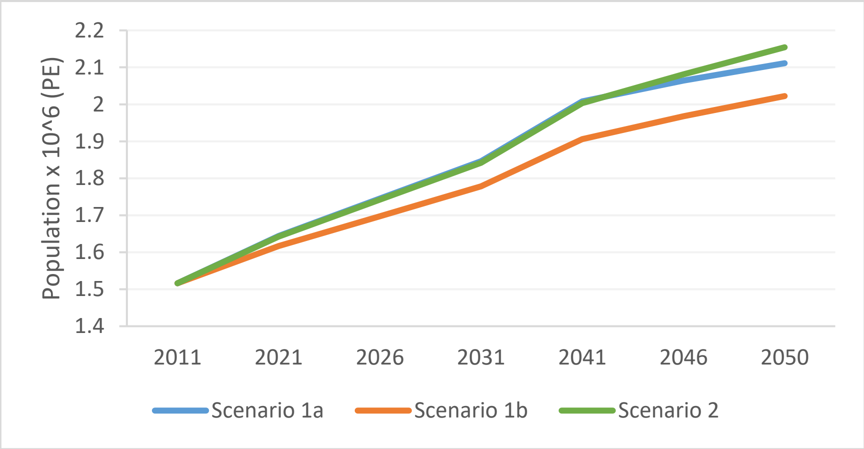


Figure 1.1 Projected population growth in Dublin Region under different planning scenarios (Scenario1a, Scenario1b, and Scenario 2) Source: Irish Water 2015b.

The current water supply system suffers from serious technical problems, including; (i) the maximum sustainable production capacities of existing sources are not entirely deployable throughout the network due to infrastructure capacity constraints; (ii) the system operates on a knife-edge regime with significant sections operating continuously and cannot be taken out from service for essential maintenance; and (iii) lack of strategic headroom and connectivity between sources (DCC 2010a, Irish Water 2015a). As such, the system is susceptible to short-term contingences (e.g. reduced production output due to a source disruption or increased demand due to severe climatic conditions), and consequently not resilient to maintain a satisfactory level of service to customers in such conditions (DCC 2010a, Irish Water 2015a). Furthermore, leakage from the supply network is significantly high and estimated to be in the region of 35-40% of total supply (including customer side leakage). This figure is twice the leakage level in the UK, where assets are quite comparable but have been subject to intensive management over the last 20 years (Irish Water 2015b). In order to address the projected deficit of water supply, the current governance approach relies heavily on a combination of identifying a new source for water supply to secure long-term water needs of the region along with achieving ambitious water conservation targets aimed to reduce leakage and water usage for various sectoral users (Kelly-Quinn et al. 2014, Irish Water 2016b). Climate change also constitutes another pressure on the system, with assessments suggesting that reliable yields of existing sources are likely to decrease under such conditions. Yet, the precise degree of this reduction is still unknown and requires evaluation to allow designing appropriate climate change adaption plans for water supply (Irish Water 2016b). Hence, information from such assessment can help generate water resources plan that are robust against climate change and associated uncertainties.

On the other hand, the urban drainage system of the region is a mixture of separate and combined sewers, with the prevailing of considerable number of sewer overflows discharging directly to receiving waterbodies. The system also comprises wastewater treatment works, with varying degrees of treatment efficiencies of foul flows. The greater Dublin strategic drainage study (GDSDS) conducted an in-depth assessment of the existing drainage system; it concluded that the existing system is overloaded, and it has insufficient capacity to cater for future development (DDC 2005a). For example, the biggest wastewater treatment work for the Dublin Region (Ringsend) is designed to treat 1.64m PE however approximately 1.9m PE currently arrives at the treatment work. New developments will increase the level of urbanisation, which in turn may result in accelerated runoff response, increased risk of flooding, and decline in water quality and loss of habitat and biodiversity. Climate change also is anticipated to reduce the level of service of the drainage system, due to increased rainfall intensities and higher sea levels. Moreover, there is substantial inflow and infiltration into the system, which will continue to compromise its capacity to service future development. Exfiltration of foul flows from the system contaminates surrounding soils and possibly groundwater bodies. The storm water drainage system and in particular spills from combined sewer overflows has resulted in an elevated level of pollution in our watercourses, which in turn poses a challenge for local authorities to achieve good ecological status for all waters as set out in the EU water framework directive (WFD). The environmental protection agency (EPA) indicates that 80% of rivers within the Eastern River Basin District are classified as below good status (http://www.dublincity.ie). Given population and land use projections, the GDSDS indicated the need for additional system capacity (in term of treatment and conveyance) to cater for future development and a shift toward sustainable drainage practices to deal with storm water. As set out in the GDSDS, the strategy to meet the future needs includes a combination of a new regional wastewater treatment plant, optimisation and upgrading of existing infrastructure, and implementation of five output policy documents, including: new development, environmental policy, climate change, inflow/ infiltration and exfiltration, and basements. The policy documents were established to ensure that future development does not continue the trend toward increased flooding in the region and pollution of its rivers. For instance, in accordance with the new development and environmental policies, all developers are required to incorporate SuDS facilities to reduce runoff to pre-development limits whilst partially treat the effluent.

The current state of the existing water resources system in Dublin is that urbanised areas consume large quantities of fresh water while discharging ever-increasing volumes of wastewater and storm water to receiving waterbodies. This in turn requires costly and energy-intensive treatment processes and also results in detrimental impacts on our environment (Van Lennep & Finn 2008). In such traditional approach of supply and disposal system, interrelationships and synergies among different water components are sometimes overlooked, which would otherwise bring relative benefits to the system to adequately solve water resources goals (Rodrigo et al. 2012). Therefore, IWRM has been proposed as a viable strategy to address existing and future challenges facing water resources in the Dublin region where all water components - which comprise water supply, wastewater and storm water - are ideally managed in a single holistic and comprehensive strategic plan (DDC 2005a, DCC 2010b). This strategy requires a systematic investigation in which alternative sets of water management options can be evaluated in a scenario-based approach under possible future conditions of land use, water use patterns and climate change. Willuwiet and O'Sullivan (2013) conducted a study to assess water supply and demand in Dublin by investigating the effects of urban development and climate change on the urban water cycle using the dynamic urban water simualtion model (DUWSiM). The DUWSiM model primarly focused on quantification of demand and stormwater runoff, but neglected other imporatnt aspects such as infrastructre and operating rules, water uses, groundwater storage, wastewater available for recycling, and availability of rainwater for supplies. This highlights a gap in previous water resources management model for Dublin and hence the need for models to consider water options such as rainwater havrvesitng, wastewater recycling and groundwater recharge – which are important for the implementation of integrated water resources management plan.

1.3 Overall aim

The current PhD study aims at addressing the above-mentioned identified gap by developing a more comprehensive water resources planning model for Dublin using the Water Evaluation and Planning Software (WEAP21) – developed by the Stockholm Environment Institute, US. WEAP21 allows the user to build a customised model of the water resources system in an interconnected manner with representation of the hydrology, sectoral water uses and the human-managed system including major infrastructure and operating rules. WEAP21 is a "systems model" capable of representing different components of the overall water system. This in turn allows WEAP21 to evaluate the impact of one management decision on multiple sectors of the system.

Moreover, another water resources modelling requirement tasks is to quantify uncertainty in model predictions before communicating the final modelling results to decision makers. The main sources of uncertainties in streamflow predictions of water resource models are (i) model parameters, (ii) input forcing data, and (iii) model structures (Walker et al. 2003; Beven 2009; Mockler et al. 2016a). This study couples WEAP21 with the statistical parameter optimisation tool (SPOTPY) and stochastic climate models to quantify effects of these sources of uncertainties on model output and to estimate an overall predictive uncertainty in streamflow predictions of WEAP21. The results from WEAP21 are also compared with results from HBV-light modelling in order to investigate the effects of using different model structure on flow predictions.

1.4 Research objectives

i. To develop an integrated water resources management model for Dublin using WEAP21 software package,

ii. To extend the capability of WEAP21 software for estimating uncertainty in model output due to parameter estimation and forcing inputs.

iii. To compare uncertainties in flow simulations using two different model structures: WEAP21 and HBV-light.

iv. To demonstrate the use of the developed model for assessing the impacts of a number of water management scenarios on the existing water system - under what-if scenarios of land-use and water-use patterns.

v. To evaluate the relative benefits of sustainable water resources management options over traditional approaches,

1.5 Research methodology

The objectives of the study are achieved using an approach based on two “state of the art” guidelines on development of IWRM models used in water resources planning. The two guidelines are (i) the Central European simulation group (HSG) (Muschalla et al. 2008); and (ii) total water management analysis protocol (Rodrigo et al. 2012). The adopted approach involves development of IWRM model for the Dublin region using the WEAP21 software and then applying the resulting model to evaluate water management alternatives under plausible future scenarios of population growths and urban development. Figure 1.2 (page 12) summaries the adopted approach and shows the four main elements, which comprise: (1) Literature review of IWRM modelling; (2) Data collection and processing; (3) Model development and uncertainty analysis; and (4) Evaluation of “what-if” scenarios. These elements are discussed in details in subsequent chapters.

1.6 Report outline

Chapter 1 provides an introduction describing the background and motivation for the research, with emphasis on recent modelling software being used in water resource planning. It then states research objectives and outlines the research methodology.

Chapter 2 describes the principle concepts in integrated water resources management modelling, and presents a literature review of different integrated water resources management models. It also presents a literature review of the application of WEAP21 software in different river basin across the world for the purpose of water resources planning.

Chapter 3 describes the WEAP21 modelling software and its modular structure, illustrating the computation algorithm and model parameters used in each module.

Chapter 4 describes the data collection and the data preparation processes.

Chapter 5 presents the development of the WEAP21 model for Dublin. It mainly focusses on configuration and parameterisation of model components including the WEAP21 catchments, demands and infrastructure.

Chapter 6 discusses the calibration and the validation of the WEAP21 model. The graphical and the statistical methods, which have been used to assess the model performance, are also presented.

Chapter 7 focuses on analysing and estimating uncertainty in streamflow predictions of two modelling software: WEAP21 and HBV-light. In particular, it describes the use of uncertainty analysis methods and tools for understanding and reducing parameter uncertainties. It also describes the use of stochastic climate modelling for considering uncertainties due to climate forcing data. It finally presents predictive uncertainties of simulated flows resulted from combining the behavioural parameter sets of each model structure and stochastic climate data.

Chapter 8 reviews recommendations of different studies pertaining to future water demands, potential water supply options, and storm water management options. It also describes the development of four water management scenarios that are evaluated using the developed WEAP21 model for Dublin.

Chapter 9 demonstrates the use of the developed model for simulating the four water management scenarios, and then evaluates their performances in terms of variables such as water balance and supply reliability, urban runoff generation and groundwater recharge.

Chapter 10 states the conclusion of the thesis and suggests possible directions for future research.

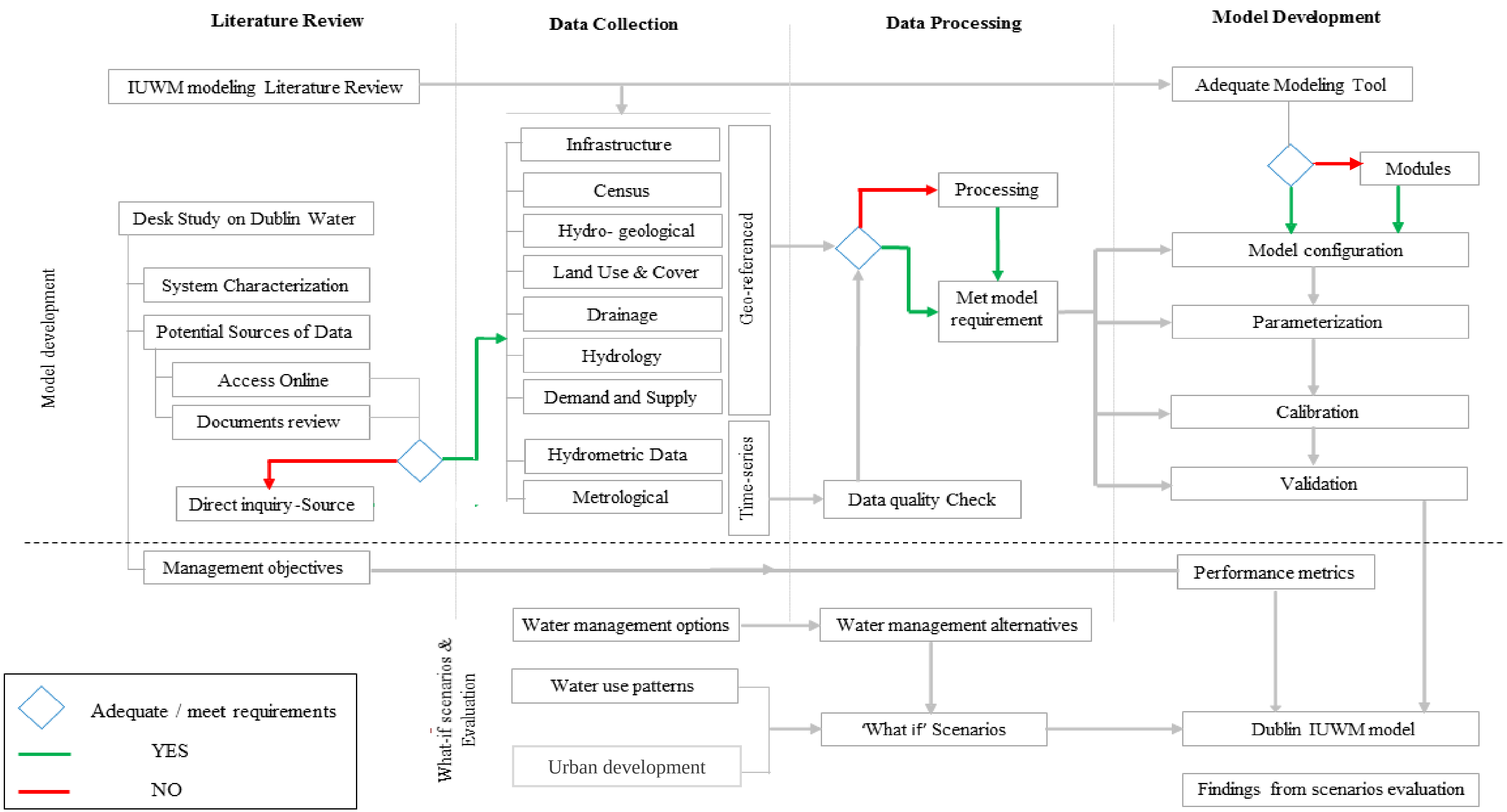


Figure 1. 2 Work flow diagram of the current research

Chapter 2 LITERATURE REVIEW

2.1 Introduction

In the context of the urban water resources management system, mathematical models are used to understand and predict the behaviour of the system (Mitchell et al. 2007; Vojinovic & Seyoum 2008; Loucks et al. 2005; Diaz-Granados et al. 2009). Traditionally, these models were developed on a sectoral basis, and in most cases no interactions among sectors were accounted for (Welsh et al. 2013, Bach et al. 2014). More recently, a new paradigm of water resources management has emerged which requires all water components to be managed in a fully integrated manner. The new paradigm, known as Integrated Water Ressources Management (IWRM), emphasises on the interrelationship between the different components and require a more holistic view of the system (Rodrigo et al. 2012, GWP 2012). Consequently, the new paradigm has led to more stringent regulatory requriments and a greater emphasis on environmental quality and ecological status. For example, the EU water framework directive (WFD) requires all member states to manage water at river basin level in an integrated manner, and to achieve good ecological and chemical status for all water (EU Commission 2000). As such, water planning and management tools have evolved along the same path as management (Bach et al. 2014). Integration of the system components has become a necessary feature to capture the inherent complexity of the system and its interconnected components (Bach et al. 2014, Welsh et al. 2013, Elliott & Trowsdale 2007, Yates et al. 2005).

This chapter first provides a review on integration in urban water resources modelling; then it illustrates the distinction in the literature between hydrologic models, water management models, and recently developed "combined" models – which seamlessly integrates both components (i.e. hydrology and water management) in one platform. Based on this classification, a review of a number of existing water resources modelling software has been undertaken in order to highlight the potential uses and limitations of each model. The current study uses the Water Evaluation and Planning software WEAP21 (i.e. seamlessly integrates hydrology and water management components) and hence a number of studies showing its application in different river basins across the world for planning purposes are presented.

2.2 Integration in urban water resources modelling

Modelling the urban water system in an integrated manner has been a challenging task for researchers and practitioners. The complexity of the urban water system prevents simple integration of physically-based of the individual sub-systems. Bach et al. (2014) and Vojinovic & Seyoum (2008) attributed this limitation to; (i) models being quite complex and require sophisticated algorithms to integrate them; (ii) models vary in purpose at their time of development; and (iii) other issues such as incompatibility among parameters, variables and scales. This approach also is argued to result in expensive computational costs, making physically based models impractical and inefficient for use in strategic purposes – where the focus is to perform many simulations in order to derive the optimal solution.

To address these challenges, there has been a tendency to adopt integrated conceptual modelling to replicate the larger urban water system. The philosophy behind this approach is that strategic planning seems to require computationally less expensive and less complex models, yet capable of producing accurate results comparable to those obtained from physically-based models. With such simplification, multiple scenarios can be assessed at the planning stage, which otherwise would require excessive data and long running times (Yates et al. 2005; Vojinovic & Seyoum 2008; Bach et al. 2014; Diaz-Granados et al. 2009).

Other challenges in the field of integrated urban water management (IUWM) modelling include institutional barriers, data requirements, and limitation in computational capabilities. Over the past few decades, advancements in the research have focused on addressing all above issues, and so different integration approaches have emerged over the time (Bach et al. 2014, Mitchell et al. 2007). The literature is rich with diverse IUWM models; which vary in structure, purpose, level of integration and other key features (i.e. configuration, temporal and spatial detailing).

In term of structure, IUWM models may either be in the form of a single comprehensive model or a single computational framework integrating various sub-system models. In the latter form, sub-system models may be either loosely coupled in which simulations of processes occur sequentially (simulation of processes run one after another in each time step) or tightly coupled in which simulations of processes are synchronised and occur simultaneously (Bach et al. 2014; Mitchell et al. 2007; Diaz-Granados et al. 2009). Mitchell et al. (2007) argues that the shortcoimg of the loosely coupled modeling approach is that processes are modeled in a unidirectional form and flows are configured in a tree-like structure, with no feedbacks passing between sub-systems. In contrast, tightly coupled modeling allows feedbacks to pass back and forth among sub-system models at each time step, and hence their use outwieght losely coupled models (Schmitt & Huber 2005). It has been added that no single model is able to adequately integrate all sub-system models, and that there were no better alternative than tightly coupled modelling approach (Mitchell et al. 2007).

Modelling approaches may also vary in accordance with the purpose or development objective of the model such as; planning, optimisation, design or operational purposes. The main differences between the various approaches as identified by Vojinovic & Seyoum (2008) include data requirements, generated results, sophistication of analysis and running times. Models are also classified as being online or offline. In online models, results are used to simultaneously evaluate and control real-time operations. On the other hand, offline models are unidirectional and are used more for design and planning purposes (Diaz-Granados et al. 2009; Bach et al. 2014).

Integration in the field of urban water resources modelling is summarised by Bach et al. (2014) as follows; (i) representation of multitude components (biophysical / economic and beyond) and their interactions (ii) modelling of acute, chronic and delayed water quantity and quality processes and (iii) ability to capture processes at small and large scales. Against this definition, Bach et al. (2014) proposed a typology where IUWM models are classified into one of four 'degrees of integration' - thus to bring literature into order and to allow constructive improvements in the ongoing research. The four degrees of integration are integrated component based models (ICBMs), integrated urban drainage models (IUDM), integrated urban water cycle models (IUWCMs) and integrated urban water system models (IUWSMs). At the lowest level of this typology are ICBMs which integrate components within an individual sub-system (e.g. wastewater treatment processes). At the highest level, IUWSMs links total water cycle to other aspects in the broader environment (e.g. climate, ecology, economics, energy and societal issues). Figure 2.1 below outlines the typology only and further details and examples on each type can be found in Bach et al. (2014).

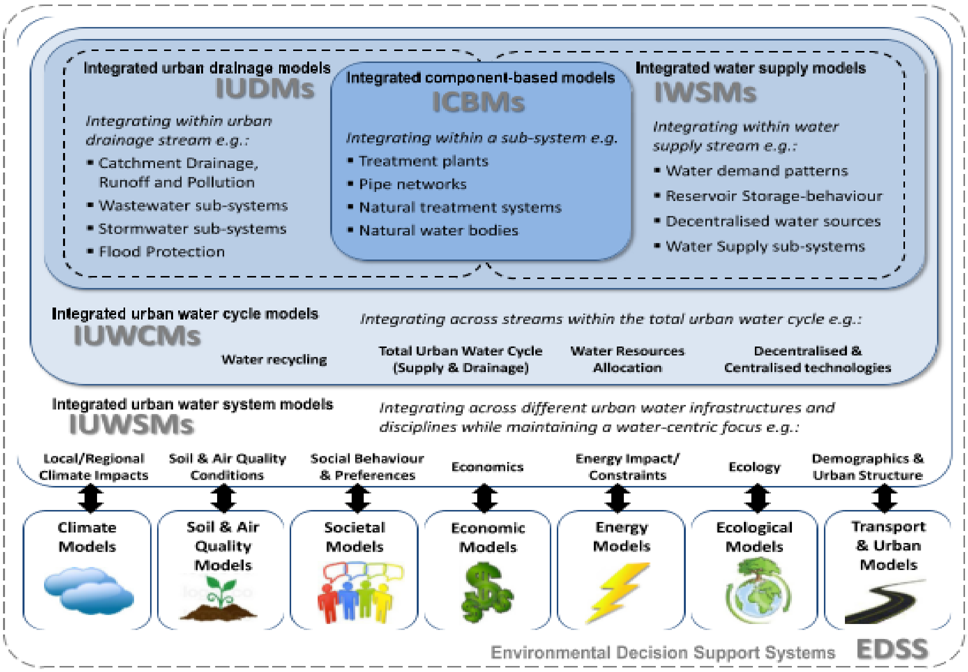


Figure 2. 1 'Four Degrees of Integration' Typology for IUWM models. Source: Bach *et al* 2014

As referred by Bach et al. (2014), three models are considered to be at the highest level of integration, being able to draw links between the urban water system and other aspects of the wider environment. The three models are: Dance4Water (Urich et al. 2013), VIBe (Sitzenfrei et al. 2013), and ReVISIONS (Ward et al. 2012). Dance4Water and VIBe are tools developed based on the concept of virtual infrastructure benchmarking; in which virtual urban water systems are stochastically generated to allow statistical evaluation of multiple strategies and technologies in an evolving urban environment (both spatially and temporally). These models incorporate urban development modules and biophysical modules linked together by means of complex interactions (conductor for information management, storage and execution among sub-modules). In the case of Dance4Water, a societal transition module is introduced to account for societal needs. The concept behind developing these models is to address the limited availability of case studies that document the impact of transition from centralised technologies to increased utilisation of decentralised technologies i.e. i.e. sustainable urban drainage systems (SuDS) in the

UK (CIRIA 2015), low impact developments in the USA and Canada, or , water sensitive urban design in Australia (Lloyd 2001) and New Zealand (https://www.landcareresearch.co.nz/). Thus, Dance4Water and VIBe models intend to provide better understanding of the impacts of such transition in strategies through generation of virtual case studies, which would also help to understand the interaction between existing centralised and decentralised options in an urban setting. On the other hand, ReVISIONs utilises a range of models based on an integrated framework to assess urban environment sectors (i.e. water, waste, energy and transportation) in order to support decision- making on a combination of infrastructure measures for future development at a regional scale. These models are still in their development phase.

The 'four degrees of integration' typology is understood to be framed within the environmental decision support system. Whilst it attempts to assess IUWM models in relation to the full scope of the environment, it gives little attention to the nature of local processes (e.g. natural or anthropogenic), and how modelling approaches vary in their representation and integration of these processes. It therefore might be difficult to make a decision on which model type to use in case local processes of the total water cycle are of greater interest.

2.3 Hydrology and water management models

A more technically appealing classification of IUWM models is described by Yates et al. (2005) and Bellin et al. (2016) in which models either tend to focus on how water flows within a catchment in response to a hydrologic event (hydrologic simulation) or tend to focus on the allocation of water which becomes available after these events (management-oriented). Hydrologic simulation models attempt to capture important land – atmosphere components of the hydrologic cycle (Singh 2012), but also, some may incorporate simplified management components (Bellin et al. 2016). Under this group comes the following models (Yates et al. 2005; Bellin et al. 2016); MIKE SHE (DHI 2009), Army Corp of Engineers Hydrologic Engineering Centre HEC-HMS (Feldman 2000), US Department of Agriculture's Soil Water Assessment Tool SWAT (Arnold & Allen 1993; Neitsh et al. 2011) and HSPF (Bicknell et al. 1997; Lampert & Wu 2015).

On the other hand, the management-oriented category includes (Yates et al. 2005; Bellin et al. 2014): MODSIM DSS (Labadie et al. 1989), MULINO DSS (Giupponi et al. 2004), IQQM (Simons et al. 1996), RiverWare DSS (Zagona et al. 2001), HEC-ResSim (USACE 2003). These models focus on representing anthropogenic processes (human activities such as reservoir operations, hydropower generation, storage, diversions, water uses and administrative aspects of the river basin), but also may adopt simple hydrological components. Yates et al. (2005) added that in some cases, management models were linked to external sources to feed in hydrologic information for achieving a higher level of integration; For example, the US Geological Survey's Modular Modelling System established a framework in which Riverware was linked to a rainfall-runoff model to define boundary flows for the model. Similarly, MODSIM DSS and MULINO DSS can accommodate catchment hydrology models.

Nalbantis et al. (2011) introduced the terms 'monomeric' and 'holistic' models. 'Monomeric' models are used to describe models in which parts of the system are being modelled in a greater level of details than others are. 'Holistic' models are used to describe models that attempt to study all parts of the system at an equal level of detail, and incorporate feedback mechanisms to link them. Bellin et al. (2016) lists the following models MIKE Hydro (DHI 2003), RIBASIM (Deltares 2010) and DSF (MRC 2004) as being 'holistic' models. However, they added that transferability of these models to contexts different to what they have been based on seems to be problematic and limits their applications. WaterWare DSS (Fedra and Jamieson 1996) can be inferred to fall within this group, as it integrates both the hydrology and water management components (Yates et al. 2005); however, it needs high hardware requirements and sophisticated level of user – which renders it as not suitable for general use.

In the context of holistic models, WEAP21 (Yates et al. 2005) and source IMS (Welsh et al. 2013) integrate physical hydrologic processes (i.e. runoff, groundwater and surface water interactions) and anthropogenic/ management processes (i.e. reservoirs, water uses and demands, hydropower) in a relatively balanced manner. These models adopt an object-oriented programming approach, and hydrologic and anthropogenic processes are conceptualised through nodes and links (Yates et al. 2005; Bellin et al. 2016; Welsh et al. 2013). Bellin et al. (2016) added HYDROGEIOS (Efstratiadis 2008) to this group, but the particular focus was given to the previous two models. It can be inferred from the literature that WEAP21 and source IMS have advantages over other 'holistic' models in being more user-friendly, readily available to a wider water resource community and more generally applicable. Table 2.1 below classifies these model based on type (specific domain / holistic) and theme (hydrological / management or both), and provide a summary of their potential use and limitations.

Strategic studies for water supply (DCC 2010b) and for drainage (DDC 2005a) have recommended an integrated approach for water resources management to address existing and future challenges facing water resources management in Dublin. This can be achieved by incorporating sustainable water management options in all aspects of water supply and drainage aspects (DDC 2010b, DDC 2005a). Hence, a suitable modelling package for this study should be able to compute water mass balance including water supply and drainage, compute changes in water quality, able to

Table 2.1 Classification of models based on their domains as either hydrologic, management with potential uses and limitations of each

Type	Theme	Software	Source	Developer: software full name	Potential use and limitations
Domain – specific	Hydrologic	SWAT	(Arnold & Allen, 1993)* (Neitsh et al. 2011)**	US Department of Agriculture Soil Water Assessment Tool	Potential use: Sophisticated physical hydrologic modules which describe, among, others rainfall-runoff processes, irrigated agriculture, point and non-point watersheds dynamics Limitation: Relatively simple reservoir operations, and no feedback system in between natural and human systems
		MIKE-SHE	(DHI, 2009)**	Danish Hydraulic Institute	Potential use: Capable to simulate all land-phases processes of the hydrologic cycle Limitation: Simplifications on water use component and minimal attention given to natural – human components interactions
		HEC-HMS	(Feldman, 2000) **	United States Army Corps of Engineers: Hydrologic Engineering Centre –Hydrologic Modelling System	Potential use: Simulates rainfall-runoff processes of dendritic watersheds Limitation: Simplifications on water use component and minimal attention given to natural – human components interactions
		HSPF	(Lampert and Wu, 2015) **	Hydrological Simulation Program in Fortran – An open Source Software Package	Potential use: used more for hydrologic simulations Limitation: Simplifications on water use component and minimal attention given to natural – human components interactions
		HYMOS	(Cited in Singh, 2012)	Delft Hydraulics Laboratory	Potential use: Simulates rainfall-runoff and surface and groundwater hydrology Limitation: limited representation of water management components

Domain – specific	Management	IQQM	(Simons et al. 1996) **	Integrated Water Quantity and Quality Simulation	Potential use: Water management-oriented adopts simple hydrologic components Includes instream water quantity and quality modules. And rainfall-runoff pollutant generation and groundwater, and quantity and quality module on a development phase (as author's publication 1996) Limitations: limited representation in hydrologic components
		MODSIM DSS	(Labadie et al. 1989)*	MODSIM DSS	Potential use: A river basin network flow model incorporates physical, hydrological and institutional / administrative aspects including water rights. It is able to represent river transbasin issues, large-scale water supply projects and complex, and multi-purpose reservoir systems Limitations: require boundary flows from an external physical hydrologic model
		RiverWare^{TM} DSS	(Zagona et al. 2001)*	RiverWare^{TM} DSS	Potential use: To develop multi-objective simulation and optimisation of river and reservoir operations, i.e storage, hydropower operations, river reaches, diversions and water uses) Limitations: require boundary flows from an external physical hydrologic model
		MFSP	(Li et al. 2009)**	Multistage fuzzy-stochastic programming mode	Potential use: Decision support system for sustainable water allocation and management, developed to deal with high uncertainties
		HEC-ResSim	(USACE, 2003)*	US Army Corp of Engineers: Hydrologic Engineering Centre – Reservoir Simulation	Potential use: Able to describe reservoir operations; release requirements and constrains, hydropower operations and multiple reservoirs operations

	Management	HEC-ResSim			Limitations: require boundary flows from an external physical hydrologic model
		MULINO DSS	(Giupponi et al. 2004)*	MULINO DSS	Potential use: A decision support system to inform sustainable use of water. It integrates socio-economic aspects and environmental modelling, with geo-spatial references and multi-criteria analysis. It places more emphasis on DSS as a Multi Criteria Decision Aid.
Holistic	Hydrological and Management	MIKE HYDRO	(DHI 2003)**	Delft Hydraulics Modelling Group	Potential use: A GIS-based model capable to investigate water supply and demand issues under climate change projections for long time planning horizons
		RIBASIM	(Deltarea 2010) **	Delft Hydraulics River Basin Simulation Model	Potential use: A water resource planning model able to investigate the behaviour of river basin in response to hydrologic events
		HYDROGEIOS	(Efstratiadis et al. 2008)**		Potential use: able to represent hydrologic system influenced by water uses. It has a relatively sophisticated human components, which incorporate a linear programing network technique, Limitation: lack to a feedbacks with groundwater and stream components
		DSF	(MRC, 2004)**	Decision Support Framework	Potential use: Designed as a long term planning tool
	Sophisticated level of user and high hardware requirement	Waterware	(Fedra and Jamieson, 1996)*	Waterware	Potential use: A sophisticated Water Resource DSS which incorporate and integrate a variety of physical (rainfall-runoff, water quality groundwater) and management components (demand / supply , benefit – cost analysis)

	More Applicable and User Friendliness	WEAP	(Yates et al. 2005)	Stockholm Environment Institute: Water Evaluation and Planning System	Potential use: WEAP places supply-side *rainfall-runoff, groundwater, surface water and interactions* with demand-side *water uses, reservoirs, instream flow, WWTPs, hydropower operations* on an equal footing basis It adopts a scenario-based approach allowing analysis of multiple scenarios, incorporating changes in climate or anthropogenic stressors (i.e. land use, change in demand). Limitations: Hydrologic and human components are loosely coupled meaning that interactions are taken into account to the only nearest node; the model has no built-in functions for performing uncertainty analysis and estimation of predictive uncertainty
		Source IMS	(Welsh et al. 2013)	Source Integrated Modelling System (IMS)	Potential use: It allows modelling of regulated river systems by integrating complex hydrological processes, regulatory mechanisms and drivers for change, at spatially scales ranging from sub-catchment to river basin and at a primarily daily temporal scale Its components include simulation of catchment runoff, river system network, Interactions between river and flood plains and groundwater, water quality, river regulation and storages, Urban Irrigation and environmental needs and complex river management rules Limitations: Hydrologic and human components are loosely coupled meaning that interactions are taken into account to the only nearest node.

* Cited in Yates et al. 2005 ; ** Cited in Bellin et al. 2016

represent sustainable water management options (e.g. rainwater harvesting and wastewater reuse), to estimate potential impacts on ecology, can be linked to other ad-hoc modelling software for energy uses, groundwater and water quality, and can be expanded using scripting features to assess and reduce uncertainties in model outputs.

A comparison of features and capabilities of the different water resources modelling packages has been performed to find a suitable modelling package for the current study (Table 2.2). Compared to all other software packages, WEAP21 and source IMS encompass a wider range of features in terms of simulating hydrology, water demand management, and storm and wastewater drainage to water bodies. WEAP21 has additional features over source IMS such as scripting using standard programming languages (e.g. Python, Visual basic and Java script) to write new functions, and can be linked to other modelling software such as LEAP for studying and analysing the water-energy nexus, QUAL2K for water quality modelling and MODFLOW for groundwater modelling. The capabilities of the different water resources modelling packages are also mapped in the score matrix (Figure 2.2) which shows that WEAP21 and IMS source software have scored the highest compared to all other modelling software.

Based on this review, two water resources modelling software can be seen as fit for the purpose of our study; WEAP21 and Source IMS. However, additional features of WEAP21 such as scripting in standard programming language and linkage to other ad-hoc software for energy and water quailty make it more appealing. Also, a closer investigation revealed that Source IMS were developed to address the need of Australian agenices for a tool that combines planning with operational asspects; most of Source IMS applications are within the Australian context. On the other hand, it was revleaed

Table 2.2 A comparison of water resources modelling packages in terms of representing hydrology, water demand management, wastewater and storm water and other programming features.

Software	Reference	Hydrology			Water management							Wastewater & stormwater					Programming				
		Surface water	Groundwater	Water Quality	Water demands	Surface Reservoirs	Hydropower	Compensation flows	Infrastructure capacities	Leakage and losses	Costs	Collection	Treatment	Wastewater reuse	Rainwater harvesting	Sustainable drainage	Programming and scripting	Graphical user interface	User-defined variables	Uncertainty analysis	Link to other software
SWAT	(Arnold & Allen, 1993)																				
MIKE-SHE	(DHI, 2009)																				
HEC-HMS	(Feldman, 2000)																				
HSPF	(Lampert and Wu, 2015)																				
HYMOS	(Cited in Singh, 2012)																				
IQQM	(Simons et al. 1996)																				
MODSIM DSS	(Labadie et al. 1989)																				
RiverWare™ DSS	(Zagona et al. 2001)																				
MFSP	(Li et al. 2009)																				
HEC-ResSim	(USACE, 2003)																				
MULINO DSS	(Giupponi et al. 2004)																				
MIKE HYDRO	(DHI, 2003)																				
RIBASIM	(Deltarea 2010)																				
HYDROGEIOS	(Efstratiadis et al. 2008)																				
Waterware	(Fedra and Jamieson, 1996)																				
WEAP21	(Yates et al 2005)																				
Source IMS	(Welsh et al 2013)																				

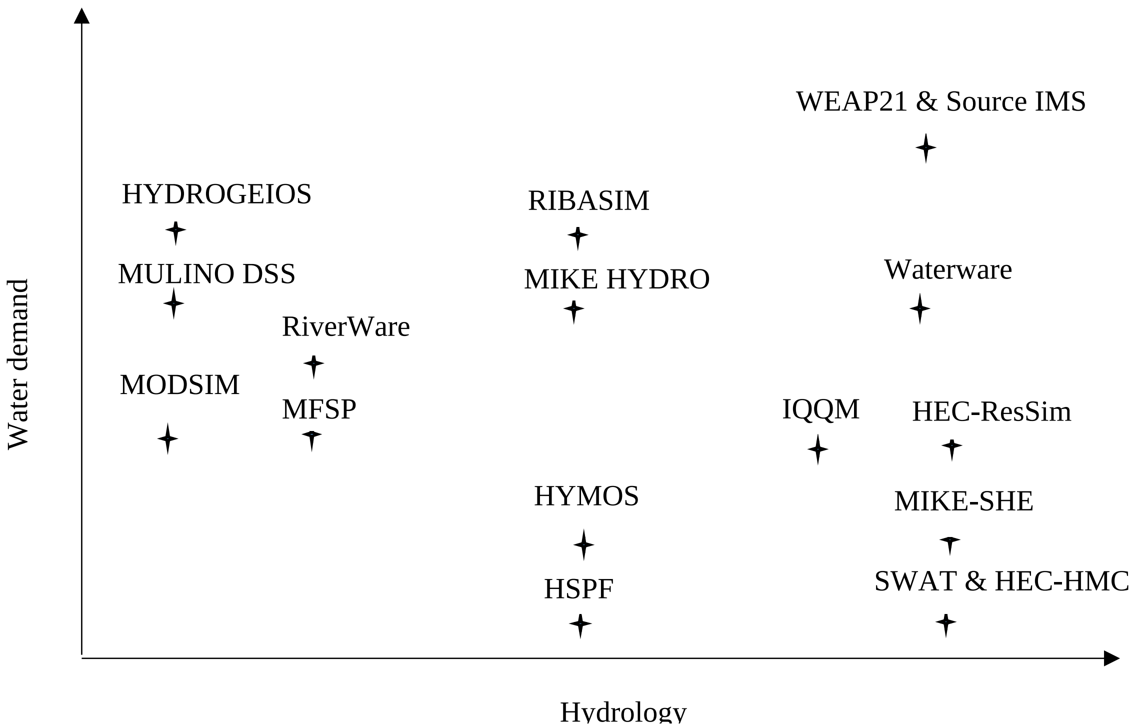


Figure 2.2 Score matrix for different water resources modelling packages based on their capabilities in representing hydrology and water demand management sides of the water resources system.

that WEAP21 have been more widely applied across the world than Source IMS. Figure 2.3 shows locations of where WEAP21 were or has currnely been applied.

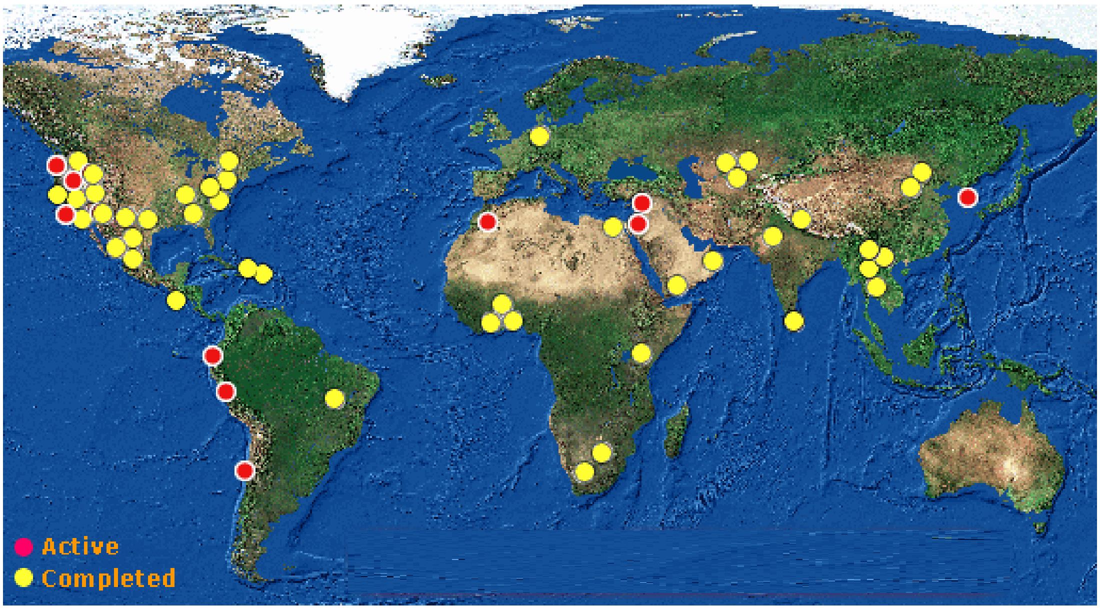


Figure 2. 3 Locations of river basins where WEAP21 were / has been currently applied. Source: www.weap21.org

The detailed review of the models has identified a gap which is the lack of uncertainty analysis methodlogies for assessing and reducing uncertainty in model outputs due to sources such parameter estimation and forcing input. Integration of such uncertainty analysis metholdogies in the modelling framework can help produce roboust model outputs and hence enable risk-aware decision making.

2.4 WEAP21 case studies

WEAP21 has been successfully applied in different river basins across the world, ranging from small rural areas to large cities with complex infrastructure, for a variety of planning purposes;

Mccartney & Arranz (2007) used WEAP21 to evaluate historic, current and future water demands in the Olifant river catchment, South Africa. Their study incorporated three plausible future scenarios of how water demand changes over the next 20 years as a result of population growth, changes in sectoral uses (such as forestry, mining and commercial), and changes in water use practices and government policies. The application of WEAP21 allowed studying the effects of these changes in a scenario-based approach; where for each scenario the model simulated water uses for different sectors under varying rainfall and flow conditions, and then quantitatively analysed these scenarios to generate useful information for resource planning. In this case, outputs from the WEAP21 model was linked to water productivity data of the different sectors as to provide indicative economic costs of supply failures. This study illustrated the efficiency of WEAP21 in providing an insight for resource planning by enabling evaluation of different options to meet future water demands.

Young et al. 2009 used WEAP21 to assess the impacts of climate warming on water resources of Sierra Nevada, US. This work presented the first step for developing a water resources planning model, which will span from climate change through to hydrological responses, management adaption and impact assessment. Their work assessed three climate-warming scenarios with fixed increases 2 ºC, 4 ºC and 6 ºC to study possible changes in snow accumulation and runoff timing. The use of WEAP21 in this case was useful as it captured changes in hydrologic metrics at a finer resolution than previous studies, and hence more suitable for planning at individual catchment-level. The study indicated that WEAP21 is a useful analytical platform for understanding climate change effects within individual river basin, and for assessing and exploring how water managers may adapt to such effects.

Rodrigo et al. (2012) used WEAP21 to quantify relative benefits of total water management alternatives over traditional water management approach. The city of Los Angeles was used as a case study. Total water management strategies considered in their work involved different combinations of increased water conservation, increased water reuse and recycling, rainwater harvesting and groundwater recharge. The model simulated and evaluated alternatives with regard to supply reliability, wastewater production, quality of receiving waters, and total life cycle costs. The desktop analysis showed that total water management strategies are better suited to meet water resource management challenges than conventional strategies. This study can be used as a guide for water managers to establish a credible framework for resource planning. The study also indicated that WEAP21 is a powerful tool for investigating sustainable water management strategies, as it is based on the concept of systems model. Such model has the capability to estimate specific benefits of water management decisions across several sectors of the watershed (i.e. water supply and water quality); and can measure environmental, economic and social elements of sustainability. However, they argued that WEAP has limited outputs and certain performance metrics need to be evaluated outside the model.

Yates et al. (2013a) used WEAP21 to develop a climate driven water resources model for southwestern US to explore impacts of population growth, extended droughts and climate change on water allocation among competing uses. The model linked both the hydrologic cycle and human interventions within the region; and hence simulated both the natural and managed flows together with water deliveries to a variety of sectors including domestic, agriculture, industrial and thermoelectric cooling. The model placed a greater emphasis on water used for thermoelectric cooling, and in a companion paper (Yates et al. 2013b), the model was linked to outputs from a regional energy model to explore implications of energy alternatives on the water resources of the region. Their model proved to be a useful tool for exploring the relative trade-off between future energy options. The studies concluded that WEAP21 is a powerful tool for water managers to help evaluate climate change impacts and adaption strategies in catchments, where infrastructure such as thermoelectric cooling exists.

Mehta et al. (2013) used WEAP21 to assess water resource development plans for utilities in three African towns across the Lake Victoria region – Bukoba (Tanzania), Masaka (Uganda) and Kissi (Kenya). The model investigated a combination of climate change, demographic and infrastructure scenarios and evaluated them in term of projected water supply, demand, costs and revenues. The study indicated that the WEAP21 model provided a useful indication of the timing of investment in infrastructure and the size of expansion needed to meet future demands. The study also indicated that WEAP21 was an effective tool for developing water resources management plans through its ability to integrate climate driven water supplies with projected demands in a single platform.

Hall and Murphy (2010) applied WEAP21 for the Moy catchment in Ireland to analyse the vulnerability of public water supply under changing climate conditions. The model examined a combination of climate change and future water demand scenarios. The climate change scenarios comprised statistically downscaled climate scenarios from three global climate models (GCMs) forced by two emission scenarios. The GCMs are HadCM3, GCCM2, and CSIRO Mark 2. Scenarios of future water demands comprised four feasible scenarios addressing what-if questions in terms of population growth, water conservation, and improved position of infrastructure. The four future demand scenarios are themed as follow: business-as-usual (water consumption per capita remains unchanged), reduced water demand (reduction of water consumption per capita as result of increased awareness on water conservation), improved infrastructure (reduced unaccounted for water), and scenario combining both water conservation actions and infrastructure improvement. Their analysis identified areas vulnerable to climate change within the catchment, and hence alerted stakeholders and decision makers to areas requiring necessary adaption actions to mitigate such impacts. The study demonstrated that results from the WEAP21 model could be used as a basis for water resource planning and management in the Moy catchment.

In a complementing paper, Hall and Murphy (2011) used WEAP21 to establish a framework to assist in identifying robust adaption options, which accounts for uncertainty in climate change and its impacts on water resources. Their study focused on Glore sub-catchment (within Moy), where water stress is evident as revealed in the previous study. In this case, the model was used to generate multiple future streamflow time-series, which determined the ranges of future hydrological regime of the sub-catchment. Their analysis in turn provided reliable ranges within which future adaption strategies may need to function to mitigate water supply vulnerability. This study demonstrated how WEAP21 could be used to quantify associated future uncertainties and produce reliable model outputs for water policy makers to act effectively. This integration of uncertainty analysis into modelling results is shown to generate policy messages that robustly account for future uncertainties.

2.5 Uncertainty of water resources management models

One of the modelling requirements is to quantify uncertainty in flow predictions before communicating the overall modelling results to decision makers. Uncertainties in outputs of water resource models can be due to (i) model context, (ii) model structure, (iii) parameters identification and (iv) input forcing data (Walker et al. 2003; Beven 2009; Mockler et al. 2016a). If the model context is justifiable, three dominant sources of uncertainty remain which together in a modelling process produce the predictive uncertainty or total prediction error (Beven, 2009; Todini 2009).

Most studies in the literature investigated model uncertainties due to one or two aspects of the previous sources (Mocker et al. 2016a). Uncertainties due to parameter identification strategy have been widely investigated in the literature (Wheater et al. 1986, Beven and Binely 1992, van Werkhoven et al. 2008, Beven, 2009, Younger et al. 2009, Sun et al. 2012, O'Loughiln et al. 2013). A growing number of studies have recently focused on investigating uncertainties due to model structure (Clark et al. 2008, Breuer et al. 2009, Gupta et al. 2012), model structure and forcing data (Renard et al. 2010), and model structure and parameter identification (Mockler el al. 2016b).

More recently, studies have focused on understanding uncertainties in simulated flows due to the three facets of uncertainties together (e.g. Mockler et al. 2016a). Mockler et al. (2016a) assessed uncertainties in predicted flows of 31 Irish catchments by combining stochastic rainfall data with multiple parameter sets of three conceptual rainfall – runoff models: Nedbør–Afstrømnings-Model (NAM), Soil Moisture Accounting and Routing with Groundwater model (SMARG), and Soil Moisture Accounting and Routing for Transport (SMART). A limitation in the framework of Mockler *et al* 2016a is that uncertainties in forcing data focused on precipitation as the dominant driving data like most of the uncertainty studies in the literature.

Tsoukalas and Makropoulos (2015) extended the capability of WEAP21 to incorporate uncertainties in the modelling process and to inform uncertainty-aware decisions for the management and operation of large reservoir systems. This was done by coupling WEAP21 with a multivariate stochastic climate model and optimisation algorithms such as NSGAII and ParEGO. The developed framework was applied by Tsoukalas and Makropoulos (2015) to inform optimal operating rules for the trans-boundary hydro-power system of Nestos. One possible limitation of their framework is that it tends to find an optimal model or solution rather than estimating the predictive uncertainty.

2.6 Conclusion

This chapter described the principle concepts in integrated water resources management modelling. It presented a literature review of different integrated water resources management models highlighting the potential uses and limitations of each. WEAP21 modelling software is identified in this chapter as a suitable software for the purpose of the study for the following reasons: (i) it seamlessly integrates both the hydrology and water management components in one platform, (ii) it is a generic model and transferable to different contexts, and (iii) it has been widely applied in different river basin across the world. This chapter also presneted a review of different applications of WEAP21 software in different river basins across the world for the purpose of water resources planning. Moreover, this chapter reviewed studies that investigated uncertainties in flow predictions of water resources mangemenet models due to parameter identifcation, forcing input, and model strucutre. A limitation in these investigations is that uncertainties in forcing data mostly focused on precipitation as the dominant driving data. Hence, there is a need to study effects of uncertainty of different climatic variables such as temperature and evaporation on model outputs. The literature review also revealed attempts to extend the capability of WEAP21 software to incorporate uncertainties and to inform uncertainty-aware decisions water resource planners. A limitation in these attempts is that they tend to focus on finding an optimal model rather than calibrating the model using Bayesian-inference methods to provide a predictive uncertainty of model output.

Chapter 3 WEAP21 MODEL DESCRIPTION

3.1 Introduction

WEAP21 is an integrated water resources model that seamlessly integrates the two distinct sides of the water system: the supply or hydrology component and the demand-management component (Yates et al. 2005). In the supply component, a number of embedded hydrology modules in WEAP21 are used to simulate hydrological processes, crop requirements and yields, and instream water quality. For instance, the conceptual rainfall-runoff module simulates main hydrological processes including snow accumulation and melt, runoff generation, interflow and base flow pathways, and soil moisture dynamic. In the demand component, WEAP21 allows representation of sectoral water demands and the description of management policies and infrastructure operating rules to allocate water between competing demands. A supply – demand network is then defined where available water supplies simulated by the hydrology module is passed to the management module in order to optimally allocates these supplies based on the prescribed policies and operating rules. Such mode of integration enables WEAP21 to be an ideal tool to assess impacts on water supplies and on water uses due to dynamic changes within the basin including climate (Yates et al. 2009; Young et al. 2009); and demands and infrastructural operations (Yates et al. 2013a).

3.2 Hydrology component of WEAP21

Hydrologically, the catchment in WEAP21 is divided into contiguous sub-catchments. Each sub-catchment is further sub-divided into *N* fractional areas based on land cover and soil types. Each fractional area is described by a conceptual two-bucket model (Figure 3.1), and a water balance is performed for each fractional area j of *N*, as expressed in the continuous mass balance equation 3.1 (Yates et al. 2005):

$$Sw_j \frac{dz_{1,j}}{dt} = P_e(t) - P_e(t) z_{1,j}^{\frac{LAI_j}{2}} - PET(t) k_{c,j}(t) \left(\frac{5z_{1,j} - 2z^2_{1,j}}{3}\right) - f_j K_j z_{1,j}^2$$
$$- (1 - f_j) k_j z_{1,j}^2 \qquad (3.1)$$

Where:

Sw_j	:	the total effective storage of the upper soil (mm)
$z_{1,j}$	:	relative soil water storage given as fraction of total effective storage
$P_e(t)$	:	effective precipitation in (mm)
LAI_j	:	leaf and stem area index, with low values yielding high surface runoff
$PET(t)$	:	potential evapotranspiration (mm)
$k_{c,j}$	:	crop coefficient
f_j	:	a quasi-physical parameter which partitions water vertically or horizontally
K_j	:	hydraulic conductivity of upper soil layer

The conceptual model (as shown in Figure 3.1) sequentially partitions hydrologic components and tracks relative storages in the upper and lower soil layers; it uses empirical functions to estimate hydrological components.

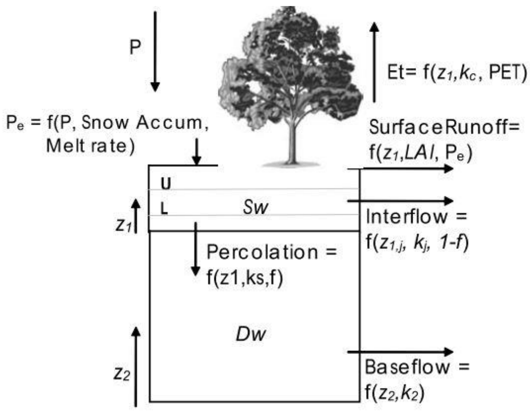


Figure 3. 1 Schematic of WEAP21 conceptual water balance model. Source: Yates et al. 2005

A temperature-index snowmelt algorithm is used first to estimate effective precipitation based on observed temperature (first term in right hand side of Equation 3.1). Effective precipitation is partitioned into runoff (second term in right hand side of Equation 3.1) or infiltration based on land cover and soil moisture status. The soil moisture in the shallow compartment is partitioned in evapotranspiration (third term in right hand side of Equation 3.1), interflow (fourth term in right hand side of Equation 3.1), percolation to lower soil (fifth term in right hand side of Equation 3.1), or storage based on potential evapotranspiration, land cover, and soil-water properties. The potential evapotranspiration is estimated in WEAP21 by the Penman-Montieth method (Monteith 1965). Percolation enters the deep storage, which then is partially routed as base flow depending on deep storage capacity and hydraulic conductivity in the lower layer. Further details in WEAP21 computation algorithms can be found in Yates et al. (2005). In addition, WEAP21 allows the user to customise data variables and create their own model; for example, Young et al. (2009) customised WEAP to emphasise on snow processes in Sierra Nevada, US. Parameters for the hydrology module for catchment object in WEAP21 are described in Table (3.1).

Table 3. 1 Description of parameters used within the hydrology modules of WEAP21. Source: SEI (2015).

Category	Parameter	Description	Unit
Land use	Area	Land area for each land class or land class share from the total area of the catchment	m^2
	Crop Coefficient, kc	Crop coefficient relative to the reference crop. Kc = 0 means doubled crop and if merely fallow, set greater than zero	
	Soil Water Capacity (Upper Zone), Swc_j	Effective water holding capacity of upper soil layer (top bucket), for each land class within the catchment	*Mm*
	Deep Water Capacity (Lower Zone), Dw	Effective water holding capacity of lower soil layer (bottom bucket). Single value for the entire catchment	*Mm*
	Runoff Resistance Factor, RRF	Factor of leaf area index and slope. Runoff tends to decrease with higher values of RRF	*Ranges from 0.10 to 10*
	Root Zone Conductivity K_j	Root zone conductivity rate at full saturation, for each land class	*mm/month*

	Deep Conductivity, K_2	Conductivity rate of the deep layer (given as a single value for the catchment)	*mm/month*
	Preferred flow direction f	Preferred flow direction (quasi-physical tuning parameter) with value of 1.0 implying 100% horizontal and 0.0 implying 100% vertical flow. This partitions the flow out of the root zone layer between interflow and flow to the lower soil layer.	*Fraction (0 to 1)*
	Initial $Z_{1,j}$	Initial relative soil storage for the upper soil at the beginning of the simulation, for each land class (fraction of the effective total effective storage of the soil layer)	*Percent*
	Initial Z_2	Initial relative soil storage for the deep soil at the beginning of the simulation , as a single value for the entire catchment (fraction of the effective total effective storage of the soil layer)	*Percent*
Climate	Precipitation	Time series of total monthly precipitation.	*mm/month*
	Temperature	Weighted mean of high and low temperature on a monthly basis, as monthly time series	$°C$
	Humidity	The average monthly relative humidity	*Percent*
	Wind Speed	Average wind speed as a monthly time series	*m / s*

3.3 Surface water and groundwater interaction

Surface water contributes to groundwater when groundwater is depleted (losing stream). When ground water level is higher than the level of surface water, surface water gains water from groundwater (gaining stream) (Yates et al 2005, SEI 2015). This dynamic link between surface and groundwater is captured in WEAP21 through a groundwater module that allows transfer of water between surface water and groundwater based on head difference. In WEAP21, the aquifer is conceptualised as a wedge (Figure 3.2) and assumed to be symmetric about the river. Based on this conceptual model, the groundwater storage can be estimated and updated at each time step based on the following equations (Yates et al 2005, SEI 2015):

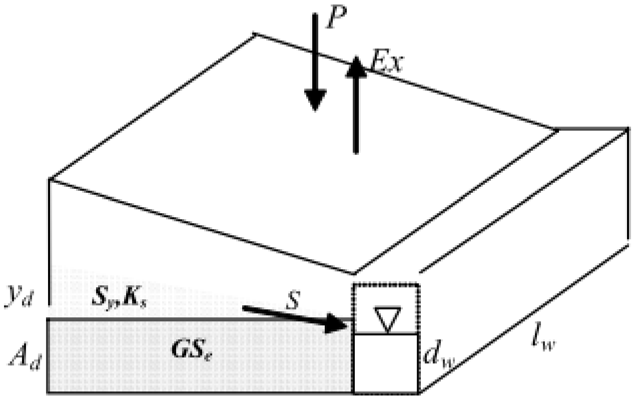


Figure 3.2 Schematic of conceptual groundwater model in WEAP21 and associated parameters. Source: Yates et al. 2005

Based on the assumption that groundwater table is in equilibrium with the river, the storage from one side of the wedge can be estimated based on Equation 3.2:

$$GS_e = h_d \times l_w \times A_d \times S_y \tag{3.2}$$

Where h_d (m) is the horizontal distance of the aquifer from the stream, l_w (m) is the wetted length of the acquirer in contact with the stream, A_d is the aquifer depth, and S_y is the specific yield of the aquifer. Thus, the initial storage of the aquifer at t(0) can be calculated from Equation 3.3:

$$GS_{t=0} = GS_e + (y_d \times h_d \times l_w \times S_{y)} \tag{3.3}$$

Where y_d(m) is the vertical height of the aquifer above or below the equilibrium level. As this height (y_d) increases, Seepage (S) (m^3/s) from the side of the channel increases (Equation 3.4):

$$S = (K_s \times \frac{y_d}{h_d}) \times l_w \times d_w \tag{3.4}$$

Where K_s is the hydraulic conductivity of the aquifer in m/s and d_w is an estimate of the wetted depth of the stream. Thus, the aquifer storage on one side of the stream channel at the current time step $GS(i)$ can be estimated using Equation 3.5:

$$GS(i) = GS(i-1) + (\frac{1}{2R} - \frac{1}{2Ex} - S) \tag{3.5}$$

Where R is the recharge from the catchment and Ex is the water supply from groundwater to meet water demands. The total aquifer storage is 2 $GS(i)$

3.4 Surface water quality

WEAP21 has capabilities for modelling point source pollutant loadings on rivers and hence allowing the assessment of wastewater impacts on receiving water bodies. The water quality module in WEAP21 is limited to modelling conservative constituents that decay according to an exponential decay function. These includes dissolved oxygen (DO), biological oxygen demand (BOD), and instream water temperature (T). The simulation of these constituents is based on first order functions developed by Chapra (1997), with mass balance equations written for each river segment to simulate water balance and mixing of DO, BOD concentration and T along the reach.

The water quality equations are solved at each node on the river from upstream to downstream. First, the mixing from all tributaries, groundwater sources and return flows j for each constituent (DO,BOD, and T) x at node i is computed based on Equation 3.6:

$$x_i = \frac{\sum_{j=1}^{n} Q_j x_j}{\sum_{j=1}^{n} Q_j} \qquad (3.6)$$

A heat budget then is computed for each reach segment based on Equation 3.7 (Chapra 1997):

$$\frac{dT}{dt} = \frac{Q_i}{V} T_i + \frac{R_n}{\rho C_p H} + \left(\frac{\sigma (T_{air} + 273)^4 a \sqrt{e_{air}}}{\rho C_p H} \right) - \frac{Q_i}{V} T_{i+1} - \frac{\varepsilon \sigma (T_{i+1} + 273)^4}{\rho C_p H} - \frac{f(u)(T_{i+1} - T_{air})}{\rho C_p H} - \frac{g(u) D}{\rho C_p H} \qquad (3.7)$$

Where the first term represents the heat input to the reach segment, the second term is the net radiation to the segment with density ρ, specific heat of water C_p and water depth in the segment H, the third term is atmospheric longwave radiation with Steffan Boltzman constant σ, air temperature T_{air}, and coefficient for atmospheric attenuation and reflection. The fourth and fifth terms are the heat and long wave radiations leaving the reach segment, respectively. The sixth and seventh terms are the conduction of heat to surrounding air and the removal of heat from river by evaporation, respectively.

After computing temperature in each reach segment, the DO and BOD concentrations are calculated for each segment. First, estimated temperature is used to calculate oxygen saturation in each segment based on Equation 3.8:

$$OS_i = 14.45 - (0.39T_i) + (0.01{T_i}^2) \qquad (3.8)$$

The oxygen concentration O_i from point source of loads of BOD is calculated in WEAP21 for each segment i based on the classic Streeter-Phelps model (Equation 3.9) (Tchobanoglous and Schroeder 1985)

$$O_i = OS_i - \left(\frac{k_d}{k_a - k_r}\right) exp^{-kr\left(\frac{L_i}{v_i}\right)} - exp^{-ka\left(\frac{L_i}{v_i}\right)} BOD_i - ((OS_i - O_i) exp^{-ka\left(\frac{L_i}{v_i}\right)}) \qquad (3.9)$$

where k_d, k_a, and k_r are decomposition, reaction and re-aeration rates respectively. L_i is the reach length and v_i is the water velocity in the reach, and BOD_i is the pollutant loading to the reach. The total removal rate of BOD is influenced by the reach depth and water temperature as given in Equations 3.10 and 3.11, respectively

$$Kr_{bod} = Kr_{bod} + \left(\frac{0.25}{H}\right) \qquad (3.10)$$

$$Kr_{bod} = Kr_{bod} + 1.047^{(T_i - 20)} \qquad (3.11)$$

The BOD removal then is calculated using Equation 3.12

$$BOD_i = BOD_i * exp^{Kr_{bod}(\frac{L}{v})} \qquad (3.12)$$

3.5 Demand-management component

The water allocation module in WEAP21 applies an optimisation routine using a set of user-defined demand priorities and supply preferences. At each time step, this module allocates available supplies based on a linear programming (LP) algorithm, whose objective function is to maximise satisfaction of demands, subject to demand priorities, supply preferences, mass balances, and hydraulic capacities of infrastructure. Each demand site, reservoir, hydropower and in-stream flow requirement is assigned an integer priority rank, ranging from 1 (highest priority) to 99 (lowest priority). Hence, entities of the same rank are grouped in an equity group for example entities of priority rank 1 are members of equity group 1. The linear program is constrained to supply an equal percentage of water to each member within the respective equity group. The priority ranks in the model specify the order in which demands are satisfied, where the model ensures that demands of higher priority are allocated water first in periods of water shortage. Similarly, supplies apply a preference ranking scheme to specify the preferences of demand to supplying sources (see Yate *et al.* 2005 for further details on the water allocation algorithm).

The water supply requirement for each demand site (DS) is modelled in WEAP21, as expressed in Equation (3.13), with a number of parameters used within the water management module provided in Table 3.2:

$$S_{DS} = D_{DS} \times (1 - r_{DS}) \times (1 - \varphi_{DS})/(1 - l_{DS}) \tag{3.13}$$

Where S_{DS} the supply requirement for the demand site, D_{DS} is water demand for the site calculated from annual activity levels and water use rates, r_{DS} is the reuse rate, φ_{DS} is water savings and l_{DS} is loss rate in the demand site.

Table 3. 2 Description of parameters used within the water management module of WEAP21. Source: SEI (2015)

Category	Parameter	Description
Water use	Annual activity level	Annual activity level driving demand i.e. number of population / agricultural area
	Annual water use rate	Annual water use rate per unit of activity
	Monthly variation	The monthly share of annual demand
	Consumption	Percent inflow consumed – lost from the system
Loss and reuse	Loss rate, l_{DS}	Losses within demand sites that otherwise unaccounted for resulting in increase in the supply requirement

Demand Management	Reuse rate, r_{DS}	Reuses within demand sites resulting in decrease in water supply requirement
	Demand site Management saving, φ_{DS}	Percent reduction in total demand due to demand side management programs

Reservoir is used in WEAP21 to store water estimated by the hydrology module. This storage provides a means of flood control during extreme events, and also a reserve of water for later use to satisfy downstream demands, instream flow requirements, and hydropower requirements in low flow periods. The user defines operating rules for each reservoir, which determine how much water is available for release at each time step and how much should be carried over to the next time step (Table 3.3). In WEAP21, the reservoir storage is split into four zones to describe reservoir operating rules, namely 'flood control zone', 'conservation zone', 'buffer zone' and 'inactive zone' (Figure 3.3). The 'flood control zone' temporarily holds water to control floods. The 'conservation zone' is where water is freely released to fully meet downstream requirements including demands, in-stream and hydropower requirements. The 'buffer zone' is where water is controlled to meet demands during shortages; when reservoir level drops into this zone, releases are restricted to a buffer coefficient as defined by the user. The 'inactive zone' represents the dead storage that cannot be allocated (Yates *et al* 2005).

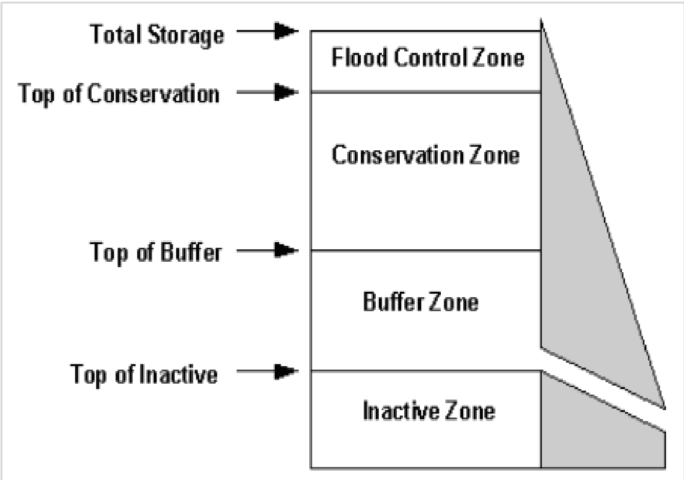


Figure 3. 3 Reservoir storage zones in WEAP21 used in describing reservoir operation rules. Source: Yates *et al* (2005)

Table 3. 3 Parameters used in modelling reservoir operations and hydropower generation in WEAP21. Source: SEI (2015)

Category	Parameter	Description	Unit
Physical	Storage capacity	Total storage capacity of the reservoir	Mm^3
	Initial Storage	Amount of water stored in the reservoir at the beginning of simulation	Mm^3
	Volume elevation curve	Defines the relationship between reservoir volume and elevation curve	$Mm^3/\ m$
	Monthly net evaporation	Monthly net evaporation rate which equals evaporation minus precipitation in reservoir surface	mm $/month$
	Loss to groundwater	Estimated seepage from reservoir to groundwater. A negative number denotes a net gain from groundwater	Mm^3
Operation	Top of conservation	The maximum volume in reservoir	Mm^3
	Top of buffer	Below this level, releases from the reservoir are constrained to a buffer coefficient	Mm^3
	Top of inactive	Volume in the reservoir not available for allocation	Mm^3
	Buffer coefficient	Fraction of water in buffer zone available each month for release [0 – 1]	*fraction*
Hydropower	Max turbine flow	Hydropower will be generated to the maximum flow only	cms
	Tail water elevation	Reservoir elevation minus this level is the working water head	m
	Plant factor	The percentage of each month that the hydropower is running	%
	Generating efficiency	Electricity generated divided by hydropower input	%
	Hydropower priority	The priority at which the energy demand will be satisfied relative to all other demands in the system	*Rank*
	Energy demand	Target monthly hydropower production requirements	*Thousands MWH*

In the WEAP21-Dublin model, the demands for domestic, non-domestic and environmental uses are prioritised, followed by demands for hydropower generation. The lowest priority is assigned to reservoirs storage. This order ensures that at a given time step the demands for domestic, non-domestic and environmental uses are first satisfied, then the demands for hydropower generation. After these demands are satisfied, any additional flows are then stored in the reservoir. This is in accordance with information on Liffey reservoir operations as provided by ESB through personal communication (Appendix A.1).

Furthermore, WEAP21 adopts a scenario-based approach whereby water planners can use to address a broad range of water issues pertaining to climate change, changes in domestic and industrial demands, alternative operating rules, assessment of available sources and infrastructure, and land-use change policies. WEAP21 allows defining alternative management options related to these issues as they can be used to establish what-if scenarios, which can be evaluated against performance metrics, e.g. supply reliability, environmental indicators and costs. The evaluation of alternative scenarios has proved to be essential to facilitate setting a water development policy.

The data required to run the model is listed in Table 3.4.

Table 3 4 List of data required to run the model

Meteorological data

- Monthly time series climate data for each sub-catchment in terms of rainfall, temperature and wind.
- Relative humidity and latitude

Land use data

- Fractional area of each land cover within the sub-catchment

Hydrological data

- Estimate of initial storages and storage capacities of groundwater bodies, estimate of horizontal distance that groundwater body extends from the river, and estimate of wetted length of groundwater in contact with the stream.
- Minimum flow requirements and their locations
- Flow measurements at control points (sub-catchment outlets) for model validation

Water demand management

- Number of population served by each water demand supply zone, monthly water consumption per capita, population growth rate during the planning horizon, areas designated for industrial, commercial and institutional activities and corresponding water use rates

Conveyance infrastructure

- Hydraulic capacities, leakage rates (unaccounted for water and customer side leakage), capacity upgrade during planning horizon, total areas (rooftop areas) designated for rainwater harvesting, total areas designated for sustainable urban drainage systems

Reservoirs and Hydropower

- Reservoir storage capacities, reservoir control curve, volume-elevation curves.
- Maximum turbine flows for hydropower generation, working head for turbines (tailwater elevation), and target monthly hydropower requirement production

3.6 Conclusion

This chapter described the individual modelling components of the water evaluation and planning software WEA2P21: the conceptual rainfall-runoff model, surface water quality and demand management components. The conceptual rainfall-runoff model simulate main hydrological process of the catchment and pass estimated water supplies to the water demand management component. The water demand component allocates water to competing water uses based on linear programming whose objective function is to maximise satisfaction of demands, subject to hydraulic capacities of infrastructure, user-defined demand priorities and supply preferences. The underlying equations and parameters of each individual component are also illustrated. Finally, a list of data required by the user of the model to run the model is provided.

Chapter 4 DATA COLLECTION

4.1 Introduction

The data collection process is highly significant to achieve the research objectives, and hence careful consideration has been given to data sourcing, data acquisition, and data quality checking. An initial review of the modelling software (WEAP21) has identified the required data to develop the model, which can be classified into six categories (1) hydrology, (2) climate, (3) hydrometric data, (4) land use / land cover, (5) water supply and wastewater infrastructure, and (6) regional population and water uses.

The data collection process started with determining data sources and accessing websites where data can be acquired on-line. Data sources include a variety of government agencies and local authorities; such as Environmental Protection Agency Ireland (EPA), Office of Public Work (OPW), Geological Survey of Ireland (GSI), Met Éireann (The Irish Meteorological service), Irish Water, Central Statistics Office (CSO), Electricity Supply Board (ESB), and relevant local authorities in counties that share the Dublin region water supply area: Dublin City Council, South Dublin County Council, Dun Laoghaire County Council, Fingal County Council, Kildare County Council, Wicklow County Council and Meath County Council. Moreover, a variety of policy documents and strategic studies were also reviewed to characterise existing conditions of Dublin water resources system and to forecast future conditions. The most notable studies are the plan water supply project – the Dublin Region (DCC 2010a), the Greater Dublin Strategic Drainage Study (DDC 2005a), Project need report: Water Supply Project Eastern and Midlands (Irish Water 2015a) and Eastern CFRAM studies: HA09 Inception report (OPW 2012a) and HA09 Hydrology Report (OPW 2016), and Liffey flood controls and flood forecasting system option (OPW 2012b).

For all other non-publically available data, formal and tailored requisition messages have been sent to appropriate agencies and authorities as to request the necessary data. In particular, formal requisition messages have been sent to (i) Irish Water and each of the above local authorities to request spatial data and detailed information in relation to: the water supply network, water flow data and water uses, the drainage system and wastewater discharges (Appendix B.1); (ii) ESB, EPA and Marine Institute to request hydrometric data of the main gauging stations in the catchment for use in model calibration and validation; (iii) ESB to request information about Liffey reservoirs and hydropower schemes (Appendix B.2).

Moreover an extensive internet searches have been conducted to obtain further data on some features of urban water resources management such as statutory compensation flows need to be maintained at relevant watercourses, soil-water and aquifer properties throughout the catchment, water consumption rates for sectoral water uses, losses and leakages in water supply system, and hydropower generation from existing schemes.

It is worth to mention that the data collection process was a challenging task because the required data were spread across a wide variety of agencies and authorities, and were available in different formats and resolutions. Another issue also was the difficulty in releasing some data by a number of Agencies due to the data ownership issue particularly the data which are under the possession of Irish Water.

Data collected to develop the model differ in type and format from geo-referenced layers and time-series data to reported information related to water use, energy, and infrastructure. Table 4.1 summarises the collected datasets, their types, their uses in the model and their sources.

Table 4. 1 Summary of datasets collected to develop water resources planning model for Dublin using WEAP21

Dataset	Type / Use	Source
Water framework directive (WFD) dataset, inclduing; Rivers network, lakes , catchment boundry and areas contributing to water bodies	Geo-referenced layers and descreptive report Used to configure the model and to establish the hydrolgic connectivity.	The Envirnemntal Portection Agency Ireland (EPA GeoPortal) http://gis.epa.ie/GetData
CORINE land cover 2012, and Soils and Subsoil maps	Geo-referenced layers and descreptive report To characterise catchments with unqiue land cover and soil water properties	Environmetal Protection Agency Ireland (EPA GeoPortal) http://gis.epa.ie/GetData
Groundwater bodies map and groundwater descriptors Irish aquifer maps and aqufier protperites database	Geo-referenced layers and descreptive reports To characterise deep soils of WEAP catchments	The Geological Survey of Ireland (GSI spatail data) https://www.gsi.ie/Mapping.htm
Locations of rainfall and synoptic weatehr stations. Estimated values of monthly rainfall, temperature, and wind speed	List of stations with Easting and Northing coordinates and time-series records To drive the model to simulate hydrolgical responses	The Irish Meteorolgical Service (Met Éireann) http://www.met.ie/
Locations of hydrogauges, and monthly mean observed streamflow data	List of stations with Easting and Northing coordinates and time-series records To calibrate and test the model	The Environemtnal Protection Agency Ireland (EPA HydroNet) http://www.epa.ie/water /wm/hydronet/ The Electricity Supply Boad (ESB), Turlough Hill & Liffey Stations https://www.esb.ie/ The Office of Public Work – Ireland (OPW HydroData) http://waterlevel.ie/hydro-data/home.html
Reserviors: storage capacities, volume-elevation curves, observed volumes, average	Technical reports and documents	The Electricity Supply Boad, (Turlough Hill & Liffey Stations)

Dataset	Type / Use	Source
heads and maximum turbine flows	To characterise reserviors and their operation rules	
Locations and capacties of major water and wastewater infrastructre, water supply zones , and urban wastewater treatment UWWT agglomeration boundries	Geo-referenced layers and studies To configure the model and to establish a link between the hydrolgy and demand components	City Coucils (Dublin, South Dublin, Dun Laoghire, Fingal, Wicklow, Kildare and Meath); Irish Water and the Environmental Protection Agency Ireland (EPA GeoPortal)
Water uses; domestic, commerical and industrail. Population, per capita water consumption, water use per ha of commerical / industrial lands ,and losses	Geo-referenced layers and studies To characterise pressures on the water resoruces of Dublin	Centeral Statastics Office, Water demand review by Jacobs Engineering Ireland and Tobin on belhalf of Irish Water

4.2 Data pre-processing

Data pre-processing entails manipulation of the raw data to match required format of the WEAP21 software. This preliminary step prepares data for use in the subsequent stages of model development i.e. configuration, parameterisation, calibration and validation/testing. For instance, geo-processing of geographic information (GIS) datasets includes; intersection of hydrology maps with land cover and soil maps to inform hydrology parameters of WEAP21; intersection of supply zones of the Dublin region with census data to populate the domestic level of activity for each supply zone.

Moreover, time-series data were subject to data quality check to ensure that only data with acceptable quality are used in further processing. One of the data quality checks comprised plotting time-series data and performing visual assessment to identify gaps and artificial outliers. Also occasionally, when records of certain rainfall station are doubtful, a comparison with neighbouring stations was performed to ensure that records are not due to measurement errors but rather representing actual rainfall events.

For instance, the data quality check included producing a data status table for rainfall data of 31 rainfall stations as shown in Appendix C.1. This table shows the timeline over which monthly rainfall is available for each of the 31 stations. A quality check of rainfall data for 31 potential stations was undertaken, in particular the data corresponding to the simulation period 2012-2017, using quality control guidelines suggested by OPW (2016a; 2016b). These guidelines are:

- Check for any missing intervals and accept stations that only have no more than one missing record during the period of interest (i.e. one month). These records have been included to increase the network coverage and provide a higher spatial resolution for rainfall data.
- Check for extreme values (outliers) by plotting time-series data and performing visual inspections. Accept stations with outliers for further processing if they showed consistency with neighbouring stations.
- Validating estimated values of records. Accept stations with estimated values for further processing if they only showed consistency with other neighbouring stations and if they had no more than one estimated value in the period of interest. This is in agreement with guidance of the world meteorological organisation which suggests that no more than 5% of a climate record should contain estimated data (Subramanya 2005)

Figure 4.1 shows an example of the results of the quality check process performed by plotting time-series rainfall data (station No. 5323 - NAAS) to identify missing time intervals. The plot for the rainfall time-series data of this station was compared against plots of rainfall time-series data of two other adjacent stations 8423 (Figure 4.2) and 9323 (Figure 4.3) to ensure consistency in term of extreme values. The locations of these stations are shown in Figure 5.4. The results of the quality check for the 31 rainfall stations are further discussed and summarised in Section 5.2.2

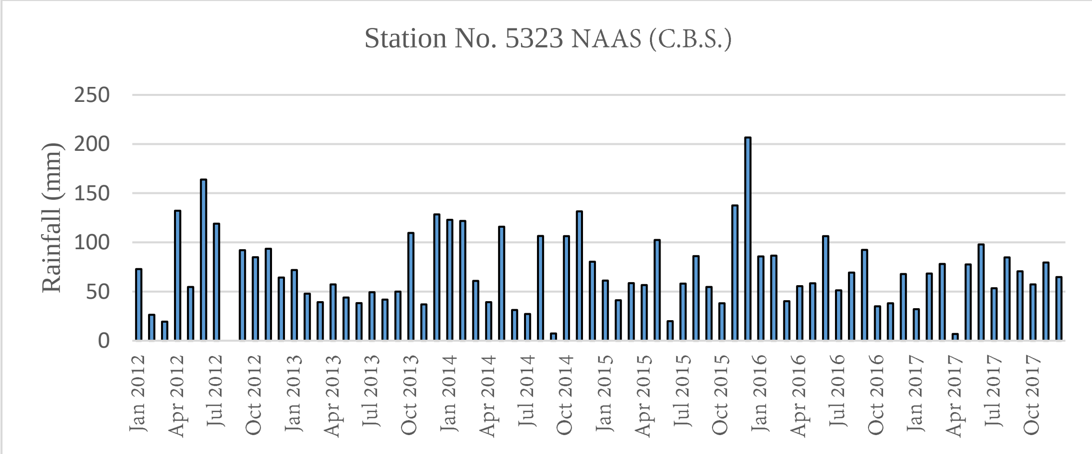


Figure 4. 1 Time series rainfall data for station no. 5323 "Naas (C.B.S)" for the period 2012 –2017. The figure indicates a missing record (August 2012).

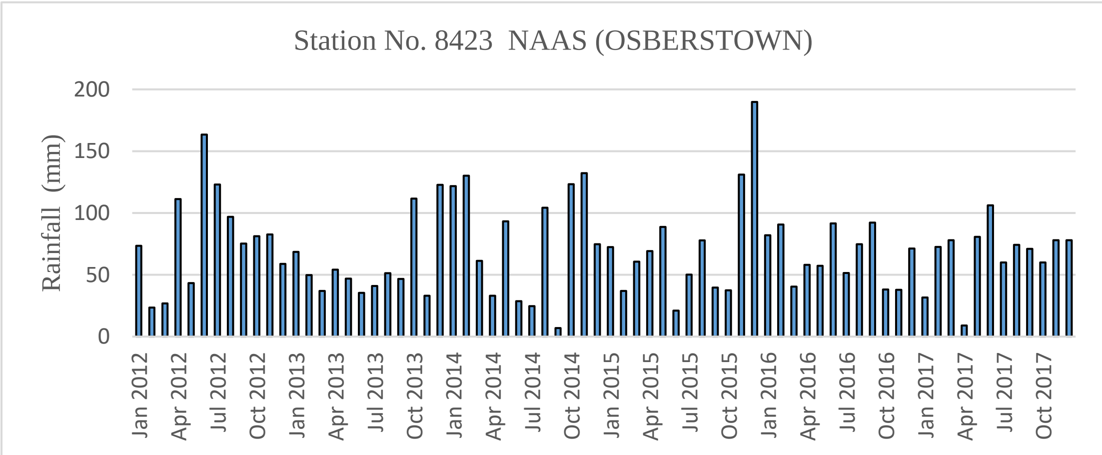


Figure 4. 2 Time series rainfall data for station no. 8423 "Naas (Osberstown)" for the period 2012 – 2017.

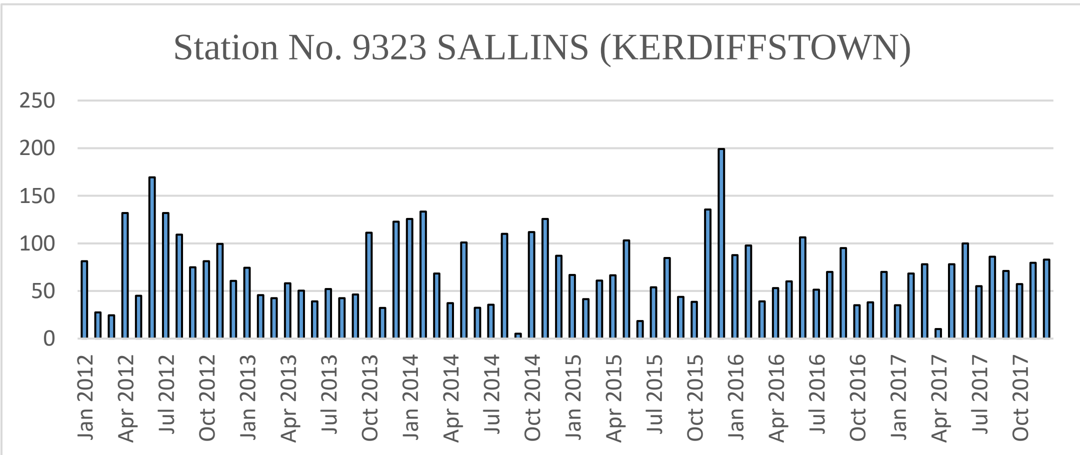


Figure 4. 3 Time series rainfall data for station no. 9323 "SALLINS" for the period 2012 –2017

Moreover, quality control check has been performed for flow data. Observed flow data for each control point have been checked for the presence of significant gaps and outliers in the data by conducting a visual assessment on the time-series plots of the flow and the corresponding rainfall. Outliers were included in the data only if they showed consistency with rainfall measurements and also if there were evidences such as published warnings for historic floods to confirm their occurrence. For instance, Figure 4.4 shows times-series plots of monthly mean observed flows at station 09032 in Phollaphuca and the corresponding rainfall values which have been calculated based on data from nearby weather stations, namely 1420, 2415, 3223, 3524, 3823, 5623, 7923, and 8623. The consistency between rainfall and flow data is apparent in the graph. Moreover, review of previous record of flood warnings revealed that such warnings have already been issued at Phollaphuca during months with extreme flows (e.g. Jun 2012, Feb 2014 and Dec 2015) (https://www.esb.ie/tns/press-center/) and (http://hydrologyireland.ie/).

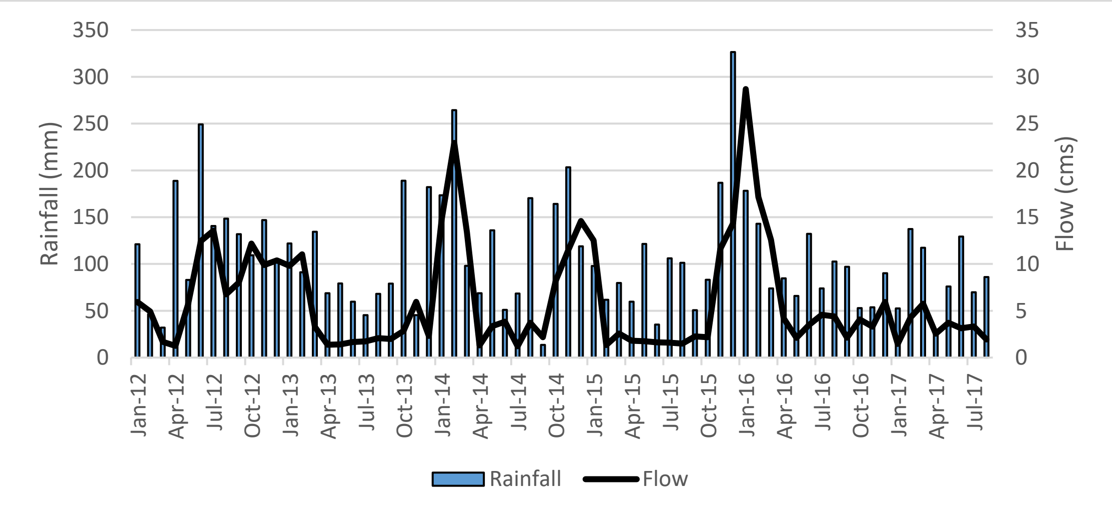


Figure 4. 4 Monthly mean streamflow (in cms) of Liffey river at Phollaphuca 09032 against total monthly rainfall data (in mm) of nearby / contributing weather stations.

Additional detailed pre-processing of time-series data included derivation of monthly time-series data from daily records some stations whose monthly records were missing. Further and detailed descriptions of data pre-processing will be discussed as part of the model development chapter.

Chapter 5 DEVELOPMENT OF WEAP21 MODEL FOR DUBLIN

5.1 Introduction

This chapter describes development of a water resources planning model for the Dublin region using the Water Evaluation and Planning Software – WEAP21, herein after will be called WEAP-Dublin. The model development process involved configuration and parameterisation of the WEAP-Dublin in order to ensure that (i) it robustly replicates the existing water supply system; (ii) it can be used to investigate different water management scenarios.

5.2 Model configuration and parameterisation

This section describes the process of building a customised model for the water system of the Dublin region using WEAP21 objects which represent various components of the system, such as supply catchments, rivers, reservoirs, distribution, demands, discharges and in-stream flow requirements.

5.2.1 WEAP21-Dublin catchments

Approximately, 85% of the water in Dublin is supplied from the Liffey and Dublin Bay catchment, in particular from major Liffey schemes at Phollaphuca and Lexilip reservoirs. Analysis of GIS layers of water framework directive (WFD) river sub-basins, rivers network, stream gauges and major infrastructure was carried out to disaggregate the Liffey and Dublin Bay catchment into contiguous sub-catchments and representative rivers. Catchment objects in WEAP21 were configured to represent the hydrologically-delineated sub catchments, which are characterised by unique climate, land cover, and soil-water characteristics.

The process of delineating WEAP catchments was performed by (1) identifying the boundary of the source catchment based on the WFD designation (2) identifying pour points within the catchment where there is a dam or gauge on modelled rivers (3) merging WFD river sub-basins based on identified pour points to create the WEAP-Dublin catchments; (4) intersecting land covers with catchments to estimate fractional areas of major land covers occurring within each WEAP catchment; and (5) determining the underlying groundwater body of each catchment. Figure 5.1 shows the WFD river sub-basins within the Liffey and Dublin Bay catchment, and locations of active hydrometric gauges, major infrastructure and Liffey river tributaries.

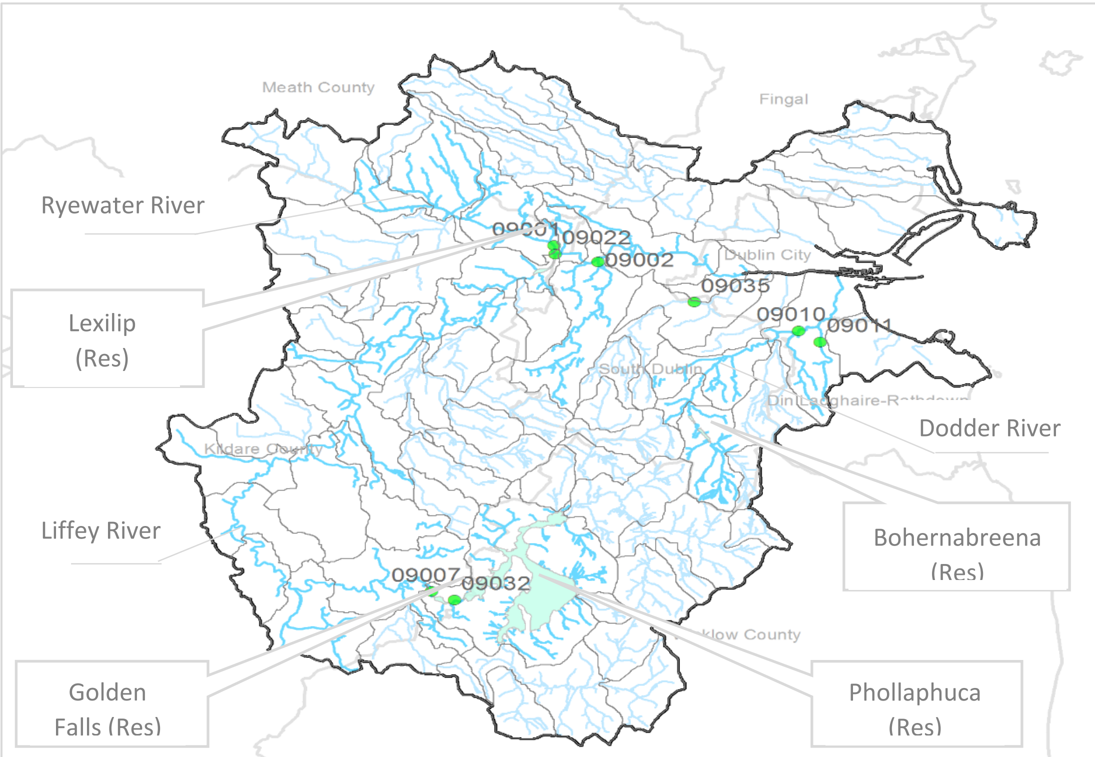


Figure 5. 1 The Liffey and Dublin bay catchment overlaying WFD river sub-basins, with locations of active gauges, major infrastructure and rivers. WFD river sub-basins (light grey nested with the catchment); active gauges (green and labelled); rivers (blue), reservoirs (light blue and labeled).

The catchment delineation process resulted in five main sub-catchments and three major rivers. The five sub-catchments are Upper Liffey (UL), Middle Liffey (ML), Lower Liffey (LL), Ryewater (RW), and Dodder (DD) (Figure 5.2); the areas of these sub-catchments are 306 km^2, 496 km^2, 211 km^2, 171 km^2 and 148 km^2 respectively. The major rivers include Liffey and Dodder rivers, which represent sources of water supplies

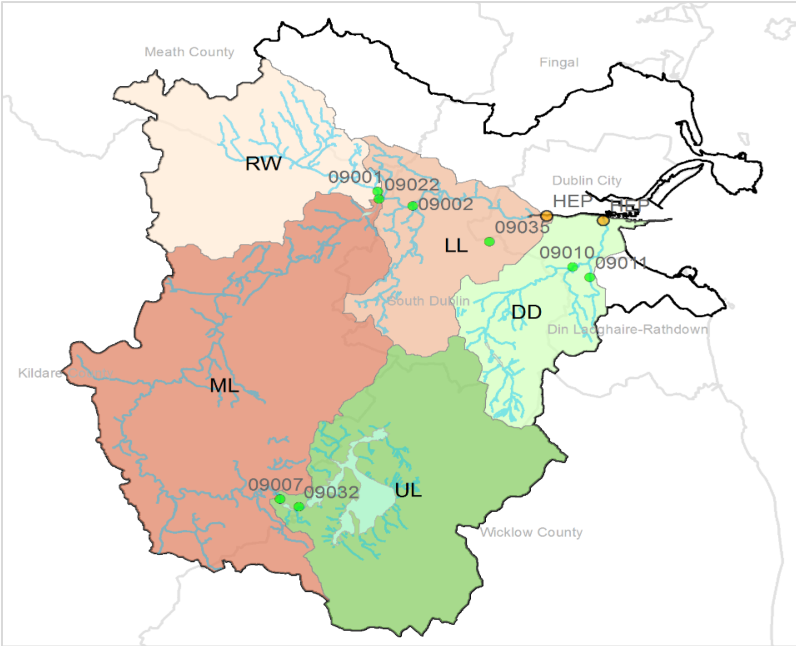


Figure 5. 2 The Liffey and Dublin bay catchment disaggregated into representative sub-catchments, each symbolised with a unique colour.

for Dublin; and the Ryewater river, which joins the Lower Liffey river. The latter is used to validate the WEAP-Dublin model. It is worth mentioning that the WEAP-Dublin model excluded all other rivers in the catchment vicinity which do not constitute sources of water supply for the region e.g. Tolka river.

5.2.2 Climate data

Rainfall in the catchment varies from an annual average of 1750 mm at upstream to 790 mm at downstream (Figure 5.3). To provide adequate resolution for capturing the rainfall variability, sub-catchments were further disaggregated into smaller river sub-basins.

Time-series climate data in WEAP-Dublin are used as an input for the hydrological rainfall-runoff module to drive the model to simulate hydrological responses of the catchment and hence to produce water fluxes. Historical climate data are available from Met Éireann rainfall gauging stations in monthly and daily time steps while hourly time step data are only available in the synoptic weather stations. A list of all rainfall gauging

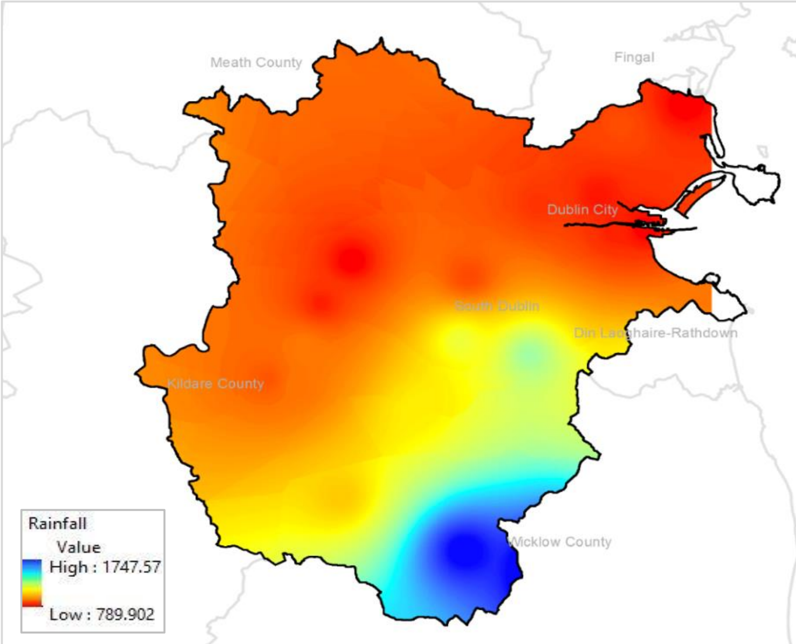


Figure 5. 3 Average annual rainfall (mm) within the Liffey and Dublin bay catchment, estimated based rainfall values from Met Éireann rainfall gauges during the period 2012-2017.

stations and synoptic weather stations are available online from Met Éireann (https://www.met.ie/) along with their easting and northing coordinates. A GIS map showing the spatial distribution of these stations was prepared and displayed in ArcGIS for further geo-processing; a 10-km buffer was applied to the Liffey and Dublin Bay catchment to identify weather stations which can be potentially used in the model development. The total number of all stations located within the extended area (including the 10-km buffer zone) was 31 stations including three weather synoptic stations, namely: Dublin Airport (532), Phoenix Park (1723), and Casement (3723). These synoptic stations provide historical records for rainfall and other climatic variables; for example, temperature and wind speed.

Following the quality check process for all 31 potential stations, in accordance with the above-mentioned guidelines, it has been found that:

- Data of five stations were not suitable as they contained significant gap. The five stations are: 1923 (Glenasmole D. C.), 2420 (Oldbridge), 2931 (Warrenstown), 5523 (Glensamole), and 7523 (Simmonscourt).
- Six stations had only one missing record, and have been considered for further processing: 1332 (Malahide Castle), 1420 (Glenmacnass), 2523 (Dunshaughlin Lagore), 3524 (Ballyedmonduff house), 5323 (Nass C.B.S), 9223 (Dun Laoghaire)
- Twenty stations have complete monthly rainfall data for the period 2012-2017.

This process yielded a network of 26 suitable rainfall stations, which were used to generate a monthly rainfall time-series for each river sub-basin (Figure 5.4) as an input for the hydrological model.

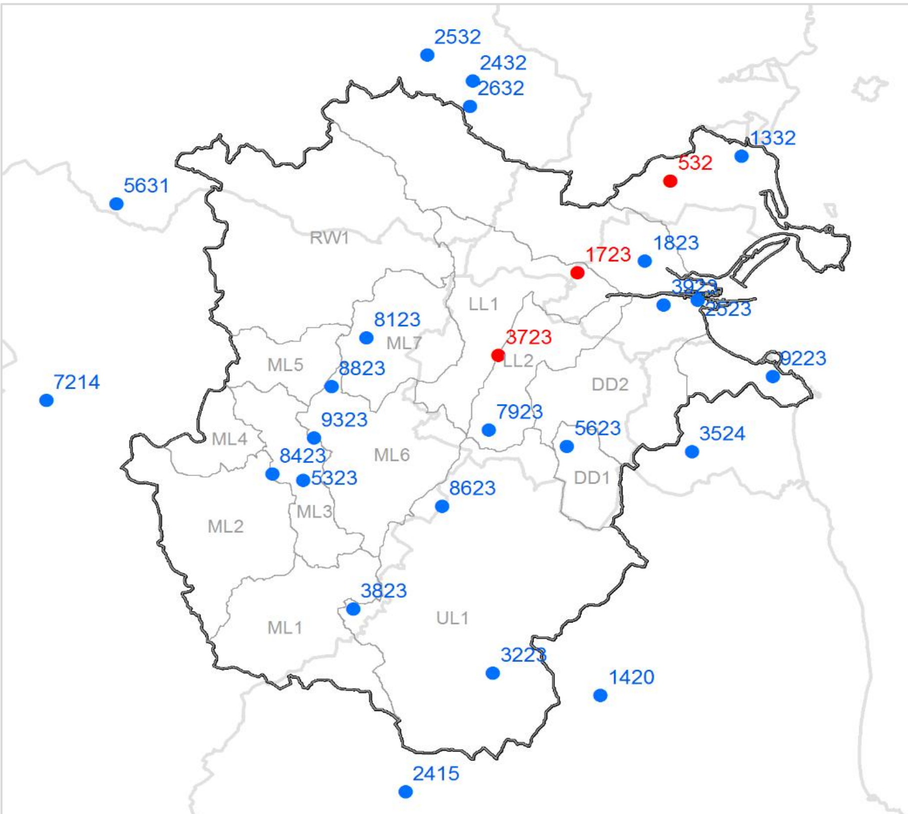


Figure 5. 4 Final network of weather and rainfall stations used to generate monthly rainfall time-series data for river sub-basins, with rainfall stations (blue and labelled), synoptic weather stations (red and labelled) and river sub-basins (light grey and labelled) nested within the catchment (black borderline).

In order to obtain a network of adequate coverage and higher spatial resolution, all stations with one missing value (i.e. missing month) have been included and the missing value has been rather estimated. This is in agreement with guidance of the world meteorological organisation which suggests that no more than 5% to 10% of a record should contain interpolated data (Subramanya 2005). The Normal Ratio method (Subramanya 2005) for estimating missing data was used to fill the gap in each of the six stations above. This method estimates missing data based on the performance of a group of neighbouring stations (adjacent stations within the same sub-catchment), as mathematically expressed in Equation 5.1:

$$r_x = \frac{N_x}{M}\left[\frac{r_1}{N_1} + \frac{r_2}{N_2} + \ldots\ldots + \frac{r_m}{N_m}\right] \tag{5.1}$$

Where,

r_x	:	the missing monthly rainfall at station x
r_i	:	respective monthly rainfall value at neighbouring station i, where i=1:m
M	:	Number of neighbouring stations
N	:	Normal annual rainfall at certain station calculated as the average annual rainfall based on a 30-year record.

Equation 5.1 estimates the missing record (r_x) in the subject station by weighting the corresponding rainfalls at various neighbouring stations, each by the corresponding ratio of normal annual rainfall (N).

Accordingly, neighbouring stations for each of the six stations of concern were identified (Table 5.1). For each station in Table 5.1, the length of historical records was examined to ensure the most suitable interval is selected to calculate the normal annual rainfall (*N*). It was found that not all the stations have a 30-year record, and in such case, calculation of *N* was based on the longest available record. To ensure that a representative *N* is calculated, only years with no missing monthly records were considered (i.e. years with full 12–month record). Equation 5.1 was then applied for

Table 5. 1 Stations with one missing record and their neighbouring stations.

Station	Neighbouring stations
1332	5623, 9223,2523, and 3923
1420	3223 and 2415
2523	3923, 1823, and 9223
3524	5623, 9223,2523 and 3923
5323	8423 and 9323
9223	3524, 2523 and 3923

each individual case of the six stations to fill their gaps and provide continuous time-series for each case.

The monthly total rainfall time-series for each river sub-basin during the simulation period 2012-2017 was derived by interpolating monthly rainfall values of respective surrounding stations using the area-weighted thiessen-polygon method.

- First, the polygons of the rain gauges were constructed in ArcGIS using the geo-processing toolbox (analysis tool > proximity > create Thiessen Polygons) (Figure 5.5).
- The polygons were then intersected with the river sub-basins layers to determine intersected polygons for each river sub-basin as visualised (Figure 5.6).
- The area of each intersected polygon was then determined and divided by the area of the respective river sub-basin to provide the proportion it represents from this river sub-basin (i.e. area weightage factors).
- The monthly area-weighted rainfall for each river sub-basin is then calculated as the sum of the products of the proportional area and the corresponding monthly record for each associated station.

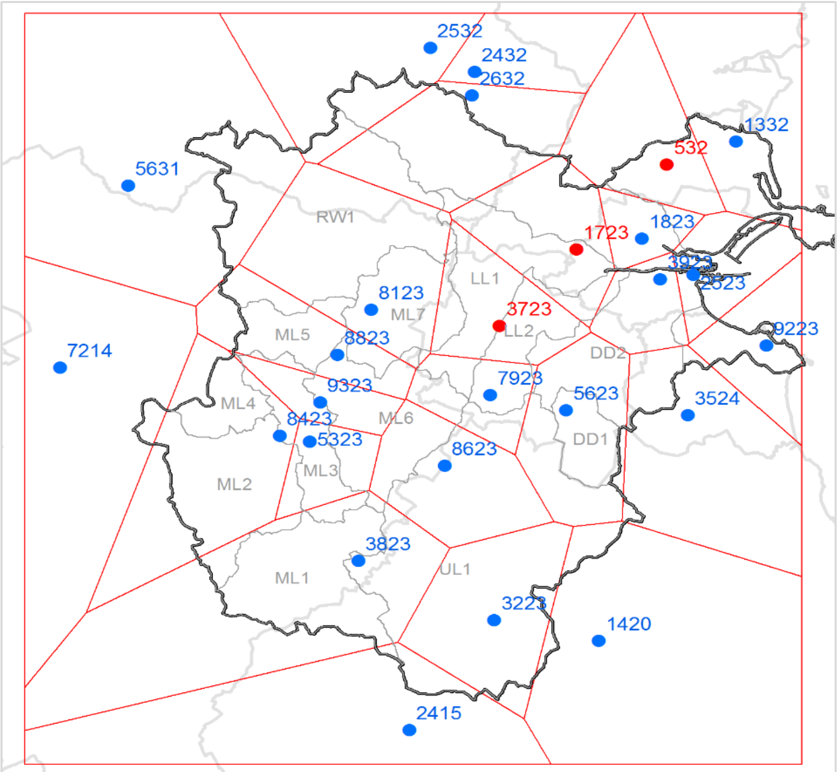


Figure 5. 5 Thiessen polygons (red lines) constructed from the rainfall point stations and overlaying river sub-basins.

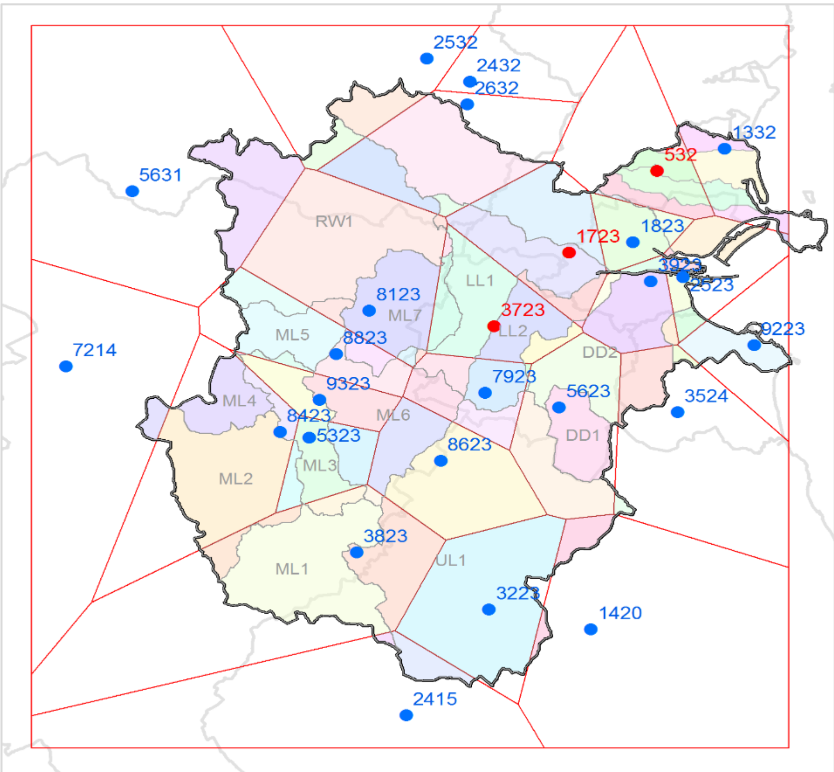


Figure 5. 6 Intersection of thiessen polygons with river sub-basins. Each of intersect polygons derived from this process is symbolised by a unique colour.

Table 5.2 illustrates the estimation of total monthly rainfall in January 2012 for the river sub-basin ML2. This procedure was repeated for each river sub-basin in all months through the simulation period 2012-2017 to derive area-weighted monthly time-series rainfall data for each sub-basin (Appendix C.2). The derived time-series rainfall data was subsequently defined for each river sub-basin in the model. For example, Figure 5.7 shows the data view for the rainfall input for river sub-basin ML2 in the WEAP-Dublin model.

Table 5. 2 Estimation of area-weighed monthly rainfall, with the estimation of rainfall for river sub-basin "ML2" in January 2012 provided as an example.

Station No.	Intersect polygon area (km^2)	Proportion by area	Rainfall e.g. Jan. 2012 (mm)	Area-weighted rainfall(mm)
	a_i	p_i	r_i	$p_i\ r_i$
3823	11.21	0.11	91.60	9.73
5323	7.08	0.067	72.80	4.89
7214	5.55	0.053	86.70	4.56
8423	81.69	0.77	73.40	56.81
Total	105.50	1		**75.99***

$p_i = a_i$ / total river sub-basin area; monthly area-weighted rainfall = $\sum p_i r_i$

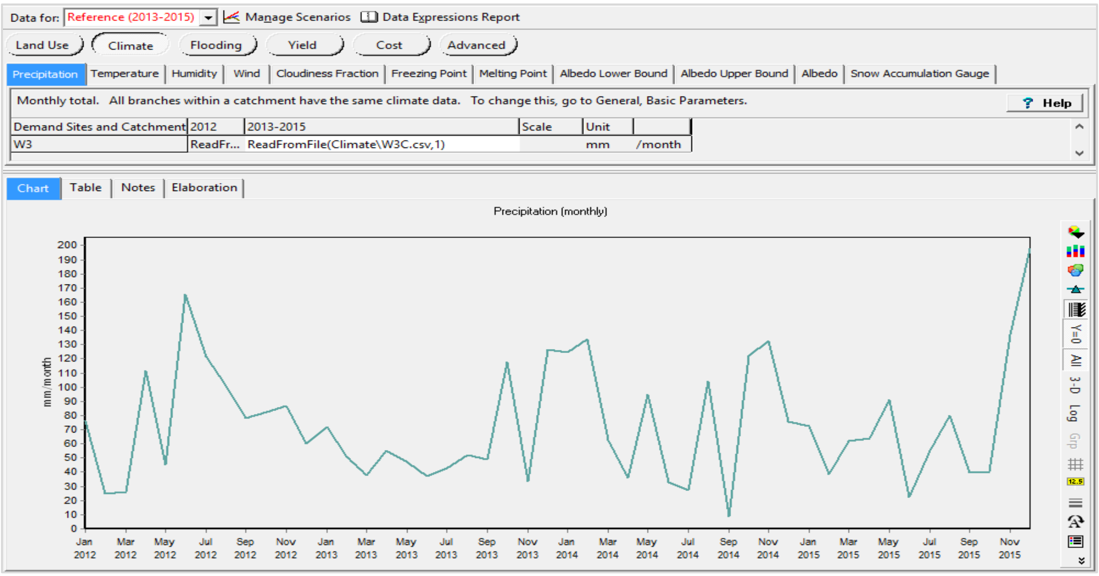


Figure 5. 7 Area-weighted monthly rainfall time series for river sub-basin ML2, as populated in the WEAP-Dublin model for the period 2012-2015.

The model also requires other climatic inputs, for example, temperature and wind speed. Historical records of these variables are only available at the three synoptic stations located inside the catchment area; Dublin Airport (532), Phoenix Park (1723), and Casement (3723). For temperature, the monthly records at these stations include the maximum and minimum temperatures in the month. A time-series of average monthly temperature was calculated from the maximum and minimum monthly temperature in order to obtain an equivalent to the time-series of a single value "weighted mean of high and low temperature" as required by the WEAP21 model. As shown in Figure 5.5, the three synoptic stations are located close to each other in the downstream area of the catchment only. Despite this limitation, it has been assumed that their temperature values are representative of the entire catchment and hence the required temperature variable for the model has been calculated as the mean of average monthly values at the three stations. For wind-speed, the monthly records of mean wind speed at the synoptic stations for each month in (knots) have been converted into m/s and used on the WEAP-Dublin model. Similar to temperature, wind-speed values were assumed to be representative of the entire catchment and their averages have been calculated and used in the model. Appendix C.3 shows time-series data of temperature and wind speed as used in the WEAP-Dublin model for all river sub-basins.

5.2.3 Land-use parameters

All parameters related to land cover and soil-water properties in the hydrological module in WEAP21 within each sub-catchment have been estimated from land covers and soil types derived from the CORINE land-cover dataset (Lydon & Smith 2014), and the national soil survey (The Agricultural Institute 1980) / EPA soil maps (Fealy et al. 2009).

The CORINE land cover dataset includes 34 land cover classes, classified under five major land cover categories; artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands and waterbodies. Such level of detail for the land cover is not required to parameterise the catchment and hence the various land cover types in the catchment have been grouped together based on their parent category. Furthermore, in order to obtain more distinct categories for the urban and agriculture categories, the first group has been subdivided into urban and green urban categories and the second group has been subdivided into non-irrigated lands and pastures. Hence, the final grouping of land cover classes in the catchment yielded seven representative categories; urban, green urban, non-irrigated lands, pasture, forest, wetlands, and waterbodies (Figure 5.8). As shown in the figure, the land cover varies across the catchment; with wetlands dominating the upstream part of the catchment, agricultural areas (pasture in particular) dominating the middle part of the catchment, and urban fabric dominating the downstream part of the catchment.

Two soil maps are available; the national soil survey map (The Agricultural Institute 1980) and the EPA indicative soil map (Fealy et al. 2009). The first map classifies soils into 44 associations with detailed physical and hydraulic properties of each layer in the soil profile; The second map classifies soils into 25 types based on a set of forming factors (such as vegetation and geology or parent material) and provides little information on soil properties (i.e. functional sub-division of soils). Therefore, the soil survey map has been used mainly to define soil-water properties, and the EPA soil and sub-soil maps were used occasionally to validate it or supplement it in cases where soil information are limited or unclear.

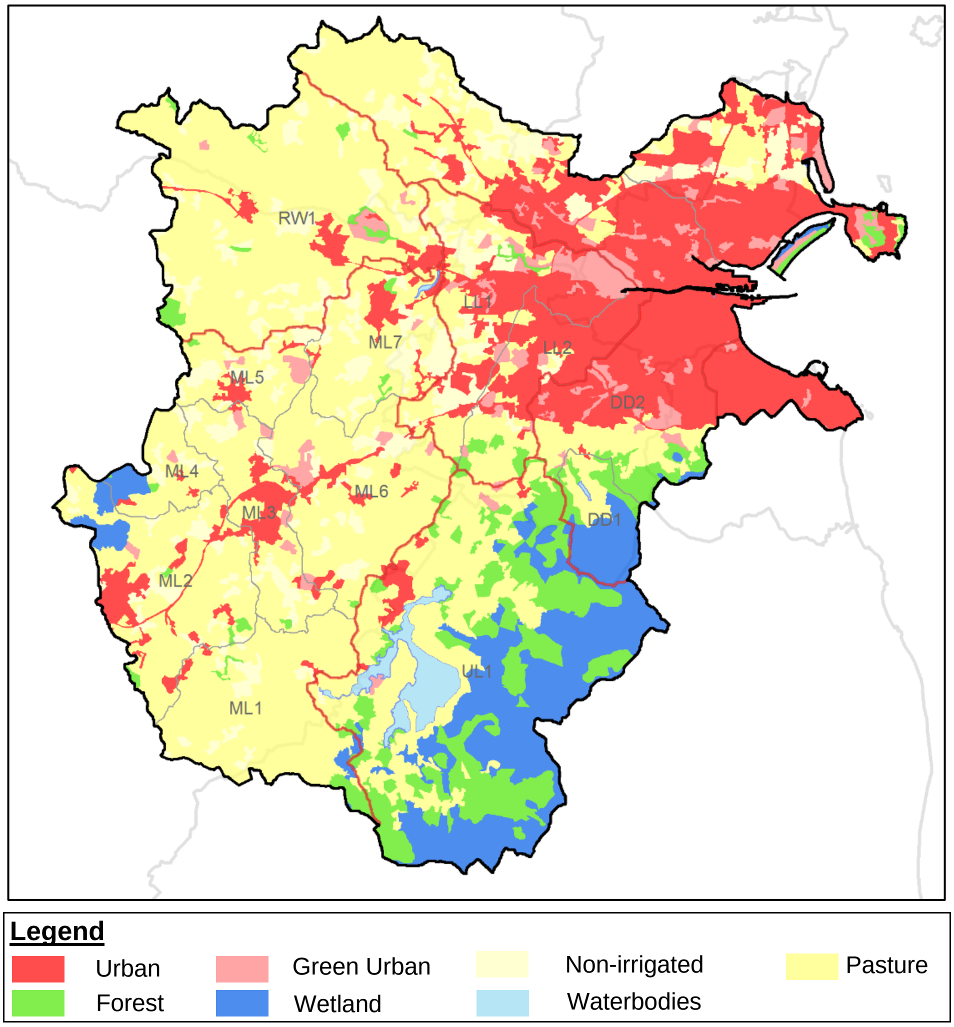


Figure 5. 8 CORINE land covers grouped into seven major categories within the Liffey and Dublin bay catchment (black borders), its representative sub-catchments (red border) and river sub-basins (light grey and labelled).

To define initial values for land use parameters for each sub-catchment in the WEAP-Dublin model, first the sub-catchments (including nested river sub-basins) layer was intersected with the land covers layer in order to characterise each sub-catchment with unique land cover characteristics. The resulting map is further intersected with the soil map and this in turn produced a combination of land cover and soils segments within each sub-basin. The fractional area of each segment within each sub-basin was determined. For example, Figure 5.9 shows fractional areas of land cover-soil combinations for river sub-basins "UL1", given as percentage of the total area of the river sub-basin.

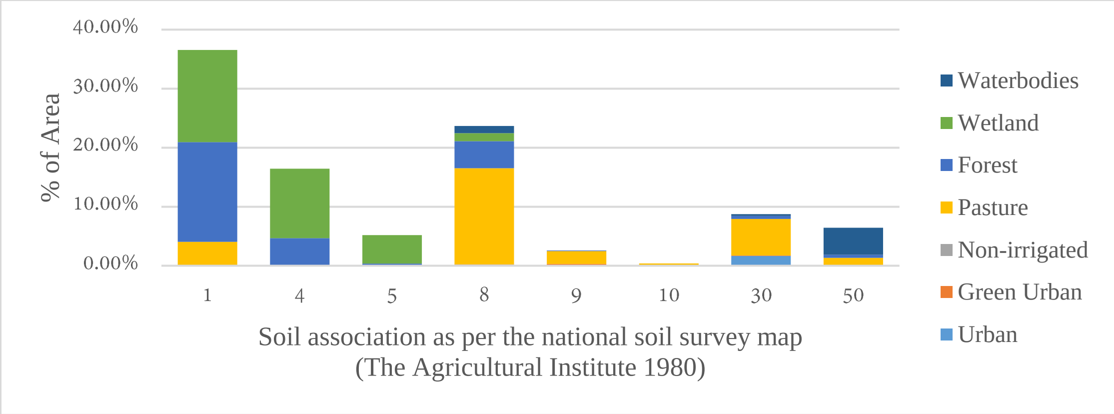


Figure 5. 9 Fractional area of each land cover and soil combination within river sub-basin UL1, provided as percent of the area

Secondly after determining unique land cover/soil segments in each sub-catchment, a range of techniques have been applied to obtain initial estimates of land-use parameters for each unique segment. The techniques include software and tools which estimate soil hydraulic properties from the basic soil physical properties (e.g. soil texture, particle size and bulk density) using empirical formulas. For example, basic soil data provided in the national soil survey classification were processed in pedotransfer functions (PTFs) of WEAP to provide estimates for effective water-holding capacity and hydraulic conductivity for each unique land cover – soil segment.

A review also was conducted to a variety of previous WEAP studies (Table 5.3) to support the parameterisation of WEAP-Dublin catchments.

Table 5. 3 Initial values of hydrological parameters for land cover – soil combinations within sub-catchment UL, as applied in the WEAP model.

	Land cover	Yates *et al* 2013	Young *et al* 2009	Rand Co. 2008	CRWR 2006	Yates *et al* 2009
Kc	Urban			0	0.77	
	Bare				0.30	
	Agriculture		1.1	0.90	0.90	0.90 – 1.1
	Shrubs		1.1	0.40		0.90 – 1.1
	Forest			0.40	0.40	0.90 – 1.1
	Trees		1.1			0.90 – 1.1
	Wet		1.1		0.90	0.90 – 1.1
RRF	Urban	1	4	5	8	
	Bare		4	5		
	Agriculture	6	8	6	2.5	
	Shrubs	3	14	6	4.2	

	Forest	4		16	5.2	
	Trees		20		4.2	
	Wet		4		6.3	
Swc (mm)	Urban	300	80	500	5-25	180
	Agriculture	500-700	80-1180	540	5-25	180-1050
	Shrubs	450-600	80-1180	600	5-25	180-1050
	Forest	600-850	80-1180	1200	5-25	180-1050
kj (mm/month)	Urban	125 – 300	130	150		150
	Agriculture	200-300	400-1004	153	220-18000	150-225
	Shrubs	200-600	400-1004	153	220-18000	150-225
	Forest	240-800	400-1004	360	220-18000	150-225
F		0.40 – 0.80	0.50 – 0.80	0 – 0.50		
Dwc (mm)	All covers	500-850	200-300		3-25	
k2 (mm/month)	All covers	200-400	87-240		2800-32400	60

5.2.4 Water uses data

The Dublin Region Water Supply Area (WSA) includes administrative areas of Dublin, South Dublin, Fingal, Dún Laoghaire counties and significant parts of counties Wicklow, Kildare, and Meath. The Dublin region WSA receives water from five major treatment schemes supplemented by three smaller schemes (Irish Water 2015b) as shown in Figure 5.10. The major schemes are:

- Ballymore Eustace treating water from Phollaphuca reservoir at the Upper Liffey river
- Lexilip treating water from Lexilip reservoir at the Middle Liffey river
- Roundwood treating water from Vartry impoundment
- Ballyboden treating water from Bohernabreena reservoir at river Dodder
- Srowland (newly commissioned scheme) treating water from river Barrow

The smaller schemes are:

- Bog of the Ring, in Fingal, treating groundwater and supporting Lexilip treatment scheme
- Rathangan wellfield and Monasterevin wellfield, in Kildare, treating groundwater and supporting srowland scheme

Figure 5.10 Locations of existing water supply schemes for the Dublin Region WSA. Source: Irish Water (2015b).

The Irish Water published map of WSA (2015a) was first geo-referenced in ArcGIS using the electoral division map of the central statistics office (CSO 2011) as a reference map (Figure 5.11). This WSA is then divided into water supply zones, each of which receives water from one or a combination of the above sources. The boundaries of the water supply zones and sources of supply for each respective zone were determined based on publically available information on water supplies from local authorities' websites (Figure 5.12).

The existing water treatment schemes have a potential combined treatment capacity of 650 Ml/day. However, due to physical constraints at a number of treatment plants and the bottleneck conditions in the supply network, not all of this potential production can be deployed and delivered to customers (Irish Water 2015b).

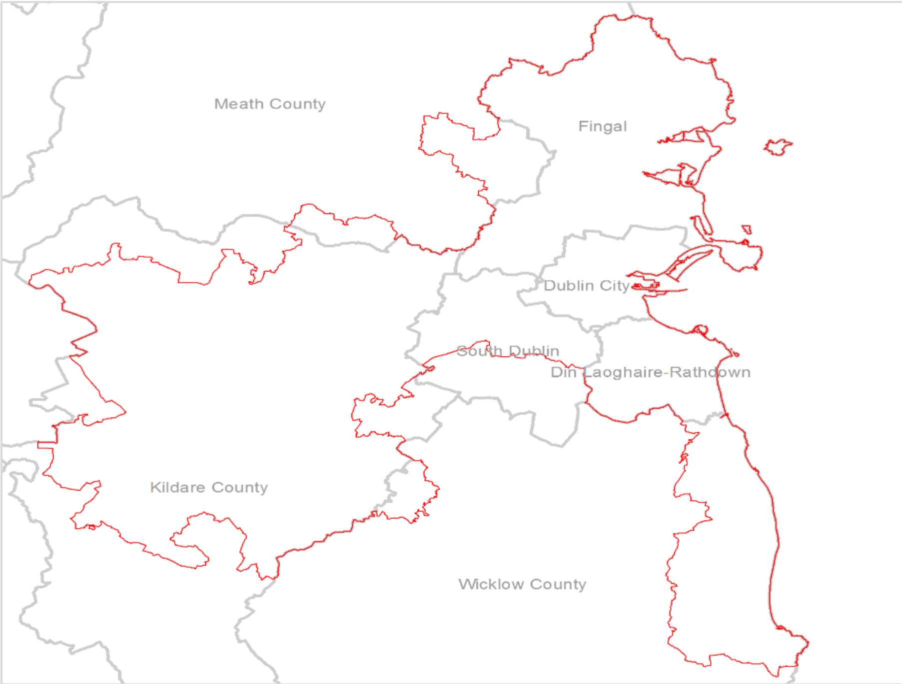


Figure 5. 11 Dublin Region water supply area (red lines). The underlying map of administrative counties (light grey) is sourced from central statistics office (CSO 2011).

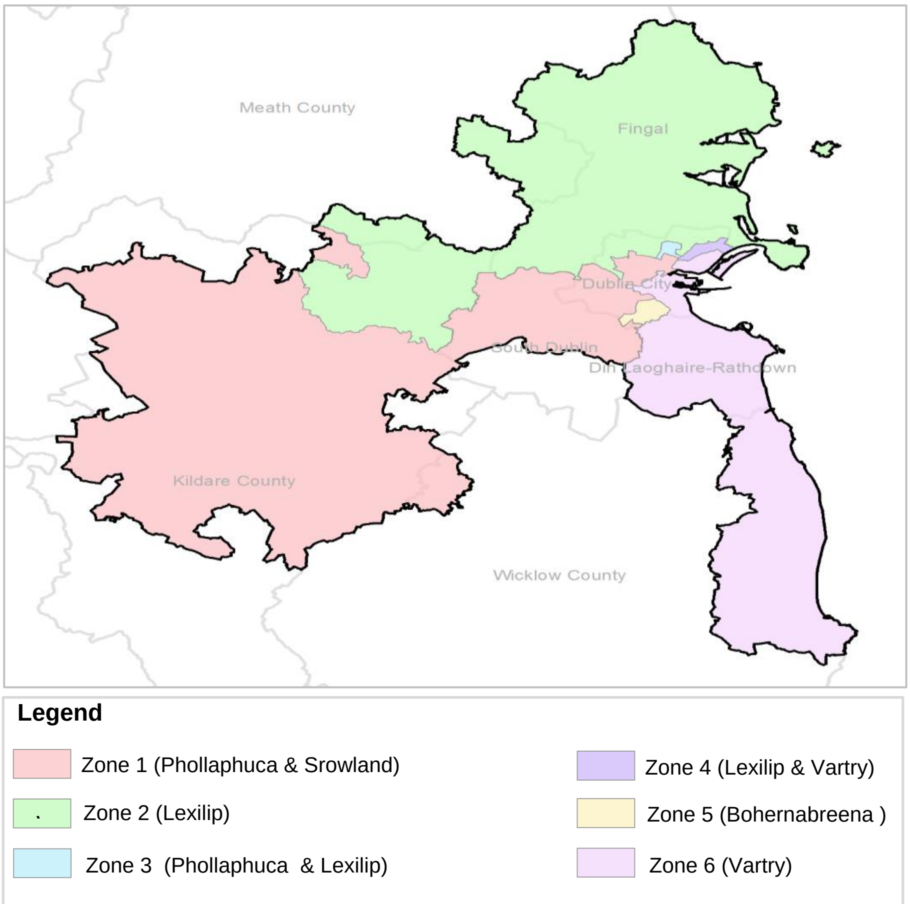


Figure 5. 12 Water supply zones within the Dublin Region WSA characterised based on the supply source(s).

Table 5.4 summarises the maximum deployable output from each scheme for 2011 and 2015 and the water supply zones which they supply. As shown, the maximum deployable output from all schemes was 543 Ml/day in 2011, and this has been increased to 623 Ml/day in 2015. It is also worth mentioning that approximately 525 Ml/day (85% of current maximum deployable output) is available from the river Liffey with 310 Ml/day supplied by Ballymore Eustace and 215 Ml/day by Lexilip.

Table 5. 4 Outline of water supply schemes for the Dublin Region and associated deployable capacity, categorised into major and supplementing schemes

Source (river)	Treatment Scheme	Capacity (2011)	Capacity (2015)	Supply Zone
Major Schemes				
Phollaphuca (Liffey)	Ballymore Eustace	310	310	Zones 1, 3
Lexilip (Liffey)	Lexilip	148	215	Zones 2,3, and 4
Vartry (Vartry)	Roundwood	65	65	Zones 4 and 6
Bohernabreena (Dodder)	Ballyboden	12	12	Zone 5
Barrow (Barrow)	Srowalnd	0	13	Zone 1
Supplementing Schemes				
Groundwater, Fingal	Bog of the Ring	3	3	Zone 2
Groundwater, Kildare	Rathangan	3	3	Zone 1
Groundwater, Kildare	Monasterevin	2	2	Zone 1
		545	615	

Bog of the Ring supplements Lexilip
Rathangan and Monasterevin supplement srowland

The water uses within the WSA include domestic uses, non-domestic uses (i.e. industrial, institutional, and commercial), hydropower generation as well as other ecosystem services. In the WEAP-Dublin model, demand site nodes were used to represent domestic and non-domestic uses at the water supply zone level. A demand-supply network was then established using transmission links, which connect the water supply zones with their respective sources as summarised in Table 5.4. The flows in transmission links were limited only to the actual deployable capacities given in Table 5.4. The demand sites were parameterised using census data, land-use data and water-uses as reported in a review for regional water demand (Irish Water 2015b) in order to simulate monthly water uses (i.e. domestic and non-domestic uses) at the supply zone level. Parameters for demands included annual activity level and water-use rate for each sector (domestic and non-domestic), and the associated losses (Chapter 3).

Domestic water uses were estimated based on number of population and per-capita water-use. The number of population for each supply zone was determined by intersecting the geo-referenced water supply zones with the electoral divisions map of the central statistics office (CSO 2011) (Table 5.5). Population growths through the simulation period 2012-2017 were accounted for by deriving annual growth rates for each county based on CSO preliminary results of census 2016 (Table 5.6). As shown in Table 5.5, it was necessary to disaggregate population in the water supply zone by county as growth rates were only reported at the county level at this stage. A value of 45.80 m^3/capita/year (125.50 litre per capita per day) for domestic water uses was used, as suggested by data from the Irish water-metering programme (Irish Water 2015b).

Table 5. 5 Domestic level of activity characterised by county for each supply zone based on CSO census data 2011.

Zone	WEAP code	County	Population estimate (10^4)
Zone 1	Z1	Dublin City	25
		Kildare	11.80
		South Dublin	24.40
		Wicklow	0.180
Zone 2	Z2	Dublin	12.30
		Kildare	5.40
		Fingal	27.30
		Meath	2.30
Zone 3	Z3	Dublin	1.60
Zone 4	Z4	Dublin	2.80
Zone 5	Z5	Dublin	4.60
Zone 6	Z6	Dublin	10.2
		Dun Laoghaire	16.70
		Wicklow	5.5

Table 5. 6 Estimated annual growth rates by county as derived from CSO preliminary results - census data 2016. The growth rates were used to project population in WEAP from 2011 to 2012 and so on until 2015.

County	Census 2011 (10^4)	Change by 2016	Annual growth rate
Dublin City	56.50	+ 4.8 %	0.009
South Dublin	24.4	+ 5.1 %	0.010
Fingal	27.30	+ 8.1 %	0.016
Dun Laoghaire	16.70	+ 5.3 %	0.010
Kildare	17.20	+ 5.6 %	0.011
Meath	2.30	+ 5.9 %	0.012
Wicklow	5.68	+ 4.2 %	0.008

On the other hand, non-domestic water-uses were estimated based on areas designated for non-domestic activities (i.e. industrial, institutional and commercial) and water usage rate defined in Mm^3/year/km^2. The areas designated for non-domestic activities (non-domestic level of activity in km^2) within each supply zone was determined by intersecting geo-referenced water supply zones with the CORINE land cover (Table 5.7). The non-domestic water usage rate was estimated for each county based on non-domestic water usages data provided in Irish Water (2015b). For instance, non-domestic water usage rate for a county is calculated as the given non-domestic water usage for this respective county divided by total area designated for non-domestic activity within the county (Table 5.8). It was assumed that non-domestic water usage rate for any county is constant through the water supply zones e.g. the water usage rate for non-domestic activities for Dublin is the same for zones 1, 2 and 6.

Table 5. 7 Non-domestic level of activity characterised by county for each water supply zone, based on CORINE land cover 2012.

Zone	WEAP code	County	Area (industrial and commercial) km^2
Zone 1	Z1	Dublin City	7.20
		Kildare	5.42
		South Dublin	15.50
		Wicklow	–
Zone 2	Z2	Dublin	6
		Kildare	1
		Fingal	14.30
		Meath	–
Zone 3	Z3	Dublin	–

Zone 4	Z4	Dublin	–
Zone 5	Z5	Dublin	–
Zone 6	Z6	Dublin Dun Laoghaire Wicklow	1.80 2 0.62

Table 5. 8 Estimated water usage rates for non-domestic activities given by county. Water usages for non-domestic activities in 2011 by county were given in Irish Water (2015b). Areas designated form non-domestic activities were estimated from CORINE land cover.

County	Usage in 2011 (Mm^3/year)	Area (km^2)	Annual water use rate (Mm^3/year/km^2)
Dublin City	15.51	15	1.03
South Dublin	4.70	15.53	0.30
Fingal	12.08	14.11	0.86
Dun Laoghaire	4.27	2.65	1.60
Kildare	8.37	6.38	1.31
Wicklow	1.25	0.62	2

Another significant component that needs to be accounted for water demand calculation in the region is water losses. Water losses are a serious problem in Ireland, which is estimated to be in excess of 40% of total amount of produced water (Irish Water 2015b). This figure includes both customer side leakage (CSL) and unaccounted for water (UFW) (or distribution losses). The customer side leakage (CSL) is defined as losses and wastages that occur at the private side of customer connections. CSL was estimated to be 40.80Ml/day in the Dublin Region in 2011 (Irish Water 2015b). UFW is defined as the volume of water that passes into the supply network and cannot be accounted for as legitimate use; it is calculated as the difference between the total distribution input and the total accounted for water (i.e. domestic, non-domestic, CSL and allowance for operational use). UFW was estimated to be 178.10 Ml/day in 2011 (Irish Water 2015b). Hence, total water losses were estimated to be 218.90 Ml/d out of 535 Ml/d produced in 2011. This is twice the level of leakage in the UK where assets are comparable but have been subject to intensive leakage management over the last 20 years (Irish Water 2015b).

In the WEAP-Dublin model the customer side leakage was estimated based on the number of households (i.e. connections) and a pre-defined customer leakage rate of 0.025 m^3/property/year (66 litre / property / day) as identified by Irish Water (2015b). Estimate of number of households within each water supply zone was derived by intersecting water supply zones with 2011 census map. The resulting number of households was further refined based on the preliminary results of 2016 census data. For example, the number of households for a supply zone was estimated based on number of permanent occupied properties plus an allowance to account for household growths or vacant houses filled since last available census 2011 (Appendix D.1). The customer side leakage can be divided into 'internal losses' occurring within the dwelling (e.g. leaking cisterns / internal plumbing issues) and 'external losses' occurring on the pipe that connects the dwelling to the supply network. The internal dwelling losses of the customer side leakage was only considered in parameterising 'demand sites', since such losses possibly return to a wastewater treatment plant. On the other hand, the external pipe losses were considered as part of 'transmission link losses', since these subsurface losses flow into the groundwater. It was assumed that internal losses account for 40% of CSL and external pipe losses account for the reminder based on findings of the pilot project implemented as part of the Irish Water first fix leak repair scheme (Irish Water 2015c).

In 2011, total UFW in the region was estimated to be 178 Ml/day, an equivalent of 33% to total input to the supply system (Irish Water 2015b). UFW in the WEAP-Dublin model was considered under "transmission link losses", together with external pipe losses at the customer side. To calculate an adjusted percentage of distribution losses (i.e. considering both UFW and external pipe losses), the total accounted for water (AFW) was estimated as the sum of all legitimate demands including domestic (D), non-domestic (ND), customer side leakage (CSL) and an allowance for operational use and maintenance (Op) (1% of all the previous) (Equation 5.2). For each supply zone, the total water supply requirement S represents the sum of AFW and UFW (Equation 5.3). The UFW for each supply zone (i.e. demand site) was considered to represent 33% of total water supply requirement, and hence total water supply requirement for the supply zone can be expressed as in Equation 5.4. The amount of losses due to external pipe leakages ($CSL_{external}$) at the supply zone level was then estimated (i.e. 60% x number of households served x CSL). The distribution losses (L_{adj}) was finally re-calculated as a percentage of the sum of UFW and external pipe losses to the total water supply requirement of the supply zone (Equation 5.5). For each transmission link, this adjusted loss rate represents leakage as percent of flow passing through to the respective demand site. Table 5.9 summarises calculation of water demand components for each water supply zone, which were used to parameterise demand sites and their associated transmission links. The above-mentioned approach to estimate demand components for supply zones was derived from Irish Water (2015b).

$$AFW = D + ND + CSL + Op \qquad (5.2)$$

$$S = AFW + UFW \qquad (5.3)$$

$$S = AFW / (1 - 0.33) \qquad (5.4)$$

$$L_{adj} = (UFW + CSL_{external}) / S \qquad (5.5)$$

Table 5. 9 Summary of water demand components for each supply zone, calculated to parameterise demand sites in the WEAP-Dublin model — Adapted from Irish Water (2015b).

Component			**Unit**	**Z1**	**Z2**	**Z3**	**Z4**	**Z5**	**Z6**
Accounted for water	Domestic	Population	Cap	613800	473000	15742	28561	46532	324000
		PPC	m^3/cap/yr	45.80	45.80	45.80	45.80	45.80	45.80
		Domestic demand	Mm^3/yr	28.11	59.36	1.98	3.58	5.84	40.66
	Non-domestic	Non-Domestic	Ml/d	21	59	0	0.001	0	14

	Customer side Leakage	Nr. house-holds	Nr.	214879	164297	5840	10745	20871	147748
		CSL rate	m^3/pr/yr	0.025	0.025	0.025	0.025	0.025	0.025
		CSL	Mm^3/yr	5.18	3.96	0.14	0.26	0.50	3.56
	Operational use	Operational use factor	%	1%	1%	1%	1%	1%	1%
		Operational use allowance	Mm^3/yr	0.55	0.47	0.007	0.014	0.025	0.24
	Accounted for water (AFW)		Mm^3/yr	56	47.63	0.87	1.58	2.66	23.74
Unaccounted for water (UFW) / Distribution losses		As % of Demand	%	33%	33%	33%	33%	33%	33%
		UFW	Mm^3/yr	27.58	23.43	0.43	0.78	1.31	11.70
Estimated supply requirement			Mm^3/yr	83.60	71.06	1.30	2.36	3.97	35.44
Adjustment of losses for WEAP model									
Internal household losses (40% CSL)		26 l/prop/d	Ml/d	5.59	4.27	0.15	0.28	0.54	3.84
External pipe supply losses (60% CSL)		40 l/prop/d	Ml/d	8.60	6.57	0.23	0.43	0.83	5.91
Demand site losses		Losses return to WW system	%	5.36	4.77	8.17	8.26	9.54	5.72
Transmission losses		Losses from system	%	37.15	36.62	39.56	39.64	40.67	37.47

Table 5.9 represents our best estimates for sectoral water demands across the region, which drive the model to allocate water among the competing users from associated sources. Water at these sources become available based on rainfall-runoff modelling at connected sub-catchments to each source.

Non-consumed water from representative demand sites was diverted out to discharge points / water bodies using “return flow” pathways. To determine the routes of each demand site, a GIS analysis was carried out for the following spatial data: urban wastewater treatment (UWWT) agglomeration, locations of UWWT plants, geo-referenced supply zones, and Dublin and Liffey Bay and its river network.

First, the UWWT agglomeration layer was intersected with geo-referenced supply zones layer to identify UWWT plants serving each zone. It was revealed that some of these UWWT plants are located within or in close proximity to the Liffey and Dublin Bay catchment, and discharge effluents into its waterbodies. Other UWWT plants are located in other adjacent catchments and discharge effluents to their waterbodies. Figure 5.13 shows locations of the UWWT plants with respect to the Liffey and Dublin Bay catchment. As only the hydrology of the Liffey and Dublin Bay catchment is explicitly considered in the WEAP-Dublin model, and as the primary focus is to reproduce the regional water balance, it was decided to group UWWT plants identified as not discharging to the Liffey and Dublin Bay catchment into schemes based on their locations. For instance, all the 12 UWWT plants located outside the catchment in Kildare County (on the left hand side of the catchment in Figure 5.13) were grouped into Kildare scheme WwTP. Such grouping aimed to simplify the model and reduce the computational times. Also, examination of the UWWT plant loads revealed that these plants vary in capacity and in size; the largest of which is Ringsend WwTP with an existing load greater than 2 million PE (population equivalent), and the smallest being Newtown Cottages with an existing load less than 500 PE. To further simplify the model, relatively small UWWT plants (which discharge effluents into water bodies within the Liffey and Dublin Bay catchment) was grouped into larger schemes based on their locations and the receiving waterbody. For instance, Ardclough, Kilcloon and Rathcoffey UWWT plants were grouped into the Lower Liffey regional scheme; since they are in close proximity to this scheme, they have relatively small loads and their effluents eventually reach the discharge point of the Lower Liffey scheme. Table 5.10 summarises return flow routes from each supply zone to its associated treatment schemes, as represented in the WEAP-Dublin model. In the model, however, non-consumed water was routed directly to the discharge points of the outlined schemes, as the model does not simulate wastewater treatment processes or water quality.

The loads of UWWT plants in PE were used to determine the percent of outflow each route carries from total outflows of a demand site (i.e. routing fractions). Where the

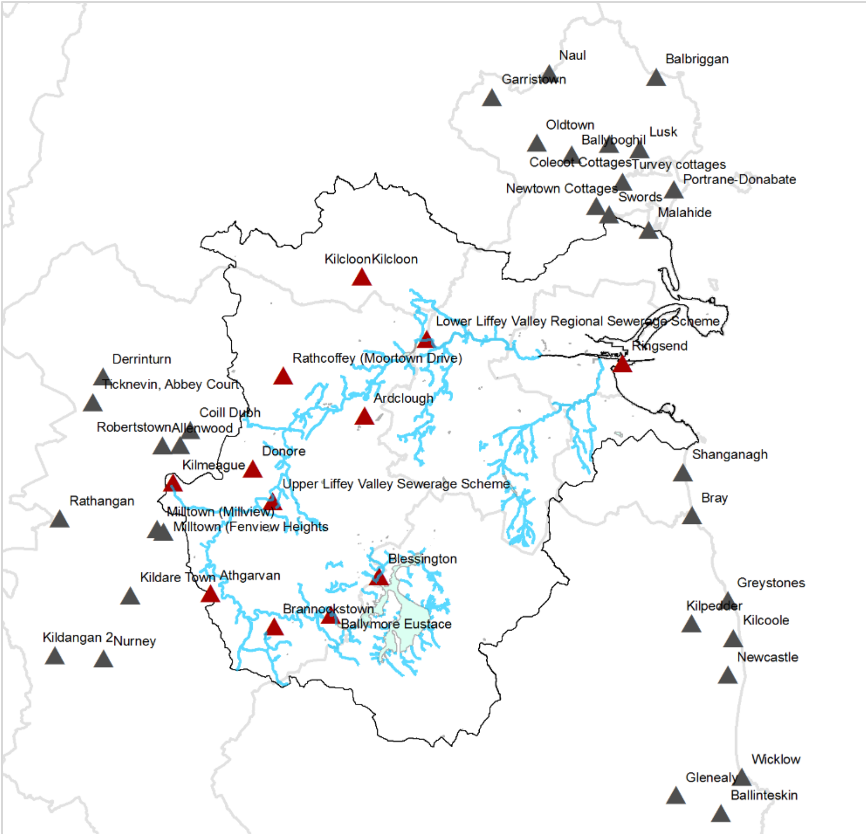


Figure 5.13 Locations of UWWT plants of the Dublin Region WSA, with respect to the Liffey and Dublin bay catchment. UWWT plant located within the catchment (red triangles); located outside the catchment (grey triangles); Liffey and Dublin bay catchment (black boundaries); and counties (grey boundaries).

scheme is a group of UWWT plants, the loads of all group members were summed to provide a representative total load e.g. Kildare WwTP scheme. Also, in cases where a particular wastewater was found to serve more than one supply zone (e.g. Ringsend WwTP), an area-weighted load was calculated to represent the contribution of each supply zone to the respective wastewater treatment plant. The weighting factor for the supply zone in this case was calculated as the fractional area of the UWWT agglomeration within the supply zone divided by the total area of the UWWT agglomeration. Table 5.10 summarises load of each scheme in PE and the percent of outflow each route carries from total non-consumed water of a demand site.

Table 5. 10 Summary of return flow routes from demand sites as represented and parameterised in the WEAP-Dublin model.

Return flows to WwTPs / discharge point	Contributing WwTPs	Population Equivalent (PE)	% Share of demand site total non-consumed water
Demand site: Z1			
Blessington	Blessington	6913	0.80
Osberstown	Upper Liffey, Athgarvan, Ballymore Eustace, Brannockstown, Donore, Kilmeague	107311	12.80
Kildare side WwTPs	Allenwood, Coill Dubh, Derrinturn, Kildangan 1, Kildanan 2, Kildare Town, Milltown (Fenview Heights), Miltown (Millview), Nurney, Rathangan, Roberstown, Ticknevin, Abbey Court	18133	2.20
Lexilip	Lower Liffey valley regional scheme	8937	1.10
Ringsend	Ringsend	699073	83.20
Sum		840367	100
Demand site: Z2			
Lexilip	Lower liffey valley regional scheme, Ardclough, Kilcloon, Rathcoffey	94495	8.40
Seaside WwTPs	Balbriggan, Ballyboghil, Colecot Cottages, Garristown, Lusk, Malahide, Naul, Newtown Cottages, Oldtown, Portrane/Donabate, Rush, Swords, and Turvey Cottages	146903	13.06
Ringsend	Ringsend	883324	78.54
Sum		1124721	100
Demand site: Z3			
Ringsend	Ringsend	19939	100
Sum		19939	100
Demand site: Z4			
Ringsend	Ringsend	38084	100
Sum		38084	100
Demand site: Z5			
Ringsend	Ringsend	560641	100
Sum		560641	100
Demand site: Z6			
Ringsend	Ringsend	427683	100
Sum		427683	100

5.2.5 Infrastructure data

Three reservoirs in the Liffey River are included in the WEAP-Dublin model, namely Phollaphuca, Golden Falls and Lexilip. Phollaphuca (located in the upstream of the Liffey River) is a relatively large reservoir with a storage capacity of approximately 200 Mm^3. However, the other two reservoirs are smaller and each has a capacity of less than one Mm^3. The three reservoirs are operated by the Electricity Supply Board (ESB), which is responsible for dam safety and for balancing competing water uses including drinking water abstractions, hydro-electric generation, fishery, leisure and amenity activities and environmental uses (EPA 2013, OPW 2016a, OPW 2012b, ESB n.d, ESB 2011).

Reservoir parameterisation in WEAP-Dublin includes defining physical properties of each reservoir, operation rules and hydropower characteristics. Parameter values for reservoirs were mainly derived from information available from different studies including studies on Liffey flood controls (OPW 2012b; OPW 2016a), ESB bulletin on Liffey hydropower station (ESB n.d.), and technical information provided by ESB (Turlough Hill office) through personal communication, including; volume elevation curves and observed storages.

ESB operates the three reservoirs in accordance with the "*Regulation and Guidelines for the Control of the River Liffey Water Management document, February 2006*", which sets out management procedures and operation rules to fulfil the above needs. The control and operation rules of the Liffey reservoirs as summarised by OPW (2016a) consist of three distinct operation modes;

- Routine operation: this mode represents the normal operation programme where no flooding threat exists and where oxygen levels in the river downstream of the reservoirs are satisfactory for ecosystem.
- Flood period operation: this mode is normally activated when Phollaphuca reservoir level rises to 186.30 m OD and/or inflow to Lexilip reservoir exceeds 50 m/s; or beforehand in case large flows are expected into Phollaphuca and Lexilip. In such conditions, ESB will prioritise the release of excessive flood

waters through spillways, as the overriding consideration is the safety of the dam in this case (OPW 2016a).

- Other variations in operational modes: this mode is used only when deficiency in oxygen levels in the river downstream of the reservoirs is significant due to abstractions and other uses.

The main control levels for each reservoir, which represent reservoir operation rules, are shown in Table 5.11. These levels were converted into corresponding volumes as to using volume-elevation curves (Appendices D.2-D.4) as to describe these rules in the WEAP-Dublin model i.e. expressing these rules as reservoir volume thresholds. For example, the volume corresponding to the maximum normal operating level was used as "Top of conservation storage" in the model and the volume corresponding to the minimum normal operating level was used as "Top of inactive storage". The volume-elevation curve for each reservoir is also used within the model for reservoir calculations to convert elevation to volumes and vice versa.

Table 5. 11 Main control levels for Liffey reservoirs, source: OPW 2012b

Main control level	Level (m OD)		
	Phollaphuca	Golden Falls	Lexilip
Maximum crest level	189.59	140.55	46.74
Maximum normal operating Level	186.30	139.00	45.60
Minimum normal operating Level	179.90	136.00	43.00
Zero storage level	174.00	135.00	43.00

* Levels referenced to Ordinance Datum – Poolbeg

The hydropower characteristics for each reservoir is summarised in Table 5.12, which were used in the WEAP21-Dublin as parameters for hydropower generation.

Table 5. 12 Hydropower characteristics for Liffey reservoirs, source ESB n.d.

	Phollaphuca	Golden Falls	Lexilip
Max. Turbine Flow, CMS	80	30	50
Tailwater Elevation, m OD	136.2	120.1	26.8
Hydropower Head	46.90	17.50	17.50

It is worth mentioning that the Golden Falls reservoir acts as a regulating reservoir to discharges from Phollaphuca by allowing the generating turbines at Phollaphuca to run for four hours before filling the Golden Falls reservoir. This is then released downstream at a lower discharge rate over a period of 24 hours (Fitzpatrick & Bree 2001; ESB 2011). Flow releases from Golden Falls to the Liffey River occur through the "Francis and Propeller" turbine, which is capable of passing 30 m^3/s at full load. This turbine has shown to be not effective when operating at partial load, and hence discharges from Golden Falls are dominated by intermittent or cyclical patterns to handle this limitation in turbine efficiency.

In addition, according to the Liffey Reservoir Act 1936, the reservoirs operator (ESB) is required to maintain a compensation flow in the Liffey for ecological requirements. The current in-stream flow requirements below are 1.5 m^3/s and 2 m^3/s below Golden Falls and Lexilip (Kolb et al. 2008). These compensation flows shall be maintained at all times by the operator to preserve a healthy ecosystem (DCENR 2007). To reflect this regulatory requirement, the model was programmed to pass the threshold flows at respective locations by using instream flow objects.

Chapter 6 APPLICATION OF WEAP21 MODEL FOR DUBLIN

6.1 WEAP-Dublin model schematic

Figure 6.1 shows a schematic of WEAP-Dublin model configuration. The blue lines represent the Liffey, the Dodder, and the Ryewater Rivers and the green nodes show their sub-catchments which are given as Upper Liffey (UL), Middle Liffey (ML), Lower Liffey (LL), Ryewater (RW), and Dodder (DD). Hydrologic connections between the five sub-catchments and their respective rivers are shown by the blue dashed lines. The green triangles on the Liffey show the three reservoirs Phollaphuca, Golden Falls, and Lexilip and the purple circles are used to represent the in-stream flow requirements below Golden Falls and Lexilip Reservoirs. The red circles are dedicated for the demand sites Z1 to Z6, which are connected to green and red lines. The green lines connect each demand site with its supply source(s), and the red lines route return flows from a demand site to the respective receiving water bodies. Furthermore, supplies from supplementing schemes (Vartry, Bog of the Ring and Srowland), whose water supply source are not within the Liffey and Dublin Bay catchment, are represented by the green quadrants. These schemes are included in the model for estimating the water balance at the level of Dublin Region WSA. Also, two outside wastewater treatment schemes in Fingal and Kildare receiving return flows from the Liffey and Dublin bay catchment are shown in brown circles. Finally, the blue circles show locations of six control points along the Liffey, the Dodder, and the Ryewater Rivers used for model calibration and validation. Four of these six points are actual hydrometric gauges number 09032 (Phollaphuca), 09007 (Golden Falls), 09022 (Lexilip Station), and 09001 (Lexilip) whilst the two remaining points are hydrological estimation points.

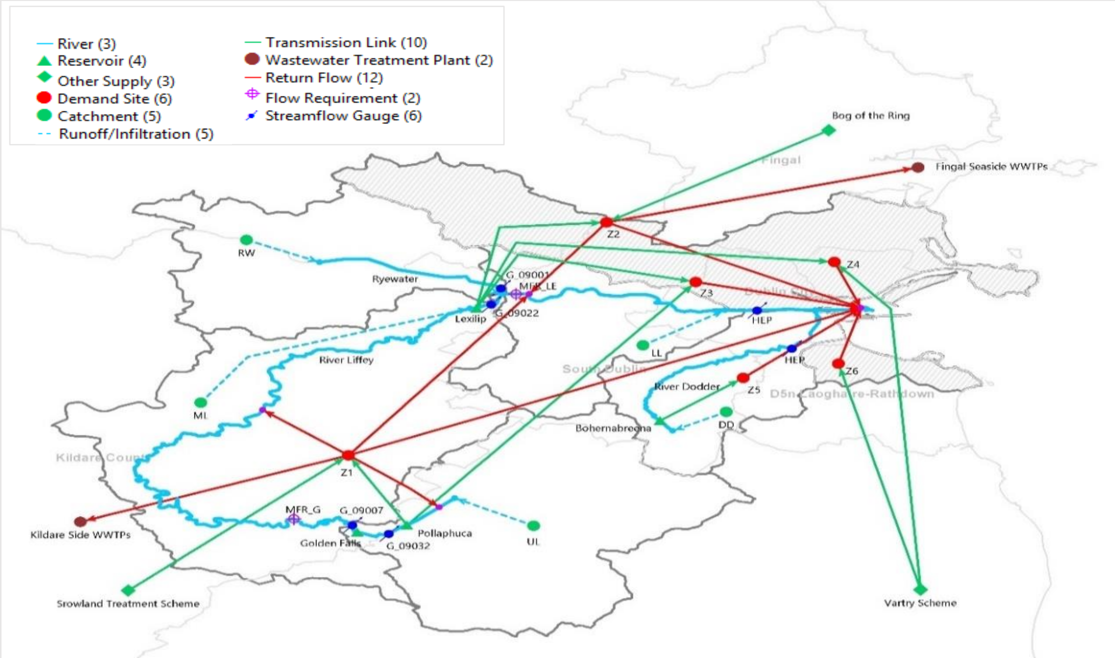


Figure 6. 1 A schematic of the WEAP-Dublin model, with counties (light grey and labelled); boundaries of representative sub-catchments of the Liffey and Dublin bay catchment (grey); and shaded areas represent parts within the catchment, which do not provide water.

6.2 Model calibration and validation

After completing its configuration, the WEAP-Dublin model has been calibrated and validated. In calibration, the main model parameters have been adjusted in such a way to obtain adequate match between the simulated and the observed flows at specific control points. On the other hand, model validation involved assessing the performance of the calibrated model in reproducing flow values for a period different from the one used in calibration (Moriasi et al. 2007). Flow data for the period 2012-2017 have been used for calibrating and validating the model.

Figure 5.2 above shows locations of the five control points which have been selected to account for flows at the five main sub-catchments. Flow data at these control points are either measured at a hydrometric station in the site or estimated from measurements at nearby hydrometric stations for the period 2012-2017. For instance, flow data at the outlet of the Lower Liffey sub-catchment were estimated by adding flows at stations 09002 in Lucan (Griffen), 09035 in Killen Road (Cammock), and 09001 in Lexilip

(Ryewater) to flows at station 09022 in Lexilip. Likewise, flows at the Dodder River before its confluence with the Liffey River were estimated by adding flows at station 09010 in Waldron's Bridge (Dodder) to flows at station 09011 in Frankfort (Slang).

Table 6.1 summarises the main information about the hydrometric stations. Data of the EPA and OPW hydrometric stations were downloaded from their websites whilst data of the ESB hydrometric stations were acquired through personal communications.

Table 6. 1 Gauges used for calibration and validation of WEAP-Dunlin model, and associated owners.

Control point	Water body	Sub-catchment	Type	Owner
Phollaphuca–09032	Liffey	Upper Liffey	Water level and flow	ESB
Golden Falls–09022	Liffey	Upper Liffey	Water level and flow	ESB
Lexilip–09022	Liffey	Middle Liffey	Water level and flow	ESB
Lexilip–09001	Ryewater	RyeWater	Water level and flow	OPW
Lucan–09002	Griffen	Lower Liffey	Water level and flow	EPA
Killen Road–09035	Cammock	Lower Liffey	Water level and flow	EPA
Waldron's– 09010	Dodder	Dodder	Water level and flow	EPA
Frankfort– 09011	Slang	Dodder	Water level and flow	EPA

6.2.1 Quality check and processing of flow data

Observed flow data for each control point have been checked for the presence of significant gaps and outliers in the data by conducting a visual assessment on the time-series plots of the flow and the corresponding rainfall. Outliers were included in the data only if they showed consistency with rainfall measurements and also if there were evidences such as published warnings for historic floods to confirm their occurrence. For instance, Figure 6.2 shows times-series plots of monthly mean observed flows at station 09032 in Phollaphuca and the corresponding rainfall values which have been calculated based on data from nearby weather stations, namely 1420, 2415, 3223, 3524, 3823, 5623, 7923, and 8623. The consistency between rainfall and flow data is apparent in the graph. Moreover, review of previous record of flood warnings revealed that such warnings have already been issued at Phollaphuca during months with extreme flows (e.g. Jun 2012, Feb 2014 and Dec 2015) (https://www.esb.ie/tns/press-center/) and (http://hydrologyireland.ie/).

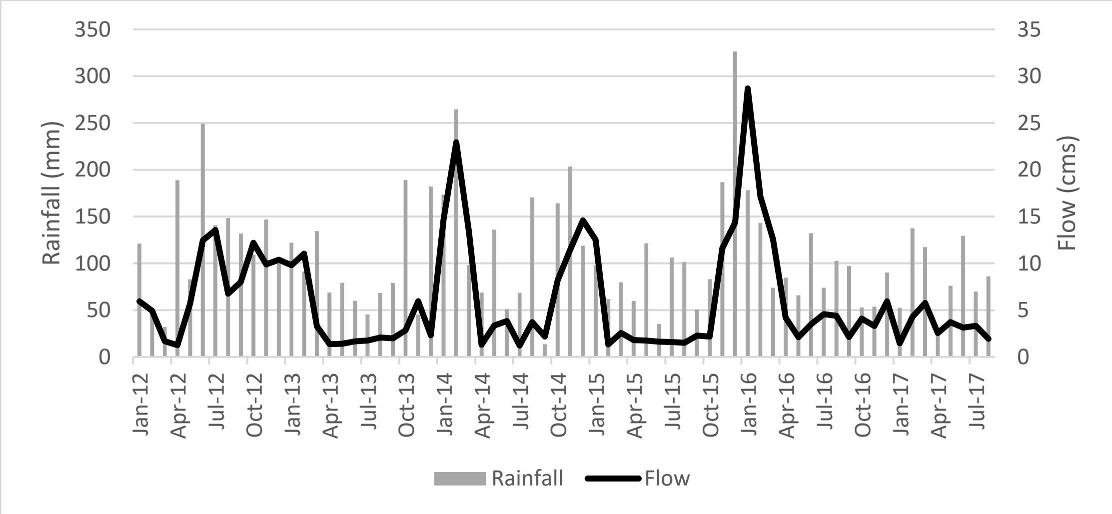


Figure 6. 2 Monthly mean streamflow (in cms) of Liffey river at Phollaphuca 09032 against total monthly rainfall data (in mm) of nearby / contributing weather stations.

6.2.2 Strategy for model calibration and validation

Model calibration involved adjusting the hydrological and the demand management parameters of the model to produce good match between the actual and the simulated flow values at selected control points in the catchment. Subsequently, the overall model performance was then validated based on evaluation of the simulated flows at the same selected control points but for period different from the one used in calibration. In terms of water management, the calibration and validation were conducted based on comparing the modelled values of the sectoral water uses and the regional water supply to the corresponding data reported by water authorities such as Irish Water and Dublin City Council.

Data for the period 2012-2017 have been used to calibrate and validate the model. The first year was used as warm-up period whilst the remaining period was split into two parts with 2013-2014 used for calibration and 2015-2017 used for validation. Manual calibration of model parameters was carried out only in the Upper Liffey and the Ryewater sub-catchments. The first sub-catchment accounts for 50% of water supplies in the catchment (i.e. water supplies to zone 1 and 3); whilst the second sub-catchment is the only one where flows at the outlet of the sub-catchment is not influenced by any water abstractions or reservoir operations. The calibrated parameters in the two sub-catchments were then transferred to the other three sub-catchments in a similar fashion to proxy basin test approach (Klemeš 1986). In this approach, calibrated parameters were transferred based on similarity in land covers between the sub-catchments. For instance, the calibrated parameters of the pasture land in the Ryewater sub-catchment were transferred to the corresponding land cover in the Middle Liffey sub-catchment while calibrated parameters of the wetland in the Upper Liffey sub-catchment were transferred to the corresponding land cover in the Dodder sub-catchment. Following the transfer of parameters, the parameters of each of the three sub-catchments were slightly tuned to provide better match between observed and simulated flows at the outlet of the sub-catchment.

Due to the large number of model parameters, calibration has been conducted only on the most sensitive parameters which have been identified through sensitivity analysis where the rate of change in model outputs corresponding to changes in model parameters is assessed (Moriasi et al. 2007). The scenario explorer view of WEAP was suitable to carry out this sensitive analysis as it provides a tool to visually examine the effect of changing model parameters on model outputs. Figure 6.3 is a typical explorer view of WEAP window with the upper part in this window shows a set of hydrological parameters along with their plausible ranges (upper and lower limits), and the lower part shows different model outputs e.g. streamflow, runoff, interflow, baseflow, and soil moisture. To determine sensitive parameters of the model, the effect of each parameter with respect to model outputs was examined. Five parameters, namely *Swc*, *Kc*, *RRF, Dwc, and K2* have been identified as the most sensitive parameters and they have been subjected to calibration.

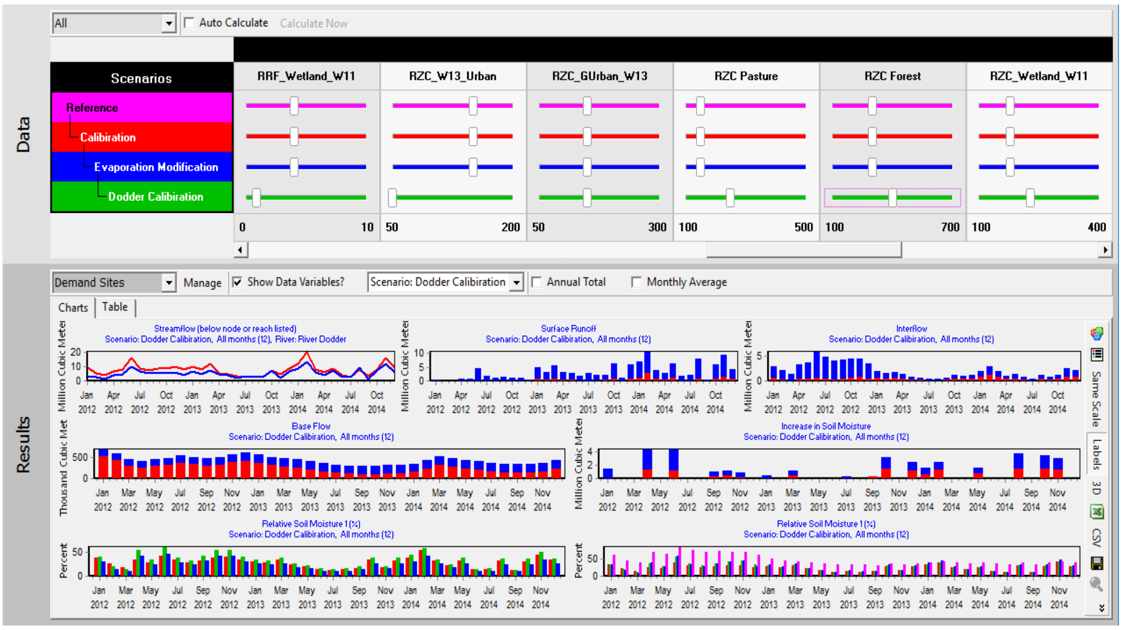


Figure 6. 3 Screenshot of WEAP scenario explorer used to aid sensitivity analysis and calibration.

A number of graphical and quantitative statistical techniques recommended by Moriasi et al. (2007) and Yates et al. (2013a) were employed to assess model performance in both calibration and validation. In particular, the following statistical indices have been used to assess the model performance in simulating streamflow values where in each index Q_i^{Sim} and Q_i^{Obs} represent the ith simulated and observed monthly streamflow discharges respectively:

- Nash-Sutcliffe efficiency (NSE) $= 1 - \dfrac{\sum_{i=1}^{n}(Q_i^{Obs} - Q_i^{Sim})^2}{\sum_{i=1}^{n}(Q_i^{Obs} - \overline{Q^{obs}})^2}$ (6.1)

The NSE value ranges between 1.0 and -∞. An NSE value of 1.0 suggests a perfect match between observed and simulated values. An NSE value greater than 0.65 indicates good simulation. An NSE value between 0.50 and 0.65 indicates satisfactory level of performance, whereas an NSE value less than zero indicates that the mean of observed values is a better predictor than simulated values. The NSE criterion measures the fit between observed and simulated values with emphasis on peak flows, whereas NSE with log values (LogNSE) evaluates the fit with emphasis on low flows.

- Percent bias (*PBIAS*) $= 100 \times \dfrac{\sum_{i=1}^{n} Q_i^{Obs} - Q_i^{Sim}}{\sum_{i=1}^{n} Q_i^{Obs}}$ (6.2)

PBIAS measures the average tendency of simulated values to be larger or smaller than the corresponding observed values. An optimal value for *PBIAS* is 0.0; A positive value indicates an underestimation of the flow values by the model, whereas a negative value indicates the opposite. A bias of less than 15% indicates a simulation of good quality, while a bias of 10% and 25% in either direction is considered satisfactory.

- The root mean square error to the standard deviation ratio *(RSR)*

$$= \frac{\sqrt{\sum_{i=1}^{n}(Q_i^{Obs} - Q_i^{Sim})^2}}{\sqrt{\sum_{i=1}^{n}(Q_i^{Obs} - Q^{Mean})^2}} \qquad (6.3)$$

RSR quantifies the deviation of the simulated values from observed values. An optimal value for *RSR* is 0.0, which indicates a zero error, and hence a perfect model simulation. Values less than 0.70 are considered satisfactory.

- The ratio of simulated versus observed flow standard deviation (*SDR*)

$$= \frac{\sqrt{\sum_{i=1}^{n}(Q_i^{Sim} - \overline{Q^{Sim}})^2}}{\sqrt{\sum_{i=1}^{n}(Q_i^{Obs} - \overline{Q^{Obs}})^2}} \qquad (6.4)$$

SDR quantifies the degree of matching in variability between the simulated and the observed values. An *SDR* value of 1.0 indicates a perfect match whereas values between 0.90 and 1.10 are considered satisfactory.

In addition, Person's correlation coefficient *(r)* was evaluated. The correlation coefficient measures the degree of co-linearity between simulated and observed data. It ranges between - 1.0 and 1.0; and *r* value of zero suggests that no linear relationship exists, whereas a value of - 1.0 or 1.0 suggests that a perfect negative or positive linear relationship exists. Values of *r* close to the upper bounds are considered satisfactory.

Figure 6.4 summarises the overall procedure for model calibration and validation.

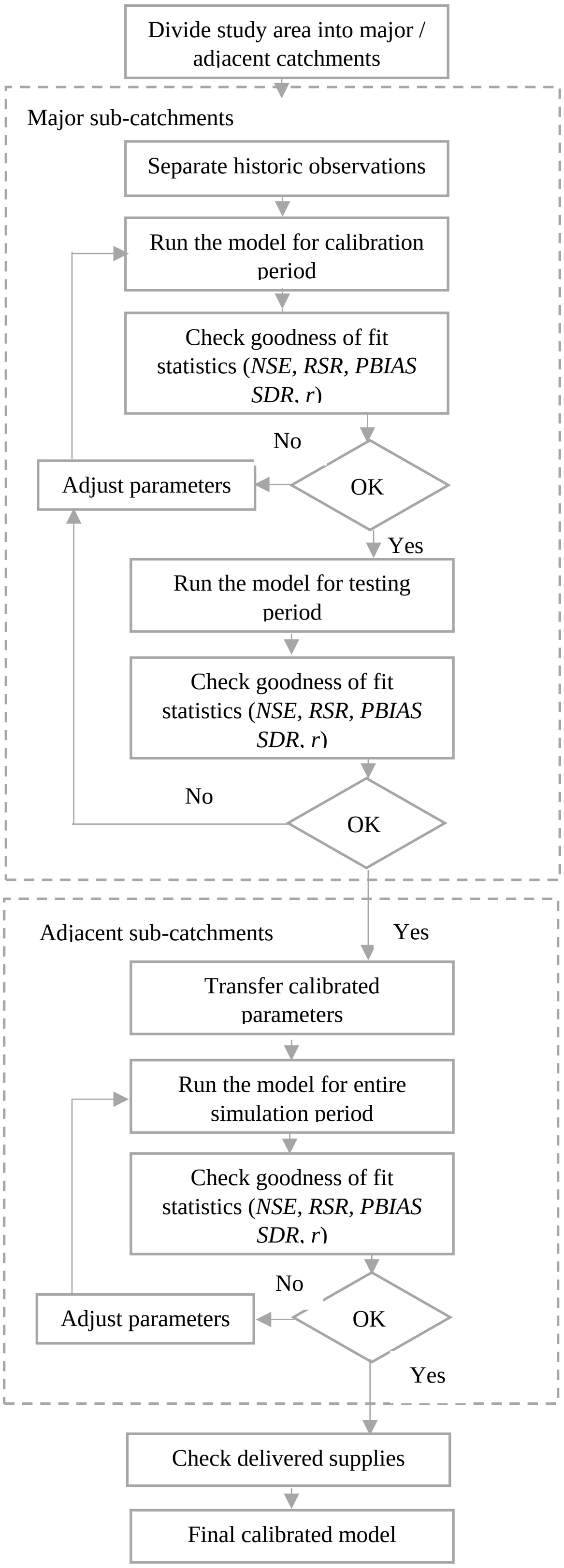


Figure 6. 4 Diagram illustrating calibration and validation of the model

6.2.3 Calibration and validation results of UL and RW sub-catchments

The five most sensitive parameters (*Swc, Kc, RRF, Dwc,* and *K2*) were manually calibrated in the UL and RW sub-catchments using data for the period 2013-2014. This process involved trial and error procedure by changing one parameter at a time between its lower and upper limits which have been identified by the sensitivity analysis. In each trial, simulated and observed flows at the outlet of sub-catchment under consideration were visually compared, and goodness of fit statistics (*NSE, PBIAS, RSR, SDR,* and *r*) were examined. This visual assessment was conducted in the WEAP21 software while the goodness of fit statistics were calculated using excel spreadsheet. The trial and error procedure was repeated multiple times until achieving a good match between the observed and the simulated streamflow associated with satisfactory values for the goodness of fit statistics. It is worth mentioning that calibration of the model for UL sub-catchment was very challenging since the available flow data represent flow measurements at hydrometric stations located below the abstraction point (or the reservoir). Table 6.2 shows the calibrated set of the most sensitive parameters for the Upper Liffey and Ryewater sub-catchments.

Table 6. 2 Final set of calibrated parameters for the WEAP-Dublin model major sub-catchments. Swc — soil water capacity in mm; kc — root zone conductivity in mm/month; *RRF* — surface runoff resistance factor (ranges indicate monthly variation); *Dwc* — deep water capacity in mm and *K2* — deep conductivity in mm/month, each of *Dwc* and *K2* applied in the model as single values for all the catchment

Parameter	Land Cover	UL	RW
Swc	Urban	100	100
	Green Urban	—	—
	Shurbs	250	300
	Pasture	200	250
	Forest	300	450
	Wetland	300	—
K	Urban	50	100
	Green Urban	—	150
	Shurbs	200	300
	Pasture	180	450
	Forest	300	150
	Wetland	200	—
RRF	Urban	0.05	0.10
	Green Urban	—	2

RRF	Shurbs	3	0.20-1.0
	Pasture	2	0.5-1.20
	Forest	4	4
	Wetland	1	0.50
Dwc	All Landcovers	200	400
K2	All Landcovers	300	500

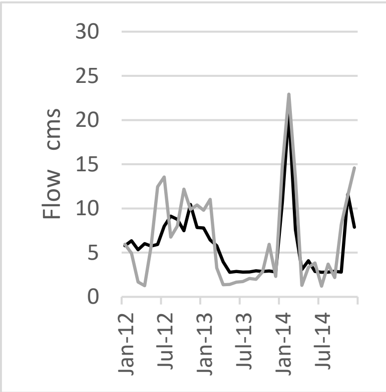
The calibrated model was then run in each sub-catchment for the year 2015-2017 in order to assess the validity of its performance at this independent period. Figure 6.5 shows the observed and the simulated hydrographs along with the results of the goodness of fit statistics for both the calibration and the validation periods at two locations in the UL sub-catchment (station 09032 downstream of Phollaphuca Reservoir and station 09007 downstream of the Golden Falls) and one location in Ryewater sub-catchment (station 09001 Lexilip). The model reasonably captured the main features of streamflow hydrographs at the three tested locations. The model generally overestimated some low flows at the three tested locations. This partly may be due to the continuous function of WEAP21 which does not easily represent very low flows (Young et al. 2009). On the other hand, the model underestimated some high flows at the three tested locations. A reason for this variation possibly could be due to errors in precipitation and flow measurements. For instance, rainfall volumes of Ryewater sub-catchment in Jan and Feb 2016 were less than the corresponding flow observations (Figure 6.6) which may have caused the model to underestimate flows at these months.

The model showed better performance in simulating flows of Ryewater at Lexilip flow gauging station (09001) than simulating flows of Liffey at Phollaphuca (09032) and Golden Falls (09007). The reason for this is that flow data used in the calibration of the model for Ryewater sub-catchment are not influenced by abstractions or reservoir operations. However, calibration data for the Upper Liffey sub-catchment represent flow measurements below the abstraction point, hence resulting in uncertainty pertaining to natural flows upstream of the reservoirs. This uncertainty prevents one

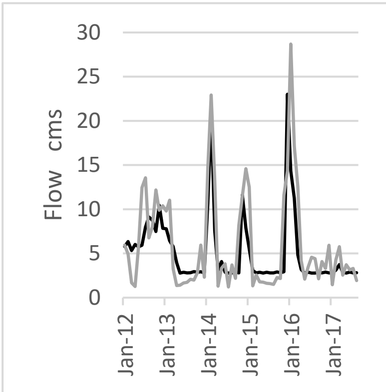
<table>
<tr><th></th><th>Stats</th><th>Monthly (2012-2014)</th><th>Monthly (2012-2017)</th><th>% of time exceedance curve</th></tr>
<tr><td>Liffey – Pollaphuca [09032]</td><td>Calibration
NSE=0.74
logNSE=0.63
PBIAS=13.4
RSR=0.51
SDR=0.71

Validation
NSE=0.50
logNSE=0.55
PBIAS=21
RSR=0.70
SDR=0.72

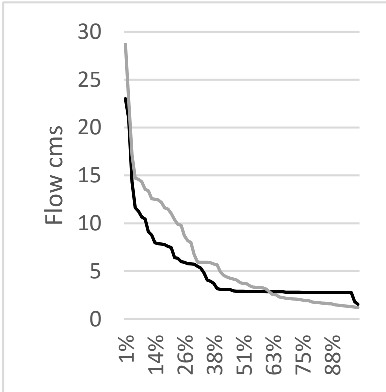
r=0.79</td><td>



</td><td>



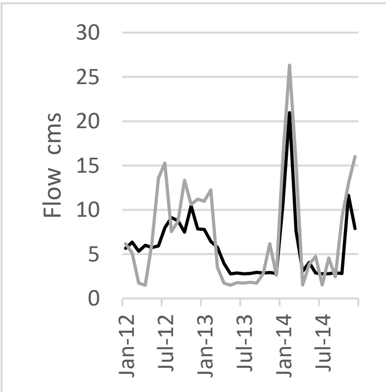
</td><td>



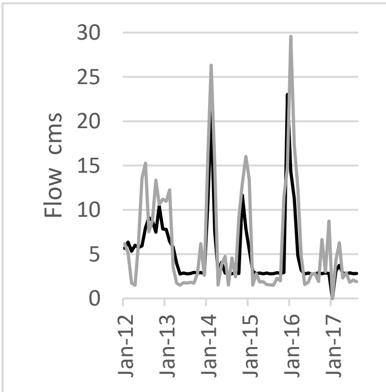
</td></tr>
<tr><td>Liffey – Golden Falls [09007]</td><td>Calibration
NSE=0.68
logNSE=0.60
PBIAS=22
RSR=0.57
SDR=0.65

Validation
NSE=0.50
logNSE=0.59
PBIAS=21
RSR=0.70
SDR=0.72

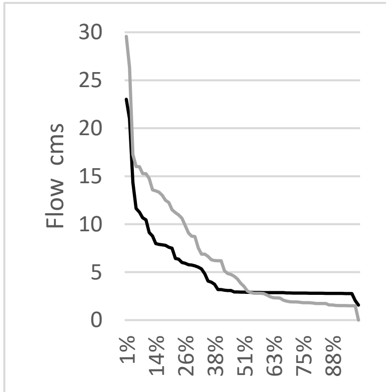
r=0.78</td><td>



</td><td>

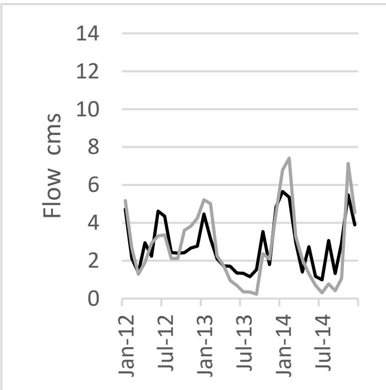


</td><td>

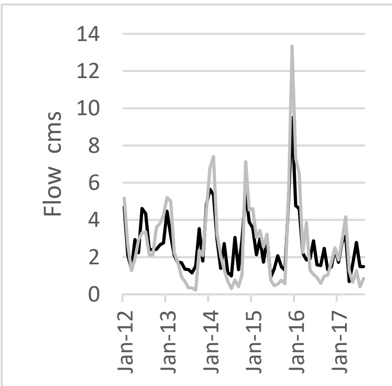


</td></tr>
<tr><td>Ryewater – Lexilip St. [09001]</td><td>Calibration
NSE=0.76
logNSE=0.52
PBIAS=-6.65
RSR=0.50
SDR=0.65

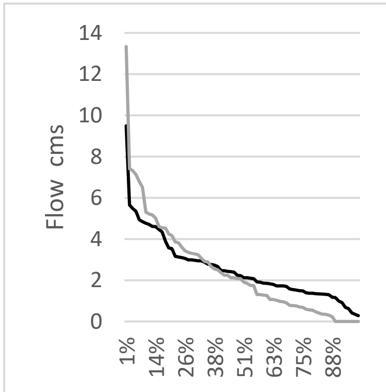
Validation
NSE=0.75
logNSE=0.56
PBIAS=8.23
RSR=0.50
SDR=0.65
r=0.90</td><td>



</td><td>



</td><td>



</td></tr>
</table>

Figure 6. 5 Simulated and observed streamflow volumes of river Liffey at the following gauge locations; Phollaphuca 09032, Golden Falls 09007 and Lexilip station 09022. Dark lines represent simulated volumes and light lines represent observed volumes. NSE is Nash-Sutcliffe; PBIAS is percent bias; RSR is root mean square error to the standard deviation ratio; SDR is the ratio of simulated versus observed flow standard deviation; r is the Person's correlation coefficient.

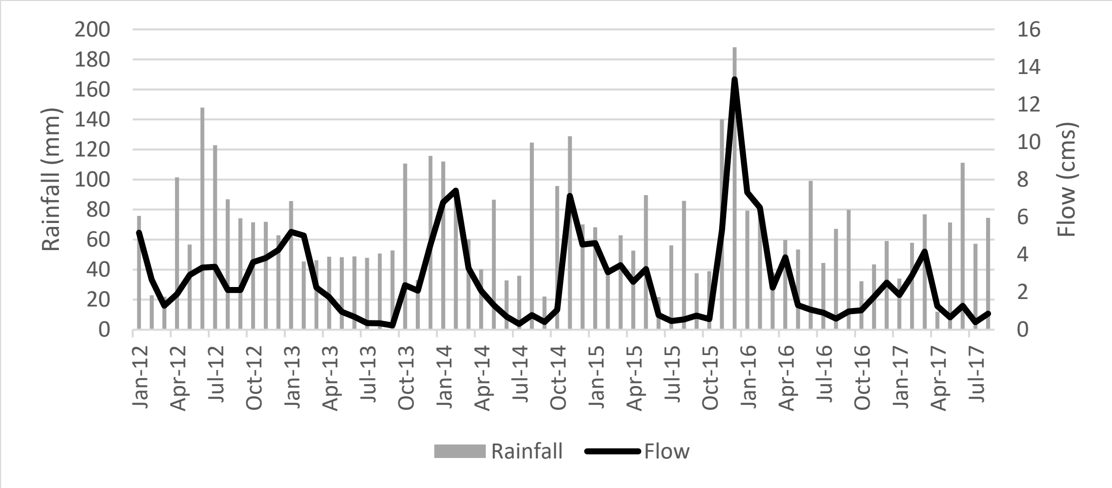


Figure 6. 6 Monthly mean streamflow (in cms) of Ryewater river at Lexilip 09001 against total monthly rainfall data (in mm) of nearby / contributing weather stations.

from assessing whether the model perfectly reproduced the water balance of the sub-catchment upstream of the abstraction point before the operating rules of the respective reservoirs are applied.

The models of the UL and RW sub-catchments have been run for the period 1980-2011 where data in terms of water uses and management are less available compared to the period 2012-2017. Figure 6.7 shows the simulated and observed flow hydrographs for the UL and RW sub-catchments at Phollaphuca (09032) and Lexilip (09001) respectively during the period 1980-2011. The model poorly predicted outflows of Phollaphuca reservoir in the UL sub-catchment during this period (NSE ≤0.10), which is attributed to the lack of reservoir inflow data. On the other hand, the model predicted flows of RW with a satisfactory level of accuracy (NSE≥0.60).

A review of historic floods and droughts occurred during the simulation period has been conducted to support evaluation of the models performance (OPW 2016c; EPA 1996). The model has generally captured the historic flood events occurred in the UL sub-catchment during Jun 1993, Nov 2000 and Nov 2009 (Figure 6.8); and the historic floods occurred in the RW sub-catchment during Nov 2000, Nov 2002 and August 2008

(Figure 6.7). On the other hand, the modelled sub-catchments have reproduced the very low flow conditions of summers 1989, 1990, 1991, and 1995.

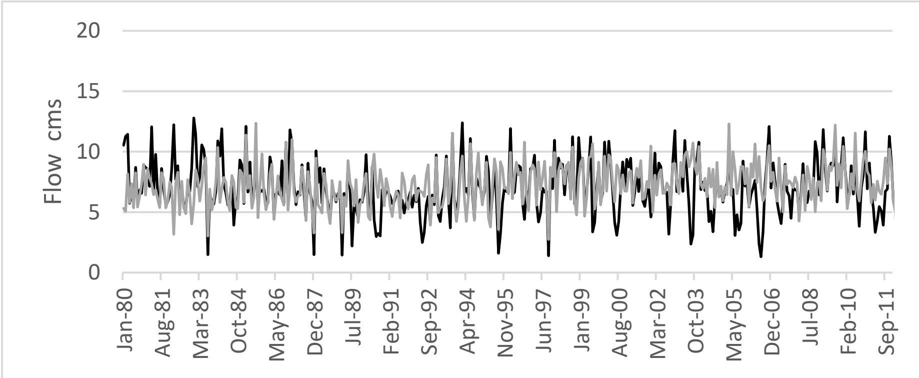
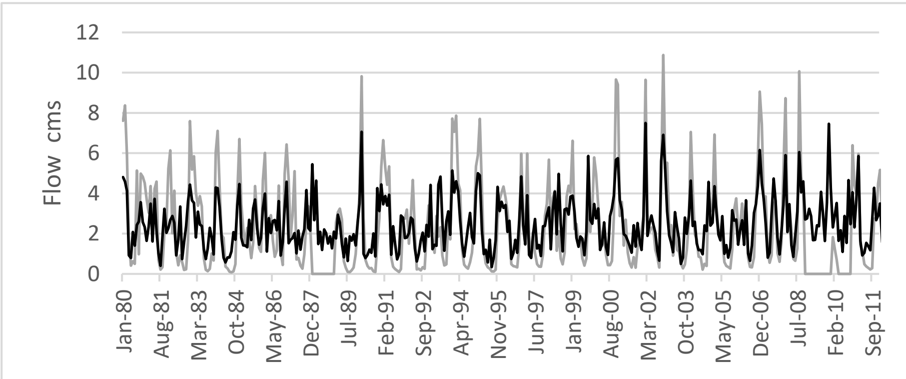
	Stats	**Monthly flows (1980-2011)**
Liffey – Phollaphuca 09032	NSE=0.10 PBIAS=-2 RSR=0.99 SDR=1.15 r=0.70	
Ryewater – Lexilip 09001	NSE-0.64 PBIAS=2 RSR=0.59 SDR=0.64 r=0.81	

Figure 6. 8 Simulated and observed streamflow for (i) Liffey at Pollaphuca 09032 (ii) Ryewater at Lexilip 09001 during the period 1980-2011. Dark lines represent simulated flows and light lines indicates observed flows.

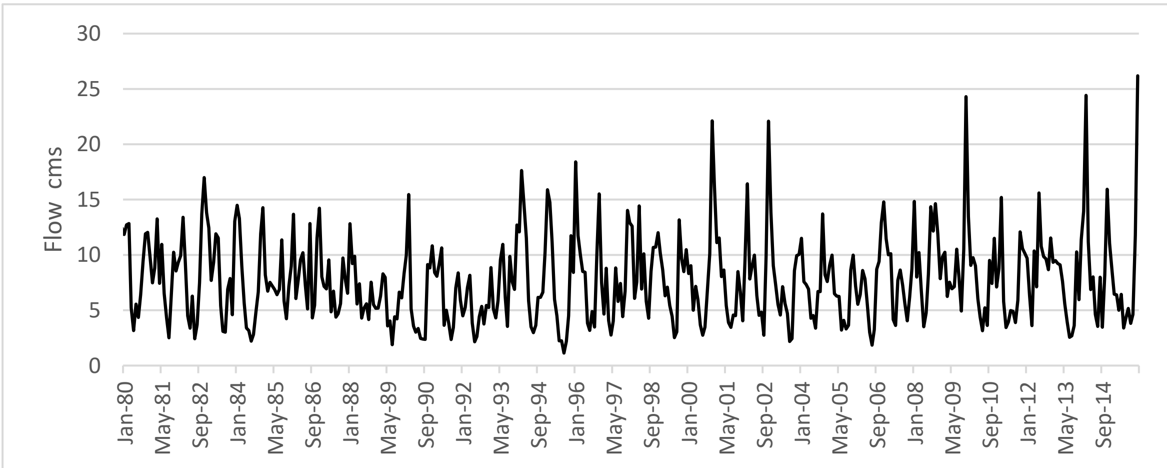
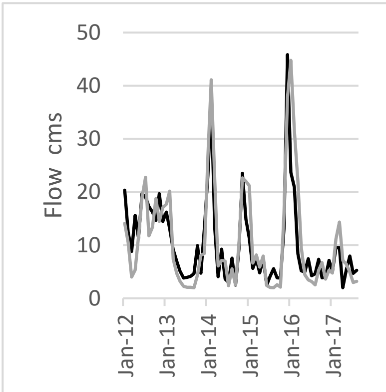
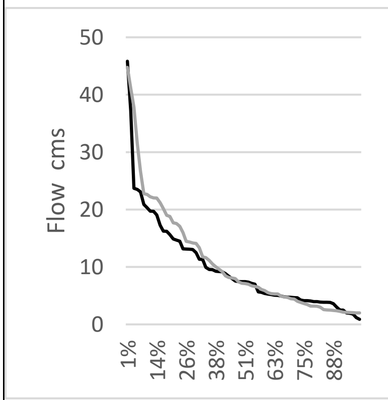


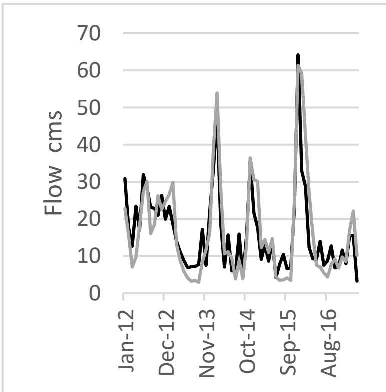
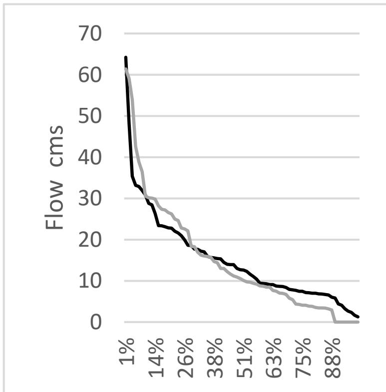
Figure 6. 7 Simulated inflows to Phollaphuca reservoir in the UL sub-catchment by WEAP21 model during the period 1980-2015

6.2.4 Validation results of LL, RW and DD sub-catchments

The calibrated set of model parameters at the UL and RW sub-catchments has been transferred to the Middle Liffey, Lower Liffey, and the Dodder sub-catchments. Each sub-catchment then was assessed based on its performance in simulating the flow values for the period 2013-2017. The actual and simulated hydrographs along with the results of goodness of fit statistics are all shown for the three sub-catchments in Figure 6.9.

<table>
<tr><th></th><th>Stats</th><th>Monthly (2012-2017)</th><th>% of time exceedance curve</th></tr>
<tr><td>Liffey – Lexilip 09022</td><td><u>Validation</u>
NSE=0.76
LogNSE=0.69
PBIAS=1.02
RSR=0.48
SDR=0.81

r=0.80</td><td>
</td><td>
</td></tr>
<tr><td>Liffey –Liffey HEP</td><td><u>Validation</u>
NSE=0.80
PBIAS=13
RSR=0.49
SDR=0.77

r=0.93</td><td>
</td><td>
</td></tr>
</table>

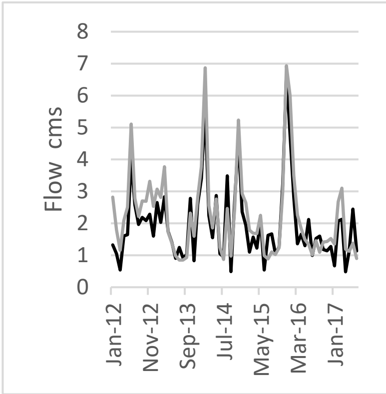
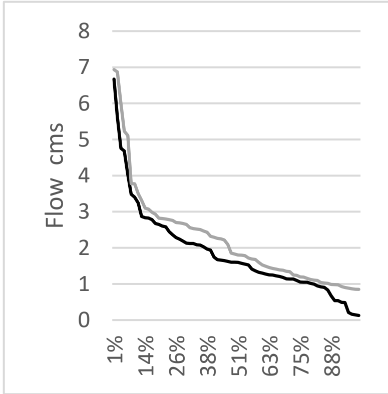
Dodder – Dodder HEP	Validation NSE=0.82 PBIAS=12 RSR=0.39 SDR=0.90 r=0.94		

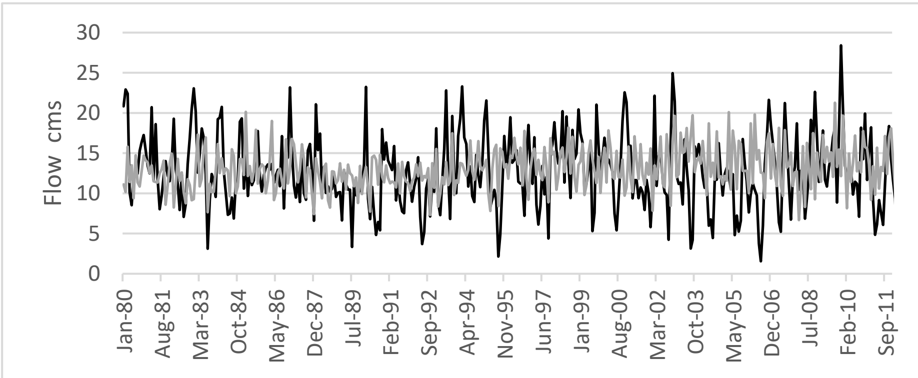
Figure 6. 9 Simulated and observed streamflow / estimate flows for (i) Liffey at Lexilip 09022 (ii) Liffey at HEP located at the confluence with Cammock river (iii) Dodder at HEP located just before its confluence with the Liffey. Dark lines represent simulated flows, and light lines represent observed / estimate flows. HEP is hydrological estimate points with flows derived from gauge of smaller tributaries.

Performance of the model during the period 2012-2017 in the three sub-catchments is generally good as the model managed to capture the main features of the flow hydrographs. The model generally overestimated some low flows of the Liffey river at the two tested locations; Lexilip (09022) and Liffey (HEP). Results of the goodness of fit statistics were consistently good in all three sub-catchments with except to slight deviation of SDR values for the Middle Liffey and Lower Liffey catchment. Hence, these results suggest satisfactory performance of the model in capturing flows of the three sub-catchment during the period 2012-2017.

Moreover, the simulation of low flows at Lexilip is found to be better than the simulation of low flows at Phollaphuca and Golden Falls. The logNSE value for flow simulation at Lexilip is 0.70, whereas the logNSE values for simulations at Phollaphuca and Golden Falls is 0.59. This discrepancy may be attributed to the stable volume-elevation relationship in the Lexilip reservoir compared to the one in the Phollaphuca reservoir and this is mainly due to smaller storage in the Lexilip Reservoir (less than 1 Mm^3) compared to the larger storage reservoir in the Phollaphuca Reservoir (150 Mm^3). Similar results were also reported by Young et al. (2009) and Yates et al. (2013) where the model showed relatively poorer performances in capturing very low flows downstream of large reservoirs used in the two studies.

Furthermore, the models for these three sub-catchments have been run for the period 1980-2011. Figure 6.10 shows the simulated and observed flow hydrographs for the ML and DD sub-catchment at Lexilip St. (09022) and Dodder (HEP) respectively during the period 1980-2011. The model poorly predicted outflows of Lexilip reservoir due to the absence of reservoir inflow data, which prevented proper calibration of the catchment upstream along with the reservoir. The model predicted flows of DD with a satisfactory level of accuracy (NSE≥0.60).

<table>
<tr><th></th><th>Stats</th><th>Monthly flows (1980-2011)</th></tr>
<tr><td>Liffey –Lexilip St. 09022</td><td>NSE=-2
PBIAS=-2
RSR=1.5
SDR=1.4

r=0.46</td><td>
</td></tr>
<tr><td>Dodder – Dodder HEP</td><td>NSE=0.70
PBIAS=15
RSR=0.55
SDR=0.78

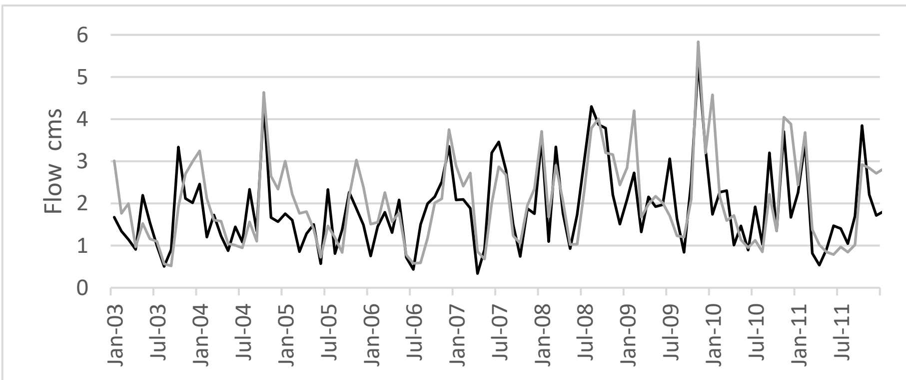
r=0.83</td><td>
</td></tr>
</table>

Figure 6. 10 Simulated and observed flow hydrographs of (i) Liffey river at Liffey river at Lexilip st. 09022 (iii) and (iv) Dodder at HEP. Dark lines represent simulated flows and light lines indicates observed flows Simulation of dodder flows starts from 2003 in line with available flow data for dodder river.

Furthermore, the model has generally captured historic floods occurred in the ML sub-catchment during Nov 2000, Nov 2002 and August 2008 (OPW 2016c), and the very low flow conditions of summers 1989, 1990, 1991, and 1995 (EPA 1996) (Figure 6.11).

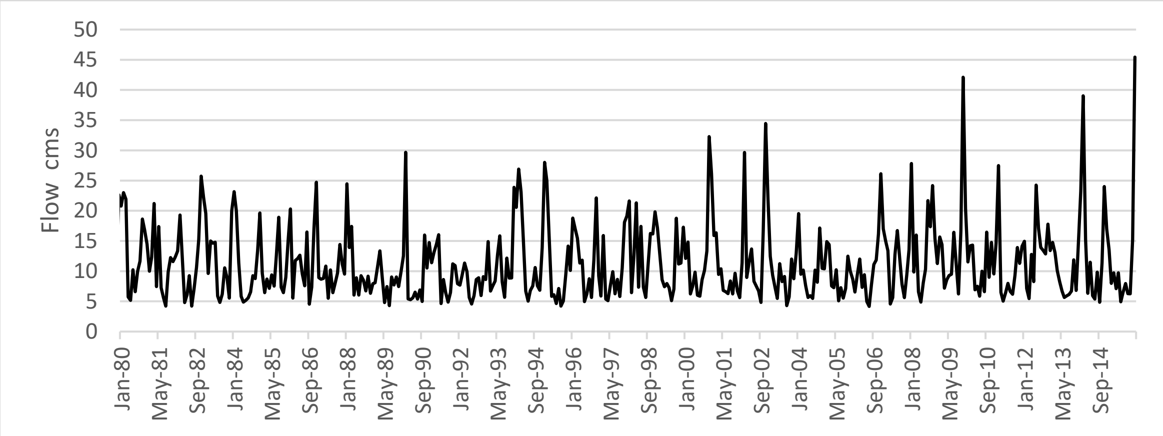


Figure 6. 11 Simulated inflows to Lexilip reservoir by WEAP21 during the period 1980-2015.

It is worth mentioning that improvement of the model accuracy has been attempted by re-calibrating the model based on climate and flow data during the period 1980-2005. The re-calibration attempts followed the calibration strategy illustrated above but with more focus given to calibration of parameters pertaining to reservoirs and their operation rules. For instance, the volume-elevation curve of the reservoirs has been increased by 1-10% to account for any possible bank storage effects. Moreover, different synthetic time-series of energy demands for reservoirs have been developed by applying rules to the observed outflows of reservoirs and used for model calibration. Validation results of the model during the period 2006-2015 have not resulted in any significant improvements in results obtained from the previously calibrated WEAP-Dublin model.

6.2.5 Validation results of water uses

Table 6.3 shows estimation of the annual average water supply input for each zone across the Dublin region by the WEAP-Dublin model. The total annual average water supply is estimated to be 201 Mm^3, which is close to the average regional water distribution input reported by DCC (2012) (Figure 6.12) and Irish Water (2018a). It is

Table 6. 3 Average annual water supply input for each zone as simulated in WEAP-Dublin. A breakdown of these supplies to water deliveries to each sector and associated losses are summarised in Figure 6.9.

Supply zone	Annual average supply (Mm3)
Zone 1	90
Zone 2	79.50
Zone 3	1.50
Zone 4	2.40
Zone 5	3.80
Zone 6	24

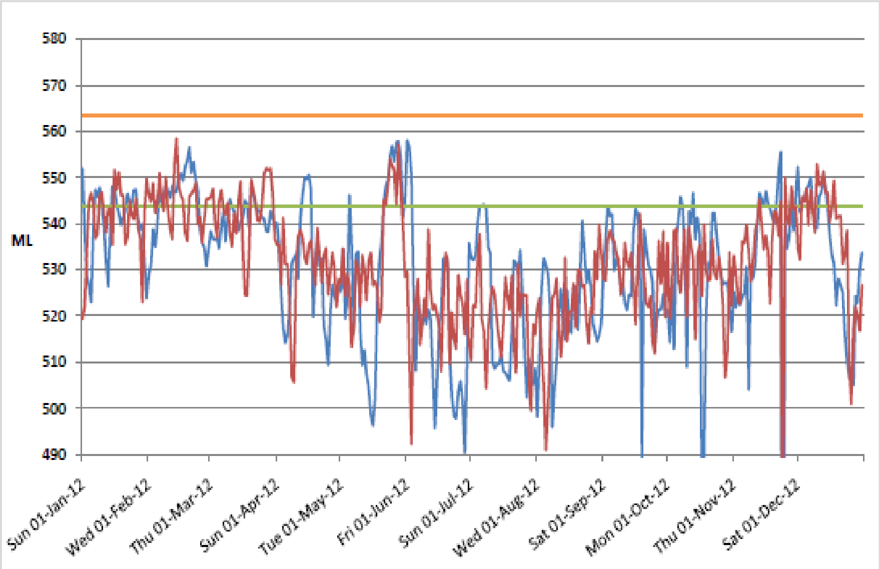


Figure 6. 12 Demands for drinking water in the Dublin Region for year 2012, with average demand (green), daily demands (red), total production (orange), rated production (blue). Source: DCC (2012a)

worth mentioning that the simulated supplies from the Liffey schemes (Phollaphuca and Lexilip) represented around 85% of total regional supply i.e. supplies to zones 1–4.

Figure 6.13 shows the results of WEAP-Dublin for the sectoral water uses/deliveries and losses for the six zones. WEAP estimates of the total deliveries for sectoral water uses (domestic / non-domestic) were comparable to those reported by Irish Water (2015b). On the other hand, the estimated water losses across the region summed up to 79.60 Mm^3/year (39.5% of total regional water supply) is comparable to the amounts reported by DCC (2010), Irish Water (2015a), (2015b).

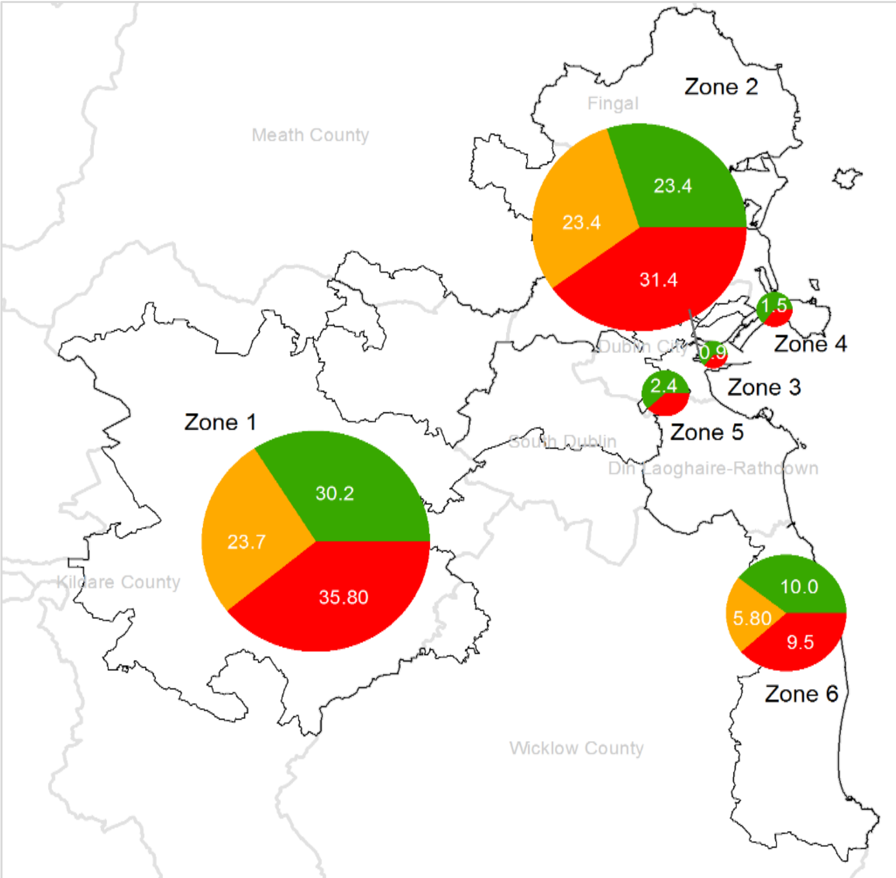


Figure 6. 13 WEAP estimates of average annual water supply to each zone in Million Mm^3, disaggregated by losses (red), water deliveries to domestic (green), water deliveries to non-domestic (yellow).

It is worth mentioning that integrated water resources management model differs from hydrological models in that they require a wide range of data for modelling the water resources system such as climate data, hydrological data, land-cover, historic water supplies, population exerting demands on the system, domestic and non-domestic water uses, infrastructure capacitates and changes during the historic period. It is very challenging to obtain a long record of these variables all together. For this study, the period 2012-2017 is the most recent period where there is a balanced availability of data in relation to climate, hydrology, water supply, water uses and water and wastewater infrastructure. Furthermore, the length of the calibration of dataset is not as important as the information contained in the dataset. The selected period contained wet periods (or high flows) and dry periods (very low flows) during both calibration and validation period and hence this period can be used for calibration and validation.

Moreover, a long historic period for a water resources system can include many human-intervention changes in the system (i.e. changes in policies, changes in infrastructure capacities and operational rules). Hence, a water resources management model for the very past may not be suitable to represent the system in a recent period due to changes happened in the system. It was attempted to calibrate the model during a longer period (1980-2011) however missing information in terms of water uses, water supply and operation rules did not allow proper calibration of the model for this period. Given this, the period 2012-2017 is used as the period to represent the current system and to estimate the water balance in the Liffey and Dublin Bay catchment, and hence to provide a baseline period for assessing impacts of different future water management scenarios on the water resources system.

6.3 Conclusion

The WEAP-Dublin model reproduced natural and managed flows of the Liffey and Dublin bay catchment during the simulation period 2012-2017. Simulation results indicate that the model has better accuracy to predict flows of un-managed catchments compared to the accuracy of predicting flows of managed catchments. Adequate calibration of managed catchments was not possible due to the nature of information available. Moreover, the representation of reservoir operations in the model is generalised and not reflective of the detailed reservoir operations in place. Hence, the use of the model for informing reservoir management decisions is questionable. Coupling WEAP21 with ad-hoc reservior models (e.g. RiverWareTM DSS) can help detailed representation of reservior operations and hence improve accuracy of the model. The overall performance of the model can be improved when reservoir inflow data become available.

Given these limitations, the current model represents our best estimate for the water balance in the Liffey and Dublin Bay catchment. Hence, it can be used with some caution as a tool for various water resources planning applications such as evaluation of different water management scenarios, evaluation of the impacts of climate change on water resources and on competing water uses, and also designing and assessing the suitability of any relevant climate change adaption strategies.

Chapter 7 UNCERTAINTY OF WEAP21 FLOW PREDICTIONS

7.1 Introduction

This chapter aims to explore uncertainty in flow predictions of a case study sub-catchment (Ryewater) due to parameter identification, forcing data, and model structure. The main selection criteria for the case study sub-catchment is (i) availability of long records of climate and flow data, and (ii) flows at the outlet of the catchment are actual measurements (i.e. not estimated from flows of other flow gauging stations) (iii) flow measurements at the outlet of the sub-catchment are not influenced by abstractions or hydropower operations (i.e. natural flows). Of the five sub-catchments in this study, Ryewater sub-catchment is the only one that fulfilled the selection criteria. For all other sub-catchment (Upper Liffey, Middle Liffey, Lower Liffey and Dodder), flows measurements are influenced by hydropower and abstraction activities. Moreover, flows at the outlet the Lower Liffey catchment are estimated from flows of other flow gauging station in the river network.

Uncertainties in flow predications of Ryewater sub-catchment have been explored using two different modelling software: WEAP21 and HBV-light. The effect of parameter identification and forcing data uncertainty on flow predictions of Ryewater by the two software is examined by combining multiple parameter sets of each model with stochastic climate data. This involved extending the capability of WEAP21 software to estimate uncertainties in model outputs by coupling it with statistical parameter optimisation tool. Moreover, this analysis is not limited to uncertainty analysis of precipitation only but it included uncertainty analysis of temperature and evaporation data as well. This differs from other uncertainty assessments which mostly focused only on precipitation as the predominant forcing data (Kavetski et al. 2006; Chun et al. 2009; Younger 2009; Sapriza-Azuri et al. 2015 and Mockler et al. 2016a).

7.2 Parameter uncertainty analysis for the WEAP21 model

A parameter uncertainty analysis for the WEAP21 model of Ryewater sub-catchment has been performed using the generalised likelihood uncertainty estimation (GLUE) method (Beven and Binely 1992). The steps for performing a GLUE analysis are as follow (Beven and Binely 1992; Beven 2012): (i) create prior distribution for parameters; (ii) sample from the prior distributions of parameters using a sampling algorithm; (iii) use one or more performance metrics as likelihood functions to determine behavioural parameter sets based on pre-defined criteria; and (iv) use the behavioural parameter sets to build posterior distribution of parameters and to estimate the predictive uncertainty. A multiple GLUE analysis can be carried out by using the resulting posterior parameter distribution of the first analysis as prior distribution for the subsequent analysis (Kellner et al. 2017).

A multiple GLUE analysis for the WEAP21 hydrological model of Ryewater sub-catchment has been performed using the statistical parameter optimisation tool (SPOTPY) (Houska et al. 2015). SPOTPY is an open source python package that contains a comprehensive set of methods commonly used for performing sensitivity analysis, calibration and uncertainty analysis of ecological/environmental models. The package contains eight parameter distributions, eight sampling algorithms, and 11 objective functions. Further details on the package and tutorial examples on the use of the package can be found in Houska et al. (2015) and http://fb09-pasig.umwelt.uni-giessen.de/spotpy/.

An initial GLUE analysis for the model has first been performed as illustrated by the uncertainty framework (Figure 7.1). Prior distributions for parameters of Ryewater sub-catchment model have been created in SPOTPY by assuming a uniform probability distribution with ranges outlined in Table 7.1. These ranges have been identified based on some knowledge on the model as obtained from the sensitivity analysis which was illustrated in Chapter 6. The Latin Hyper Cube sampling algorithm then was used to sample from the assumed parameter space and to generate an initial 10,000 parameter sets.

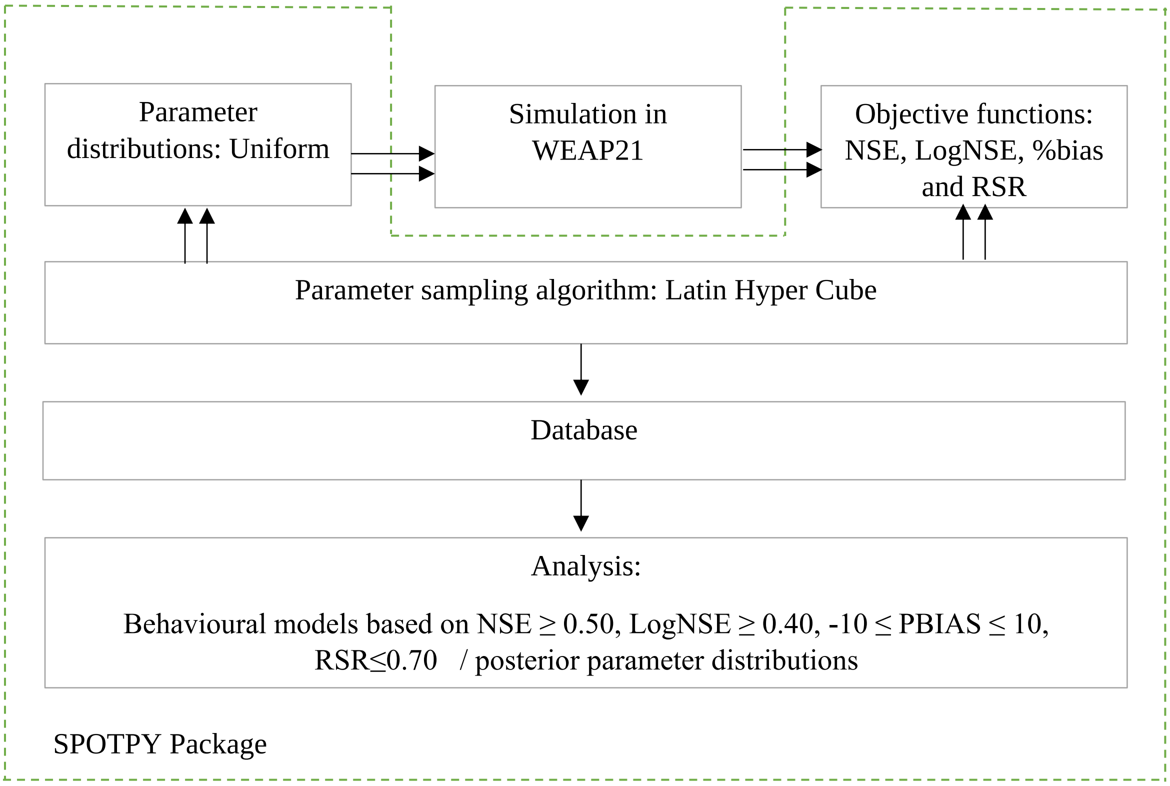


Figure 7. 1 Framework linking SPOTPY and WEAP21 for assessing parameter uncertainty. Adapted from Houska et al. (2015)

Using the initial 10,000 parameter sets generated from Latin Hyper Cube sampling algorithm, the WEAP21 model for Ryewater sub catchment was run 10,000 times and each of the corresponding simulated flows was evaluated against the observed one using a combination of objective functions: Nash Sutcliffe Efficiency (NSE), the log value of Nash Sutcliffe Efficiency (LogNSE), percent bias (PBIAS), and root mean square to the standard deviation ratio (RSR) (See Chapter 6). The criteria used for defining a behavioural parameter set are set as follow: NSE ≥ 0.50, LogNSE ≥ 0.40, -10 ≤ PBIAS ≤ +10, and RSR ≤ 0.70. The number of behavioural models which met the previous criteria are 80 models. The parameter sets of these models have been used to define

Table 7. 1 Prior uniform distributions and assumed ranges for parameters as used in the initial GLUE analysis for the WEAP21 model of Ryewater sub-catchment.

Parameter	Description	Min	Max
kc_NI	Crop coefficient for non-irrigated land cover	0.10	3
kc_P	Crop coefficient for pasture land cover	0.10	2
kc_F	Crop coefficient for forest land cover	0.10	5
swc_NI	Soil water capacity for non-irrigated land cover	50	1000
swc_P	Soil water capacity for pasture land cover	50	1000
swc_F	Soil water capacity for forest land cover	50	1000
Dwc	Deep water capacity for the entire catchment	100	1000
rrf_NI	Runoff resistance factor for non-irrigated land cover	0	5
rrf_P	Runoff resistance factor for pasture land cover	0	5
rrf_F	Runoff resistance factor for forest land cover	0	10
rzc_NI	Root zone conductivity for non-irrigated land cover	50	1000
rzc_P	Root zone conductivity for pasture land cover	50	1000
rzc_F	Root zone conductivity for pasture land cover	50	1000
Dc	Deep soil conductivity for the entire catchment	10	1000
pfd_NI	Preferred flow direction for non-irrigated land cover	0.40	0.90
pfd_P	Preferred flow direction for pasture land cover	0.40	0.90
pfd_F	Preferred flow direction for forest land cover	0.40	0.90

posterior parameter distributions as presented in Figure 7.2 and Table 7.2. Table 7.2 also presents the reduction in uncertainty ranges of the posterior distributions relative to the prior parameter distribution. Python codes linking SPOTPY and WEAP21 software for performing the GLUE analysis are provided in Appendix E.1.

A second stage GLUE analysis has been conducted for the model of Ryewater sub-catchment by using the resulting posterior parameter distributions of the initial analysis as prior parameter distributions. Under the second analysis, the number of behavioural parameter sets or models satisfying the pre-defined criteria increased to 250 models. This increase occurred due to narrowing uncertainty ranges of parameters around the optimal values which were identified from the initial analysis. Hence, the second GLUE analysis yielded the following results:

- 4865 of the 10,000 models have an NSE value greater than 0.50. The NSE values for these models ranged from 0.50 to 0.551 with a median of 0.52.
- 1356 models have a LogNSE value greater than 0.40. The LogNSE values for these models ranged from 0.40 to 0.50 with a median of 0.42.

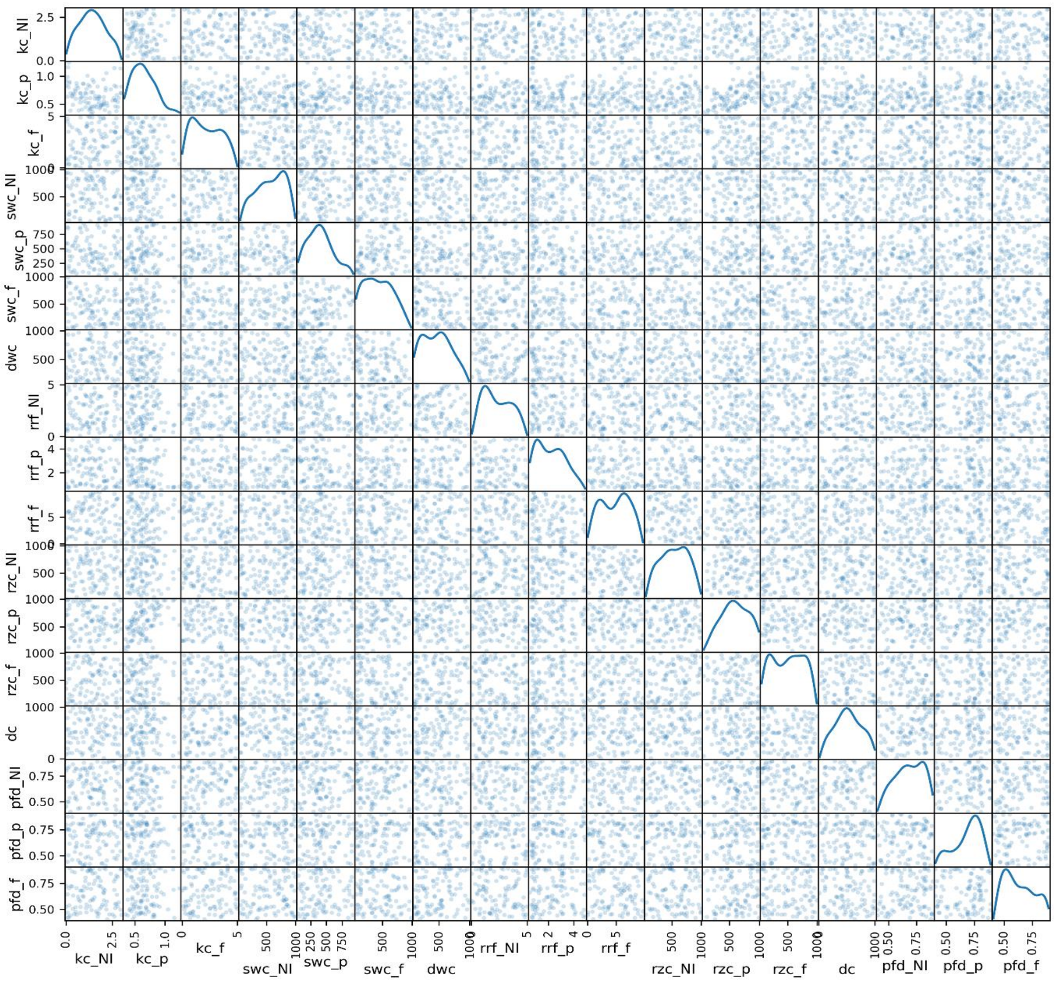


Figure 7. 2 Parameter interactions and posterior parameter distributions for the behavioural model runs from the initial GLUE analysis. Parameter interactions are shown as scatter plots, parameter uncertainty are shown as density distribution.

Table 7. 2 Posterior distributions for parameters of Ryewater sub-catchment model resulting from the initial GLUE analysis and reductions in ranges relative to the prior distributions.

Parameter	Description	Min	Max	Reduced by (%)
kc_NI	Crop coefficient for non-irrigated land cover	0.7	2.50	38
kc_P	Crop coefficient for pasture land cover	0.35	0.90	71
kc_F	Crop coefficient for forest land cover	0.80	3.50	45
swc_NI	Soil water capacity for non-irrigated land cover	500	1000	47
swc_P	Soil water capacity for pasture land cover	200	500	68
swc_F	Soil water capacity for forest land cover	100	700	37
Dwc	Deep water capacity for the entire catchment	100	400	67
rrf_NI	Runoff resistance factor for non-irrigated land cover	2.50	5	50
rrf_P	Runoff resistance factor for pasture land cover	2	4	60
rrf_F	Runoff resistance factor for forest land cover	5	10	50
rzc_NI	Root zone conductivity for non-irrigated land cover	500	1000	47
rzc_P	Root zone conductivity for pasture land cover	500	1000	47
rzc_F	Root zone conductivity for pasture land cover	0	500	47
Dc	Deep soil conductivity for the entire catchment	500	1000	49
pfd_NI	Preferred flow direction for non-irrigated land cover	0.70	0.95	50
pfd_P	Preferred flow direction for pasture land cover	0.40	0.95	50
pfd_F	Preferred flow direction for forest land cover	0.40	0.75	30

- All models have a satisfactory percent bias, between −10% and +10%.
- 3740 models have RSR value less than 0.70. The RSR values for the 3740 model runs ranged from 0.671 to 0.70 with a median of 0.69.

Moreover, the correlation between NSE values and values of the other objective functions (i.e. LogNSE, %bias, and RSR) for the behavioural models of Ryewater have been investigated (Figure 7.3). NSE values are strongly negatively correlated with values of PBIAS and RSR (r=-0.70 and -1.0, respectively). This is because NSE evaluates model performance based on the residual variance compared to observed data variance, while PBIAS and RSR are directly related to the error between simulated and observed data (See chapter 6 for mathematical expressions of objective functions). On the other hand, NSE values are found to have less correlation with LogNSE values (r=-0.28). The reason for this is that NSE measures the correlation of the time-series giving more weigh to peak flows, whereas the LogNSE focuses more on low flows (Mockler et al. 2016a; Yates et al. 2013).

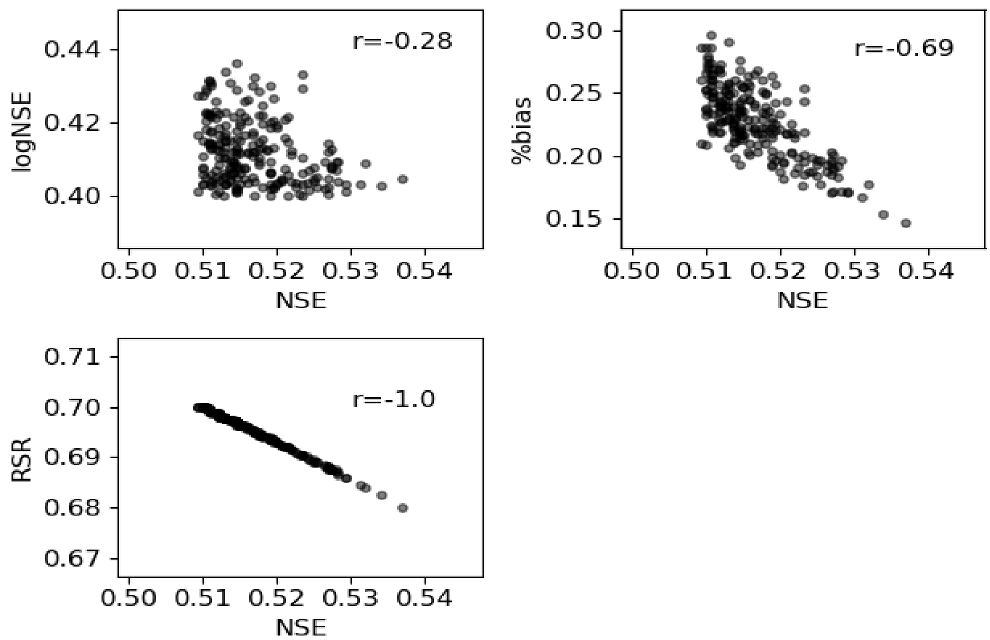


Figure 7. 3 Correlation of NSE values with (1) logNSE values, (2) PBIAS values and (3) RSR values for the behaviour for the 250 behavioural models of Ryewater catchment.

The performances of the best 100 models for NSE (focusing on peak flows) and 100 models for LogNSE (focusing on low flows) of Ryewater have been compared as shown in Figure 7.4 which displays NSE and LogNSE values for both model groups. All best 100 models for NSE (with NSE≥0.54) showed relatively poor performances in simulating low flows (LogNSE≤0.40). Similarly, all best 100 models for LogNSE (with LogNSE≥0.45) showed relatively poor performances in simulating peak flows (NSE≤0.50). Moreover, performances of models of Ryewater sub-catchment in this study have been compared with performances of corresponding models in Mockler et al. 2016a. Models of this study showed better performances in simulating low flows of Ryewater sub-catchment than performances of the corresponding NAM, SMART and SMARG models of Mockler et al. 2016a. However, the models of this study showed lower performances in simulating peak flows of Ryewater than performances of the corresponding ones of Mockler et al. 2016a.

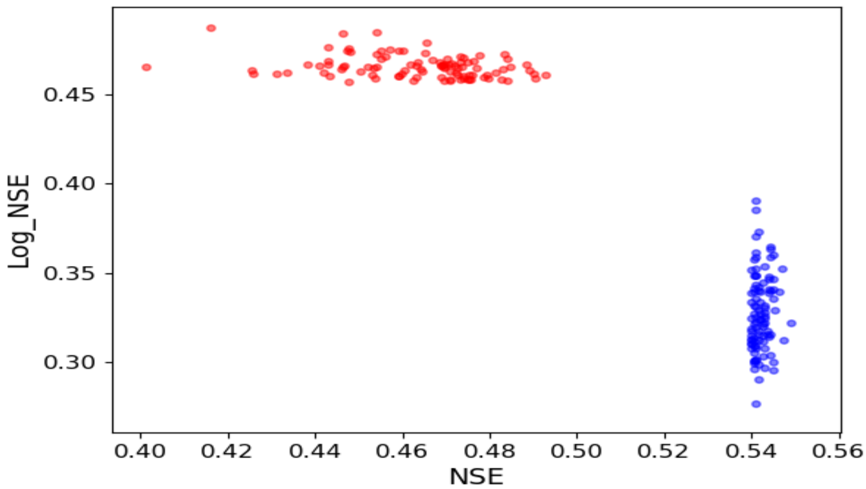


Figure 7. 4 NSE and LogNSE values for best 100 models for predicting peak flows (blue circles) and 100 best models for predicting low flows (red circles).

It is worth mentioning that results from the Latin Hyper Cube sampling algorithm was compared to results from other parameter sampling algorithms such as Monte Carlo and Markov Chain Monte Carlo methods. The Latin Hyper Cube sampling algorithm showed slightly better simulation results over the two Monte Carlo methods. The highest

NSE value for all Latin Hyper Cube simulations is 0.55, whilst the highest NSE value for all Monte Carlo simulations is 0.54. The highest LogNSE value for all Latin Hyper Cube simulations is 0.50, whereas the highest LogNSE value for all Monte Carlo simulations is less than 0.50.

7.3 Hydrograph simulations due to uncertainties in WEAP21 parameters

Figure 7.5 shows results of 10,000 ensemble simulations for Ryewater flows at the outlet of the catchment produced from the WEAP21 model by using all parameter sets generated from the Latin Hyper Cube sampling of parameter ranges in Table 7.2. The 95% confidence interval of the 10,000 simulated flow ensembles has mostly captured the seasonal patterns of observed flows during the simulation period 1978-2013. All models have underestimated some peak flows and overestimated the majority of low flows. The reason for this could possibly be due to errors in measured precipitation or flow data. Another reason for not capturing low flows by the model is that the continuous mathematical function of WEAP21 does not easily represent low flows (Yates et al. 2013). An example of python code for plotting an ensemble of simulated flow from the SPOTPY database is given in Appendix E.1 – Code 4.

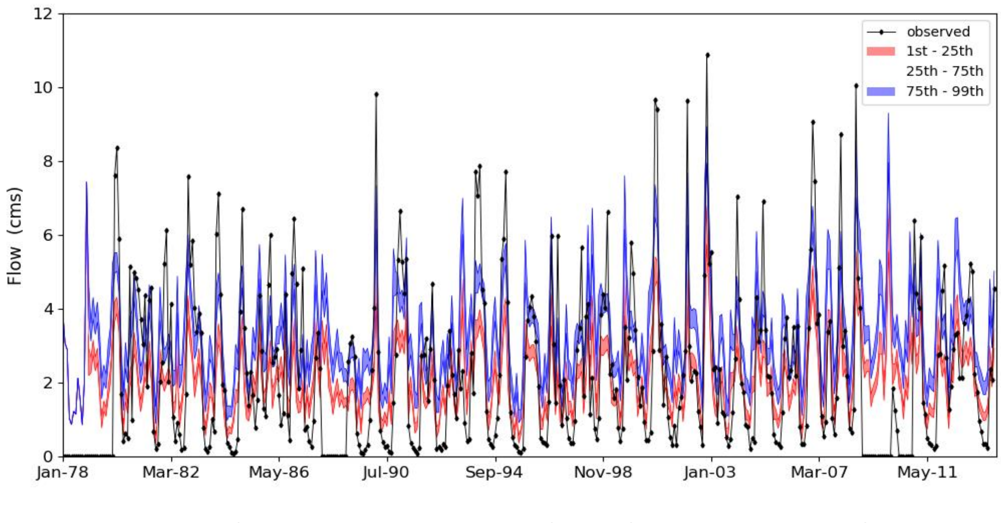


Figure 7. 5 Results of 10,000 ensemble simulated flows of Ryewater at Lexilip flow gauging station during the period 1978-2013, generated from WEAP21 model of Ryewater sub-catchment using all Latin Hyper Cube sampling algorithm. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is shown as black line.

Uncertainties in modelled flows of Ryewater for different parameter groups are also presented in Figures 7.6 and 7.7. Figure 7.6 shows an ensemble of 250 simulated flows produced by using the behavioural parameter sets identified based on the selection criteria in Section 7.2. Figure 7.7 shows plots of ensemble simulated flows for Ryewater produced by using the best 100 performing parameter sets for each individual criterion (a) NSE, (b) LogNSE, (c) PBIAS, (d) RSR. The NSE group showed slight improvement in capturing the peak flows of Ryewater compared to the LogNSE group, while the LogNSE group showed slight improvement in capturing the low flows. The NSE, PBIAS and RSR groups produced comparable ensembles of simulated flows as most parameter sets that produced high NSE values produced low PBIAS and RSR values. These results also reflect the strong negative correlations between the NSE values and values of PBIAS and RSR as presented in Figure 7.3.

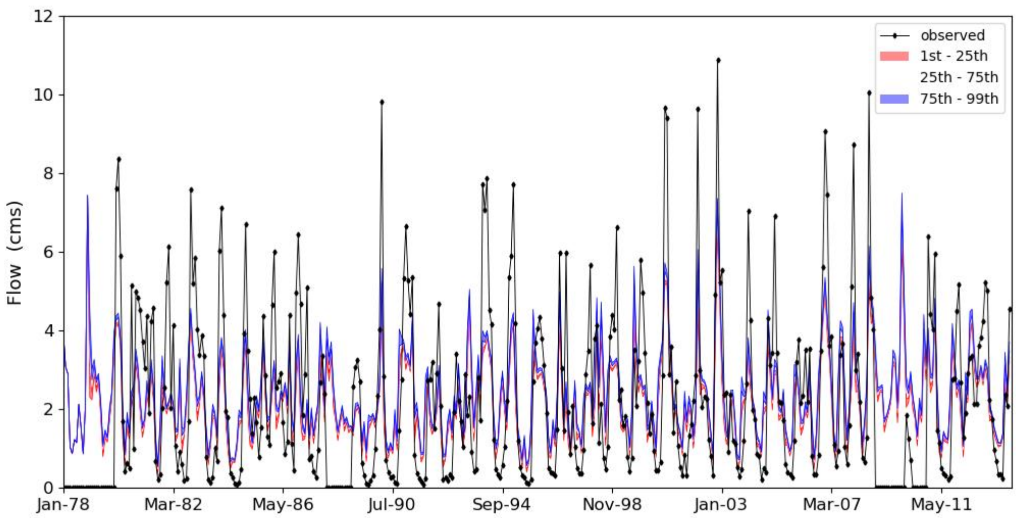


Figure 7. 6 Results of 250 ensemble simulated flows of Ryewater at Lexilip flow gauging station during the period 1978-2013 generated from the WEAP21 model of Ryewater sub-catchment using the behavioural parameter sets from the Latin Hyper Cube sampling algorithm. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly flows are shown as black line

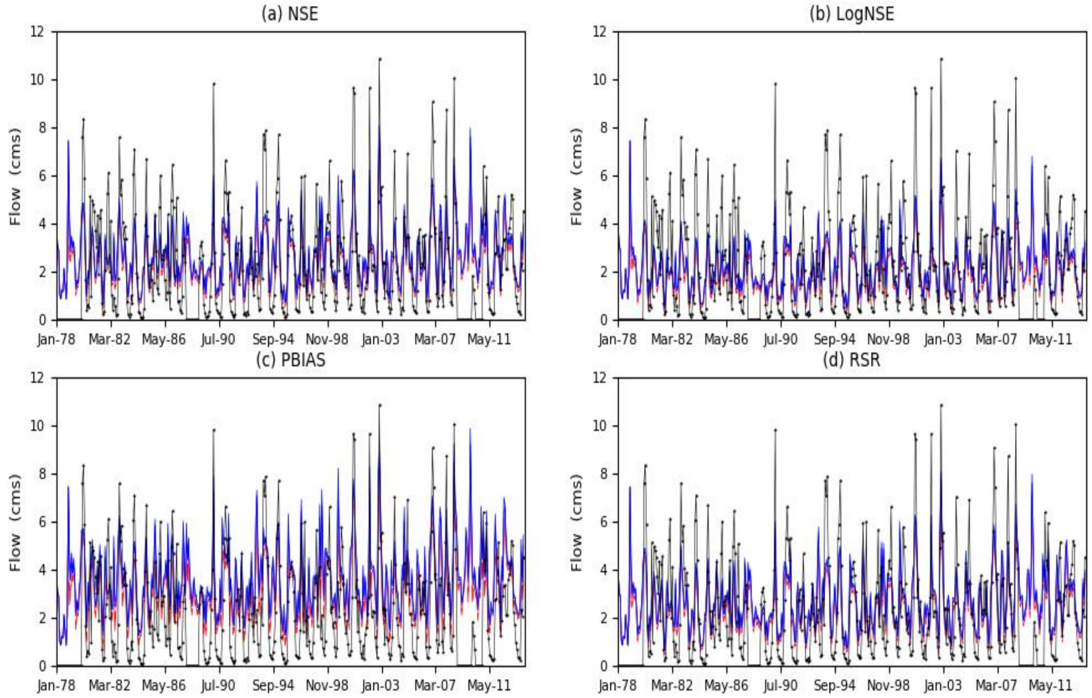


Figure 7. 7 Results of ensemble simulated streamflow of Ryewater at Lexilip flow gauging station during the period 1978 -2013 generated from the WEAP21 model of Ryewater catchment using the best 100 performing parameter sets of the (a) NSE, (b) LogNSE, (c) PBIAS and (d) RSR groups. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is shown as black line.

7.4 Global sensitivity analysis

One of the most commonly used sensitivity analysis methods is the Sobol's method (Sobol, 2001). Sobol's method is a variance-based global sensitivity analysis method that decomposes output variance of a mathematical model into contributions from input variables and interactions (i.e. Mockler et al. 2016b; Shin et al. 2013; van Werkhoven et al. 2009; Tang et al. 2007). Two sensitivity indices are calculated by this method: the first order sensitivity index and the total order sensitivity index. The first order sensitivity index (S1) represents the relative importance of a driving variable (x_i) to the variance output of the model and can be written as (Mockler et al. 2016b, Saltelli et al. 2010):

$$S1 = \frac{Var(E(Y / X_i))}{Var(Y)} \qquad (7.1)$$

where Var(.) and E(.) denote the variance and expectation functions, respectively. The total order sensitivity index (TSI) represents the total effect of the parameter and its interactions with other parameters on the model output and can be written as (Mockler et al. 2016b, Saltelli et al. 2010):

$$TSI = \frac{E(Var(Y \mid X_{\sim i}))}{Var(Y)} \qquad (7.2)$$

where $X_{\sim i}$ is the matrix of all factors except X_i.

The variance output of the Ryewater model, produced by using the 10,000 parameter sets of the Latin Hyper Cube sampling algorithm, has been analysed using the Sobol's sensitivity analysis method. First order and total order sensitivity indices of the Sobol's method for model parameters during the simulation period 1980-2013 have been estimated using the SALib python library (Herman and Usher 2018) (See full code in Appendix E.2). Table 7.3 presents means (long-term average values) and standard deviations for S1 and TSI indices of all parameters of Ryewater catchment. These results indicate that the sample size of 10,000 has achieved convergence as it produced relatively tight uncertainty bounds i.e. average confidence intervals are between 0.01 and 0.10. These intervals are in line with average confidence intervals reported by other studies Mockler et al. 2016b and Tang et al. 2007. The long-term average values of S1 and TSI indices for all model parameters are also displayed in colour-coded grids (Figure 7.8) with dark blue indicating high values (≥0.80) and light blue indicating low values (≤0.10). The values of TSI indices for all model parameters are substantially larger than the corresponding values of S1 indices. Hence, this indicates the presence of higher order interactions between all parameters (Herman and Usher 2018).

Table 7. 3 Mean and standard deviation for first order sensitivity indices (S1) and total order sensitivity indices (TSI) for all parameters of Ryewater sub-catchment period resulted from 35 year simulation period (1980-2013)

Parameter	S1	TSI
Kc_NI	-0.03 ± 0.09	1.00 ± 0.08
Kc_p	0.01 ± 0.04	1.05 ± 0.07
Kc_f	0.02 ± 0.06	1.09 ± 0.04
swc_NI	0.01 ± 0.09	1.04 ± 0.04
swc_p	-0.01 ± 0.03	1.13 ± 0.06
swc_f	0.01 ± 0.05	0.94 ± 0.03
Dwc	-0.08 ± 0.04	1.06 ± 0.04
rrf_NI	0.01 ± 0.04	0.95 ± 0.03
rrf_p	0.07 ± 0.05	1.02 ± 0.02
rrf_f	0.06 ± 0.02	1.02 ± 0.05
rzc_NI	0.03 ± 0.06	1.13 ± 0.09
rzc_p	0.04 ± 0.08	1.07 ± 0.03
rzc_f	0.03 ± 0.02	1.07 ± 0.04
Dc	-0.01 ± 0.04	1.03 ± 0.06
pdf_NI	-0.08 ± 0.07	1.03 ± 0.02
pdf_p	-0.06 ± 0.03	1.06 ± 0.04
pdf_f	-0.03 ± 0.05	1.06 ± 0.03

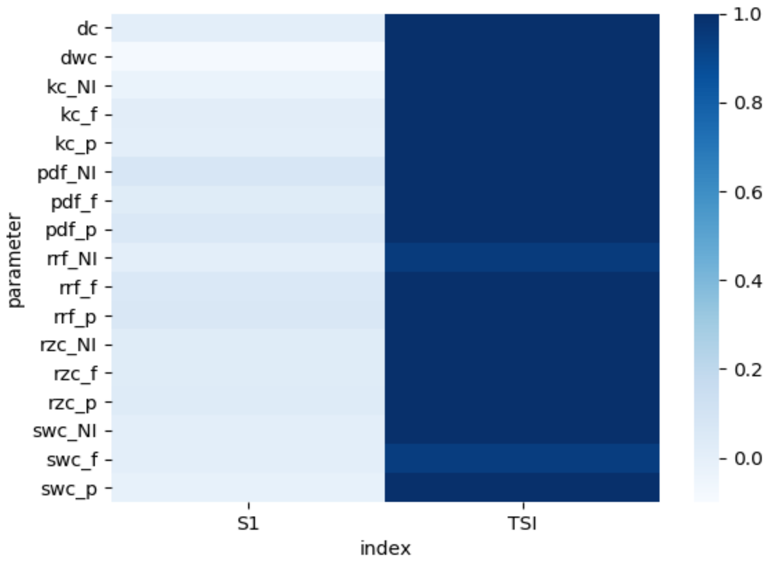


Figure 7. 8 Long-term average values of first order sensitivity indices (S1) and total order sensitivity indices (TSI) for all parameters of Ryewater sub-catchment produced from analyzing the variance output of the model during the period 1980-2013.

Correlations between TSI indices and input data such as precipitation and temperature have been investigated to explore the seasonal effects on sensitivity of model parameters. Figure 7.9 presents correlation of TSI indices for each parameter with the monthly precipitation data of Ryewater catchment along with values of spearman correlation coefficient and the p-value. TSI for crop coefficient (*Kc)*, runoff resistance factor (*rrf)*, and root zone conductivity (*rzc)* are negatively correlated with monthly rainfall values (r= -0.50 − -0.89, p-value ≤ 0.001); sensitivity indices for these parameters increase with decreasing rainfall values. This indicates *Kc*, *rrf* and *rzc* parameters are more identifiable in dry periods. *Kc* is more sensitive in dry periods as it facilitates more evaporation from the upper soil layer to meet evapotranspiration demands. *rrf* and *rzc* are more sensitive in dry periods as they possibly contribute to increasing availability of water in the upper soil layer. This in turn helps satisfy evapotranspiration demands in dry periods. On the other hand, TSI for soil water capacity (*SWC)*, deep water capacity (*DWC)* and deep conductivity (*dc)* are positively correlated with monthly rainfall values (r= 0.50 − 0.70, p-value ≤ 0.001) indicating that these parameters are more identifiable in wet periods. SWC are more sensitive in wet months as it possibly allows for storing additional water in the upper soil layer when evaporation are relatively low. This in turn reduces potential errors between predicted and observed streamflow values at the outlet of the catchment. *DWC* and *DC* are also more sensitive in wet months as they facilitate more groundwater contributions to streamflow proportionate to the amount of monthly rainfall.

Figure 7.10 presents correlation of TSI indices for each parameter with monthly average temperature data of Ryewater sub-catchment along with corresponding values of spearman correlation coefficient and the p-value. TSI indices are found to have weaker correlations with temperature data (r≤0.45, p-value=0.001–0.56) compared to correlations with precipitation data. These results indicate that variance of the model output is less affected by temperature inputs compared to effects of precipitation input.

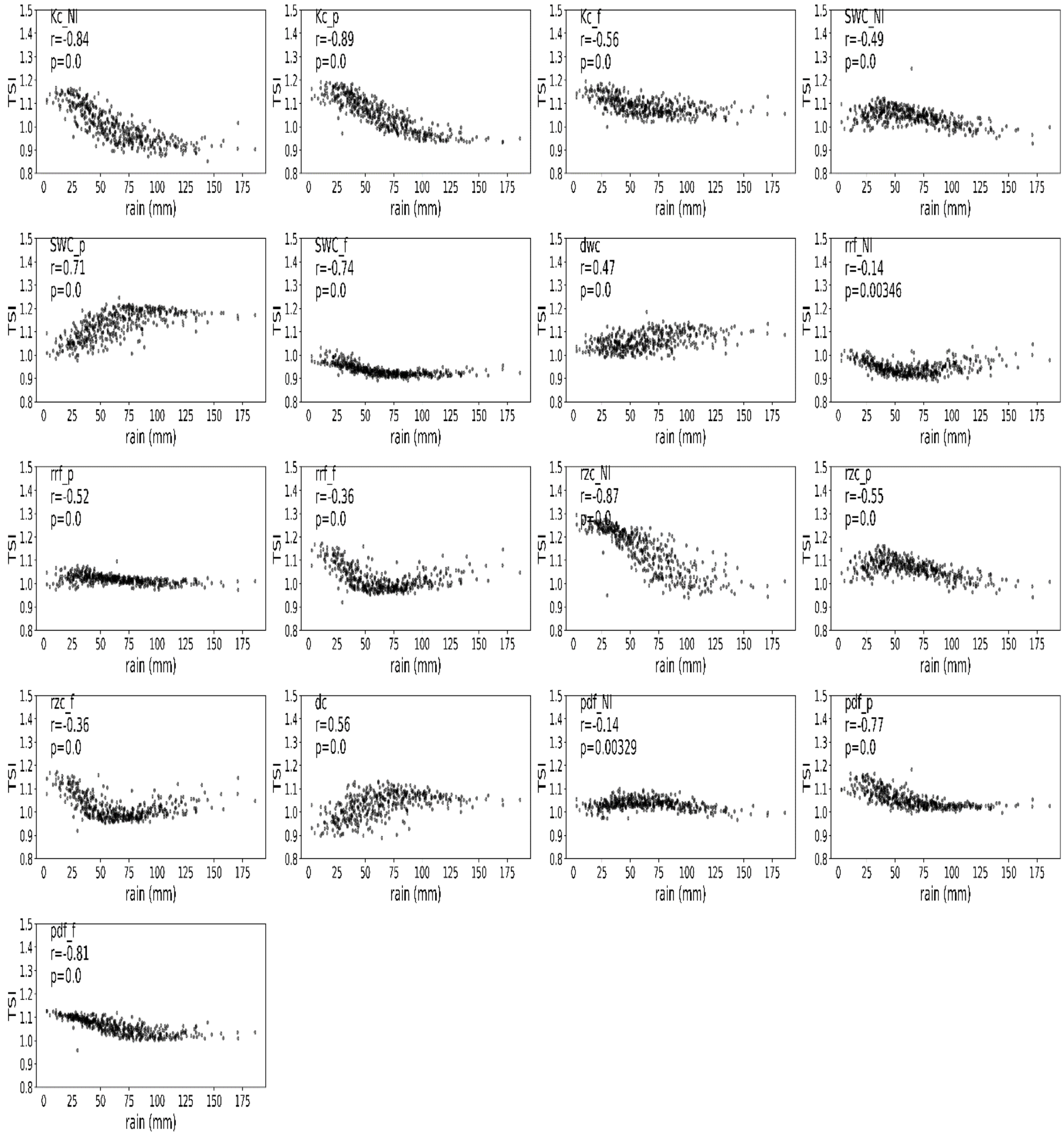


Figure 7. 9 Correlations of TSI indices with monthly precipitation data across all parameters of the WEAP21 model of Ryewater sub-catchment.

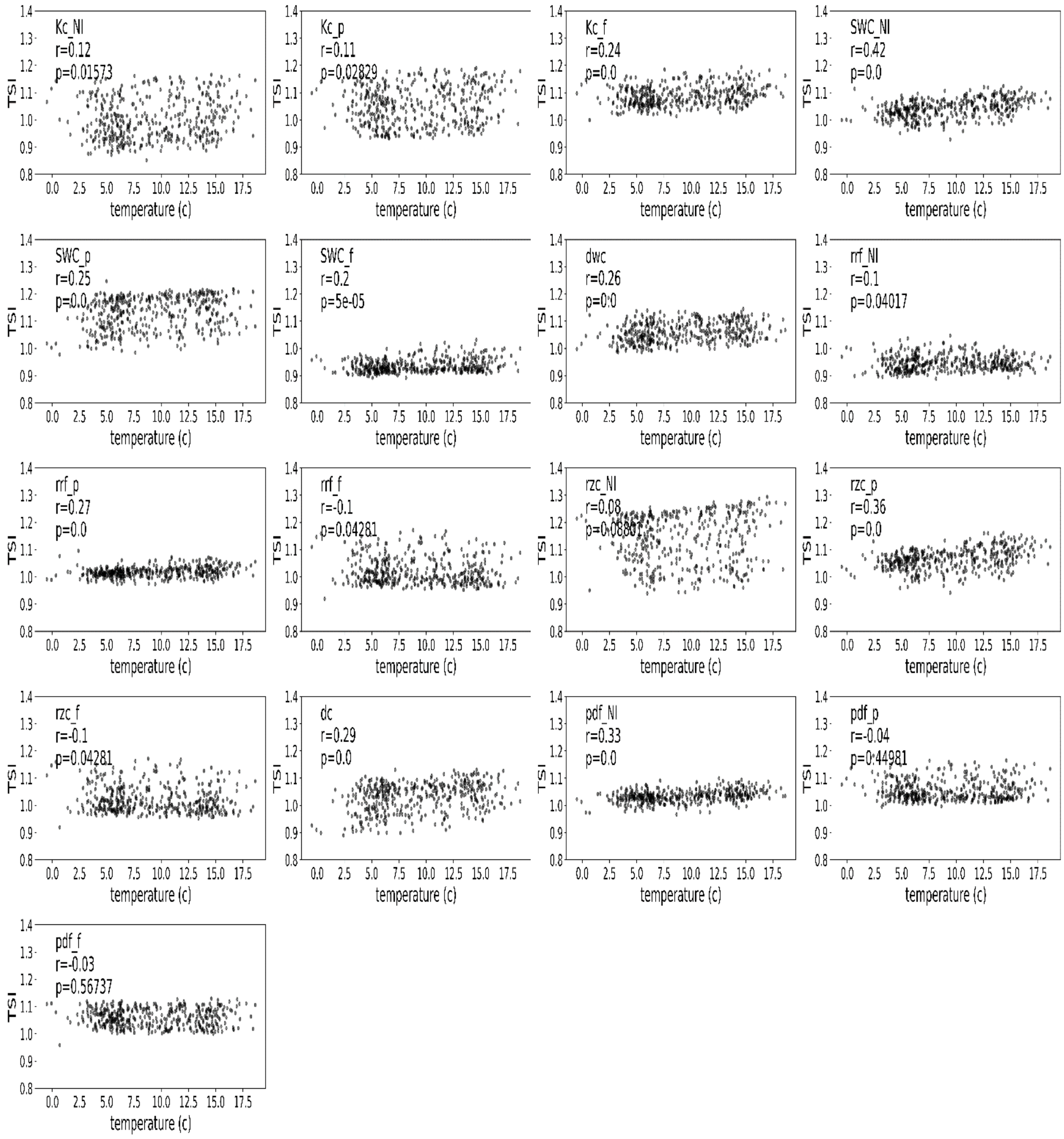


Figure 7. 10 Correlations of TSI indices with monthly average temperature data across all parameters for the WEAP21 model of Ryewater sub-catchment.

7.5 Separate models for the dry and wet seasons

Separate models for predicting flows of Ryewater sub-catchment in dry and wet seasons have been developed by using the sensitive parameters and the corresponding flow values for each season separately. First, flow measurements of Ryewater at Lexilip gauging station during the period 1980-2013 have been split into two subsets: dry months (April – September) and wet months (October – March). The corresponding subset for each season has then been used to calibrate only model parameters that showed higher sensitivities in the respective season. For instance, calibration of sub-catchment models for the dry season has focused on parameters that showed higher sensitivities in dry months such as *Kc*, *rrf*, and *rzc*. For modeling the wet season, calibration has focused on other parameters which showed relatively higher sensitivities in wet months such as *SWC*, *DWC*, *dc*. The corresponding ranges for each parameter in Table 7.2 have been used to generate 10,000 parameter sets for each parameter group (i.e. dry and wet season) using the Latin Hyper Cube sampling algorithm and by assuming uniform parameter distributions.

The performance for each of the 10,000 resulting dry season models in predicting the corresponding monthly flow values has been assessed using the LogNSE, while the performance for each of the resulting wet season models has been assessed using the original NSE. The best 100 performing models for each season have been selected by ranking the fit of each of the 10,000 Latin Hyper Cube simulations of each season to the corresponding observed flow values. Figures 7.11 and 7.12 show ensembles of predicted seasonal flows of Ryewater resulting from the best 100 performing models of the dry season and wet seasons, respectively. The models for the dry seasons have overestimated some low flows, and the models for the wet seasons have underestimated some peak flows. The simulations resulting from the dry season models yielded a median LogNSE value of 0.36 and a maximum value of 0.47. The simulations from the wet season models yielded a median NSE value of 0.46 with a maximum value of 0.52. These results indicate no significant improvements over simulations resulted from the full model of Ryewater sub-catchment (i.e. including all seasons) (see Section 7.3).

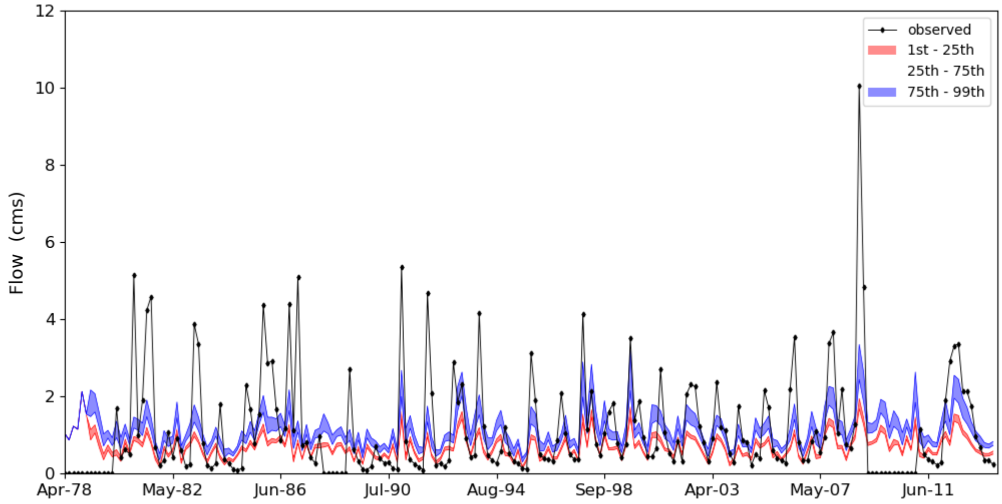


Figure 7. 11 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging in the dry season (April – September) generated from the best 100 WEAP21 models of Ryewater for the dry season. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is shown as black line.

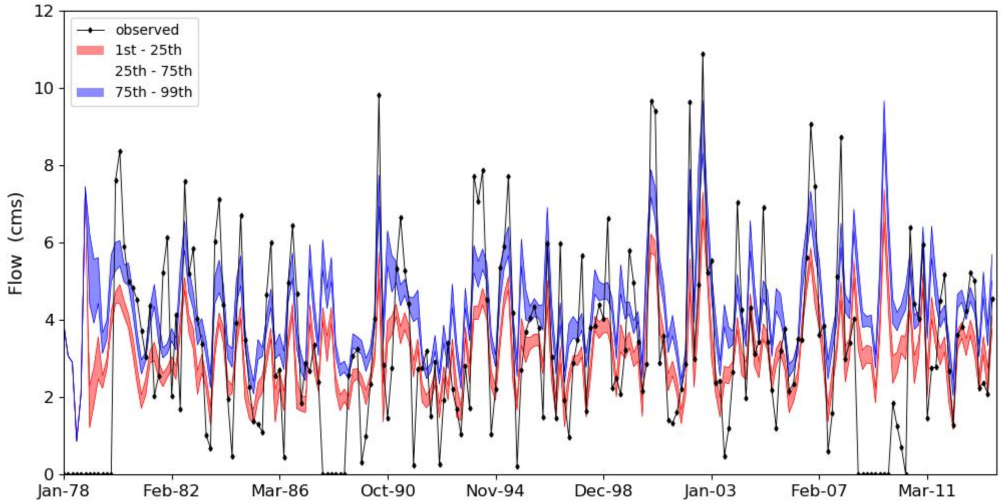


Figure 7. 12 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging in the dry season (October – March) generated from the best 100 WEAP21 models of Ryewater for the wet season. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is shown as black line.

7.6 Analysis of precipitation and flow data

A check of precipitation and flow volumes of Ryewater sub-catchment suggested inaccuracies in precipitation input data or flow data. Also, a review of the drainage system for the urban centres within this sub-catchment including Kilcock and Maynooth (DDC 2005a) revealed that the sub-catchment is not affected by any external flows.

About 10% of the monthly precipitation data has been found to have monthly precipitation volume lower than the corresponding measured flow at Lexilip flow gauging station. An example of such inaccuracies in precipitation and flow data is provided in Figure 7.13, which shows that precipitation values in Jan and Feb are lower than the corresponding flow values. This has likely influenced the model to show underestimation of flows at these months (Figure 7.14). It is rarely that measured data are free from errors and all measurements contain uncertainties that need to be considered in calibration and validation of the model (Moriasi et al. 2007; Beven 2009).

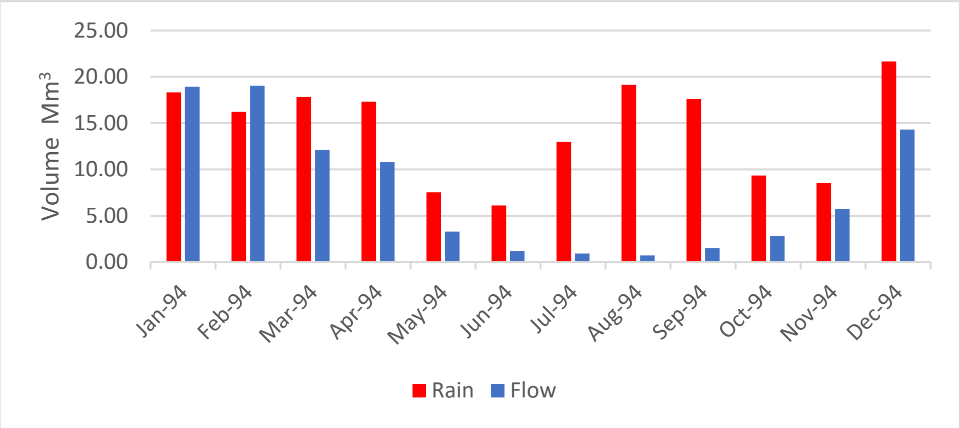


Figure 7. 13 Monthly precipitation and flows volumes of Rye water during the year 1994.

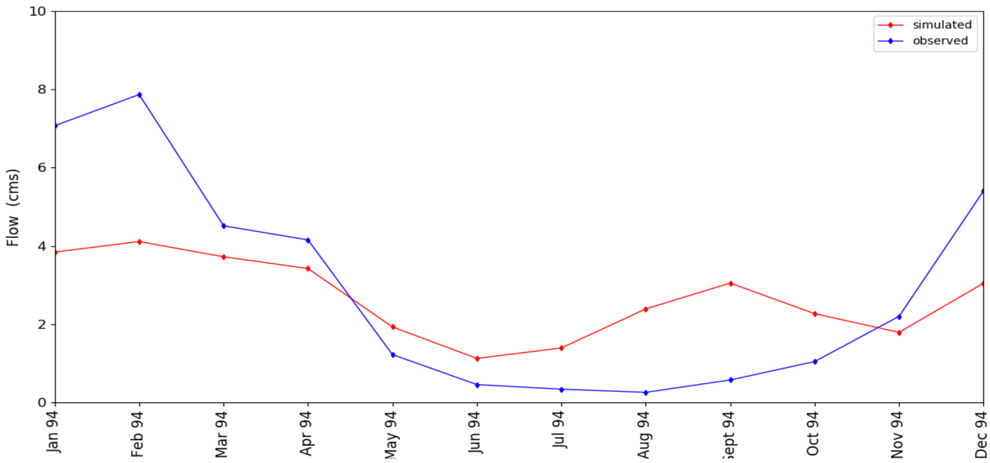


Figure 7. 14 Simulated and observed flows of Ryewater at Lexilip flow gauging station during the year 1994 as produced by WEAP21 model. Simulated flows are in red and observed flows are in blue.

7.7 Stochastic climate modelling

Stochastic climate time-series data have been generated using stochastic climate generators to assess the impacts of forcing data such as rainfall and temperature on the output of Ryewater catchment model. Precipitation sequences have been generated using the spatial generalized linear modeling (GLM) framework (Chandler and Wheater 2002) and the stochastic climate library (SCL) http://toolkit.ewater.org.au/Tools/SCL. The SCL software has also been used to generate stochastic temperature data for the Ryewater catchment. This section presents simulation results of Ryewater flows at Lexilip flow gauging station using the stochastically generated climate data.

7.7.1 Rainfall sequences using the Spatial GLM framework

The spatial GLM framework is used for fitting GLM models to daily climate data which can be used to simulate ensembles for the climatic variable of interest (Chandler and Wheater 2002; Chandler 2015, Mockler et al. 2016b). The GLM model can be defined in terms of internal and external climate driving covariates. The internal covariates describe the spatiotemporal effects and can include seasonality, autocorrelation in the time-series, site effects and inter-site dependences. Seasonality in the framework can be accounted for using Fourier representation of the annual cycle (cosine and sine coefficients). Autocorrelation is accounted for by including previous days' rainfall values. Site effects are represented by Legendre polynomials of latitude and longitude. Inter-site dependences can be represented using different correlation based-structures which are functions of the Euclidean distance between the sites. On the other hand, external covariates are non-deterministic time varying quantities such as sea surface temperature series, teleconnection indices and North Atlantic Oscillation.

The spatial GLM framework is composed of a rainfall occurrence model and an intensity rainfall model. In the rainfall occurrence model, a time-series of zeros/non zeros representing dry/wet days respectively is generated based on the rainfall occurrence probability (p_i) which is determined at each time step using a logistic regression model (Equation 7.3):

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i^T \beta \qquad (7.3)$$

where x_i^T is the ith day transposed vector of covariates representing spatiotemporal effects and external interactions, and β is the coefficient vector of the logistic regression model. In the intensity model, the mean rainfall value of the ith wet day (μ_i) is calculated using a gamma distribution (Equation 7.4):

$$\ln(\mu_i) = \xi_i^T \gamma \qquad (7.4)$$

where ξ_i^T is the ith day transposed vector of covariates corresponding to the intensity model, and γ is the shape parameter. In building the models, the candidate covariates are added to the model one at a time in a stage-wise procedure. At each fitting stage, the coefficient vector of the model is determined using the Newton-Raphson method which maximizes the likelihood of non-linear equations. The statistical significance of the added covariate is also examined by formal statistical tests based on the likelihood ratio and deviance (Chandler 2015). Further details on the spatial GLM approach and algorithms can be found in Chandler 2015. Moreover, the spatial GLM framework has been used in different hydrological applications such as Mockler et al. 2016a, Yang et al. 2005, and Chandler and Wheater 2002.

The spatial GLM framework has been applied for the Ryewater sub-catchment using rainfall data at six different sites during the period 2005-2015. The rainfall sites are Dunshauglin, Fairyhouse Racecourse, Casement, Enfield, Celbridge, and Straffaan.

Daily rainfall measurements at these sites for the period 2005-2015 were obtained from Met Éireann website (https://www.met.ie/). Using these data, the spatial GLM framework has been formulated and executed via the multisite weather generator (RGLIMCLIM), which is based on the R statistical programming environment – available from http://www.ucl.ac. uk/ ~ucakarc/work/glimclim.html. A full R code for fitting the rainfall occurrence and intensity models for Ryewater sub-catchment is provided in Appendix E.3. The final structures of the rainfall occurrence and intensity models are provided in Table 7.4. An initial check for the performance of the fitted models was performed by constructing a Quantile – Quantile (Q-Q) plot of standardised errors under these models (Figure 7.15). This figure suggests that there is a good agreement between the resulting theoretical relationship and the observed data indicating satisfactory performance of the models and hence the validity of the model for simulating rainfall sequences.

Table 7. 4 Final rainfall model structure for the GLM framework applied to the Ryewater sub-catchment.

a) occurrence model	
1	Constant term
2	First order Legendre polynomial representation for easting
3	First order Legendre polynomial representation for northing
4	Daily annual cycle representing seasonal effects – cosine component
5	Daily annual cycle representing seasonal effects – sine component
6	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-1])>0)
7	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-2])>0)
8	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-3])>0)
9	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-4])>0)
10	Interaction: 1 day rainfall occurrence and the cosine component of the seasonal effect
11	Interaction: 1 day rainfall occurrence and the sine component of the seasonal effect
12	Rainfall trace value (0.50 mm)
13	Parameter representing spatial structure based on conditional independence given the weather state and the mean of the predicted rainfall occurrence probabilities at the site
b) intensity model	
1	Constant term
2	First order Legendre polynomial representation for easting
3	First order Legendre polynomial representation for northing
4	June indicator – an indicator to reduce Pearson residual for month June
4	Daily annual cycle representing seasonal effects – cosine component
5	Daily annual cycle representing seasonal effects – sine component
6	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-1])>0)
7	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-2])>0)
8	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-3])>0)
9	Previous day rainfall occurrence indicator for autocorrelation – (Rainfall[t-4])>0)

10	Interaction: 1 day rainfall occurrence and the cosine component of the seasonal effect
11	Interaction: 1 day rainfall occurrence and the sine component of the seasonal effect
12	Previous days' rainfall amounts with a logarithmic transformation
13	Dispersion parameter
14	Parameter for the spatial dependence model

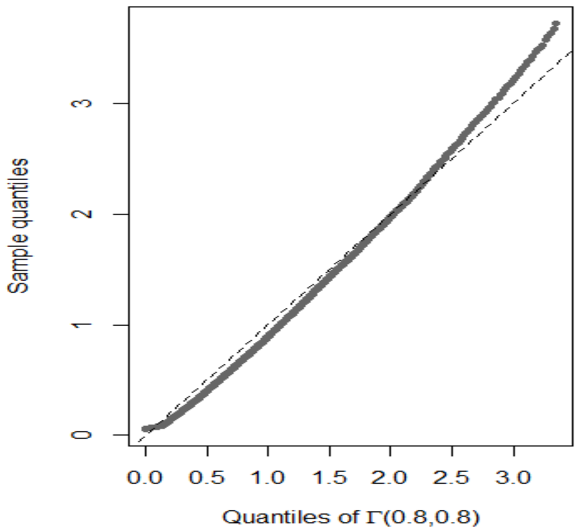


Figure 7. 15 Quantile-Quantile plot of standardised error under the fitted intensity model.

The fitted rainfall models above have been used to simulate 100 daily rainfall sequences at the six rainfall sites during the period 2005-2015 for use in the WEAP21 model of Ryewater sub-catchment. This size of stochastic rainfall ensembles has been chosen so that the computational time required for combining stochastic rainfall data and behavioural parameters is reasonable. Figure 7.16 shows simulated distributions of annual time-series for the seasonal mean rainfalls produced from the spatial GLM (coloured bands) along with the envelope of rainfall observations (black). The envelope of observations represents the range obtained from multiple imputations of observed rainfall data where in each imputation the missing values are sampled from their conditional distributions given available observations. The quality of simulations is assessed qualitatively by checking whether the 95% interval of simulated rainfalls encloses the corresponding observed rainfalls. The 95% intervals of simulations were found to enclose most of the rainfall observations in all seasons but with except to summers of 2006, 2008 and 2012 and winters of 2007 and 2013. One limitation of this

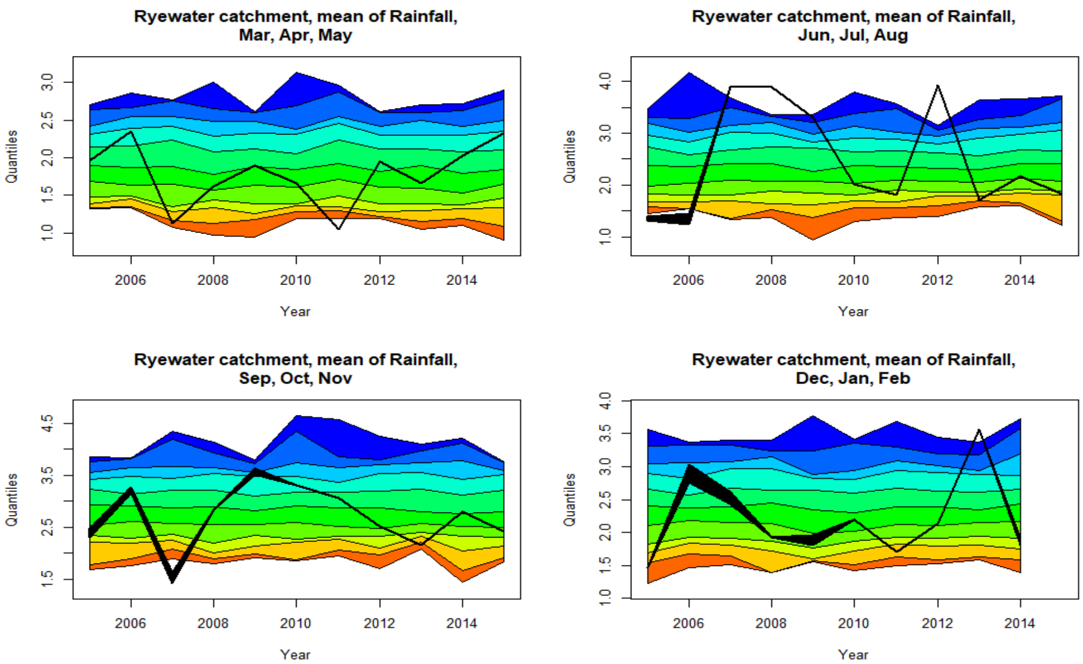


Figure 7. 16 Simulated distributions of annual time series of mean seasonal rainfall (coloured bands) along with envelope obtained from 39 imputations of rainfall observations for the Ryewater sub-catchment (black). Colour bands indicate the quantiles of 100 rainfall time-series simulations.

study is the exclusion of external climate driving variables in building up the spatial GLM. Such external variables could be used to further condition the spatial GLM which in turn can improve the quality of simulations (Mockler et al. 2016a).

An ensemble of simulated flows for Ryewater at Lexilip gauging station were generated by combining the resulting 100 rainfall sequences from the GLM framework with the best 100 performing parameter sets from the Latin Hyper Cube sampling based on the NSE and LogNSE criteria as shown in Figures 7.17 and 7.18, respectively. The ensembles of simulated flows in both figures mostly captured the seasonal patterns of observed flows of Ryewater during the simulation period. However, the ensembles underestimated some peak flows (e.g. in Dec 2006 and Jan 2007) and overestimated some low flows (e.g. Mar 2010 and Jun 2011). This also suggests that simulations may be influenced by errors in observed rainfall or flow data. The python code for combining rainfall sequences with best 100 best performing parameter sets to generate ensemble flows of Ryewater in WEAP21 is provided in Appendix E.4.

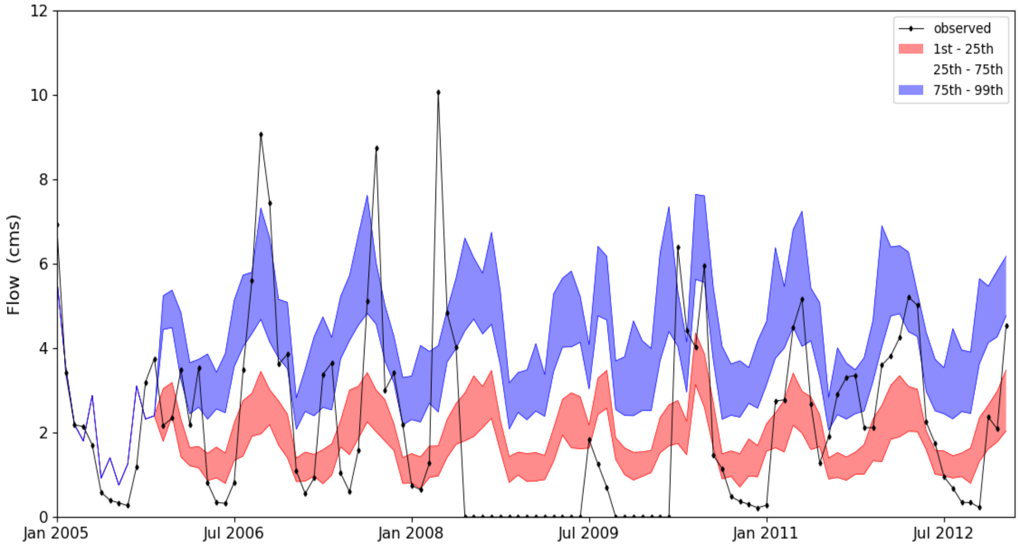


Figure 7. 17 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 rainfall time-series from the spatial GLM framework with the best 100 performing parameter sets from the Latin Hyper Cube sampling based on NSE. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

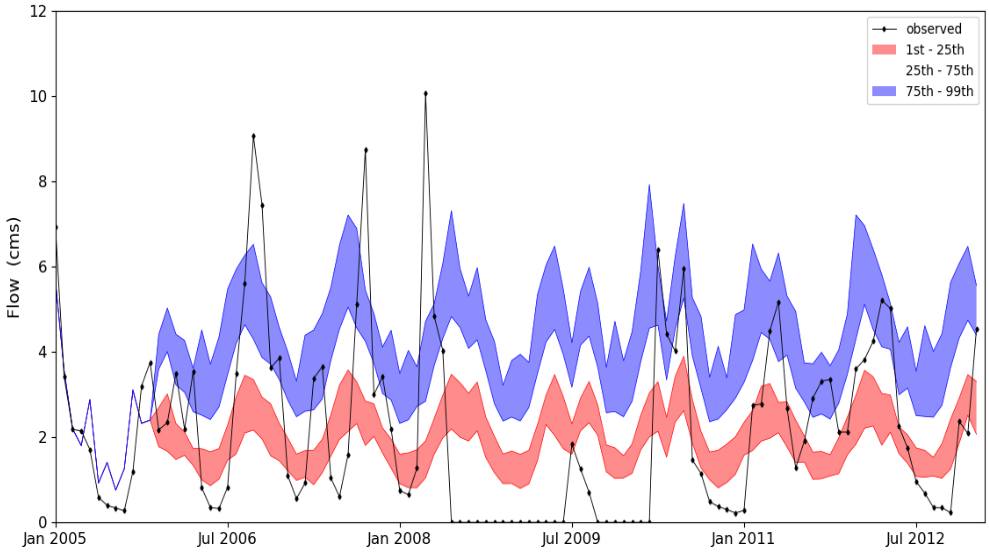


Figure 7. 18 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combing the 100 rainfall time-series from the spatial GLM framework with the best 100 performing parameter sets based on LogNSE. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

7.7.2 Rainfall sequences using the stochastic climate library (SCL)

Another ensemble of 100 simulated rainfall time-series data for Ryewater sub-catchment during the period 1980-2013 have been generated using the SCL. The cumulative distributions of these simulations are plotted against the distribution of observed rainfall data in Figure 7.19, which suggests good match between the stochastically simulated data and observed data. Moreover, the quality of stochastic rainfall data has been assessed by comparing different statistics in the stochastic data with corresponding ones in the observed rainfall data. The assessed statistics included monthly means, standard deviation, maximum and minimum values, coefficient of skewness, and coefficient of auto-correlation. The differences between the means of these statistics in the stochastic data and the corresponding statistics in observed data were found to be within acceptable tolerance levels (shown in Table 7.5), with except to differences in minimum values for months June to November which were slightly larger. Figure 20 presents scatter and whisker plots for the means of the statistics in stochastic data against the corresponding statistics in rainfall observations. These results suggest that the SCL model for Ryewater catchment has satisfactorily reproduced most of the statistics in the corresponding observed rainfall data. It is therefore plausible to assume that the stochastic rainfall data have a satisfactory quality and hence can be used in the hydrological model as alternative realisations for past rainfall records.

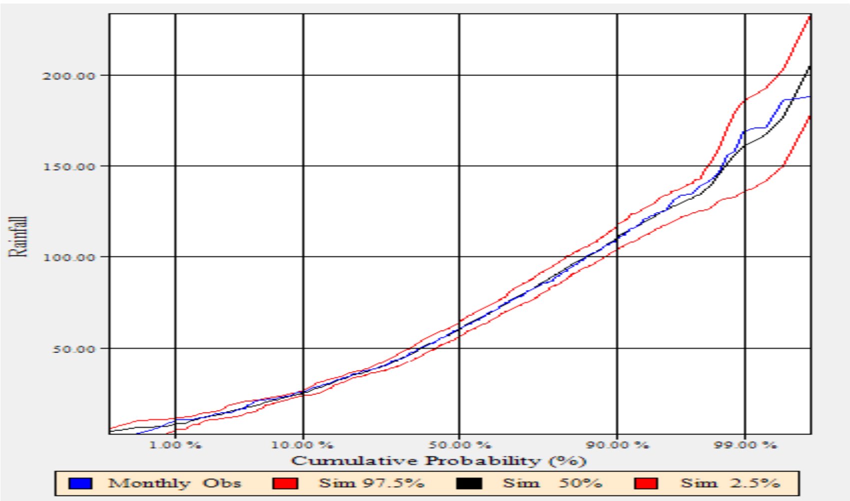
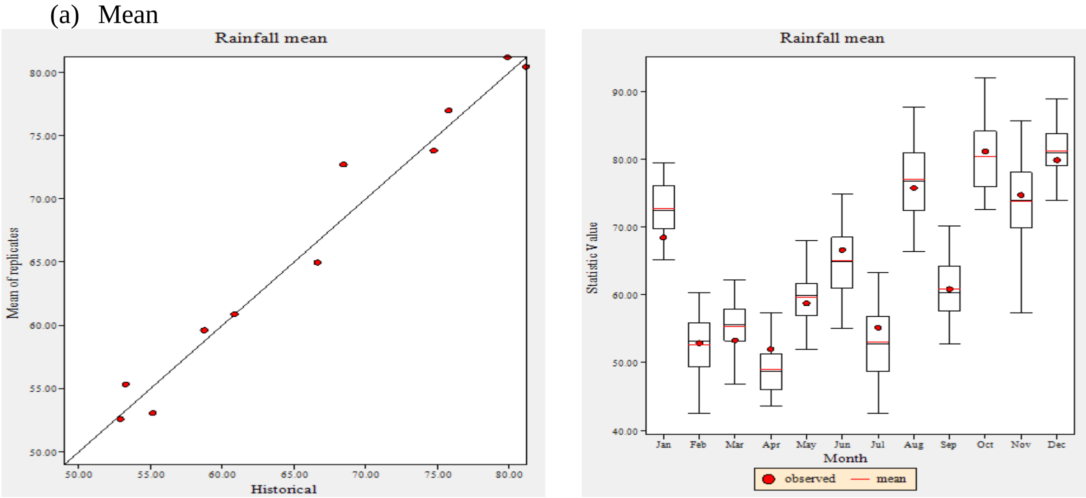


Figure 7. 19 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated rainfall data for Ryewater sub-catchment during the period 1980-2013 produced by SCL against corresponding distribution of observed rainfall data.

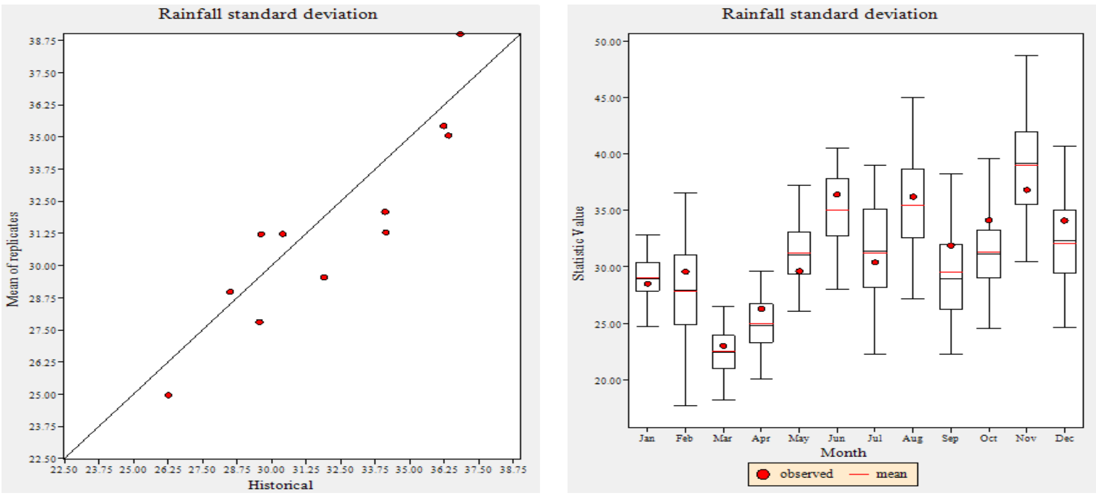
Table 7. 5 Acceptable tolerance levels for differences in statistics used in assessing the quality of SCL models (Sirkanthan et al. 2007)

Statistic	Tolerance
Mean (%)	7.50
Standard deviation	7.50
Maximum (%)	10
Minimum (%)	10
Coefficient of skewness	0.75
Coefficient of autocorrelation	1.5

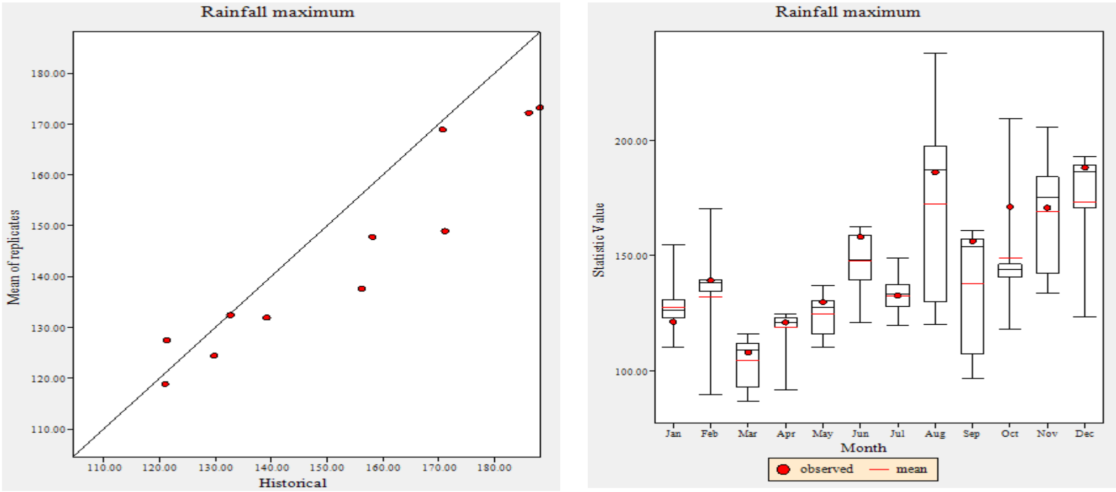
(a) Mean



(b) Standard deviation



(c) Maximum



(d) Minimum

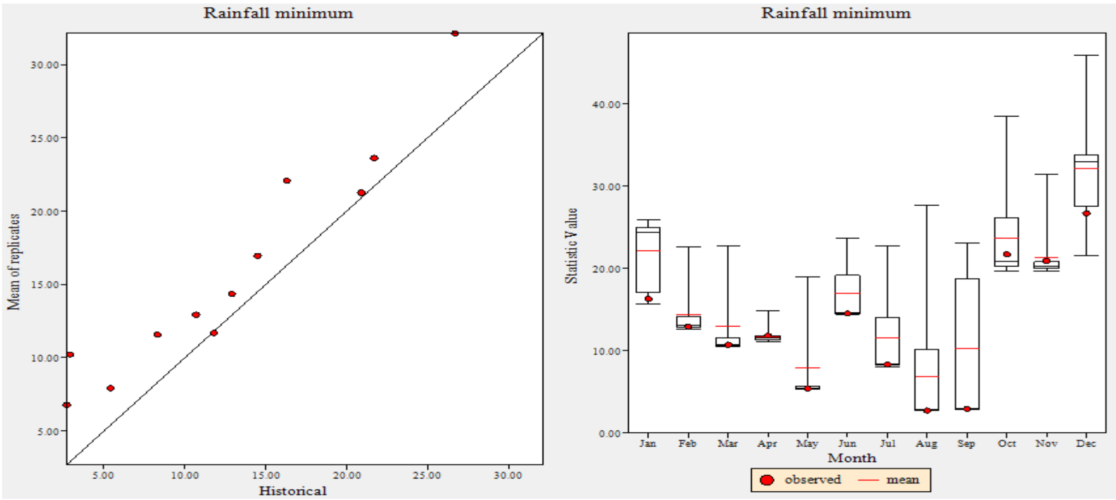


Figure 7. 20 Scatter and whisker plots for means of different statistics in the stochastic rainfall data generated by SCL and corresponding statistics in the observed rainfall data.

The 100 stochastic rainfall simulations for Ryewater sub-catchment from the SCL model have been combined with the best 100 performing parameter sets of the Latin Hyper Cube Sampling for the NSE criterion to generate an ensemble of 10,000 simulated streamflows for Ryewater (Figure 7.21). This ensemble captured the seasonal pattern of observed flows but with larger uncertainty interval compared to the one produced by rainfall data from the spatial GLM. Unlike the interval produced from the spatial GLM, the interval produced using the SCL rainfall data captured some peak flows for example in Dec 2006 and Jan 2007. The interval produced using the SCL

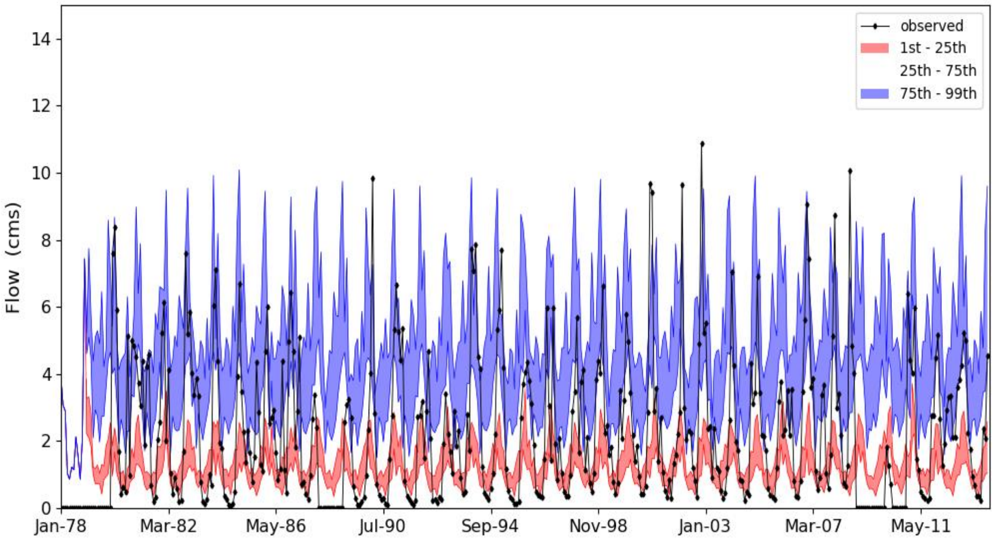


Figure 7. 21 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 rainfall time series from the SCL and the best 100 performing parameter sets from the Latin Hyper sampling based on NSE.

rainfall also better captured the very low flows for example in months May to Sept 2011. These results suggest that the WEAP21 model for Ryewater catchment may have not accurately estimated the water balance of the catchment due to potential errors in rainfall or streamflow data.

7.7.3 Temperature sequences using the stochastic climate library (SCL)

An ensemble of 100 simulated temperature time-series data for Ryewater sub-catchment during the period 1980-2013 have been generated using the SCL. Input to the SCL model for simulating temperature included rainfall, temperature and evaporation data. Data for temperature and evaporation from the nearest synoptic station (Casement) was obtained from the Met Éireann website (https://www.met.ie/). The cumulative distributions of the resulting simulations of temperature are plotted against the distribution of observed temperature data in Figure 7.22, which suggests good match between the stochastically simulated temperature data and observed data. Moreover, the differences between the means of select statistics in the stochastic data and the corresponding statistics in observed data were found to be within acceptable tolerance levels (shown in Table 7.5), with except to differences in standard deviations and minimum values for months Jan-Mar and Jun-Jul which were slightly larger. Figure 7.23 presents scatter and whisker plots for the means of different statistics in stochastic temperature data against the corresponding ones in observed temperature data. These results indicate that the SCL model for Ryewater sub-catchment has satisfactorily reproduced most of the statistics in the corresponding observed temperature data. Therefore, the stochastic temperature data can also be used in the hydrological model as alternative realisations to the past records of temperature.

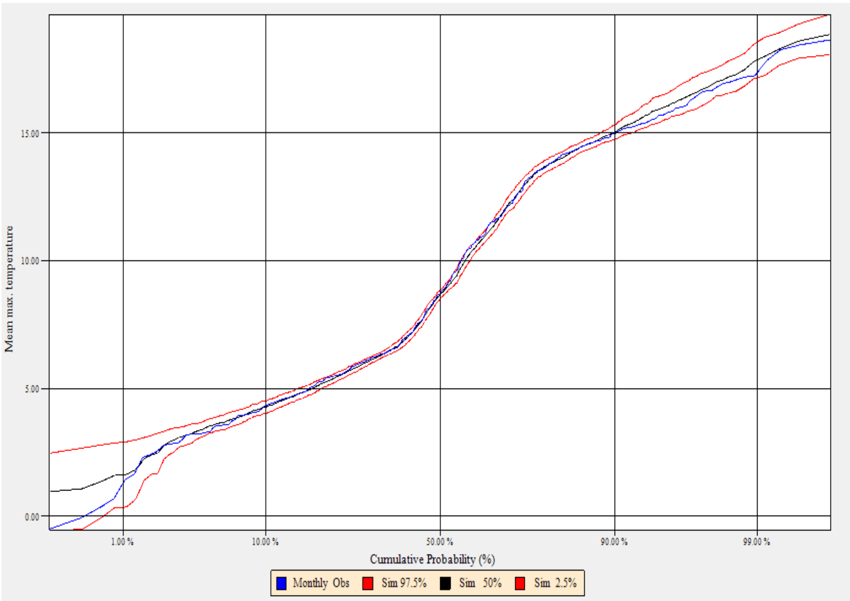
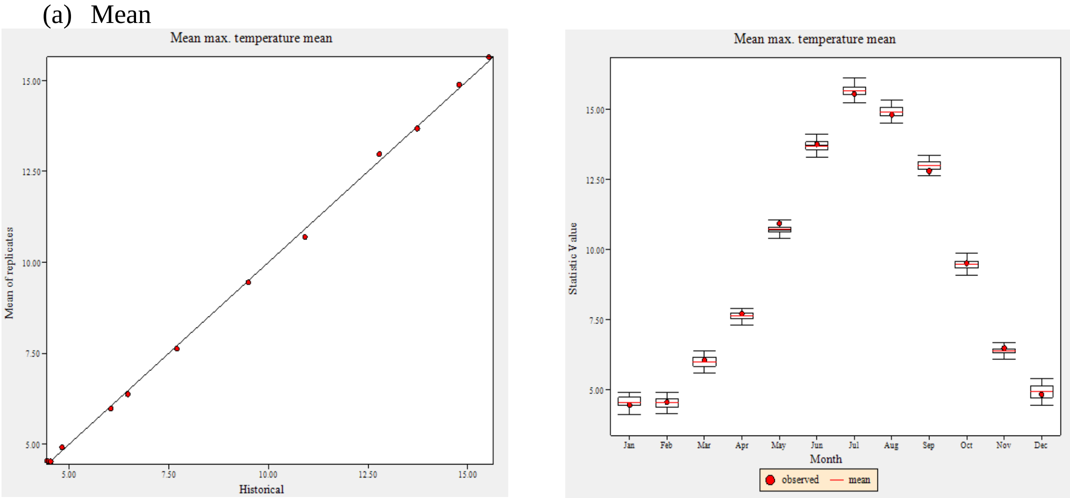


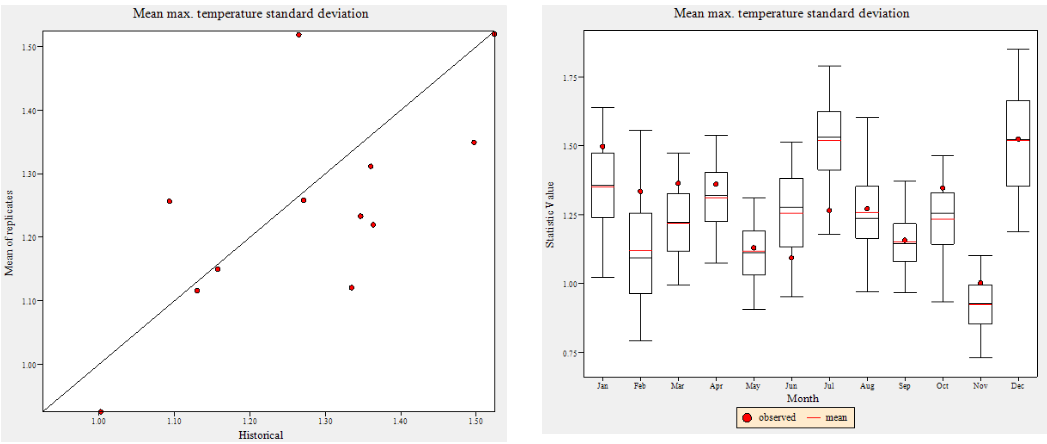
Figure 7. 22 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated temperature data for Ryewater sub-catchment during the period 1980-2013 produced by SCL against corresponding distribution of observed data.

The 100 stochastic temperature simulations for Ryewater sub-catchment from the SCL model have been combined with the best 100 performing parameter sets of the Latin Hyper Cube Sampling for the NSE criterion to generate another ensemble of 10,000 simulated streamflows for Ryewater (Figure 7.24). This ensemble of simulated flows, similar to previous ensembles from stochastic rainfall simulations, has captured the seasonal patterns of the observed flows. However, it has a tighter uncertainty interval compared to the ones produced from using the stochastic rainfall data. All the simulations resulted from combining stochastic temperature data with best parameter sets for NSE has underestimated some peak flows (e.g. Nov – Dec 2000) and overestimated some low flows (e.g. May – Aug 2011). These results suggest that the model is less influenced by temperature data than by the precipitation data.

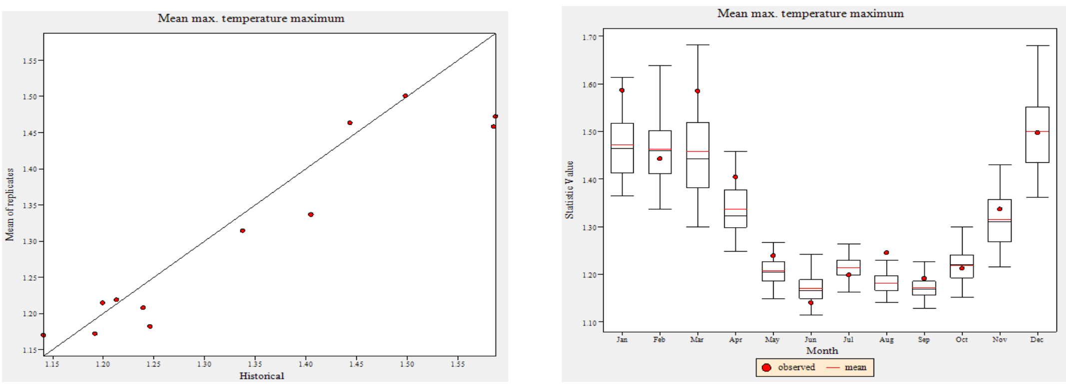
(a) Mean



(b) Standard deviation



(c) Maximum



(d) Minimum

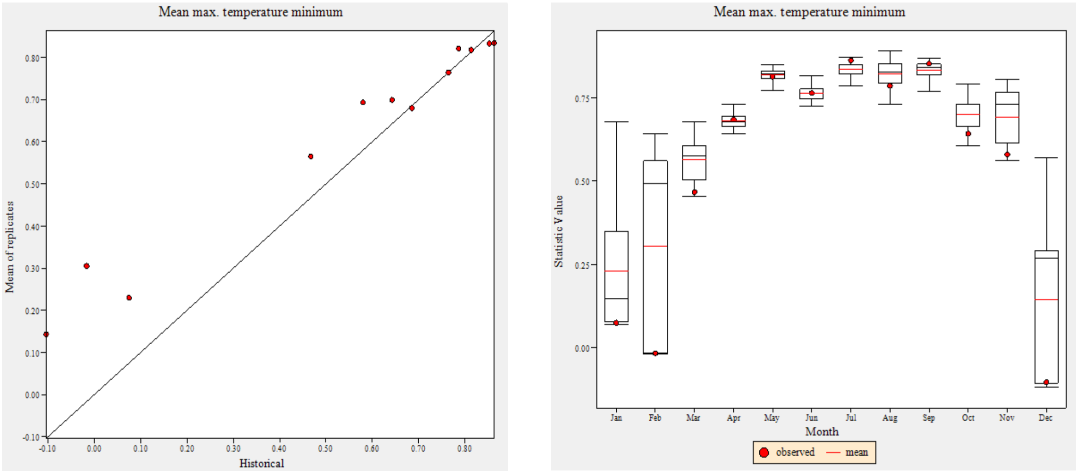


Figure 7. 23 Scatter and whisker plots for means of different statistics in the stochastic temperature data generated by SCL and corresponding statistics in the observed rainfall data.

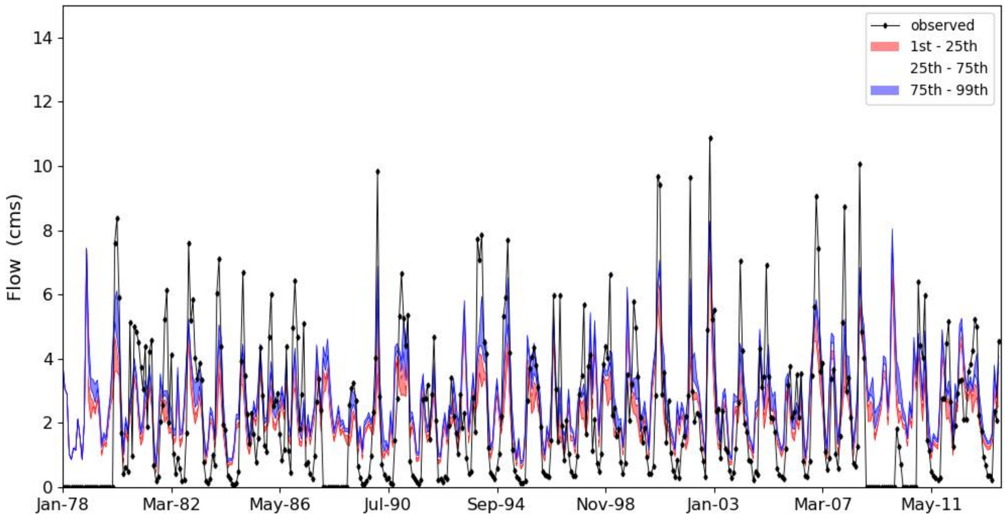


Figure 7. 24 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 model by combining the 100 temperature time-series from the SCL with the best 100 performing parameter sets from the Latin Hyper sampling based on NSE. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

7.7.4 Flow simulations by combining parameter sets and stochastic climate data (temperature and rainfall)

An ensemble of 100,000 simulated flows for Ryewater sub-catchment at Lexilip flow gauging station during the period 1980-2013 have been generated using WEAP21 from all possible combinations of the 100 stochastic rainfall data (Section 7.7.2), 100 stochastic temperature data (Section 7.7.3), and the 10 best performing parameter sets for the NSE criterion from the Latin Hyper Cube sampling (Figure 7.25). The python code for running the simulations from these combinations is provided in Appendix E.5. The resulting ensemble of flow simulations has captured the seasonal patterns of the flow observations. However, it has a relatively wider uncertainty range compared to ranges from previous combinations using either stochastic rainfall or temperature data only (Sections 7.7.2 and 7.7.3). This could be due to the combined effects of uncertainties in rainfall and temperature data. Similar to previous combinations, all flow simulations underestimated some peak flows e.g. Dec 2000 and Nov 2002; all simulations have overestimated some low flows e.g. May-Sept 1990 and 2011. Hence, these results suggest that simulations are influenced by potential errors in precipitation or observed flow data.

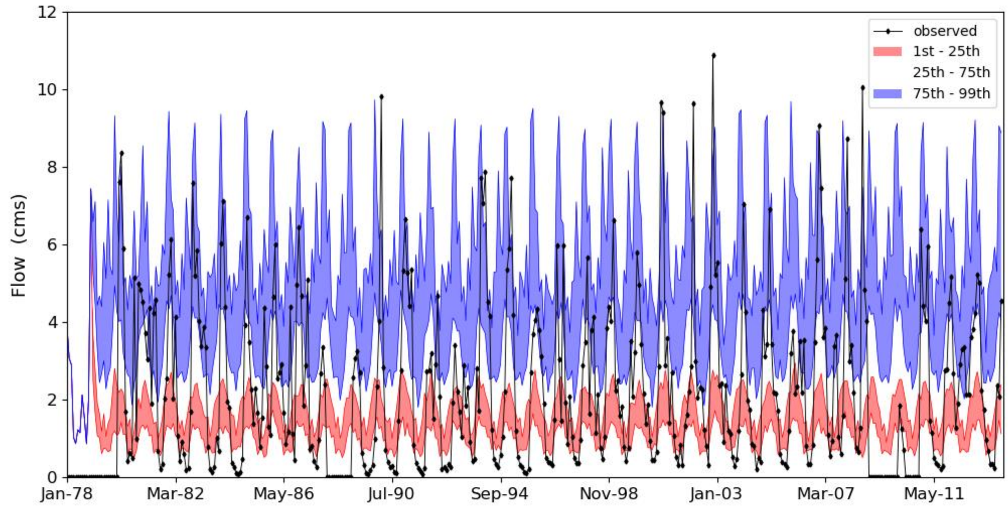


Figure 7. 25 Results of 100,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the WEAP21 from all possible combinations of stochastic rainfall data, stochastic temperature data, and the 10 best performing parameter sets for the NSE criterion. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

7.7 HBV-light modelling of Ryewater sub-catchment

Another hydrological modelling software used for modelling the Ryewater sub-catchment is HBV-light (https://www.geo.uzh.ch/en/units/h2k/Services/HBV-Model.html). HBV-light is a semi-distributed hydrological model in which the catchment can be divided into different elevation and vegetation zones (Seibert 2005; Seibert & Vis 2012). It is a multi-tank model comprising different routines (Figure 7.26): (i) snow routine which estimates snow accumulation and snow melt using a degree-day method; (ii) soil routine which calculates groundwater recharge and actual evaporation as function of actual water storage; (iii) response routine which estimates runoff as function of actual water storage; and (iv) routing routine which uses a triangular weighing function to simulate the routing of runoff from the catchment. Using this structure, the model simulates daily discharges from the catchment based on precipitation, temperature and evaporation input data. Further details on HBV-light and its model structure can be found in (Seibert 2005; Seibert & Vis 2012).

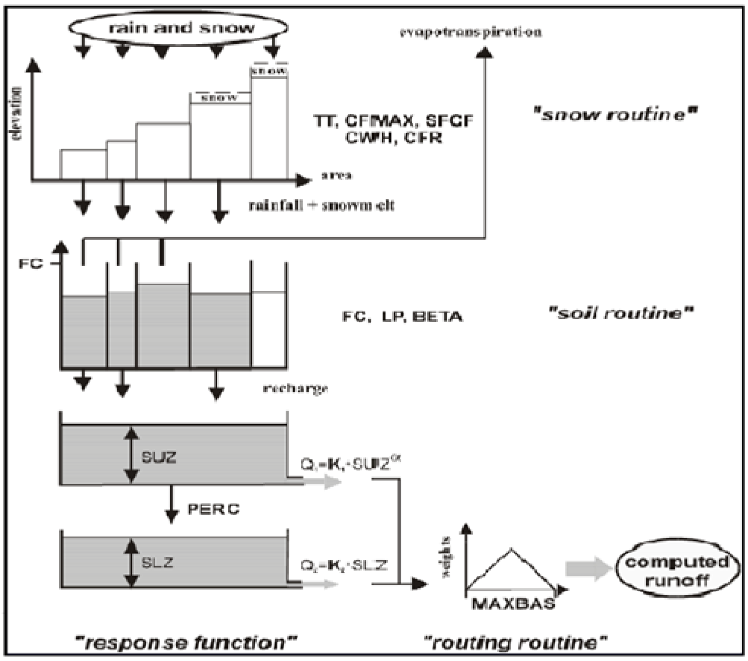


Figure 7. 26 Schematic diagram for the model structure of HBV light (Seibert 2005)

The hydrology of Ryewater sub-catchment has been modelled in HBV-light using daily precipitation, temperature and evaporation data from the nearest synoptic weather station (Casement) during the period 1978-2013**.** The corresponding flow data of Ryewater at Lexilip flow gauging station has been used for calibration and validation of the model, with the first two years 1978-1979 used as a warming-up period for the model to estimate the initial state variables. The remaining period has been split into two sets: calibration data (1980-2005) and validation data (2006-2013). The model then has been automatically calibrated by using the Genetic Algorithm and Powell (GAP) optimisation with parameter ranges identified according to the reasonable parameter ranges for HBV-light reported by Steele-Dunne el al. (2008). In the GAP optimisation, random parameter sets are first generated using the Genetic Algorithm, which then are finely tuned using the Powell's quadratically convergent method to define an optimal set based on a given objective function (e.g. NSE).

The HBV-light model for Ryewater has been calibrated 100 times resulting in 100 different parameter sets. The highest NSE value resulted from this calibration was 0.71 and the corresponding parameter set is presented in Table 7.6. This calibrated model then has been validated by assessing its performance in reproducing the measured flows at Lexilip flow gauging station during the period 2006-2013. The NSE value during the validation period was 0.63. The corresponding LogNSE values during calibration and validation periods were 0.65 and 0.54, respectively. Figures 7.27 and 7.28 show observed and simulated flow hydrographs of Ryewater at Lexilip flow gauging station during the calibration and validation periods, respectively. The best HBV-light model for Ryewater has noticeably underestimated some peak flows during both calibration and validation periods, which also suggests potential errors in measured precipitation and flow data.

Table 7. 6 Calibrated parameter set for the HBV-light of Ryewater sub-catchment.

Parameter	Description	Unit	Value
FC	Maximum of soil moisture storage	Mm	212.12
LP	Fraction of FC above which actual ET equals PET	-	0.84
BETA	Shape coefficient	-	4.03
K0	Recession coefficient for the upper box	C^{-1}	0.16
K1	Recession coefficient for the upper box	d^{-1}	0.31
K2	Recession coefficient for the lower box	d^{-1}	0.13
MAXBAS	Length of triangular weighting function in routing routine	D	2.18

PERC	Maximum rate of recharge between the upper and lower groundwater boxes	mm d^{-1}	2.06
UZL	Threeshold for Q_o	Mm	12

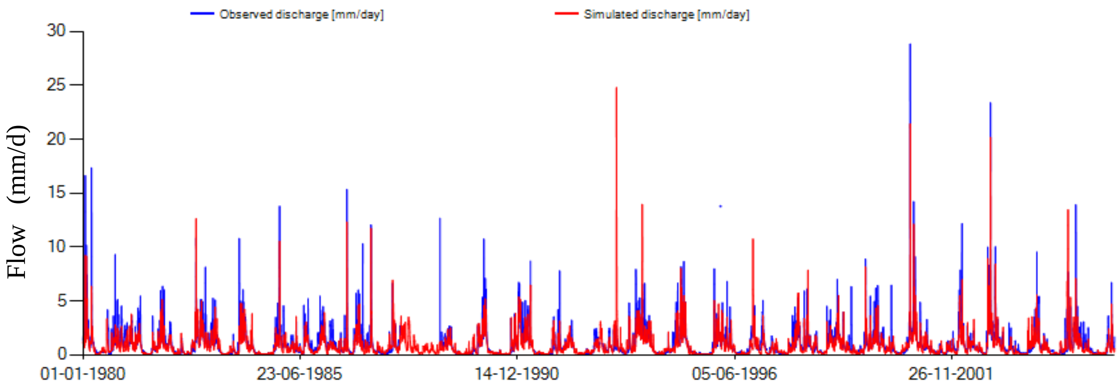


Figure 7. 27 Simulated (red) and observed (blue) daily flows of Ryewater at Lexilip flow gauging station during the period 1980-2005 (calibration period), produced by the HBV-light model.

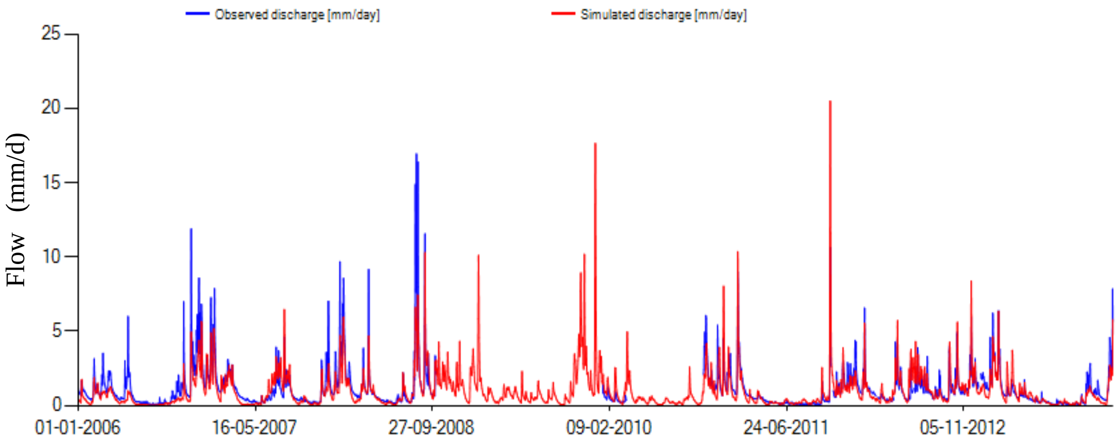


Figure 7. 28 Simulated (red) and observed (blue) daily flows of Ryewater at Lexilip flow gauging station during the period 2006-2013 (validation period), produced by the HBV-light model.

Figure 7.29 shows the corresponding monthly flow simulations of Ryewater for the best HBV-light model against the actual monthly flow observations during the period 1980-2013. For monthly simulations, the best HBV-light model yielded an NSE and LogNSE values of 0.77 and 0.76, respectively. This suggests improvements over simulation results of the WEAP21 models of Ryewater sub-catchment, which yielded maximum NSE and LogNSE values of 0.55 and 0.50, respectively (see Section 7.2).

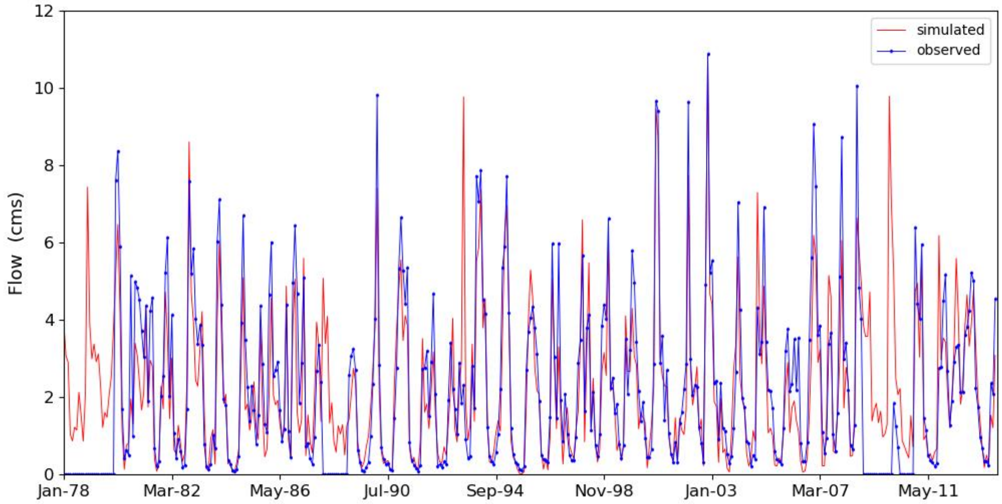


Figure 7. 29 Observed and simulated monthly flow hydrographs of Ryewater at Lexilip flow gauging station during the period 1980-2013, based on the best HBV-light model of Ryewater catchment.

Moreover, the performances of the 100 HBV-light models of Ryewater produced from the GAP optimisation have been compared against the best 100 WEAP21 models of Ryewater for the NSE and LogNSE criteria (Figure 7.30). All the HBV-light models have produced higher NSE and LogNSE values than have the WEAP21 models produced. For NSE, the median NSE values for HBV-light and WEAP21 models are 0.72 and 0.54, respectively. For LogNSE, the median values for the models are 0.66 and 0.46, respectively.

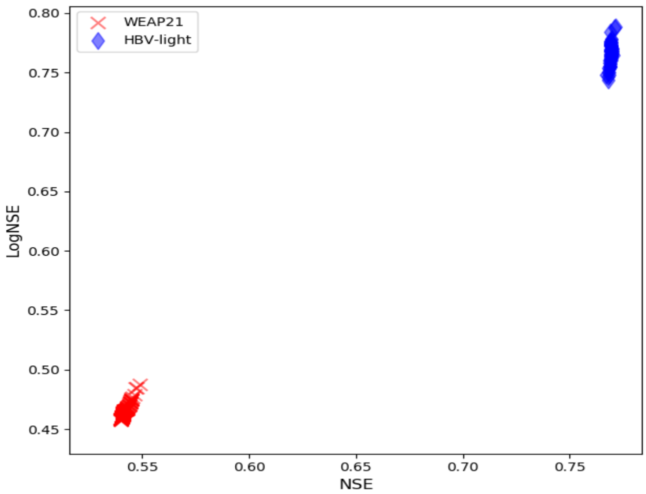


Figure 7. 30 NSE and LogNSE evaluation results of best 100 simulations of HBV-light (blue) and WEAP21 (red).

An ensemble of 100 simulated streamflow of Ryewater at Lexilip flow gauging station during the period 1980 – 2013 has been generated using the different 100 HBV-light parameter sets resulted from the GAP optimisation (Figure 7.31). A python code for performing multiple runs of the HBV-light model and generating monthly ensemble of simulated flows can be found in Appendix E.6. The resulting ensemble of simulated streamflow of Ryewater has mostly captured the seasonal patterns of flow observations. All the HBV-light models have underestimated some peak flows e.g. in months Dec 2006 and Jan 2007, which may be influenced by some errors in precipitation and flow measurements. The resulting ensemble of simulated flows from the HBV-light has better captured low flows of Ryewater compared to the simulations produced by WEAP21, which were presented in Figures 7.5-7.7.

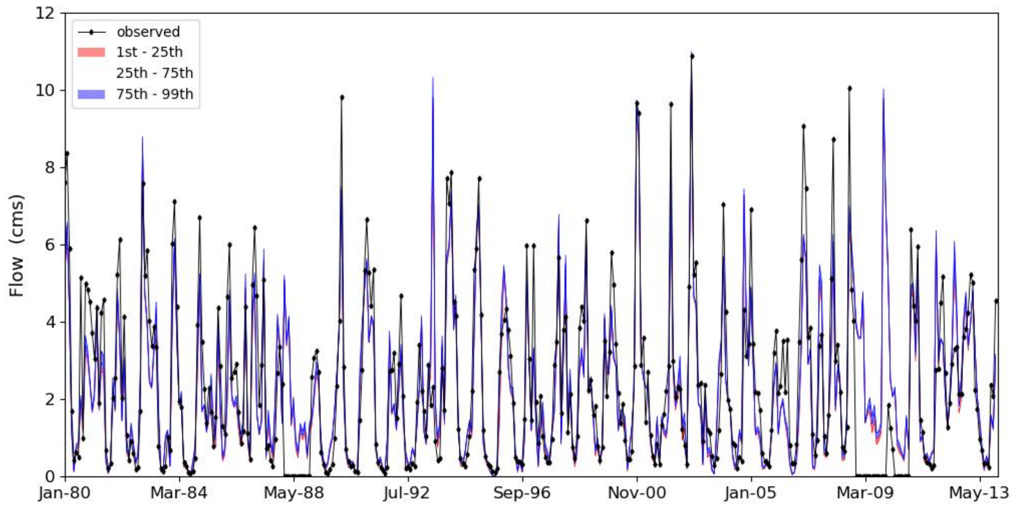


Figure 7. 31 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light using parameter sets produced from the GAP optimisation process. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour

Stochastic daily climate data for Ryewater sub-catchment in terms of rainfall, temperature and evaporation have been generated using the SCL library to provide alternative forcing inputs for the HBV-light model. The cumulative distributions of the 100 stochastically generated data for rainfall, temperature and evaporation are plotted against the corresponding distributions of observed values as shown in Figures 7.32, 7.33 and 7.34, respectively. The distribution of observations for each of the climatic variables is bounded by the 95% confidence interval of the corresponding distribution for stochastically generated data. Moreover, the differences between the means of some statistics (e.g. mean, maximum, minimum, standard deviation and skewness) in observed data and the corresponding statistics in stochastic data for each climatic variables were mostly within acceptable tolerance levels for daily statistic (Sirkanthan et al. 2007). About 85% of the assessed daily statistics were found to be within the acceptable tolerance levels. Only some deviations were noticeable in the minimum and standard deviation values for months Sept to Feb.

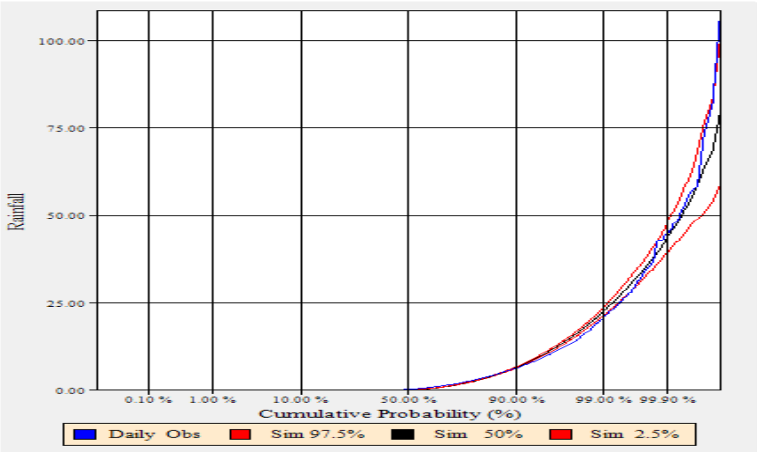


Figure 7. 32 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily rainfall data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data.

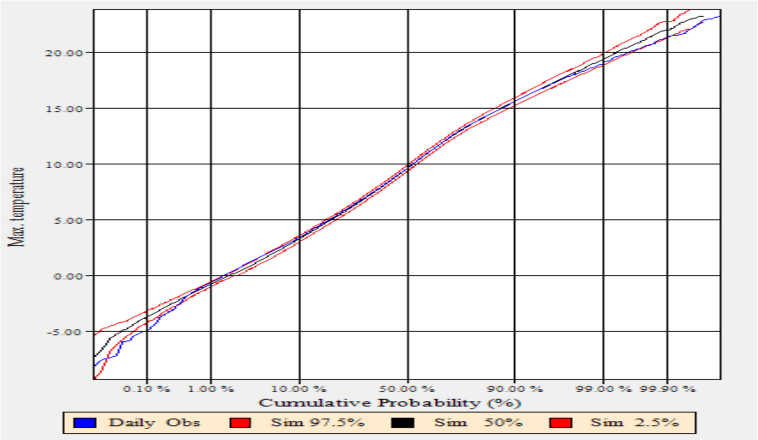


Figure 7. 33 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily temperature data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data.

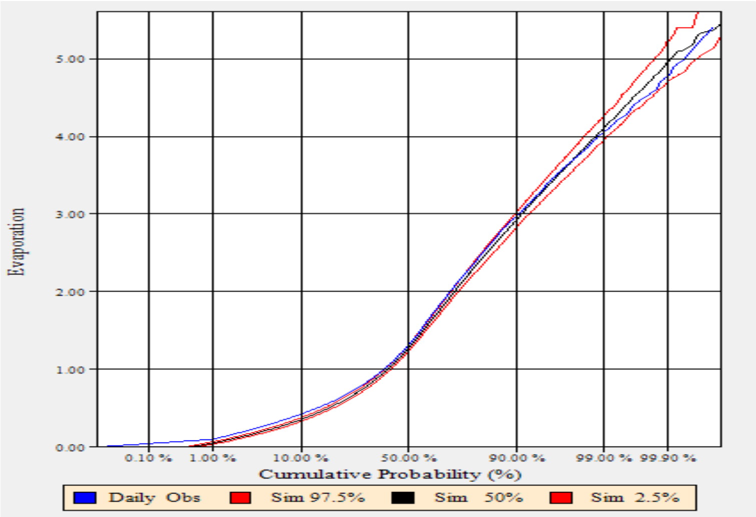


Figure 7. 34 Cumulative distributions of the 2.5, 50 and 97.5 percentiles of simulated daily evaporation data produced by SCL for Ryewater sub-catchment during the period 1980-2013 against the corresponding distribution of observed data.

The 100 stochastically generated climate data for Ryewater have been input in the best HBV-light model for the sub-catchment to explore the effects of uncertainties in forcing climate inputs on the model output (a Python code for running HBV-light using the stochastic climate data can be found in Appendix E.7). Figure 7.35 shows an ensemble of 100 simulated streamflow of Ryewater at Lexilip flow gauging station during the period 1980-2013 produced from using the stochastically generated climate data. The uncertainties in forcing inputs have produced significantly larger uncertainty interval of simulated flows compared to the interval produced due to uncertainty in parameters which is presented in Figure 7.31. This indicates that the HBV-light model for Ryewater is more sensitive to uncertainties in forcing climate inputs compared to uncertainties in parameters.

Furthermore, each of the 100 stochastically generated rainfall data and temperature data have been combined with the 100 parameter sets of HBV-light produced from the GAP optimisation to explore the effects of uncertainties in each climatic variable on the outputs of HBV-light model of Ryewater. Figures 7.36 and 7.37 show an ensemble of 10,000 simulated streamflow of Ryewater at Lexilip flow gauging station during the

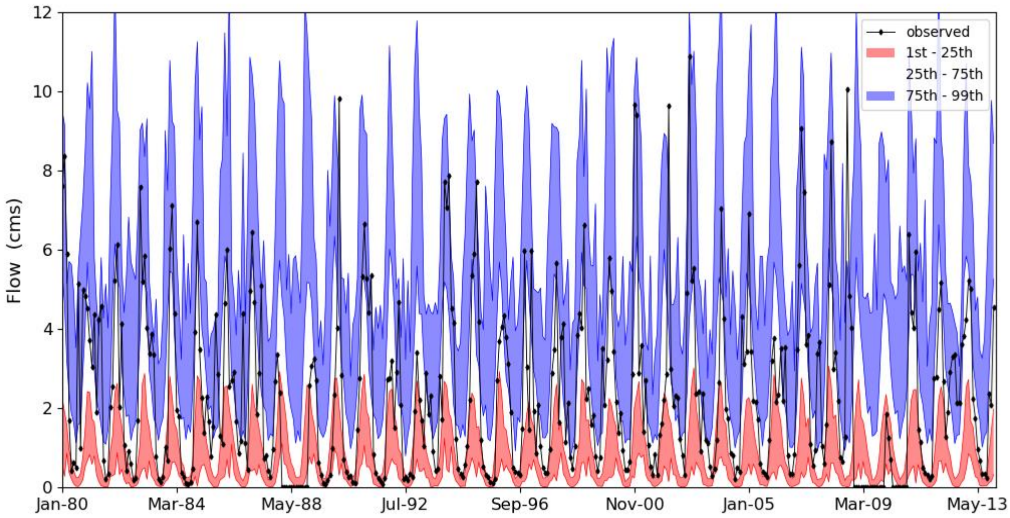


Figure 7. 35 Results of 100 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light using stochastic climate data from the SCL library. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

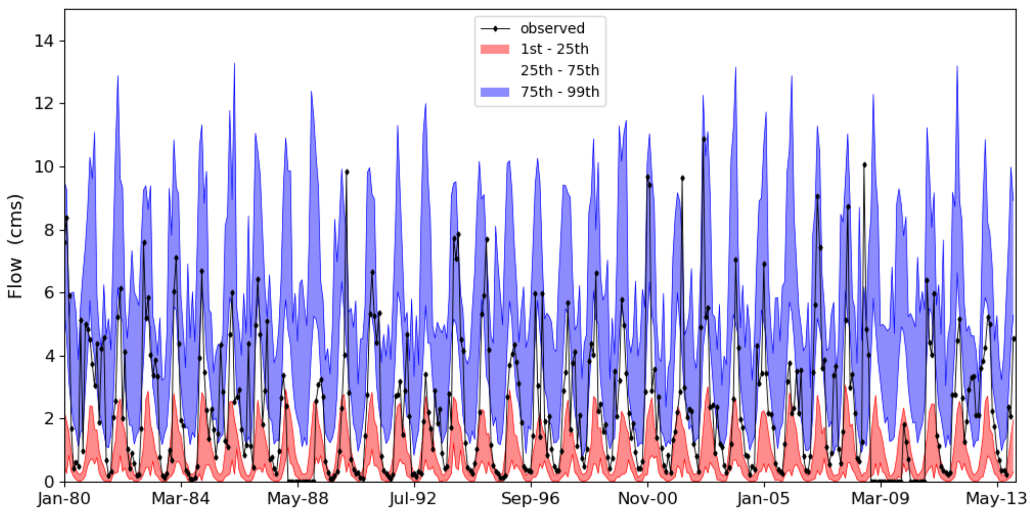


Figure 7. 36 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light model by combining the 100 stochastic rainfall data from the SCL and the 100 parameter sets produced from the GAP optimisation. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

period 1980-2013 from all possible combinations of parameter sets and (a) stochastic rainfall data and (b) stochastic temperature data, respectively. The uncertainties in rainfall data have produced significantly larger uncertainty interval of simulated flows compared to the interval produced due to uncertainty in temperature data.

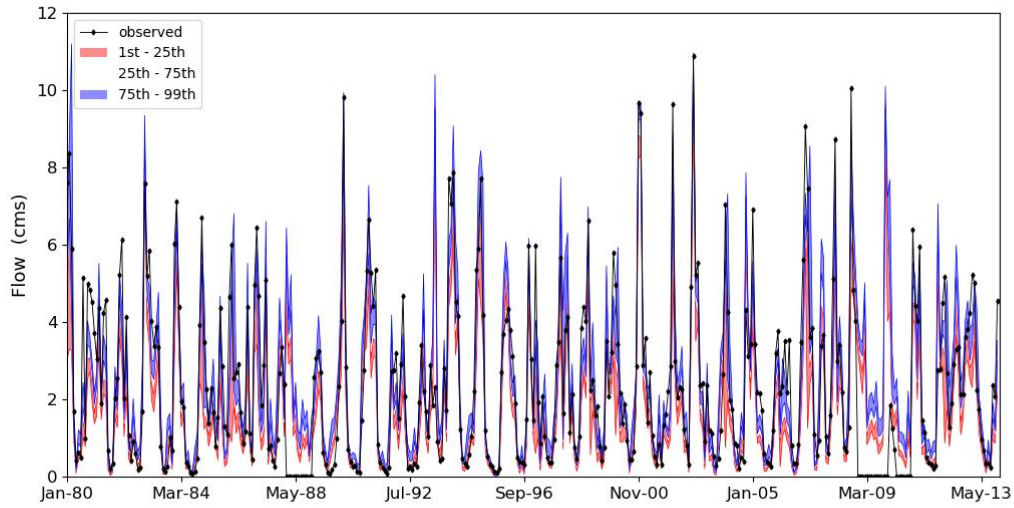


Figure 7. 37 Results of 10,000 ensemble simulated streamflow of Ryewater at Lexilip flow gauging generated by the HBV-light model by combining the 100 stochastic temperature data from the SCL and the 100 parameter sets produced from the GAP optimisation. The 1st, 25th, 75th, 99th percentiles of simulated flows are shown by the colour bands, and observed average monthly streamflow is in black. Zeros in the observations indicate missing values.

7.8 Conclusion

This chapter has extended the capability of WEAP21 for analysing uncertainty in streamflow predictions which can result from uncertainties in parameters and forcing inputs. This has been done by coupling the software with the statistical parameter optimistion tool (SPOTPY) and stochastic climate models such as the generalised linear modelling framework (GLM) and the stochastic climate library (SCL).

Using the developed framework, a parameter uncertainty analysis for the WEAP21 model of a case study sub-catchment (Ryewater) has been performed based on the GLUE method. This analysis has reduced uncertainty in parameter ranges of the model by 30-70%. . Hence, this extension can be applied by WEAP21 users to reduce parameter uncertainty and to condition model predications providing an alternative approach to the manual and automatic calibration methods that are available by WEAP21 and which mostly focuses on defining one optimum model.

A variance-based sensitivity analysis method (Sobol's method) has been used to assess the total effects of model parameters on the variance output of the WEAP21 model of Ryewater sub-catchment. TSI values for all model parameters were found to be substantially larger than the corresponding S1 values suggesting the presence of higher order interactions between all parameters. The long-term average values of TSI indices for all parameters ranged from 0.95 to 1.13, while the average values of S1 indices ranged from -0.08 to 0.07.

Moreover, the correlation between TSI indices of parameters and input data such as precipitation and temperature have been explored to identify the seasonal effects on sensitivities of model parameters. TSI indices for crop coefficient (*Kc*), runoff resistance factor (*rrf*), and root zone conductivity (*rzc*) were found to be negatively correlated with monthly precipitation values ($r = -0.50 - -0.89$, $p\text{-value} \leq 0.001$) indicating that these parameters are more sensitive in dry months. In contrast, TSI indices for soil water capacity (*SWC*), deep water capacity (*DWC*) and deep conductivity (*dc*) were found to be positively correlated with monthly precipitation values ($r = 0.50 - 0.70$, $p\text{-value} \leq 0.001$) indicating that these parameters are more sensitive in wet months. This novel framework can be used by modellers to define the most sensitive parameters of a hydrological model in a particular season, which then can be calibrated to develop specific models or set of models for the climatic season of interest (e.g. models focusing on prediction of flows during dry season or wet season).

Separate models for predicting flows of Ryewater sub-catchment in dry and wet seasons have been developed by calibrating the respective sensitive parameters in each season. All models for predicting flows in the dry season overestimated some low flows and all the models for predicting flows in the wet season underestimated some peak flows. A check of precipitation and flow data of Ryewater sub-catchment revealed that 10% of monthly precipitation input has rainfall volume less than the corresponding measured flow at the outlet of the sub-catchment. These inaccuracies in precipitation have likely caused underestimation of some peak flows and overestimation of low flows both in the complete models and the separate models for each season.

Moreover, this chapter also explored uncertainties in flow predictions of Ryewater due to parameter identification, forcing data, and model structure. All the resulting ensembles of simulated flows from combining behavioural parameter sets and stochastic climate data mostly captured the seasonal patterns of flow observations. The ensembles of simulated flows produced using the GLM data overestimated some low flows and underestimated some peak flows. On the other hand, the ensembles of simulated flows produced using the SCL data better enclosed the flow observations. These results indicate that the bias in estimating flows of Ryewater is likely influenced by errors in precipitation and flow data.

Moreover, this thesis investigated the effects of uncertainties in temperature and evaporation data on the model output − unlike most of uncertainty assessments in the literature which limited investigations of forcing inputs to rainfall. The interval of the resulting ensemble of flow simulations produced by temperature data is found to be narrower than the one produced by rainfall data. These results suggest that uncertainties in flow simulations due to rainfall forcing are more dominant over uncertainties due to temperature forcing or parameter estimation.

The effect of model structure on predicative uncertainty of Ryewater flows is investigated by comparing simulations of WEAP21 with simulations from another model HBV-light. Simulation results from both modelling software showed that HBV-light model was superior at representing flows of Ryewater at Lexilip flow gauging station. This might be because HBV-light model is based on a higher temporal resolution of climate data compared to WEAP21. These results highlight that model structure and resolution of forcing data have strong impacts on the accuracy of flow predictions. It is recommended that the modeller select an appropriate model structure for representing the hydrology of the system and use appropriate temporal resolution for forcing data when developing integrated water resources management models.

Chapter 8 WATER MANAGEMENT SCENARIOS

This chapter analyses future water demands and supplies in the Dublin Region. Previous studies on population and industrial growth suggested that water demands in the Eastern and Midlands regions will potentially increase to 330 Ml/d by 2050 (Irish Water 2016a). The existing infrastructure is under pressure to meet current demands, as evident from number of disruptions and outages that occurred over the past few years. To meet growing water demands, different options for increasing water supply have been proposed and after extensive research, assessments and public consultations, recommendations on the preferred option have been made. The key recommendations were considered in order to develop water management scenarios which can be evaluated in conjunction with future scenarios of population growths and land-uses using the WEAP-Dublin model.

8.1 Potential water supply options

The need for a new water supply source for the Dublin metropolitan area and its surrounding areas has been recognised since 1996 following the Greater Dublin Water Supply Strategic Study (GDWSSS). Dublin City Council on behalf of the Department of Environment and Local Government (DEHLG) has then conducted two phases strategic environment assessment (SEA) between 2005 and 2011. Initially, the SEA identified three feasible water supply options, and later on more options have been considered and a total of ten potential water supply options were finally proposed (Figure 8.1).

In the second phase of the SEA, the proposed ten options have been assessed through a desk study. The outcome of this study has identified four out of the ten options as technically viable options to provide water for the Eastern and Midlands region. The four options are:

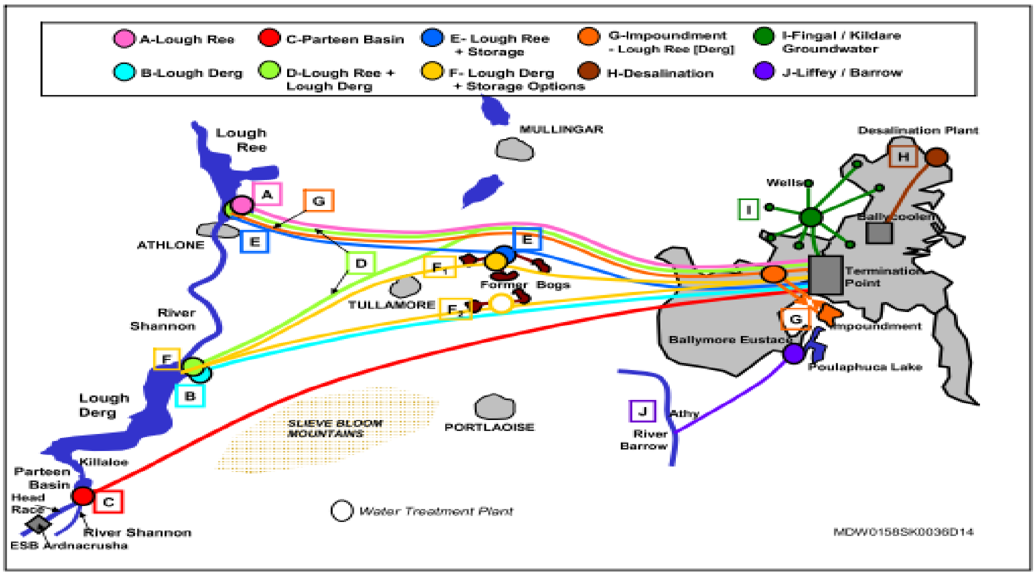


Figure 8. 1 Potential water supply options to meet future water needs of Dublin and surrounding areas. (Source: DCC 2010a).

- Lough Derg (direct) – option B,
- Lough Derg (storage) – option F2,
- Parteen Basin – option C, and
- Desalination of Irish seawater – option H.

The four technically viable options for water supply have been assessed based on field investigations, modelling of water abstraction and analysis of feedbacks from public and stakeholders (Irish Water 2016b). The assessment has suggested that abstraction from Parteen basin (Option C) is the most preferred option for the following reasons: (i) it would benefit a much wider area; (ii) it has the least impact on the environment; and (iii) it is less costly in terms of construction and operation than a desalination plant.

8.2 Parteen Basin water supply option

Parteen Basin is an artificial lake located downstream to Lough Derg on the Shannon River. The proposed water supply scheme involves the construction of an underground pipeline starting at Parteen Basin and terminating in Dublin. The abstracted water will be treated nearby in Birdhill, and then pumped to serve communities in the Midlands before connecting to the Greater Dublin network. During all flow conditions, the scheme will take a small fraction (1-2%) of flows of the Shannon river, which otherwise, would be used for power generation (DCC 2010b). Figure 8.2 shows a schematic of the proposed water supply scheme at Parteen Basin.

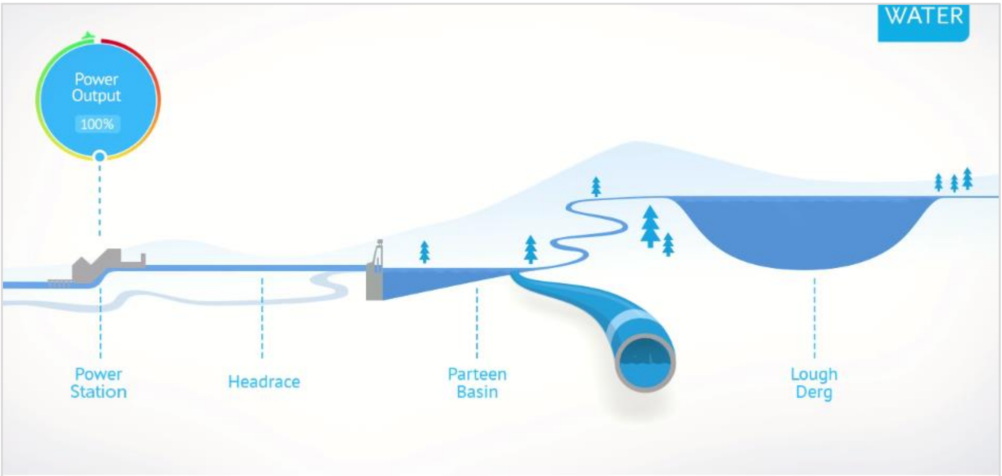


Figure 8. 2 Schematic illustrating proposed development of water supply at Parteen Basin (Source: http://www.watersupplyproject.ie/)

The proposed pipeline from Patreen Basin is suggested to be sized to deliver the full demand, but phased in such a way that it is initially operated on a gravity mode with a capability to deliver 240 Ml/d, and then later a booster pumping is incorporated to increase the capability to deliver of 330 Ml/d by 2050 (Irish Water 2016b). This proposed scheme also will benefit communities living in the area between Parteen Basin and the terminal reservoir near Dublin (known as the benefiting corridor) (Irish Water 2016b; Irish Water 2016c). In addition to the proposed scheme, Irish Water is pursuing number of measures aiming to improve deployable outputs of existing water supply sources (Irish Water 2016b). These measures will bring the deployable output of existing supply sources up to 650 Ml/d by 2050. An integral part of Irish Water strategy to provide safe and secure water for the Eastern and Midlands region is water conservation. This includes the leakage target policy, which aims to recover 51 Ml/d of water from leakage by 2031.

8.3 Development of water management scenarios

A 'water management option' refers to an individual project or decision of each of the traditionally separated water sectors i.e. drinking water, wastewater and storm water. Combining water management options into scenarios or alternatives is a key step in water resources planning since water management goals are set at the system level not at the individual sector level. For example, a water resources management plan can be set to maximise supplies whilst reducing water demands, wastewater generation and urban runoff. Combining water management options together into scenarios produce synergies between options which result in better performance of the overall system than if each option was considered separately (Rodrigo et al. 2012).

Against these definitions, four water management scenarios were developed from options ranging from traditional practices, increase in supply, on-site sources, demand reduction, manage runoff to groundwater recharge (Figure 8.3);

- Scenario 1 – 'Baseline': represents the status quo or do-nothing scenario, with absence of new water supply source, water consumption remains unchanged at 125.50 l/c/d, and supply infrastructure remains unchanged (level of leakage remains at current level, approximately 40% of total distribution input).
- Scenario 2 – 'Increase supply': represents increase in water supplies by abstracting water from a new source e.g. Parteen Basin (Lower Shannon lake) to meet growing water demands. This scenario assumes a planned and phased response to demands capable of delivering additional 330 Ml/d (3.82 m^3/s) by 2031 from Parteen Basin, per capita consumption trends downward and gradually reaches to 121 l/c/d, improved infrastructure with leakage gradually reduced to 21.50% in 2050 to provide 51 Ml/d.

- Scenario 3 – 'Intensified leakage management': represents accelerated and intensified efforts to recover more water to offset growing demands in absence of new source. As discussed in Irish Water (2016b), this option seeks to recover additional 30 Ml/d of water by 2026 on top of 51 Ml/d already proposed in the previous alternative. All other assumption remains the same as in Scenario 2.
- Scenario 4 – 'Total water management': represents larger scale incorporation of total (or sustainable) water management options to provide alternative source of water and to manage urban runoff in sustainable manner, for example; increased rainwater harvesting systems, increased water recycling, and groundwater recharge. The representation and programming of total water management options in the WEAP-Dublin model was adopted from Rodrigo et al. (2012) study, which applied WEAP21 to evaluate different water managemnt alterantives for the city of Los Angeles.

Scenario 1 in this study represented a reference scenario, where performances of other scenarios are assessed against it. Scenarios 2 and 3 included water supply options that have already been under consideration as outlined in Irish Water (2016b). On the other hand, Scenario 4 was proposed in order to examine potential benefits which may be brought by total water management options for the Dublin water system, analogous to Rodrigo et al. (2012). It is worth mentioning that all alternatives have assumed implementation of sustainable drainage systems (SuDS), pursuant to the new development policy produced as an outcome of the Greater Dublin Strategic Drainage Study (DDC 2005a) – which entails all new development to incorporate SuDS facilities or provide an alternative mean if site conditions do not allow for implementation of SuDS. Table 8.1 illustrates the scenarios and their settings.

Table 8. 1 Options and settings for the baseline and water management scenarios as configured in the WEAP-Dublin model.

Options and Settings	Units	Scenario 1	Scenario 2	Scenario 3	Scenario 4
		Baseline	*Increasse supply*	*Leakage management*	*TWM*
Supply Sources					
New source-Shannon		No	Yes	No	No
Maximum available supplies of water	cms	0	2.78 - 3.82	0	0
Conservation					
metering scheme and water efficient devices		No	Yes	Yes	Yes
reduced per capita consumption 2011-2050	l/c/d	125.5	125.5 to 121	125.5 to 121	125.5 to 121
Leakage management		No	Yes	Yes	Yes
Asset maintenance and replacement					
reduction in leakage as % of distribution input	%	40	40 - 21.50	*Intensified*	40 - 21.50
On site sources					
Rainwater harvesting		No	No	No	Yes
Estimated total rain capture area	km^2	0	0	0	23.30 - 92.30
Greywater system		No	No	No	Yes
Percentage of buildings having the system	%	0	0	0	0-25
Stormwater management					
DeCentralised stormwater technologies		Yes	Yes	Yes	Yes
Centralised technology (large scale)		No	No	No	Yes
Capacity of centralised technology for recharge	Ml/d	0	0	0	20

8.4 WEAP-Dublin model for future simulations

To evaluate the four scenarios, the WEAP-Dublin model was slightly re-configured to adapt data availability in terms of future scenarios for population growth, industrial growth and land-use changes. The growth scenarios are provided at a region level and not at the local zone level (Irish Water 2015a, 2015d and 2016b), and hence domestic and industrial demands were aggregated to the Dublin Region level and represented in one demand site. By this aggregation, the spatial uncertainty of these growths is addressed, and the water balance is computed at a regional level in future simulations. The modified configuration also includes a demand site to account for allowances for peak demands and strategic headroom as specified in Irish Water (2015b) and (2016b); a demand site to account for water needs in the benefiting corridor if water to be abstracted from Parteen Basin / Shannon (Alternative 2); and other dummy demands used for calculation purposes. The hydrology module, constructed in Chapter 5, simulates supplies at abstraction points i.e. Phollaphuca, Lexilip and Dodder (including other sources whose hydrology are not explicitly modelled, refer to Chapter 5). The hydrology module was slightly adjusted by adding a separate accounting for urban areas in order to represent urban developments projected in the region and to quantify resulting urban runoff. The adjustment of the hydrology module also facilitated the modelling of sustainable drainage systems at a regional level. This aggregation of some features of the water system allows simulation at less computational costs. This demonstrates the flexibility of structuring data in WEAP21, which can range from a highly disaggregated level to a highly aggregated level to suit data availability.

The scenarios outlined above (in Table 8.1) were modelled in WEAP-Dublin using options that can be turned on/off and which can be specified capacities or extents (e.g. rainwater harvesting and groundwater recharge facilities) based on the scenario pursued. Figure 8.3 shows an adjusted schematic of the WEAP-Dublin model including the future water management scenarios considered in this study.

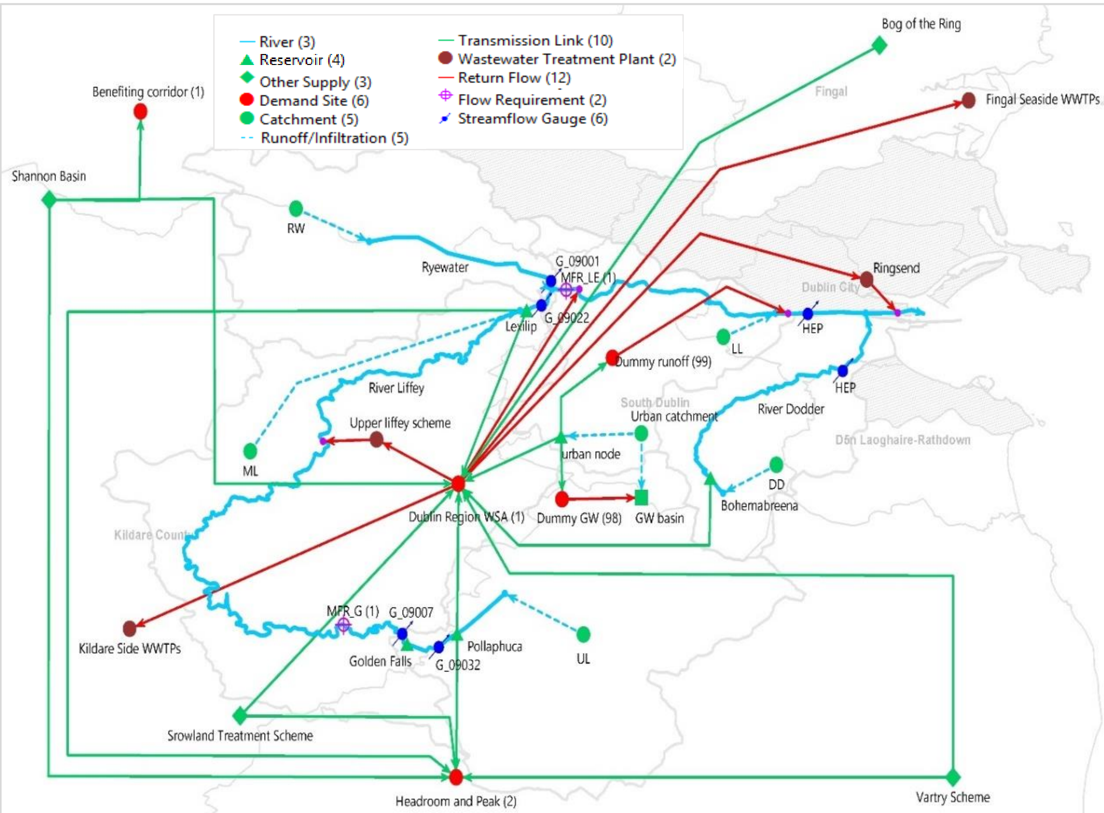


Figure 8. 3 Adjusted schematic WEAP-Dublin model used for future simulations. This schematic represents a modified structure to the original model (WEAP-Dublin) with demands aggregated to the regional level in order to adapt the model to data availability (in terms of future). The adjusted configuration also includes additional elements to represent future water management scenarios.

8.5 Water demand projections

The main drivers for water demand in Dublin are domestic water demands, non-domestic water demands, customer side losses (or household losses), operational use, unaccounted for water, and headroom and outage (Irish Water 2015b). Domestic water demands are water demands from residential properties, whilst non-domestic water demands are water demands from commercial, industrial, institutional and agricultural related activities. The customer side leakage is an allowance for losses that occur on the private side of domestic connections. It is calculated as number of domestic connections multiplied by the applied loss allowance. The operational water use is allowance for water used in the operation and maintenance of the water distribution network. The unaccounted for water is losses from the distribution network and it is calculated as the difference between distribution input and all previous components (domestic, non-domestic, customer side losses and operational use). Headroom and outage an allowance to account for uncertainties in estimating water supplies and water demands, and to offset water supplies in case of a source disruption. Future water demands in Dublin can be estimated by analysing and projecting each of the individual component described above.

Future water demands projections were based on recommendations of the WSP Project Need Report (Irish Water 2015a) pertaining population projections and economic forecasting for the period 2015 – 2050. The report recommended that only three out of the seven national planning scenarios examined in the *WSP - Demographic Report* (Irish Water 2015d) are realistic and can be used as basis for estimating water demands, namely: (i) Scenario 1(a) – planned growth high; (ii) Scenario 1(b) – planned growth low; and (iii) Scenario 2 – most likely growth. The key assumptions underlying these planning scenarios in terms of population growth, migration and economic development can be found in Irish Water (2015d) and Irish Water (2015b).

8.5.1 Domestic water uses projections

Domestic demand projections were based on projected number of population in the Dublin Region WSA and projected per capita consumption.

Population projections

The demographic report provided estimates of population number in the Dublin Region WSA up to the year 2050 for each of the planning scenarios. These projections are summarised in Table 8.2 and visualised in Figure 8.4 (Irish Water 2015b, Irish Water 2015d):

Table 8. 2 Population projections for Dublin Region WSA 2011–2050 for each planning scenario.

	2011	2021	2026	2031	2041	2046	2050
Scenario 1a – (high)	1516133	1644072	1745167	1846262	2008198	2064250	2111142
Scenario 1b – (low)	1516133	1616845	1697519	1778193	1906095	1967693	2022316
Scenario 2 – (most likely)	1516133	1642391	1742226	1842060	2003156	2081225	2154252

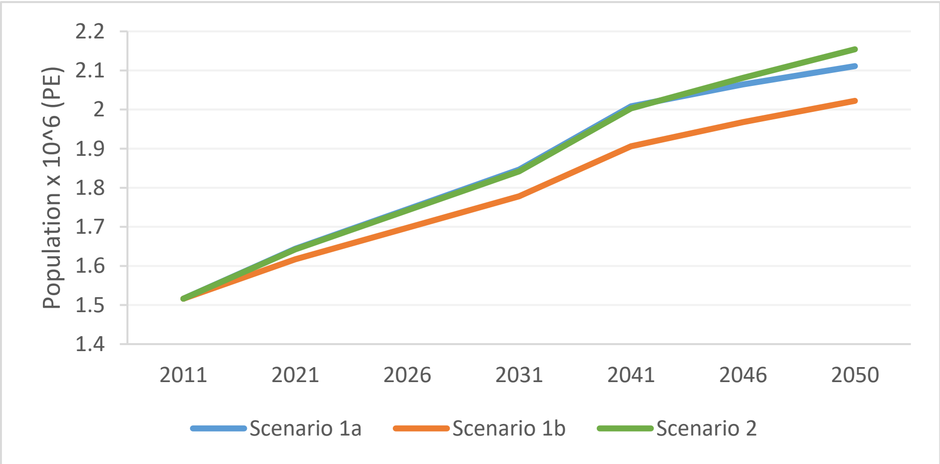


Figure 8. 4 Population projections for the Dublin Region WSA 2011 – 2050 for different planning scenarios.

As shown in Figure 8.4, Scenario 2 (most likely growth) yielded a higher population number at the end of the planning horizon than Scenario 1 (high planned growth). The importance of Scenario 2 for estimating water supply requirement in the Dublin Region is emphasised in Irish Water (2016b). The study, therefore, used population projections of Scenario 2 as the basis to estimate future domestic water demands under future water management scenarios. The population numbers of this projection was linearly interpolated in the model using WEAP21 built-in function "Interp" to provide an annual estimate for population across the planning horizon.

Projected per capita consumption (PCC)

Current per capita consumption (PCC) in the Dublin Region WSA is estimated at 125.50 l/c/d (Irish Water 2015b). This is below the average values of PCC in different cities around the world (Table 8.3). Hence, only slight reductions in PCC in Dublin Region can be achieved (Irish Water 2015b).

Table 8.3 Average PCC in different cities around the world. Source: Irish Water (2015b)

Cities	**PCC (l/c/d)**
Paris, France	276
Geneva, Swizerland	228
Sydney, Australia	210
Oslo, Norway	200
Auckalnd, Newzeland	180
Helsinki, Finland	167
Madrid, Spain	159
Amesterdam, Netherland	158
Scotland	154
England and Wales, UK	140
Copenhagen, Denmark	126

The PCC rate was projected considering a variety of factors which have different effects on the water consumption behaviour (Irish Water 2015b). The factors are: (i) new housing stocks with more water-efficient devices (likely to have reducing effects), (ii) future household composition (reduction in occupancy rates likely to result in increase in average PCC), and (iii) conservation programs (likely to have reducing effects). Table 8.4 shows projected PCC under Scenario 2 (most likely growth) due to the combined impacts of all the above factors (Irish Water 2015a).

Table 8. 4 Projected per capita consumption in l/c/d under Scenario 2 (most likely growth).

	2011	2021	2026	2031	2041	2046	2050
PCC	125.50	120.40	120.60	120.70	120.90	121	121

The conservation option in the WEAP-Dublin model is modelled as reductions in PCC. Scenarios 2,3 and 4 assumes reductions in average PCC and hence the conservation option for these scenarios in the model was switched on by using the above PCC rates for domestic water uses. The PCC rates for these scenarios were linearly interpolated using the WEAP21 built-in function to provide PCC for each year through the planning horizon. On the other hand, Scenario 1 assumes no change in average PCC and hence the conservation option was switched off by using the baseline PCC (125.50 l/c/d) throughout the planning horizon.

8.5.2 Non-domestic water uses projections

This component represents water uses in the industrial, commercial, institutional and agricultural sectors. Water demand for these sectors in the Dublin Region WSA was estimated to be 46.17 Mm^3/year (126.5 Ml/d) in the baseline year 2011 (Irish Water 2015b). This demand was projected in-line with population growths by applying the same annual growth rates (Irish Water 2015b). Moreover, a strategic allowance of 36.50 Mm^3/year (100 Ml/d) for major water using industries (e.g. integrated circuits manufacture, large-scale biotech and nano-meter technologies) also is recommended by Irish Water (2015 b) due to the significance of these sectors to the Irish economy. Table 8.5 shows the projected non-domestic water demands in the Dublin Region WSA for the planning horizon 2011-2050 under Scenario 2 (most likely growth) (Irish Water 2015b).

Table 8. 5 Projected non-domestic water demands for the Dublin Region WSA 2011–2050 in Mm^3/yr. Source: Irish Water (2015b).

	2011	2021	2026	2031	2041	2046	2050
Non-domestic	46.17	50.47	53.36	56.50	61.57	63.98	66.10
Major industry	0	12.41	18.25	27.375	36.50	36.50	36.50
Total	46.17	62.89	71.61	83.87	98.08	100.49	102.61

8.6 Projected leakage and losses

8.6.1 Projected customer side leakage (CSL)

The customer side leakage (CSL) in the baseline year was estimated to be 66 l/hd/d yielding a total loss of 40.80 Ml/d (Irish Water 2015b). Significant recovery from this component totalling 20.70 Ml/d of water has been achieved through Irish Water scheme "First Free Fix Scheme" (Irish Water 2015b). This recovery means that 20.70 Ml/d of growing water demands has been offset. It also means that the recovery level of 25 l/c/d targeted by 2031 has already been achieved (Irish Water 2015b). Therefore, the CSL level is maintained at 25 l/c/d in future simulation of all water management scenarios.

8.6.2 Projected distribution leakage

Irish Water intends to implement a leakage reduction policy which seeks to recover a total of 63.90 Ml/d of water from unaccounted for water (UFW) by 2041 yielding a leakage rate of no more than 20% of total distribution input (DI) (Irish Water 2015b, 2016b). This level of leakage is to be maintained thereafter. Table 8.6 summarises projected UFW under the Leakage Target policy, expressed both in terms of volumetric levels and as percentage of DI.

Table 8. 6 Projected UFW for Dublin Region WSA expressed in volumetric levels and % of DI (in accordance to Irish Water Leakage Target policy)

UFW	2011	2021	2026	2031	2041	2046	2050
Volume Ml/d	204.70	165.90	153.10	145.0	140.80	140.80	140.80
(Mm^3/m)	(6.20)	(5.00)	(4.60)	(4.40)	(4.26)	(4.26)	(4.26)
As % of DI	38.3%	28.70%	25.0%	22.40%	20.30%	19.70%	19.40%

Distribution leakage in the WEAP-Dublin model was represented as a percent loss of flows passing through the transmission links that connect supply sources with representative demand-sites. Scenario 1 assumes no reduction in leakage and hence percent loss of flows was set to the baseline level throughout the planning horizon. Scenarios 2 and 4 assume targeted reductions in leakage in accordance to the Leakage reduction policy (Table 8.6). Hence, the percent loss of flows was set as a decreasing rate down to 20% by 2050. Scenario 3 assumes more intensified leakage reductions targeting further recovery of 30 Ml/d of leakage by 2031 on top of 51 Ml/d already targeted by the leakage policy. The percent loss of flows under scenario 3 was set to account for the further targeted reductions.

8.7 Peak demands, strategic headroom and outages

In estimating future water demands, Irish Water considered number of other components, including peak demands, strategic headroom and outages.

8.7.1 Peak water demands

Peak water demands represent seasonal peaks occurring for example; in summer (due to increase usage of water as a consequence of a warm and dry weather); in winter (due to bursts in the network or due to consumer behaviour of running supplies to waste to prevent freezing of supplies in cold weathers). It may also happen anytime in the year due to a sport or cultural activity (Irish Water 2015b). This component was projected by applying a 15% peaking factor to the accounted for water (excluding major water using industries) as suggested by Irish Water (2015b). Table 8.7 summaries projections of peak water demands in the Dublin Region WSA (Irish Water 2015a, Irish Water 2016b);

Table 8. 7 Allowance for peak demands in the Dublin Region WSA 2021 - 2050. Source: Irish Water 2016b.

		2021	2026	2031	2041	2046	2050
Peaking allowance	Ml/d	56.9	61.4	64.3	68.1	70.9	72.50

8.7.2 Headroom and outage

Strategic headroom is defined as the difference between water available for use and the water expected to be delivered or introduced in the network. This headroom is an essential requirement for a resilient water supply network as such headroom allows addressing uncertainties on the supply side (e.g. pollution incidents, inaccuracy in supply data, climate change) and on the demand-side (e.g. inaccuracy of demand data, effects of climate change on demands). On the other hand, outage is a provision of allowance within the overall headroom to offset supplies in times where output falls below normal levels. To account for these components in future water requirements, an amount equivalent to 20% of accounted for water was used by Irish Water (Table 8.8).

Table 8. 8 Allowance for headroom and outage for the Dublin Region WSA 2021-2050. Source: Irish Water 2016b.

		2021	2026	2031	2041	2046	2050
Headroom and Outage	Ml/d	75.8	81.8	85.7	90.8	94.5	96.7

The WEAP-Dublin model represented seasonal peaks, headroom, and outage components all in a separate demand site "peaks and overall headroom". This demand site was assigned a total water demand profile equalling the sum of all projections in Tables 8.7 and 8.8. The "peaks and overall headroom" demand site in WEAP-Dublin was modelled to receive water from the existing water supply sources in the Dublin Region under all future water management scenarios; however, under scenario 2, it was modelled to receive additional amounts of water from Parteen Basin in 2026 and onwards where the WSP will be commissioned. This demand site was assigned a lower priority in order to suspend its supplies until the demands of the Dublin Region WSA (and the benefiting corridor in case of scenario 2) are satisfied.

8.8 Projected capacities of existing sources

Water treatment plants at existing supply sources is expected to increase up to 650 Ml/d by 2031 (Table 8.9). However, this capacity cannot be fully deployed and delivered to customers due to physical constraints at number of treatment plants and at some parts of the supply network (Irish Water 2015b, 2016b). The deployable outputs of these treatment plants are being improved by Irish Water through its resilience projects. This study assumes that deployable output of the existing sources will increase up to 650

Ml/d by 2031 in accordance to projected production capacities in Table 8.9. Hence, in the WEAP-Dublin model, the flows from each of the existing water supply sources to demands were limited under all scenarios in accordance to the corresponding projected capacities (Table 8.9).

Table 8. 9 Deployable output / production capacity of existing water treatment plants in Ml/d. (Source: Irish Water 2015b, Irish Water 2016b).

Source (Plant)	2011	2021	2026	2031	2041	2046	2050
Phollaphuca (B. Eustace)	310	310	310	310	310	310	310
Lexilip (Lexilip)	148	215	215	215	215	215	215
Vartry (Roundwood)	65	65	65	75	75	75	75
Bohernabreena (Ballyboden)	12	12	12	12	12	12	12
(Bog of the Ring)	3	3	3	3	3	3	3
Barrow (Srowland)	0	13	13	30	30	30	30
Rathangan wellfield	3	3	3	3	3	3	3
Monasterevin Wellfield	2	2	2	2	2	2	2
Total	543	623	623	650	650	650	650

8.9 New source of supply (Parteen Basin/Shannon)

This study considers the preferred option (abstraction of water from Parteen Basin) only in representing the water supply system where additional water supplies are provided from a new water source to meet growing water demands in the Eastern and Midlands Region (see Section 8.1). This increase in water demands includes additional 245 Ml/d for the Dublin Region WSA and an additional 72 Ml/d for communities living in the benefiting corridor between Parteen Basin and Dublin by 2050 (Irish Water 2016b; Irish Water 2016c). This option was modelled in WEAP-Dublin as "other supplies object/Shannon" connected with a "transmission link pathway" which conveys flows to demand sites such as Dublin Region WSA and the benefiting corridor (see Figure 8.3).

Scenario 2 only assumes abstracting water from a new source (Parteen Basin/Shannon) to meet growing water demands. The supply option from Parteen Basin was activated for scenario 2 with supplies phased as shown in Table 8.10. Scenarios 1,3 and 4 assumes no abstraction, and hence this supply option was turned off by setting flows from Parteen Basin/Shannon to zero.

Table 8. 10 Water production requirement from a new source. (Source: Irish Water 2015b, 2016b).

		2026	2031	2041	2046	2050
Production requirement	Ml/d	165.4	195.2	263.0	295.9	330.0

8.10 Greywater reuse systems

Greywater is relatively "clean" water collected from indoor water uses (baths, showers, hand basins, dishwashers and cloth washers); It is different from black water which arises from kitchen sinks and toilets i.e. sewage (Rodrigo et al. 2012, DCC website n.d.). After collection, greywater is minimally treated to offset outdoor uses (gardening for example). At present, the application of greywater reuse systems in Dublin is low. Dublin City Council suggests that the econmic feasability of these systems be examined against other demand-side management measurues (e.g. water-efficient appliances) before application. It is therefore uncertain to whether the greywater reuse systems will be applied on a large-scale basis in the Dublin Region. Despite this uncertainty, greywater reuse option was considered in this study in order to evaluate the potenial benefits of total water management.

Scenario 4 only inlcuded the greywater reuse option. The greywater reuse option was represented in the WEAP-Dublin model using the "internal reuse parameter" within the Dublin Region demand site. This reuse parameter acts as a reducing factor on water requirment as portion of required supplies are offset by recycled water (Rodrigo et al 2012). The internal reuse parameter (r) can be estimated using Equation 8.1:

$$r = (\%App \times HU \times PCCo \times GPt) \, / \, AFW \qquad (8.1)$$

where %App is level of application of greywater reuse system, HU is number of houses, PCCo is average consumption per connection, GPt is greywater potential factor, and AFW is accoutned for water.

This study assumes that all new developments in Dublin will apply greywater reuse by 2026 and onwards. This assumption has been made in line with recommendations of the Greater Dublin Strategic Drainge Study (DCC 2005a) to achieve an integrated water resources management approach in the region. The projected number of housing units and average consumption per connection was derived from Irish Water (2016b). The "greywater potential" factor used in this study is 60% similar to the value used by Rodrigo et al. (2012). Table 8.11 summarises estimated reuse parameters as entered in the WEAP-Dublin model under scenario 4 (total water management).

Table 8. 11 Estimated reuse parameter to represent greywater reuse application in the Dublin Region WSA (under scenario 4).

		2026	2031	2041	2046	2050
No. of housing units	No	771871	833690	934805	993311	1028165
Consumption per connection	l/con/d	365	365	365	365	365
Accounted for water (AFW)	Ml/d	459.2	503.5	554	572.6	583.4
Total greywater available	Ml/d	8.45	9.13	10.24	10.88	11.26
Internal reuse parameter	%	1.85	1.85	1.85	1.90	1.95

8.11 Storm water management

A number of storm water managmenet options were considered in this study: (i) rainfall harvesting, (ii) centralised groundwater recharge, (iii) decentralised groundwater recharge and (iv) conventional collection and disposal of storm water to receiving water bodies via the local storm water network. Scenario 4 assumes implementation of all the strom water management options, whilist scenarios 1,2, and 3 assume implemention of storm water managemnet option (iii) and (iv) only.

8.11.1 Rainfall harvesting

Rainwater harvesting refers to the technique of collecting, storing and using rainwater from rooftops of buildings. The harvested rainwater can be used to offset on-site demands, in particular outdoor demands.

The current study accounts for rainwater harvesting at a regional level. This option was represented in the model as a “transmission link” passing from the urban module (consisting of urban node fed by the urban catchment) to the Dublin Region demand node (Figure 8.3). The urban catchment represents the total urban area in the Dublin Region WSA; it includes a portion accounting for total area of rooftops in the region which is used to estimate corresponding supplies from rainwater harvesting systems.

The rooftop area dedicated for rainwater harvesting is estimated as the product of projected number of buildings incorporating such system and the average area of rooftops. The study assumed that under scenario 4 all new developments will be fitted with rainwater harvesting system and 25% of all existing buildings be retrofitted for rainwater harvesting supplies by 2021 and onwards. The year 2021 has been assumed as a start year for application of rainwater harvesting to align the timing of investemnt for a new water supply source in this scenario with the timing of infrastructure investments in all other scenarios i.e. leakage management and upgrading capacities of exisitng water supply sources. The number of existing buildings and projections of new developments were derived from Irish Water (2016b). The average rooftop area used in this study is 158 m^2. This was calculated based on a study (MCC 2016) that provided estimates of rooftop areas for similar property types to those exist in the Dublin Region.

Table 8.12 summaries number of buildings projected to incorporate rainwater harvesting systems and the corresponding rooftop area in Dublin Region WSA.

Table 8. 12 Projected number of buildings to incorporate rainwater harvesting system and the corresponding total rooftop area in the Dublin Region WSA 2021 – 2050.

		2021	2026	2031	2041	2046	2050
No. of buildings	No.	695366	771871	833690	934805	993311	1028165
Total new developments[1]	No.	103570	180075	241894	343009	401515	436369
Total rooftop area[2]	10^4 x m^2	3974	5183	6160	7758	8682	9232

[1] Total new developments relative to the baseline year = No. of buildings projected in a future year – No of buildings in the baseline year. The number of buildings in the baseline year is estimated to be 591796 units

[2] Total rooftop area dedicated for rainwater harvesting = (Total new development + 25% of existing buildings) x average rooftop area.

The upper limit of available supplies from rainwater harvesting in each month is estimated as the product of rooftop area dedicated for rainfall harvesting, the monthly rainfall depth, and rainfall capture coefficient to account for losses (Rodrigo et al. 2012). The resulting limits were used in the model as flow constraints in the transmission link passing flows from the urban catchment to the Dublin Region. This in turn restricts supplies from urban catchment to the available supplies from rainwater harvesting in each month.

The rainwater harvesting option was activated in scenario 4 by allowing supplies to pass from the urban catchment to the Dublin Region demand site throught the respective transmission link. The Dublin Region demand site was set to receive supplies from rainwater harvesting system and then from exisitng water sources; the supply preference of Dublin Region to rainwater harvesting supplies was set to 1 (higher preference), while supply preferences to other sources were set to 2 (lower preference). This allocation routine ensures that available water supplies from rainfall harvesting is first used and then the remaining water demands are satisfied from existing water sources. Otherwise, water would have been allocated based on an equal percentage of available supplies resulting in more water used from exisitng sources.

8.11.2 Centralised groundwater recharge

This option represents recharging portion of collected stormwater into groundwater through large-scale recharge facilities (e.g. percolation basins and injection wells). In the presence of such facilities, rainfall in the urban catchment that was not captured by rooftops or did not naturally infiltrate into the groundwater can be used to recharge the groundwater by means of recharge facilities. This recharge of storm water into the groundwater is limited to the capacity of associated facilities and infrastructure. Storm water in excess of the recharge capacity is then discharged into receiving water bodies through the exisitng storm water network.

This option was represented in the WEAP-Dublin model as a "transmission link" flow pathways connecting the urban module (consisitng of urban node fed by urban catchment) to the groundwater object (Figure 8.3). To force flows to pass through the respective transmission link, a dummy demand site was used in between the urban node and the groundwater object. This demand site was assigned a priority lower than the Dublin Region but higher than the other dummy demand site used for routing excess flows to receiving water bodies. It was also assigned a high demand value to ensure flows are passed through the respective transmission link as the model tries to satisfy the specified demand. Hence, this configuration routes the flows as follow: First harvested rainwater is supplied to the Dublin Region. If the centralised groundwater recharge is activated, then a portion of remaining flows is routed to the groundwater object (limited to the capacity of associated infrastrucutre) and any excess flows is routed to receiving water bodies. If not activated, then all remaining flows is routed to receiving water bodies.

Only scenario 4 assumes the implementation of centralised groundwater recharge with asscoiated facilities constructed by 2026. This year was assumed as start year for centralised recharge in line with targets set out by the Greater Dublin Strategic Drainge Study (DDC 2005a) to achieve an integrated water management appraoch in the region. The total capacity of associated recharge facilities is assumed to be 0.60 Mm^3/month. This is in accordance to the capacity used by Rodrigo et al. (2012) for a comporable urban area. Hence, the option of centralised groundwater recharge was activated in scenario 4 by setting the maxmium flow in the respective transmission link to 0.60 Mm^3/month.

8.11.3 Decentralised groundwater recharge

This option refers to the approach of recharging groundwater through smaller on-site facilities spread throughout the urban catchment. This non-conventional approach in storm water management aims to reduce impacts of urban development using onsite facilities that try to mimic the behaviour of natural environment. Such facilities are designed to increase infiltration and to control or reduce runoff to pre-development rates. Examples of these facilities are infiltration trenches, permeable pavements, swales, detention basins and integrated constructed wetlands (DDC 2005a). In Ireland and the UK, such facilities are known as sustainable urban drainage systems (SuDS) (Dublin City Council Website). The use of SuDS in the Dublin Region is now mandatory for all new developments (DDC 2005a, DDc 2005b). Therefore, as a default, the decentralised groundwater recharge or SuDS was included in all four scenarios.

The decentralised groundwater recharge option was represented in the WEAP-Dublin model as “a runoff/infiltration” flow pathway from the urban catchment to the groundwater basin with an adjusted ratio of rainwater volume. This adjustment ratio merely accounts for infiltration that would take place by the decentralised recharge facilities and not for natural infiltration occuring in pervious areas where the model employs a simplistic groundwater tracking approach. This option was turned on by specifying values for the runoff resistance factor and estimated surface area for SuDS facilities within the urban catchment in the model (see Section 8.12).

8.11.3 Simplistic groundwater modelling

The groundwater basin in the model was only included to track additional storages from improved recharge of stormwater, for example using centralised and decentralised groundwater recharge facilities; The model does not account for natural inflows/outflows and abstractions or pumping activities occuring in the basin. These aspects require further detailed anaylsis which is considered beyond the scope of this study.

The additional groundwater storages from improved recharges of storm water is simulated by setting the initial groundwater storage to zero. The simulated storages, therefore, represents cummulative increases in groundwater storage throughout the planning horizion due to incoporation of centralised and decentralised recharge facilities. In other words, the simulated groundwater storages do not represent what might be observed in real field conditions. This approach of modelling groundwater illustrates the relative impacts on groundwater storage due to implementing different options of stormwater management. The simplisitc groundwater modelling approach was adopted from Rodrigo et al. (2012) which termed such additional storages as “banked water”.

8.11.4 Traditional storm water system

This option refers to the traditional storm water drainage system in the region, where urban runoff is collected and disposed to receiving water bodies through a network of pipes, culverts, open channels and combined sewer overflows. The default pathway for urban runoff in our model is through the traditioanl storm water drainage system – an existing assest which will continue to be part of any drainage system in the future (DDC 2005a).

The traditional storm water system in the WEAP-Dublin model was represented as "transmission link" flow pathway from the urban node to the dummy "runoff demand node" and then a final pathway to a receiving water body (Figure 8.3). The dummy demand for runoff was assigned the lowest priorty among all other demand sites to represent a default flow route for urban runoff. If no other strom water management option is activated, all storm water will be routed through the "traditional storm water system" pathway to a receiving water body. If other storm water management option is activated, only storm water in excess of associated infrastructure capacities will be routed through this pathway to a receving water body. Similar to modeling centralised groundwater recharge, the dummy demand for runoff was parameterised to yeild a high-demand value in order to force the model to route excess urban runoff into the associated transmission link.

8.12 Rainfall and storm water routing

Monthly rainfall volume in the urban catchment is routed across different pathways based on the scenario pursued. First, monthly rainfall volume either infiltrates into the groundwater or flows as urban runoff. The urban runoff can then be routed through three different pathways including "harvested rainwater supplies", "centralised stromwater recharge" and the "traditional storm water system". Routing pathways for rainfall volumes in WEAP-Dublin model are illustrated in the schematic diagram in Figure 8.5. This section intends to describe methods used for estimating rainfall volumes and for routing flows across the specifed pathways in WEAP21 (Rodrigo et al. 2012).

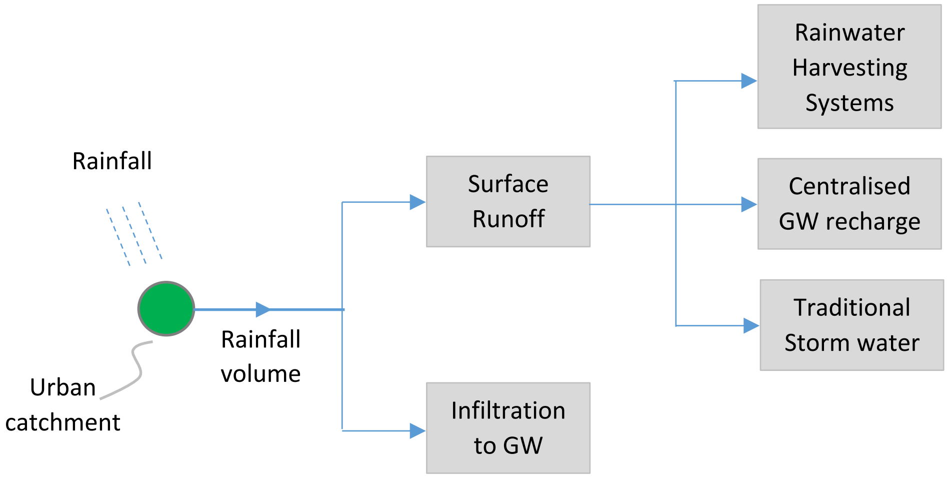


Figure 8. 5 A schematic diagram showing routing pathways of rainfall volumes as programmed in WEAP-Dublin, adopted from Rodrigo et al (2012).

The urban catchment in the model represents the total urban area in the Dublin Region. It has parameters related to landcover and climate. For landcover parameters, the catchment was divided based on landcover into three distinct classes: impervious, pervious and decentralised recharge facilities. The surface area (km^2) for each class within the urban catchment was defined in the model as will be shown later. For climate parameters, the future climate conditions in the urban catchment for the period 2020-2050 was linked to the historic climate conditions for the period 1982-2012. The historical records of monthly rainfall in the catchment was obtained from Met Éireann rainfall gauging stations located within or in close proximty to the catchment. The mean of rainfall records at all stations in each month was calculated to obtain monthly rainfall time-series data for the catchment during the period 2020 – 2050 (Appendix F.1). The means of monthly average values for temperature and windspeed at the synoptic weather stations in each month was calculated to obtain monthly time-series data in terms of temperature and windspeed respectively during the period 2020-2050. The resulting time-series climate data were used in the model as an input for the hydrological rainfall-runoff module of the urban catchment to produce future storm water fluxes.

The rainfall routing approach applied an adjustment factor to the monthly rainfall depths to account only for water infiltrated through decentralised recharge facilities (Equation 8.2):

$$RF_{(Adj)} = [(\%A_p \times c_p) + (\%A_i \times c_i) + (\%A_d \times c_d)] + [\%A_d \times (1 - c_d)] \qquad (8.2)$$

where $RF_{(Adj)}$ is the adjustment factor for rainfall depths, $\%A_p$ is percentage of urban land that is pervious, $\%A_i$ is percentage of urban land that is impervious, $\%A_d$ is percentage of urban land dedicated for decentralised recharge facilities, c_p is runoff coefficient of pervious land, c_i is runoff coefficient of impervious lands, and c_d is runoff coefficient of decentralised recharge facilities.

The adjustment factor is then applied to the total monthly rainfall depths as shown in Equation (8.3):

$$RD_{(Adj)} = RF_{(Adj)} \times RD_{month} \qquad (8.3)$$

where $RD_{(Adj)}$ is the adjusted depth of rainfall (monthly) and RD_{month} is the original rainfall depth as derived from rainfall stations (monthly).

The "adjusted" monthly rainfall volume at the level of the urban area in Dublin Region $RV_{(Adj)}$ is then calculated as the product of adjusted rainfall depth $RD_{(Adj)}$ and the total surface area of the urbanised land in the region A_{urban}, as shown in Equation (8.4)

$$RV_{(Adj)} = RD_{(Adj)} \times A_{urban} \qquad (8.4)$$

This adjusted rainfall volume is then divided into two components; groundwater recharge or surface runoff. The proportion of rainfall volume which supplies each component is determined based on a percentage of the adjusted volume as outlined in the following equations:

$$RV_{(Adj)} = Groundwater\ recharge + Runoff \tag{8.5}$$

$$\%Inf_{(Adj)} = \frac{\%A_d \times (1 - c_d)}{RF_{(Adj)}} \tag{8.6}$$

$$Groundwater\ recharge = RV_{(Adj)} \times \%Inf_{(Adj)} \tag{8.7}$$

$$\%RO_{(Adj)} = \frac{(\%A_p \times c_p) + (\%A_i \times c_i) + (\%A_d \times c_d)}{RF_{(Adj)}} \tag{8.8}$$

$$Runoff = RV_{(Adj)} \times \%RO_{(Adj)} \tag{8.9}$$

It is worth mentioning that the volume of surface runoff is the same before and after applying the adjustment factor. However, the volume of infiltration is reduced after applying the adjustment factor as the adjustment excluded volumes of natural infiltration.

Urban catchment parameterisation

Future land-use changes in the Dublin Region up to 2026 projected by Willuwiet et al. (2016) were used in the current study. Willuwiet et al. (2016) used the land-use dynamic model (MOLAND) to simulate different urban growth scenarios based on (i) economic scenarios (population and jobs); and (ii) planning scenarios (zoning, suitability and transportation network). The economic scenarios are: stagnation, delayed-adjustment and recovery. The planning scenarios are: business as usual, compact development, and managed dispersed. Under the assumption that business as usual will be ongoing until 2026, future land-use changes in the Dublin Region under the three economic scenarios were simulated. Results from MOLAND model suggested that the urban area in the region is likely to increase by 11.50%, 15.20%, and 17.25% respectively under the stagnation, delayed adjustment and recovery scnenarios by 2026 (Table 8.13) (Willuwiet et al. 2016).

Table 8. 13 Urban land-use in the Dublin Region in 2013 and projections to 2026 for the Stagnation, Delayed adjustment and Recovery. Source: Willuweit et al. 2016

	2013: *Base Year*	2026: *Stagnation*	2026: *Delayed Adjust.*	2026: *Recovery*
Urban land use (km^2)	372.7	415.4 (11.5%)	429.2 (15.2%)	436.9 (17.25%)

As shown in Table 8.13, the economic scnenario of recovery yielded the highest urban growth, with a total urban area projected to be 436.90 km^2 in 2026. This urban growth scenario was used as the basis for evaluating the different water management scenarios. The projected urban area to 2026 under this growth scnenario was then extrapolated up to 2050 using WEAP21 built-in function "linear forecast".

The surface area for each land class within the urban catchment in a certain year was specified by assuming that impervious surfaces account for 57% of the urban catchment, and both pervious and decentralised recharge (or SuDS) landcovers occupy the remainder. This assumption was based on percentages of impervious and pervious surfaces in a select of urban catchments as reported by Ebrahimian (2015) and Rodrigo et al. (2012). The total surface area of SuDS was estimated to be in the region of 2.50 km^2 based on a database of SuDS facilities in Dublin found in https://data.gov.ie/data. For exisitng developments, the percentage of total surface area of SuDS to the total area of respective developments was calculated first. This ratio then was multiplied by the projected area for new developments as given by Willuweit et al. (2016) to estimate SuDS areas for new developments. Calculation of fractional areas for impervious land, decentralised recharge facilities (or SuDS), and pervious surfaces in a year (n) are given in Equations 8.10-8.12:

$$A_{i(Year=n)} = 0.57 \times A_{urban(Year=n)} \quad (8.10)$$

$$A_{d(Year=n)} = \%SuDS \times [A_{urban(Year=n)} - A_{urban(Year=baseline)}] \quad (8.11)$$

$$A_{p(Year=n)} = [0.37 \times A_{urban(Year=n)}] - A_{d(Year=n)} \quad (8.12)$$

where A_i , A_d , and A_p are fractional areas for impervious, decentralised recharge and pervious land covers respectively, $\%SuDS$ is the percentage of SuDS area to the total area of respective developments, and A_{urban} is the total surface area of the urban catchment.

Calculation of surface areas (A_i , A_d , and A_p) and the dependent parameters $RF_{(Adj)}$, $\%Inf_{(Adj)}$ and $\%RO_{(Adj)}$ for each year during the simulation period was performed using a visual basic code (Appendix F.2). The code was written based on an algorthim shown in Figure 8.6 in order to iterate the calculations for each year and to produce time-series outputs in terms of the different surface areas (A_i , A_d , and A_p) and the parameters of $RF_{(Adj)}$, $\%Inf_{(Adj)}$ and $\%RO_{(Adj)}$ during the period 2020-2050. Figures 8.7 – 8.9 display the time-series derived by the code where (i) Figure 8.7 shows projections of surface areas in terms of impervious, pervious and decentralised surface classes; (ii) Figure 8.8 shows change in adjustment factor $RF_{(Adj)}$ over time along the planning horizon; and (iii) Figure 8.9 shows runoff and infiltration as fractions of total rainfall volume across the planning horizon.

Figure 8.7 shows that surface areas of the three landcover classes (Ai, Ap and Ad) are projected to increase in proportion to the total surface area of the urban catchment. This increase in surface areas is likely to result in increases in surface runoff and amounts of rainfall captured by decentralised recharge facilities. The $RF_{(Adj)}$ representing these components as fraction of total rainfall volume increased from 0.642 to 0.654 (Figure 8.8). Moreover, Figure 8.10 shows improved infiltration in the region over the planning horizion as a result of implementing SuDS; Infiltration is likley to increase by 5% of the adjusted total rainfall volume by 2050. Surface ruoff, however, will continue to be

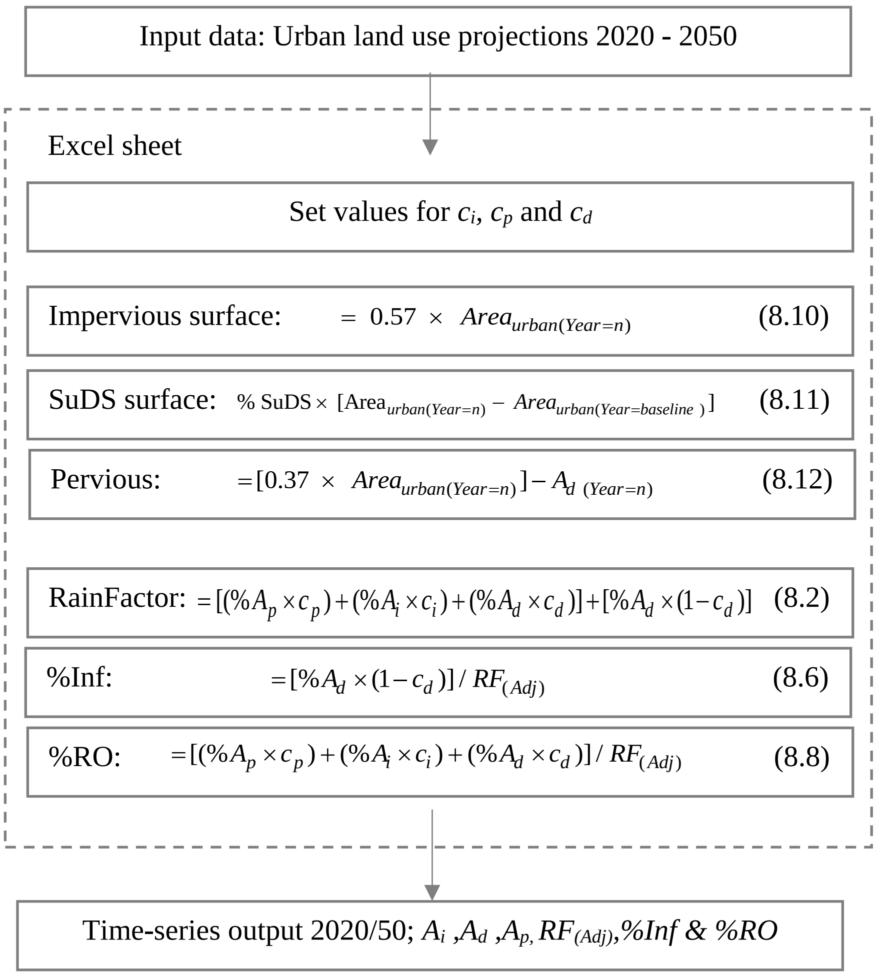


Figure 8. 6 Calculation algorithm used to derive input parameters for urban catchment in the WEAP-Dublin model during the simulation period.

a significant portion of rainfall volumes, since existing built-up areas are relatively large compared to the surface area of decentralised recharge facilities.

Time-series outputs shown in Figures 8.7-8.9 were used as inputs to the rainfall-runoff module of the urban catchment. Projections of surface areas shown in Figure 8.7 were used as an input for land-use parameters under each of the landcover classes of the urban catchment. The rainfall adjustment factor $RF_{(Adj)}$ shown in Figure 8.8 was applied to the rainfall time-series data derived from rainfall gauging stations. The adjusted time-series data were used as a climatic parameter for the ubran catchment to drive the model to simulate storm water fluxes for routing across the different pathways. Time-series outputs for %RO shown in Figure 8.9 were used as a land-use parameter "prefered flow direction *PFD*". This parameter in turn partions the monthly rainfall volume into two components; the specified fraction of monhtly rainfall volume is routed as surface runoff, and the remainder as infiltration to groundwater.

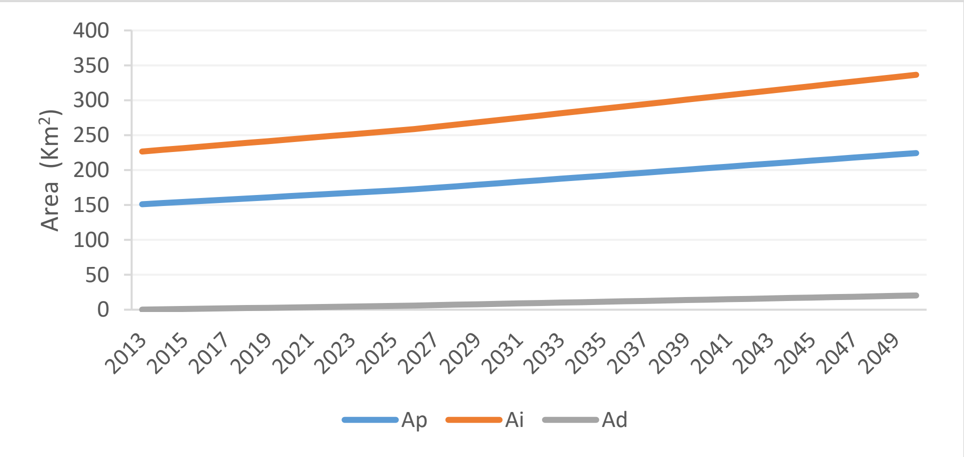


Figure 8. 7 Projections of surface areas for pervious, impervious and decentralised recharge facilities.

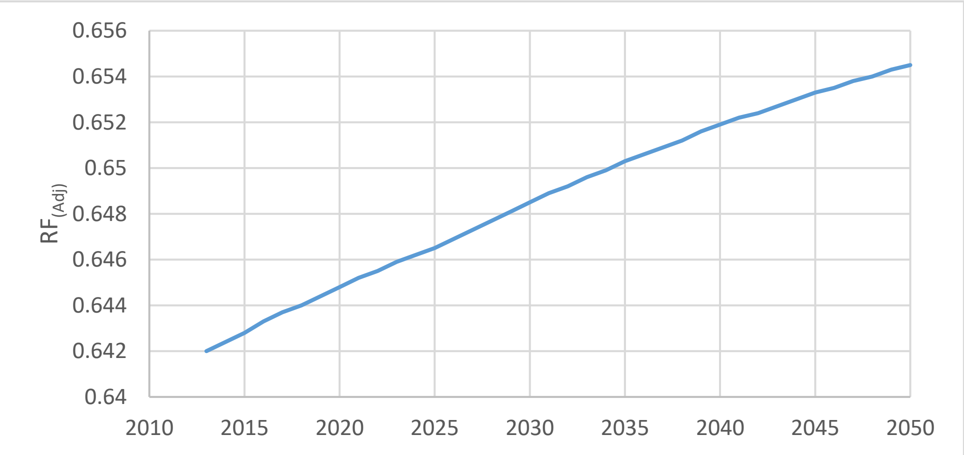


Figure 8. 8 Change in Rainfall Adjustment Factor $RF_{(Adj)}$ over the planning horizon.

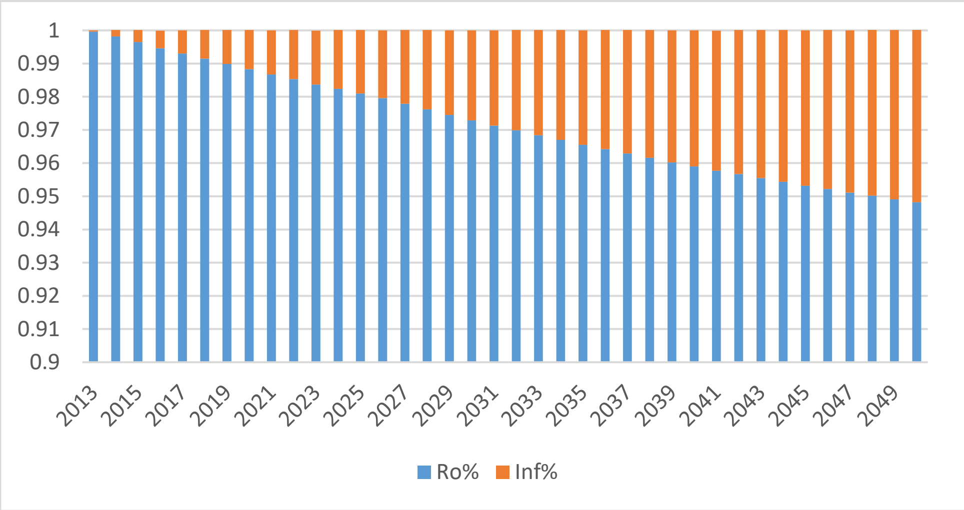


Figure 8. 9 Fractions of Infiltration (%Inf) and Runoff (%RO) of monthly rainfall volumes, used in WEAP-Dublin to route rainfall into either infiltration or runoff.

It is worth mentioning that this study did not consider the effects of climate change on water resources management scenarios, as the purpose in this study is to compare between the different water management scenarios in terms of their impacts on the system as results of incorporating different management options. The comparison between the different scenarios is based on their impacts on water resources system relative to a baseline scenario (i.e. business-as-usual or do nothing scenario). Hence, under any climate projection, the relative impacts of the water management scenarios compared to the reference scenario will not change. Furthermore, all water management scenarios assumes supplies from existing water resources and hence the effects of any climate change will be the same for all scenarios. It is therefore sufficient to use one climate projection to compare between these scenarios, and this study used a baseline climate (no change) to compare the effects of different water management options on the system.

Chapter 9 EVALUATION OF WATER MANAGEMENT SCENARIOS

This chapter presents the results of simulating the four water management scenarios (1–baseline, 2–increase water supply, 3–intensified leakage management, and 4–total water management) in the WEAP-Dublin for the period 2012-2050, under future climate conditions corresponding to the historic period 1982-2012. The performance of the scenarios are evaluated based on results of main variables characterising water resources system and these include: water balance and supply reliability, urban runoff generation and groundwater recharge. This evaluation did not include implementation cost of scenarios which is worth incorporating in future research for a more comprehensive evaluation.

It is worth mentioning that scenario 1 in this study represents the existing water management system with no change. It is used as a reference scenario where performances of other scenarios are assessed against it. Scenarios 2 and 3 are water management scenarios that have been under consideration by Irish Water (Irish Water 2016b) as an alternative plans for meeting growing water demands in the Dublin Region. On the other hand, scenario 4 is proposed in this study to examine the potential benefits of integrating total water management options in the management plan of water resources in Dublin. This is in line with recommendations given by local water authorities pertaining to the need for incorporating best management practices in all supply and drainage aspects for developing an integrated water management plan (DDC 2005a, DCC 2010a, Irish Water 2018b).

9.1 Water balance and supply reliability

9.1.1 Water demand

Figure 9.1 shows monthly water demands in the Dublin Region WSA for the period 2012 – 2050, as predicted by the WEAP-Dublin for all scenarios. The average monthly demand for domestic water uses under scenarios 2,3 and 4 is projected to increase from 6.0 Mm^3/month in the baseline year 2012 to 7.92 Mm^3/month in year 2050 (an estimated increase of 30% from baseline year). However, under the baseline scenario, which corresponds to the "business as usual" scenario, the average monthly demand is projected to increase up to 8.22 Mm^3/month – sligthly greater than demand levels under other scenarios. This slight increase is due to the absence of any reductions in domestic water consumptions under the baseline scenario while under other scenarios a gradual reduction in the same amount from 45.80 m^3/person/month to 44.0 m^3/person/month by 2050 has been assumed.

On the other hand, the average monthly demand for non-domestic water uses is projected to increase in the four scenarios from 3.85 Mm^3/month in the baseline year 2012 to 8.50 Mm^3/month in year 2050. It is clear that the water demand for non-domestic uses is projected to grow at higher rate than that of domestic uses due to the additional water allowance ranging from 2.27 to 3.00 Mm^3/month given to the anticipated expansion in industry such as integrated circuits manfacture, large-scale biotech and nano-meter technologies (Irish Water 2015b).

It is worth mentioning that the projected monthly water demands shown in Figure 9.1 did not account for water losses in the system which may increase the estimated total water supply requirment.

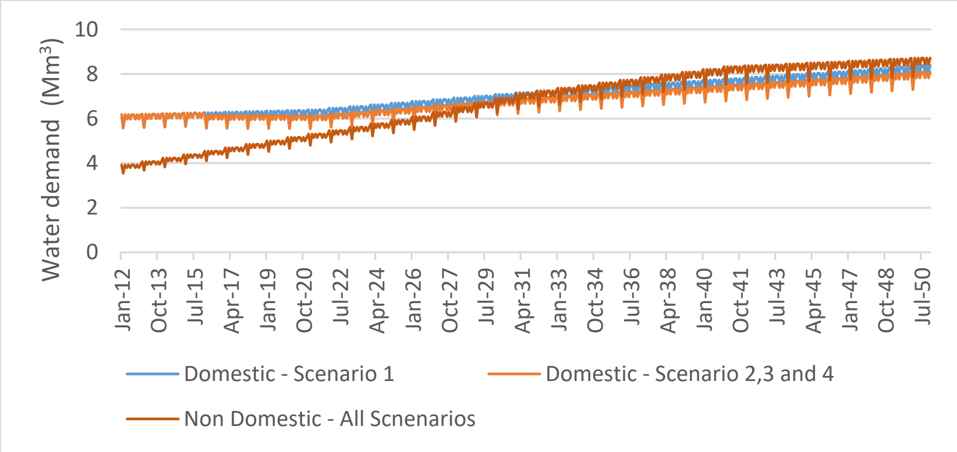


Figure 9. 1 Monthly water demands for the Dublin Region WSA during the period 2012 – 2050, as predicted by WEAP-Dublin for all scenarios. Scenarios are 1 – (baseline), 2 – (increase supply), 3-(intensified leakage management), and 4-(total water management).

The impacts of conservation and reuse measures assumed in scenarios 2, 3 and 4 on reducing water usages were examined and presented in Figure 9.2. Under scenarios 2 (increase supply) and 3 (intensified leakage management), the combined effects of reducing per capita consumption together with reducing customer side leakage are likely to lower the average annual water demands by 4.20% below the estimated demand in the baseline scenario. On the other hand, under scenario 4 (total water management), the installation of greywater reuse system will result in an additional saving. When this saving is combined with the implementation of conservation measures it is likely to lower average annual water demands by 5.52% below the estimated demand in the baseline scenario.

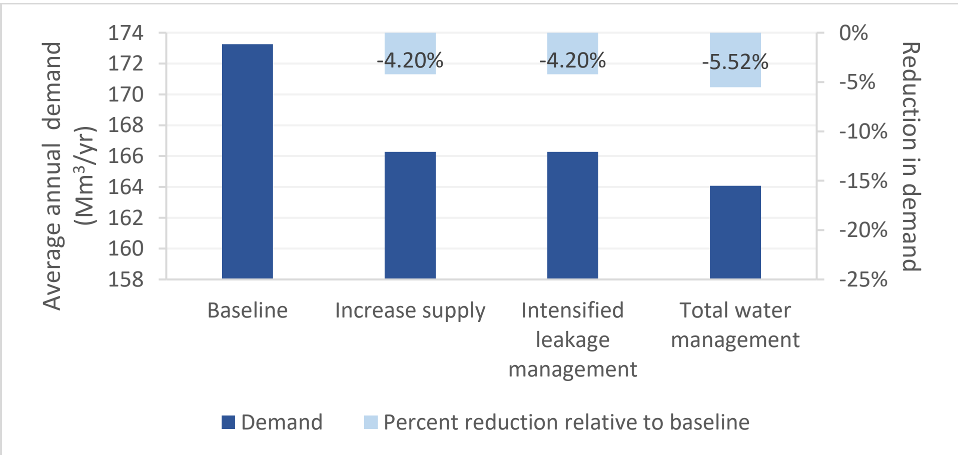


Figure 9. 2 Average annual water demand under all water management alternatives, and potential impacts of associated assumptions in terms of conservation and reuse.

9.1.2 Water supply

Figures 9.3 – 9.6 show the results of “simulated” mix of water supplies for the period 2012 – 2050 under the four water management scenarios and from different water sources, namely Phollaphuca, Lexilip, Vartry, Dodder, Srowland, Bog of the Ring schemes. In these figures, the variability in future supplies from all sources is solely attributed to corresponding changes in their hydrology as simulated by the model for the period 2012 – 2050. These figures show only the potential mix of water supplies without any account to possible supply deficits as a result of the anticipated growing water demands.

Figure 9.3 shows that under the baseline scenario the majority of supplies throughtout the planning horizion are mainly sourced from Phollaphuca and Lexilip schemes similar to the current water management practicies. Furthermore, the figure also shows that supplies from Vartry and Srowland schemes are augemented by 2021 and 2031 respectively as a result of increasing water treatment capacities of these schemes.

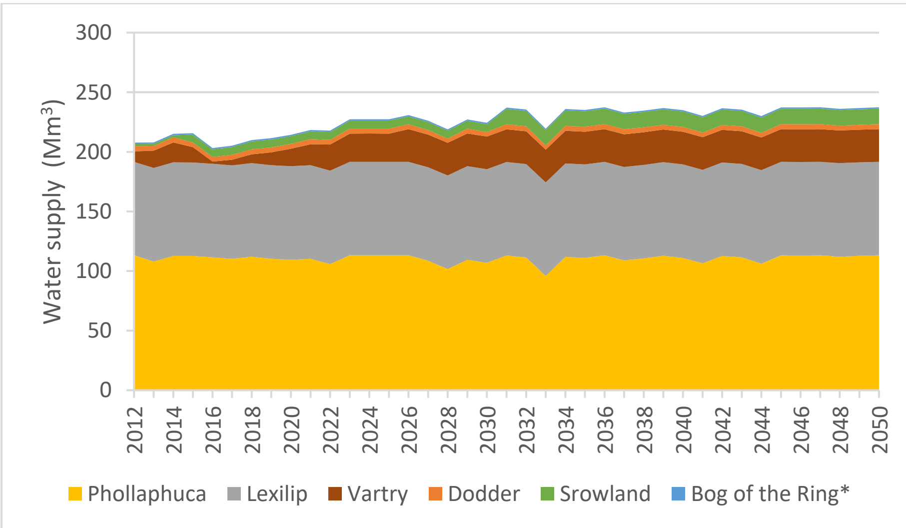


Figure 9. 3 Mix of water supplies under the baseline scenario for the period 2012 – 2050, as simulated in the WEAP-Dublin model on annual basis. * Water supplies from Bog of the Ring is <1.10 Mm3

Figure 9.4 shows that under scenario 2 additional amounts of water will be supplied from Shannon river by 2026. These supplies together with water savings achieved from

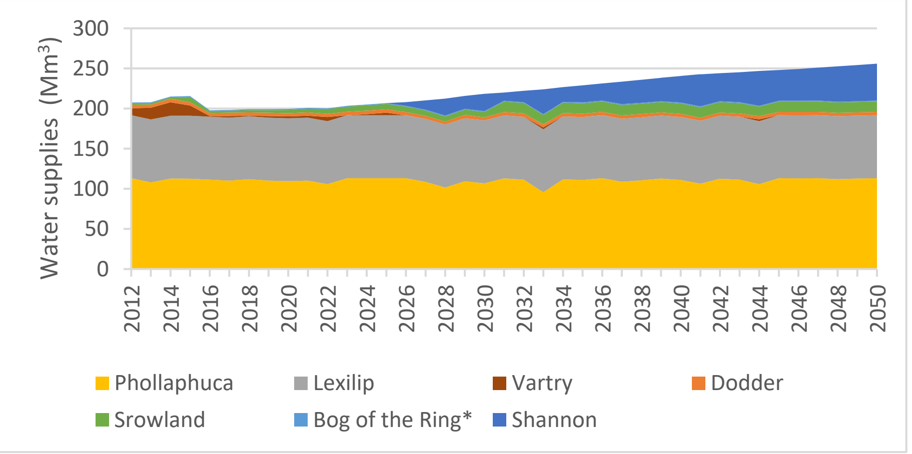


Figure 9. 4 Mix of water supplies under scenario 2 (increase supply) for the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis. *Water supplies from Bog of the Ring is < 1.10 Mm^3

implementation of conservation measures and leakage management are likley to reduce the pressure on existing water supplies.

Figure 9.5 shows that the reliance upon existing sources will be reduced relative to the baseline scenario under scenario 3, where intensified and accelerated efforts based on Irish Water Leakage Target Policy are assumed to be implemented.

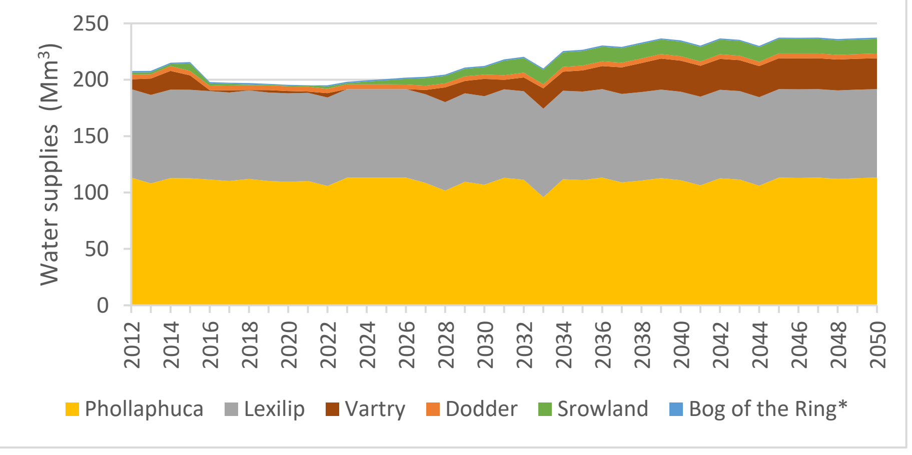


Figure 9. 5 Mix of water supplies under scenario 3 (intensified leakage management) during the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis. *Water supplies from Bog of the Ring is < 1.10 Mm^3.

Figure 9.6 shows that under scenario 4 significant reductions in supplies from existing sources relative to that in the baseline scenario will occur. This reduction will be associated with increases in localised supplies i.e. from rainwater harvesting systems.

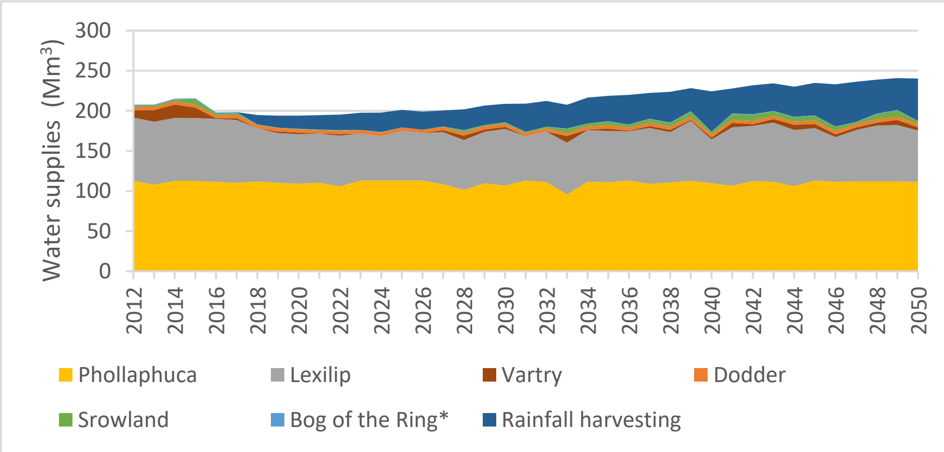


Figure 9. 6 Mix of water supplies under scenario 4 (total water management) during the period 2012 – 2050, as simulated by the WEAP-Dublin model on annual basis. *Water supplies from Bog of the Ring is < 1.10 Mm^3.

Conservation, leakage management and greywater reuse under this scenario contribute with substantial amount of water supply which in turn reduces contribution from existing sources.

Figure 9.7 summarises the average annual potential supplies from existing water sources for all scenarios in (2020-2035) and (2036-2050), and potential reductions in these supplies relative to the baseline. Under scenario 2, additional supplies from Shannon river together with water savings achieved by the implementation of conservation and leakage management measures are likely to reduce the average annual water supplies by 7% in (2020-2035) and by 12% in (2036-2050) relative to the baseline scenario. Under scenario 3, implementation of intensified and accelerated leakage management is likley to reduce the average annual water supplies by 7% in (2020-2035) and by 2% in (2036-2050) relative to the baseline scenario. The reductions under scenario 3 are less than that under scenario 2 mainly due to the absence of new water sources, which in turn result in triggering more supplies from existing sources to meet growing water demands. Under scenario 4, on-site water sources along with conservation and leakage management measures are likley to reduce the average annual water supplies by 14% in (2020-2035) and by 20% in (2036-2050) relative to the baseline scenario.

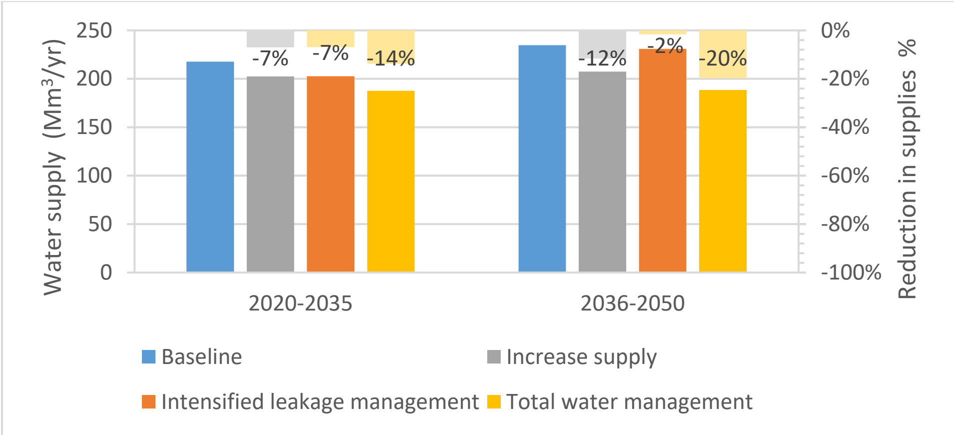


Figure 9. 7 Average annual water supplies from existing sources for (1) baseline, (2) increase supply, (3) intensified leakage management and (4) total water management in (2020-2035) and (2036-2050), and reductions in these supplies relative to baseline.

9.1.3 Water supply deficit

Figure 9.8 displays the predicted water supply deficits in meeting domestic and non-domestic demands for the period 2020-2050 under the four management scenarios. The graphs in this figure indicate that the baseline scenario has the highest water supply deficit episodes both in term of frequency and magnitude. On the other hand, the least number of water supply deficit episodes was predicted under scenario 2 while scenarios 4 and 3 are predicted to have the second and third least number of water supply deficit episodes, respectively. Table 9.1 and Figure 9.9 presents result of statistical analysis of predicted data of water supply deficits under the four management scenarios. The statistical results indicate that under the baseline scenario 343 water supply deficit episodes (ranging from 0.69% to 41.27% of the water supply requirement) were predicted while 3 episodes (ranging from 0.38% to 9.56% of the water supply requirement) were only predicted under scenario 2. These figures clearly demonstrate the benefit of a new water supply source in bringing resliance and robustness to the overall water supply system as suggested by Irish Water (2016b).

Scenario 3 (intensified leakage management) was predicted to have less water supply deficit episodes than the baseline scenario due to the recovered leakage which offset some of the unmet demands under the baseline scenario. The assumed constant abstraction from a new water source (up to 9.98 million m^3/month) under scenario 2 was the main reason for predicting the lowest water supply deficit episodes under this scenario. Unsurprisingly, scenario 4 (total water management) was predicted to have less water supply deficit than scenario 3 (intensified leakage management). This is mainly due to the substantial amount of additional water supply contributed by rainwater harvesting and greywater reuse compared to the amount of recovered leakage. However, scenario 4 (total water management) was predicted to have more water supply deficit episodes than scenario 2 (increase supply). This is entirely because the additional water supply in scenario 4 will be contributed by rainwater harvesting which represent a fluctuating water supply when compared to a constant supply from a new water source under scenario 2.

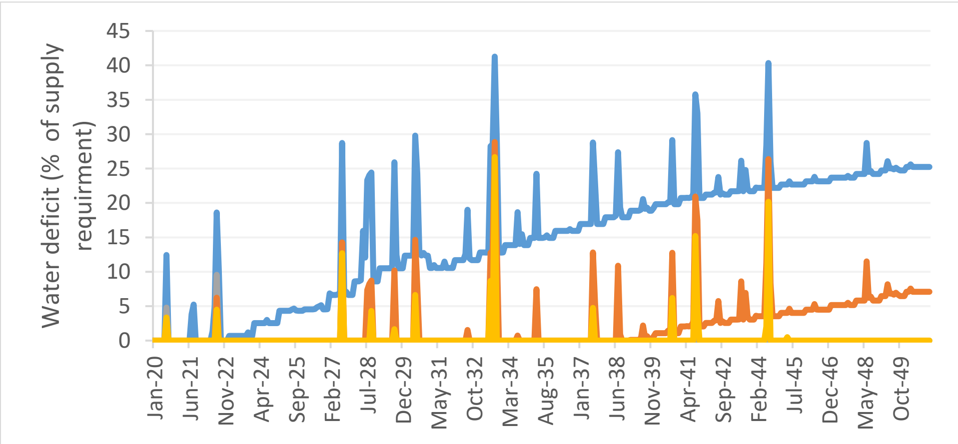


Figure 9. 8 Monthly water supply deficits in the Dublin Region WSA (% of water supply requirements) for all scenarios along the period 2020 – 2050, as simulated by the WEAP-Dublin model.

Table 9. 1 Statistical summary of predicted water supply deficits 2020 -2050, showing number of deficit episodes, minimum, maximum and quartiles for each scenario – expressed as % of water supply requirement.

	Episodes	Min	Max	25^{th} Q	Median	75^{th} Q
	No	%	%	%	%	%
Baseline	343	0.69	41.27	10.57	17.93	22.68
Increase supply	3	0.38	9.56	2.6	4.8	7.18
ILM	164	0.1	28.86	2.56	4.5	6.46
TWM	15	0.488	26.67	3.02	4.6	9.68

ILM: Intensified leakage management TWM: Total water management

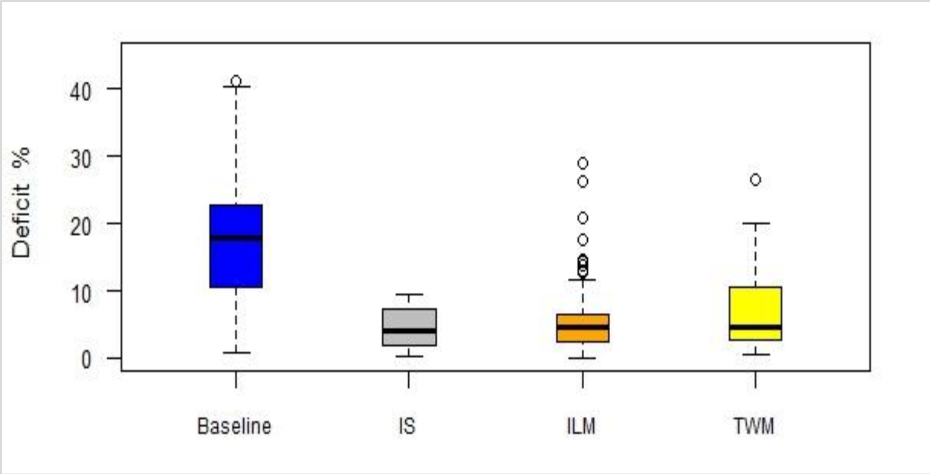


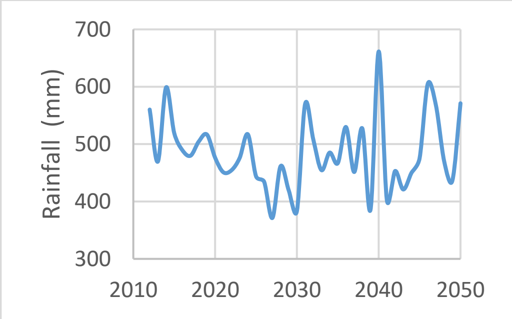
Figure 9. 9 Box plots for projected water supply deficits in Dublin Region WSA (2020 – 2050) for all alternatives: baseline, increase supply, intensified leakage management and total water management – expressed as % of water supply.

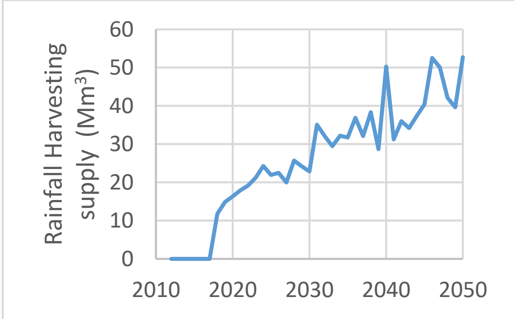
9.1.4 Water supply from rainwater harvesting

Water supply contribution from rainwater harvesting in scenario 4 (total water management) is related to (i) rainfall pattern in the urban catchment; and (ii) projections of urban developments.

The predicted water supply deficits from the rainwater harvesting supply scenario are consistently related to the hydroclimatological conditions during the simulation period. For instance, the largest water supply deficit was found to occur in August 2033 which corresponds to the extreme hydroclimatological drought of August 1995. During this month, a water supply deficit of 41.27% (6.40 million m^3/month) was predicted under the baseline scenario.

Regarding impact of urban development on rainwater harvesting supply, any increase in the rooftop areas dedicated for rainfall harvesting in the region will increase the supply. As shown in Figure 9.10b, rainwater harvesting supply is predicted to increase up to 52.70 million m^3 by year 2050 under scenario 4 (total water management), which corresponds to an estimated total rooftop area of 92.32 x 10^6 m^2.

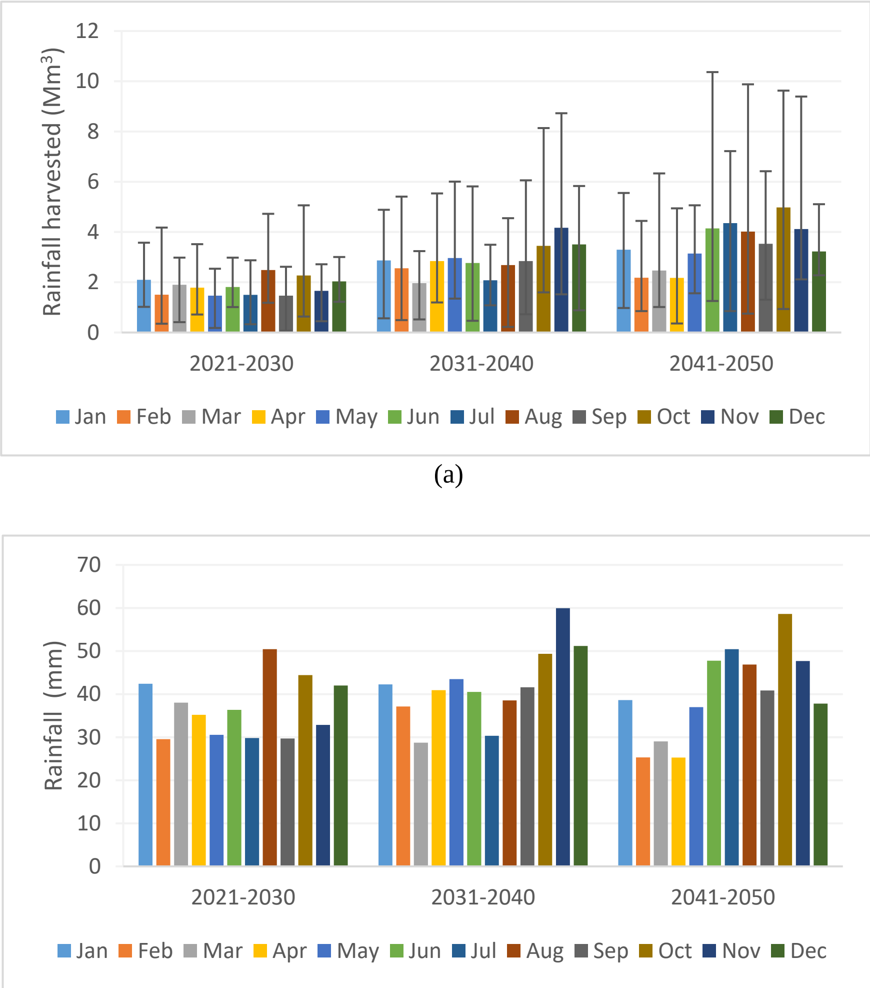




(a) (b)

Figure 9. 10 Annual time-series 2012 – 2050 for (a) rainfall in the urban catchment (in mm) as derived from respective rainfall stations and (b) supplies from rainfall harvesting systems as simulated by WEAP-Dublin under scenario 4 (total water management).

To examine the seasonality of rainwater harvesting supply, an analysis of monthly simulated data of three decades during the planning horizion (2021-2030), (2031-2040) and (2041-2050) was conducted. Figure 9.11a presents the monthly average supplies from rainwater harvesting for each decade, with upper and lower bars showing the maximum and minimum supplies observed for each month in the 10 years period. The figure indicates an increasing trend in the monthly average supplies from rainwater harvesting during the simulation period, mainly due to inter-annual increases in rooftop areas dedicated for rainfall harvesting. The monthly water supplies from rainwater harvesting system also matched the seasonal rainfall variability during the simulation period as shown in Figure 9.11b. The largest contributing months of rainwater harvesting supplies were found to be October, November, December and January. The monthly average supplies during these months ranged between 2 million m^3 and 5 million m^3. Occasionally, the summer months from June to August contribute with significant rainwater harvesting supplies due to the repeat of wet conditions in these months during the simulation period. For instance, the monthly average supply for each month from June to August slightly exceeded 4 million m^3 in the period 2041-2050 which corresponded to monthly average “adjusted” rainfall depths of approximately 50 mm.



(a)

(b)

Figure 9. 11 Monthly average (a) supplies from rainwater harvesting for decades 2021–2030, 2031–2040 and 2041–2050, as simulated by the WEAP-Dublin model under scenario 4 (total water management), and (b) adjusted rainfall depths for the decades 2021–2030, 2031–2040 and 2041–2050 which corresponds to the climatic conditions of the historic period 1982-2012.

9.2 Urban runoff generation

The current study compared between the four water management scenarios in term of their urban drainage system responses to the predicted increase in urban runoff from new developments. Under all four water management scenarios the "recovery" urban growth development scenario (Willuwiet et al. 2016) has been used as a reference scenario where by the total urban area was extrapolated to 2039 and a linear regression was used to predict the total area for the remaining simulation period up to 2050. Moreover, default storm water management options consisting of SuDS facilities and traditional storm water system are used with all four water management scenarios while additional options inlcuding centralised groundwater recharge and rainwater harvesting system is used for scenario 4 (total water management) only. Hence, the comparision refered to in this section is between scenarios 1,2, and 3 in one hand and scenario 4 on the other hand.

Figure 9.12 presents two graphs showing the simulated annual urban runoff under scenarios 1–3 and under scenario 4. The simulation results suggest that the annual runoff under scenario 4 is predicted to be less than the one for the other scenarios by 13 – 32% throughout the simulation period. The mean annual urban runoff under scenario 4 is likely to be less than the other scenarios by 22.30%, 29.10%, and 32% during the period (2020 – 2030), (2031 – 2040) and (2041– 2050) respectively. Therefore, it is possible to suggest that urban runoff could be potentially reduced by up to one third when using alternative storm water management options such as rainwater harvesting and centralised groundwater recharge.

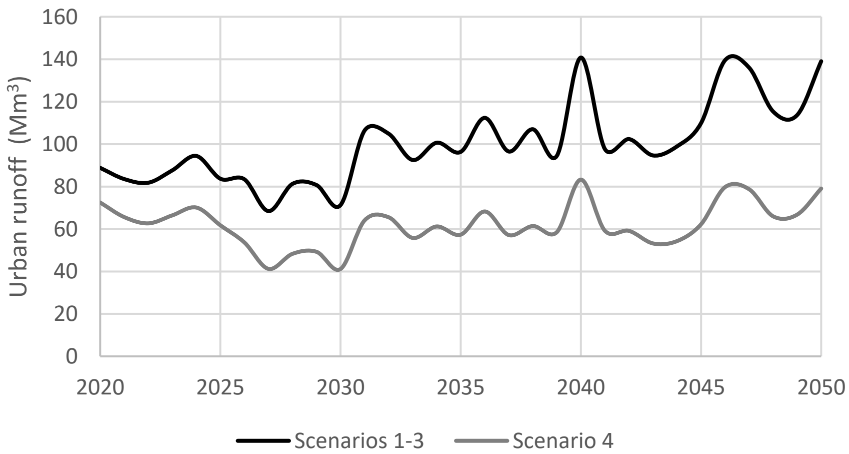


Figure 9. 12 "Simulated" urban runoff in the Dublin Region WSA for the period 2020 – 2050, for scenarios 1-baseline, 2-increase supply and 3-intensified leakage management (black line) and for scenario 4-total water management (dashed line). The simulations of urban runoff under all scenarios were based on the "recovery" urban growth.

To investigate the seasonality of urban runoff under the four water management scenarios, a monthly analysis of simulated urban runoff was conducted and shown in Figure 9.13. This figure presents the upper and lower bounds for the monthly urban

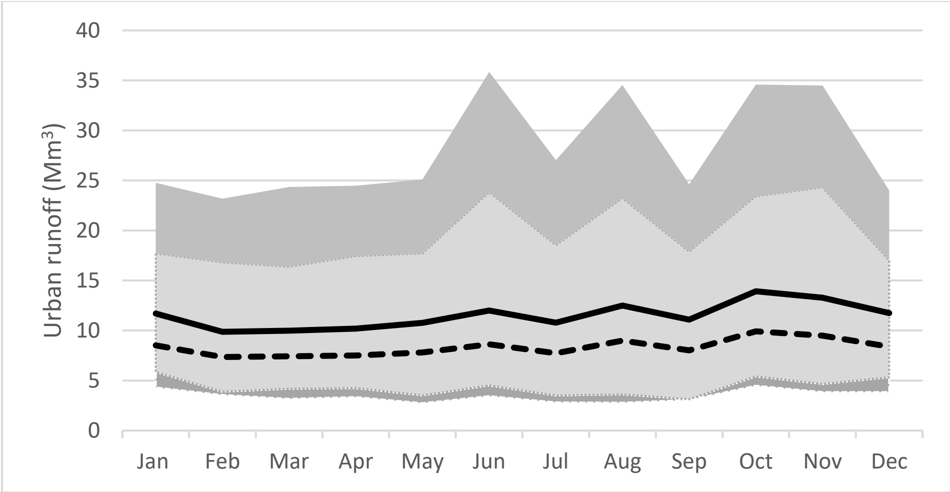


Figure 9. 13 Interval estimate of monthly urban runoff in the Dublin Region WSA for the period 2020 - 2050 under scenarios 1-3 (dark grey) and scenario 4 (light grey) – with monthly average urban runoff for scenarios 1-3 (black line) and scenarios 4 (dashed line).

runoff during the simulation period. The upper bounds of monthly runoff under scenario 4 is shown to be less than that of other scenarios during the simulation period. Moreover, the monthly average urban runoff under scenario 4 is predicted to be less than the one under other scenarios by 25 – 28% during the simulation period. Therefore, significant reductions in urban runoff may be achieved by implementing alternative storm water management measures, such as rainwater harvesting and centralised groundwater recharge.

The uncertainty in future urban runoff due to different urban growth projections was estimated under all water management scenarios. The urban growth scenarios used in this study are stagnation, delayed adjustment and recovery with urban areas projected to be 415.40 km^2, 429.20 km^2 and 436.90 km^2 by 2026, respectively (Willuweit et al. 2016). These projections were extrapolated up to 2050 using linear and exponential forecasting methods, resulting in six different urban growth projections. Future urban runoff under each of the six resulting urban growth projections was simulated for all management scenarios using the WEAP-Dublin model. The highest amounts of urban runoff are predicted under the recovery growth scenario with exponential extrapolation, while the lowest amounts are predicted under the stagnation growth scenario with linear extrapolation. The results of simulated urban runoff under all six urban growth projections for management scenario 4 and for all other scenarios are presented in Figure 9.14; each band of urban runoff in this figure represents projected uncertainty of urban runoff amounts under the corresponding water management scenario.

As shown in Figure 9.14, the uncertainty in predicted urban runoff due to the proposed urban growth scenarios varies between 3 million m^3 at the beginning of the simulation period and 34 million m^3 at the end of the simulation period. Under scenarios 1–3, the average annual urban runoff is likely to increase relative to that in the baseline year 2013 by 27–33%, 51–68% and 57–87% during the periods (2021–2030), (2031–2040) and (2041–2050) respectively. Under scenario 4, the average annual urban runoff is likely to increase relative to that in the baseline year 2013 at a lower rate by 0–1.50%, 3–21%, and 3–27% during the period (2021–2030), (2031 – 2040), and (2041 – 2050), respectively. Hence, it is clear that scenario 4 produced significant reductions in urban runoff by 20-23%, 28-33% and 36-43% during the period (2021–2030), (2031–2040) and (2041–2050). The median of the uncertainty band of urban runoff is reduced by up to 34% under scenario 4 relative to that under scenarios 1–3.

All these scenarios were also compared against a storm water management option where traditional drainage system is only used (i.e. absence of SuDS facilities). Figure 9.15 shows that in the absence of any SuDS facilities the upper and lower bounds of predicted urban runoff amounts are greater than in all other scenarios. The results suggest that in absence of any SuDS facilities the average annual urban runoff increases relative to all other scenarios where SuDS are used by 0.86 –1.10%, 1.30 – 2.00%, and 3.00 – 4.30% during the periods (2021 – 2030), (2031 – 2040), and (2041 – 2050) respectively. The slight effects of SuDS facilities on overall urban runoff may be explained by the fact that urban runoff generated from existing built-up areas are relatively large and the

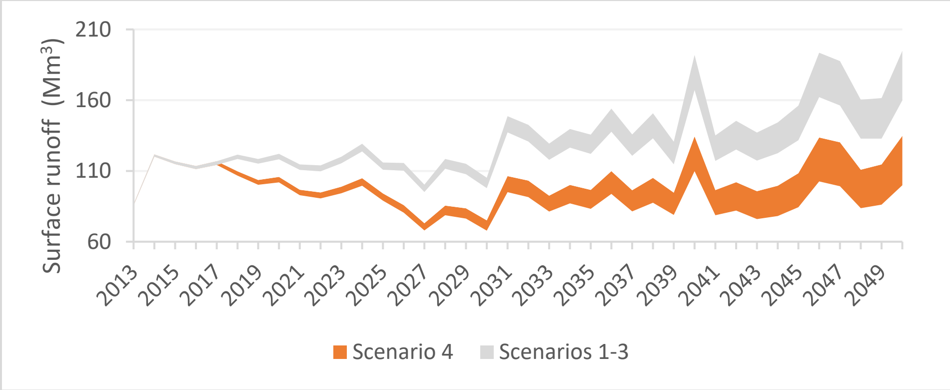


Figure 9. 14 Upper and lower bounds of urban runoff amounts in the Dublin Region 2013-2050 for scenario 4 and for all other scenarios as result of considering different urban growth scenarios.

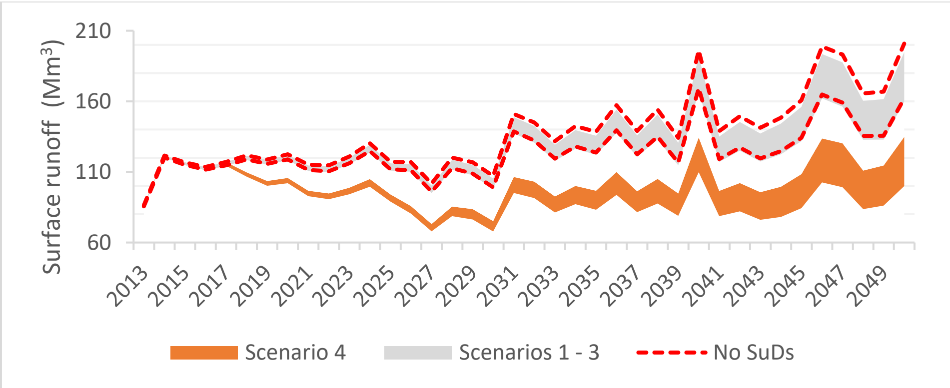


Figure 9. 15 Upper and lower bounds of urban runoff under all water management scenarios including a scenario where SuDS facilities are not implemented.

newly introduced SuDS facilities will occupy relatively small area. On the other hand, under scenario 4, the combined effects of SuDS and all additional storm water management options including harvesting systems and centralised groundwater recharge are likely to be more significant.

9.3 Groundwater storage

Groundwater modelling in the current study is limited to only estimating recharge from decentralised groundwater recharge facilities (or SuDS) and centralised groundwater recharge. Figure 9.16 displays the cumulative increase in groundwater storage during the simulation period as a result of implementing different storm water management options under scenarios 1 – 3 and under scenario 4. The graphs show that the total increases in groundwater storage by 2050 under scenarios 1 – 3 and scenario 4 are

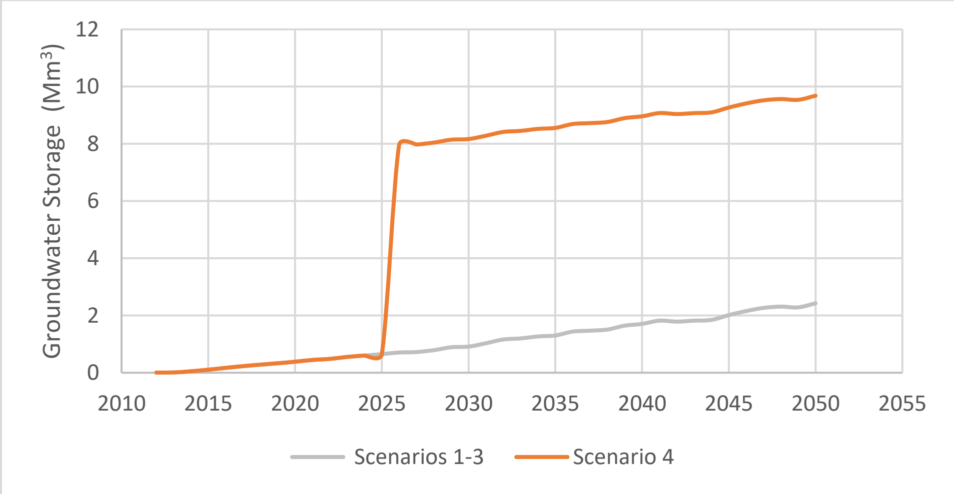


Figure 9. 16 Cumulative increase in groundwater storage during the simulation period 2012 – 2050 under scenarios 1 – 3 and scenario 4.

estimated to be 2.50 million m3 and 10 million m3 respectively. This suggests four times increase in the groundwater storages estimated under scenarios 1 – 3 when using the additional centralised groundwater recharge facilities under scenario 4. Also the graph shows a step increase in the groundwater storage from 0.70 million m3 to 8 million m3 under scenario 4 in 2026. This coincides with the commencement year of centralised groundwater recharge facilities.

Chapter 10 CONCLUSION

This chapter summarises the main contributions of this thesis and suggests possible directions for future research. The main aim of this thesis is to develop an integrated water resources management model for Dublin using the water evaluation and planning software (WEAP21). This has been achieved by configuring and parameterising the model using different datasets in terms of hydrology, water demand, infrastrucutre, census and climate data; and then calibrating and validating the model using flow and water use data. The capability of WEAP21 software for performing sensitivity and uncertainty analysis has been extended in this thesis by coupling the software with the statisitcal parameter optimisation tool (SPOTPY) and stochastic climate models such as the generalised linear model (GLM) framework and stochastic climate library (SCL). An example of using the developed model for the evaluation of different water management scenarios in the context of socio-economic growths and urban development projections is illustrated.

10.1 Contributions

An integrated water resources management model for the Dublin Region (WEAP-Dublin) is developed by integrating water supply catchments, sectoral water uses and infrastrucutre in one model. The developed model simulates the hydrology of the water supply catchments, sectoral water uses and the allocation of water between the competing water uses. The developed model reasonably reproduced natural flows, managed flows, and sectoral water uses in the catchment during the period 2012-2017. The predictions of flows of un-managed catchments by the model are more accurate than predictions of flows of managed catchments. This is mainly due to the absence of measurements of inflows to reservoirs which are located downstream of these catchments (e.g. Phollaphuca and Lexilip reserviors). These measurements are also important for detailed representation of reservior operations that are in place. Hence, the accuracy of the model, in particular for simulating managed catchments and corresponding flows, can be improved once measurements of reservoir inflows become available. Given these limitations, the model represents our best estimate for the water balance in the Liffey and Dublin Bay catchment and hence can be used with some caution as a tool for various water resources planning application.

This thesis has extended the capability of WEAP21 for analysing uncertainty in streamflow predictions which can result from uncertainties in parameters and forcing inputs. This has been done by coupling the software with the statistical parameter optimistion tool (SPOTPY) and stochastic climate models such as the generalised linear modelling framework (GLM) and the stochastic climate library (SCL). This framework has been applied for the WEAP21 model of Ryewater sub-catchment providing an example of using this framework for analysing uncertainty in streamflow predictions.

Using the developed framework, a parameter uncertainty analysis for the WEAP21 model of Ryewater sub-catchment has been performed based on the GLUE method. This analysis has reduced uncertainty in parameter ranges of the model by 30-70%. The analysis also has produced different groups of behavioural parameter sets for different objective functions such as NSE, LogNSE, %bias, and RSR, providing alternative WEAP21 rainfall-runoff models for understanding and predicting different characteristics of the flow hydrograph e.g. peak and low flows. All produced models from this analysis have underestimated some peak flows and overestimated some low flows suggesting potential errors in precipitation and flow measurement data. The median values for NSE, LogNSE, %bias and RSR statistics for each corresponding group were 0.54, 0.46, 0.22 and 0.69, respectively. Hence, this extension can be applied by WEAP21 users to reduce parameter uncertainty and to condition model predications providing an alternative approach to the manual and automatic calibration methods that are available by WEAP21 and which mostly focuses on defining one optimum model.

A variance-based sensitivity analysis method (Sobol's method) has been used to assess the total effects of model parameters on the variance output of the WEAP21 model of Ryewater sub-catchment. TSI values for all model parameters were found to be substantially larger than the corresponding S1 values suggesting the presence of higher order interactions between all parameters. The long-term average values of TSI indices for all parameters ranged from 0.95 to 1.13, while the average values of S1 indices ranged from -0.08 to 0.07. Moreover, the correlation between TSI indices of parameters and input data such as precipitation and temperature have been explored to identify the seasonal effects on sensitivities of model parameters. TSI indices for crop coefficient (*Kc*), runoff resistance factor (*rrf*), and root zone conductivity (*rzc*) were found to be negatively correlated with monthly precipitation values (r= -0.50 − -0.89, p-value ≤ 0.001) indicating that these parameters are more sensitive in dry months. In contrast, TSI indices for soil water capacity (*SWC*), deep water capacity (*DWC*) and deep conductivity (*dc*) were found to be positively correlated with monthly precipitation values (r= 0.50 − 0.70, p-value ≤ 0.001) indicating that these parameters are more sensitive in wet months. On the other hand, correlations between TSI indices of all parameters and temperature data were found to be weaker compared to their correlations with precipitation data. This sensitivity analysis framework can be used by modellers to define the most sensitive parameters of a hydrological model in a particular season, which then can be calibrated to develop specific model or set of models for the climatic season of interest (e.g. models focusing on prediction of flows during dry season or wet season).

Separate models for predicting flows of Ryewater sub-catchment in dry and wet seasons have been developed by calibrating the respective sensitive parameters in each season, which were identified from the sensitivity analysis, to reproduce the corresponding flow observations. A total of 10,000 models for each season were developed by sampling the corresponding parameter ranges using the Latin Hypercube sampling algorithm. Calibration of models for the dry season was based on LogNSE criterion, whilst calibration of models for the wet season was based on NSE. All models for predicting flows in the dry season overestimated some low flows and all the models for predicting flows in the wet season underestimated some peak flows. Simulation results from splitting the model into two seasons suggested no improvements over the results from the complete models (i.e. all seasons together). The median of LogNSE values for models of dry season was 0.36 and the median of NSE values for models of the wet season was 0.46, whilst the LogNSE and NSE for complete models of Ryewater were 0.46 and 0.54, respectively. A check of precipitation and flow data of Ryewater sub-catchment revealed that 10% of monthly precipitation input has rainfall volume less than the corresponding measured flow at the outlet of the sub-catchment. These inaccuracies in precipitation have likely caused underestimation of some peak flows and overestimation of low flows both in the complete models and the separate models for each season.

The effects of uncertainty due to forcing data input on WEAP21 model output of Ryewater sub-catchment were explored by using stochastically generated climate data. Ensembles of 100 rainfall sequences for Ryewater sub-catchments were produced using two different frameworks: the spatial generalised linear modelling (GLM) framework and the stochastic climate library (SCL). Each ensemble of simulated rainfalls was combined with each group of the 100 behavioural parameter sets of the WEAP21 model for the NSE and LogNSE criteria in order to generate ensembles of 10,000 simulated flows of Ryewater at the Lexilip flow gauging stations. All the resulting ensembles of simulated flows mostly captured the seasonal patterns of flow observations. The ensembles of simulated flows produced using the GLM data overestimated some low flows and underestimated some peak flows. On the other hand, the ensembles of simulated flows produced using the SCL data better enclosed the flow observations. These results indicate that the bias in estimating flows of Ryewater is likely influenced by errors in precipitation and flow data.

Moreover, this thesis investigated the effects of uncertainties in temperature and evaporation data on the model output − unlike most of uncertainty assessments in the literature which limited investigations of forcing inputs to rainfall. The SCL library was used to generate an ensemble of 100 stochastic temperature data for Ryewater sub-catchment during the period 1980-2013 which then were combined with the 100 behavioural parameter sets of the WEAP21 for the NSE criterion to produce ensemble of 10,000 simulated flows of Ryewater. The interval of the resulting ensemble of flow simulations produced by temperature data is found to be narrower than the one produced by rainfall data. These results suggest that uncertainties in flow simulations due to rainfall forcing are more dominant over uncertainties due to temperature forcing or parameter estimation.

The effect of model structure on predicative uncertainty of Ryewater flows is investigated by comparing simulations of WEAP21 with simulations from another model HBV-light. The comparison between performances of the best 100 models of WEAP21 and HBV-light on each of the NSE and LogNSE criteria showed that HBV-light model was superior at representing flows of Ryewater at Lexilip flow gauging station. One possible reason for this is that the modelling in HBV-light is based on higher resolution for climate and flow data than in WEAP21; HBV-light modelling is based on input data at a daily time step, while input data in WEAP21 modelling are consolidated at monthly time step. These results highlight that model structure and resolution of forcing data have strong impacts on the accuracy of flow predictions. It is recommended that the modeller select an appropriate model structure for representing the hydrology of the system and use appropriate temporal resolution for forcing data when developing integrated water resources management models.

This study has provided explicit knowledge on each source of uncertainty suggesting strategic guidance for future investments. It is suggested that future investments focus on collection and better conditioning of rainfall data and flow data (in particular for managed catchments). This in turn will ensure model results are within realistic bounds, and hence enabling a more robust water resources management model for decision-making in the catchment.

The thesis also provided an example of using the developed model (WEAP-Dublin) for assessing impacts of future water management scenarios on the water resources of Dublin. Four water management scenarios were considered: (1) baseline which represents status quo of the water resources system in Dublin, (2) increase supply as estimated by the proposed new water supply scheme for the Eastern and Midlands Region, (3) intensified leakage through recovering leakage to offset growing water demands; and (4) total water management which focuses on reducing water demands and increasing the reuse of storm water. The impacts of these scenarios on water resources of Dublin were investigated under likely future socio-economic growths and urban development projections during the period 2020-2050. The performances of these scenarios were compared based on main variables characterising the water resources system including: hydrological performance and supply reliability, urban runoff generation and groundwater recharge. Modelling results indicate that under scenario 1 the existing freshwater supplies in Dublin will be subject to severe stress and as a result a frequent water supply deficit is likely to occur. Moreover, there will also be a considerable increase in storm water discharges into receiving water bodies. Scenarios 2 and 3 were found to reduce pressure on the existing freshwater supplies, but there will still be a significant increase in storm water discharges into receiving water bodies. Scenario 4 is the only one which results in both a reduced pressure on existing freshwater supplies and reduced storm water discharges into receiving water bodies as it is assumed to use portion of storm water for recharging groundwater. Hence, integrating total water management options such as rainwater harvesting, greywater reuse, artificial groundwater recharge and sustainable urban drainage systems into the management plan of water resources in Dublin can produce tangible benefits over traditional practices in terms of lowering supplies from freshwater resources and increasing recharge of groundwater.

Hence, policy makers are advised to increase the coordination of their demands, decision-making and actions across all sectors of the water system (water, wastewater and strom water) in the Liffey and Dublin Bay basin. Like policies in relation to the use of sustainable urban drainage system, there is a need for stringent targets pertaining to the use of rainfall harvesting and wastewater re-use technologies as an alternative water supply options in order to achieve an integrated water resources management strategy. This can be supported by a sufficient budget that can provide subsidies for retrofitting existing buildings to incorporate the new on-site water supply technologies.

10.2 Study limitations

This section describes the limitations of the water resources management model of Dublin developed in this study:

- Climate data used for driving the hydrology model of each of the six sub-catchments are based on rainfall and synoptic gauging stations that are not uniformly distributed through the study catchment (Liffey and Dublin Bay catchment). This produces uncertainty flow simulations at the outlet of the catchment. The use of radar and satellite-based data may improve the accuracy of the model in predicting flows at the outlet of the sub-catchment.
- Detailed calibration of the managed sub-catchments were not possible due to absence of measurements of inflows to reservoir at the downstream of these catchments. This produced uncertainty in simulations of flows upstream of the abstraction points in these sub-catchment. Provision of flow data upstream the abstraction point in these sub-catchment are important for proper calibration of the model and for better understanding and representation of reservoir operation rules.
- The physical parameters pertaining the different land-uses and soils in the model are based on relative values to one another and not on actual measurements from field. Actual field data may improve the accuracy of the model in simulating hydrologic processes within sub-catchments and corresponding river flows.
- Water uses data were only available at regional level and hence parameterisation of the water allocation module of the water supply zones were based on estimations of water uses from different Irish studies. Actual water use data at the supply zone level will allow better estimation of water balance at the supply

zone level and hence proper calibration of the water management module in the model.

- The description of reservoir operations in the WEAP21 model are generalised and hence detailed representation of reservoir operations was not possible. The hydropower requirements used for modelling reservoirs in the model were based on annual average values reported by reservoirs operator, as actual monthly requirement were not available. This produced uncertainty in flows downstream the reservoirs in managed catchments.
- The evaluation of water management scenarios in this study is limited to analysing the performances in terms of decision variables such as supply reliability, urban runoff and groundwater recharge. The analysis did not consider the financial costs of scenarios in terms of implementation, maintenance and operation of the underlying water management options. This study also is limited to comparing the impacts of the water management scenarios on the water resources system as result of implementing different water supply and drainage options. This study did not consider the effects of climate change on the water management scenarios.

10.3 Directions for future research

Possible areas of future research are briefly discussed below:

Detailed calibiration of the managed sub-catchments were not possible due to absence of measurments of inflows to reservior at the downstream of these catchments. Provision of inflow data will allow better conditioning of the rainfall-runoff models of these sub-catchments and hence providing more reliable outputs. Moreover, availabilty of such data will allow performing the uncertainty analysis in managed catchments where the uncertainty of water demand or management parameters can be studied.

The description of reservoir operations in the WEAP21 model are generalised. Coupling WEAP21 with ad-hoc reservior models (e.g. RiverWareTM DSS) can help detailed representation of reservior operations and optimisation of the system. Hence, the extended model then can be used for informing management decisions pertaining to reservior operations.

The current study has relied on ground-based measurments for climate variables which are recorded at meterolgical stations. Recent studies have indicated that remotely sensed data or satellite-based data may offer particular advantages for improving flow predicitions of river catchments. A possible direction for future research can be the investigation of whether satellite-based data can improve flow predictions over the predicitions resulted from ground-based data.

The evaluation of water managemnet scenarios in this study is limited to analysing the performances in terms of decision variables such as supply reliability, urban runoff and groundwater recharge. The analysis did not consider the financial costs of scenarios in terms of implementation, maintenance and operation of the underlying water management options. The current work can be extended by performing a thorough cost-benefit analysis of these scenarios.

The current study so far has assessed the impacts of some future scenarios in terms of population, industrial and urban development growths on the water resources system in the Dublin Region. Future work in the project may assess additional impacts on the system due to climate and land use changes. The predicted changes in climate and land use will mainly alter the hydrology of the system which affects the reliable yeilds of existing water resources and hence the water production requirments of the region. Such analysis in turn can vaildate the estimation of potential production capacity of existing water sources of 650 Ml/day which has been made by Irish Water (2016b) without accounting for climate change impacts. Hence, the vulnerability of the water supply system in Dublin is thorougly investigated due to both climate and non-climate risks.

REFERENCES

Arnold J and Allen P (1993). A comprehensive surface-ground- water flow model. *Journal of Hydrology* **142** 47-69 (Cited in Yates et al. 2005).

Bach P M, Rauch W, Mikkelsen, P S, McCarthy D T and Deletic A (2014). A critical review of integrated urban water modelling Urban drainage and beyond. *Environmental Modelling & Software* **54** 88–107.

Bellin A, Majone B, Cainelli O, Alberici D and Villa F (2016). A continuous coupled hydrological and water resources management model. *Environmental Modelling & Software* **75** 176–192.

Beven K. and Binley A. (1992). The future of distributed models: Model calibration and uncertainty prediction. *Hydrological Processes* **6** 279–298.

Beven K. (2012). *Rainfall-Runoff Modelling*. West Sussex: John Wiley & Sons, Ltd.

Bicknell B, Imhoff J, Kittle J, Donigian A and Johanson R (1997). Hydrological Simulation Programe Fortran HSPF, User's Manual for Version 11. Athens, USA. (Cited in Bellin et al. 2016).

Brown R R, Keath N and Wong T H F (2009). Urban water management in cities: historical, current, and future regiemes. *Water Science. Technology* **59** 847-55.

Breuer L, Huisman J, Willems P, Bormann H, Bronstert A, Croke, B, et al. (2009). Assessing the impact of land use change on hydrology by ensemble modeling (LUCHEM). I: Model Intercomparison with current land use. *Advances in Water Resources* **32** 129–146. (Cited in Mokcler *et al* 2016a).

Butler D and Memon F A (2006). *Water Demand Management* International Water Association, London.

Chandler R and Wheater H (2002). Analysis of rainfall variability using generalised linear models: a case study from the west of Ireland. *Water Resources Research* **38** 1192-1201.

Chandler R (2015). *RGLIMCLIM: A Multisite Multivariate Daily Weather Generator based on Generalised Linear Models-User Guide*. University College of London, London: UK.

Chapra, S (1997) Surface Water Quality Modelling. New York: McGraw-Hill. (cited in Yates et al. 2005)

Chun K, Wheater H, and Onof C (2009). Streamflow estimation for six UK catchments under future climate scenarios. *Hydrological Research* **40** 96-112 (cited in Mockler et al. 2016a).

CIRIA (2015). *The SuDS Manual C753* (London: CIRIA Organisation)

Clark M, Slater A, Rupp D, Woods R. Vrugt J, Gupta H, et al. (2008). Framework for Understanding Structural Errors (FUSE): a modular framework to diagnose differences between hydrological models. *Water Resources Research* **44** W00B2.

CSO (Central Statistics Office) (2011). *Census 2011 Boundary Files* (Dublin: Central Statistics Office-Census).

DCC (Dublin City Council) (2010a). *The plan water supply project – the Dublin Region* (Dublin: Dublin City Council – Division of Water Waste and Environment) [Report prepared by RPS – Veolia JV consultants].

DCC (Dublin City Council) (2010b). *Environmental Report of the Dublin City Development Plan 2011 – 2017: Strategic Environmnetal Assessment (SEA)* (Dublin: Dublin City Council – Planning).

DCC (Dublin City Council) (2012a). *Demand for Drinking Water Dublin Region* (Dublin: Dublin City Council – Division of Water Waste and Environment).

DCC (Dublin City Council) (2012b). *Demographic trends in Dublin:* Dublin City Council – Think Dublin Research Series.

DCC (Dublin City Council) n.d. *Grey Water Reuse* (Dublin: Dublin City Council – Division of Water Waste and Environment) [Accessed online 30 Sept 2017]. Available from: http://www.dublincity.ie/main-menu-services-water-waste-and-environment-your-drinking-water-rainwater-harvesting/grey-water

DCENR (Department of Communication, Energy and Natural Resources) (2007). *Guidelines on the Planning, Design, Construction & Operation of Small-Scale Hydro-Electric Schemes and Fisheries*.

DDC (Dublin Drainage Consultancy) (2005a). *Greater Dublin Strategic Drainage Study*. [Accessed online 01 Nov 2015]. Available from: http://www.dublincity.ie/main-menu-services-water-waste-and-environment-drainage-services/regional-drainage-policies-overall

DDC (Dublin Drainage Consultancy) (2005a). Greater Dublin Strategic Drainage Study. *Regional policies–Volume 3 Environmnetal Management* [Accessed online 01 Aug 2017]. Available from: http://www.dublincity.ie/main-menu-services-water-waste-and-environment-drainage-services/regional-drainage-policies-overall

DDC (Dublin Drainage Consultancy) (2005b). Greater Dublin Strategic Drainage Study. *Regional policies–Volume 2 New Development* [Accessed online 01 Aug 2017]. Available from: http://www.dublincity.ie/main-menu-services-water-waste-and-environment-drainage-services/regional-drainage-policies-overall

Deltares (2010). RIBASIM (River Basin Simulation Model). Delft, the Netherlands. (Cited in Bellin et al. 2016).

DHI (Danish Hydraulic Institute) (2003). A Versatile Decision Support Tool for Integrated Water Resources Management Planning - Guide to Getting Started - Tutorial. Hørsholm, Denmark (Cited in Bellin et al. 2016).

DHI (Danish Hydraulic Institute) (2009). MIKE SHE–User Manual. Hørsholm, Denmark (Cited in Bellin et al. 2016).

Diaz-Granados M, Rodriguez J P, Rodriguez M S, Penagos J C, Camacho L, Achleitner S, Maksimovic C and Mclntyre N (2009). Towards a paradigm shift in urban drainage management and modelling in developing countries *Network of Scientific Journals of Latin America and the Caribbean, Spain and Portuga* **30** 133-55.

Ebrahimian A, Gulliver J and Wilson B (2015) *Determination of Effective Impervious Area in Urban Watersheds* Minnesota Department of Transportation, Research Services and Library [Accessed online 10th Sept 2017]. Available from: www.cts.umn.edu/Publications/ResearchReports/pdfdownload.pl?id=2626

Efstratiadis A, Nalbantis I, Koukouvinos A, Rozos E, Koutsoyiannis D (2008). HYDROGEIOS: a semi-distributed GIS-based hydrological model for modified river basins *Hydrology Earth System Science* **12** 989-1006.

Elliott A H and Trowsdale S A (2007). A review of models for low impact urban stormwater drainage. *Environmental Modelling and Software* **22** 394–405.

EPA (Environmental Protection Agency) (1996). *An assessment of the 1995 Drought* [Accessed online 05th August 2016]. Available form: Available from: https://www.epa.ie/pubs/reports/water/flows/EPA_Assessment_of_1995_Drought2.pdf

EPA (Environmental Project Agency) (2013). *Three Rivers Project* (Ref No.:MCOS/192/001/002/Rp0036 Rev F01) [Accessed online 05th August 2016]

Available form: http://www.epa.ie/licences/lic_eDMS/090151b28024963c.pdf

ESB (Electricity Supply Board International) (2011). *Preliminary Flood Risk Assessment - ESB Dams and Embankments* [Accessed online 05th April 2016] Available form: http://www.cfram.ie/pdfs-downloads/TechDocs/PFRA%20-%20ESB%20Dams%20&%20Embankments%20(draft).pdf

ESB (Electricity Supply Board International) n.d. River Liffey Hydro-Electric Stations Bullatin [Accessed online 15th August 2016]. Available from: https://ruralelectric.files.wordpress.com/2016/02/river-liffey-hydro-electric-stations-pr-pamphlet.pdf

EU Comission (2000). *Water Framework Directive*. Directive 2000/60/EC European Parliament and Council.

Fealy R. M, Green S, Loftus M, Meehan R, Radford T, Cronin C and Bulfin M (2009). *Teagasc EPA Soil and Subsoils Mapping Project-Final Report Volume I* Teagasc. Dublin

Fedra K and Jamieson D G (1996). The WaterWare decision- support system for river basin planning: II. Planning Capability. *Journal of Hydrology* **277** 177-98 (Cited Yates et al. 2005)

Feldman A D (2000). Hydrologic Modeling System HEC-HMS Technical Reference Manual. Davis, USA. (Cited in Bellin et al. 2016)

Fitzpatrick J and Bree T (2001). Flood risk management : through reservoir storage and flow control - ESB International. In the: *National Hydrology Seminar pp.87–96.*, Ireland.

Giupponi C J, Mysiak A, Fassio and Cogan V (2004). MULINO- DSS: a computer tool for sustainable use of water resources at the catchment scale. *Mathematics and Computers in Simulation* **64** 13-24.

Gupta H, Clark M, Vrugt J, Abramowitz G, Ye M (2012). Towards a comprehensive assessment of model structural adequacy. *Water Resources* **48** W08301

GWP (Global Water Partnership) (2012). *Integrated water resources management* Technical Advisory Committee (TEC) Background paper no. 12. (Stockholm: Global Water Partnership)

Hall J and Murphy C (2010). Vulnerability analysis of future public water supply under changing climate conditions: a study of the Moy catchment, western Ireland. *Water Resources Management* **24** 3527–45.

Hall J and Murphy C (2011). Robust adaptation assessment - climate change and water supply *International Journal of Climate Change Strategies and Management* **3** 302-319.

Herman J and Usher W (2018). *SALib Documentation – Release 1.1.2.post0.dev22+ngfd64136 [*Accessed online 15th July 2018] Available from: [https://media.readthedocs.org/pdf/salib/latest/salib.pdf]

Houska T, Kraft P, Chamorro-Chavez A and Breuer L (2015). SPOTting model parameters using a ready-made python package. *PLoS ONE* **10** 1–22.

Irish Water (2015a). *Project Need Report* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water).

Irish Water (2015b). *Appendix C – Water Demand Review* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water) [Report prepared by Jacobs and Tobin consultant].

Irish Water (2015c). *First Fix Leak Scheme – For domestinc water customers* (Dublin: Irish Water).

Irish water (2015d). *Summary of Demographic Projections* Water Supply Project Eastern and

Midlands Region [Report prepared by AOS planning consultant].

Irish Water (2015e). *Options Working Paper (OWP)* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water).

Irish Water (2015f). *Preliminary Options Appraisal Report (POAR)* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water).

Irish Water (2016a). *Water Supply Project - Project Overview)* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water) Available at: http://www.watersupplyproject.ie/wp-content/uploads/2014/10/Water-Supply-Project-Overview-March-2017_web.pdf.

Irish Water (2016b). *Final Options Appriasl Report (FOAR)* (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water) [Report prepared by Jacobs and Tobin consultant].

Irish Water (2016c). *Appendix –A Interim Midlands and GDA Water Resources Plan*, Final Options Appriasl Report (FOAR) (Water Supply Project – Eastern and Midlands Region) (Dublin: Irish Water).

Irish Water (2018a). *Demands has risen to concerning levels* Available at: https://www.water.ie/news/water-restrictions-will-b-5/ [accessed on line on August 2018].

Irish Water (2018b) Natitional Water Resources Plan (NWRP) [Accessed online 15 Jan 2018]. Available from: https://www.water.ie/projects-plans/our-plans/nwrp/

Jabloun M and Sahli A (2006). Development and comparative analysis of pedotransfer functions for predicting characteristic soil water content for Tunisian soil, *In: Tunisia-Japan Symposium on Society, Science and Technology proceeding, 7th Edition, pp. 170-178* (Cited in SEI 2005).

Karamouz M, Moridi A and Nazif S (2010). *Urban Water Engineering and Management* Boca Raton: Taylor & Francis Group.

Kavetski D, Kuczera, G, and Franks S (2006). Bayesian analysis of input uncertainty in hydrological modeling: 2. application. *Water Resources Research* 42 W03408 (cited in Mockler et al. 2016a).

Kellner J, Multsch S, Houska T, Kraft P and Muller C (2017). A coupled hydrological-plant growth model for simulating the effect of elevated CO2 on a temperate grassland. *Agricultural and Forest Meteorology* 246 42–50.

Kelly-Quinn M, Blacklocke S, Bruen M, Earle R, O'Neill E, O'Sullivan J and Purcell P (2014). Dublin Ireland: A city addressing challenging water supply, management, and governance issues *Ecology and Society* **19** 1-13

Klemeš V (1986). Operational testing of hydrological simulation models *Hydrological Sciences* **31** 13–24 (Cited in Hall and Murphy 2010)

Kolb B, O'Carroll J and Walker J (2008). *Revised River Risk Assessment for Abstraction Pressures* (Eastern River Basin District Project) (Dublin: Water Framework Directive Ireland)

Labadie J, Brazil L, Corbu I and Johnson L, (eds) (1989). *Computerized Decision Support systems for Water Managers* New York: American Society of Civil Engineers. (Cited in Yates et al. 2005)

Lampert D, Wu M, (2015). Development of an open-source software package for watershed modeling with the Hydrological Simulation Program in Fortran. *Environmental Modelling Software*. **68** 166-174 (Cited in Bellin et al. 2016)

Li Y, Huang G, Huang Y, Zhou H, (2009). A multistage fuzzy-stochastic programming model for supporting sustainable water resources allocation and management *Environmental Modelling Software* **24** 786–797 (Cited in Bellin et al. 2016)

Lloyd S D (2001). Water Sensitive Design in the Australian Context. Synthesis of a conference held August 30–31, 2000 Melbourne: Cooperative Research Centre for Catchment Hydrology Technical Report 01/7

Loucks D P, van Beek E, Stedinger J, Dijkman J and Villars M (2005). *Water Resources Systems Planning and Management and Applications: An Introduction to Methods, Models and Applications* Paris: UNESCO Publishing

Lydon K, and Smith G (2014). *CORINE Landcover 2012 Ireland – Final Report.* (Prepered on behalf of Environmental Protection Agency, Ireland)

Mantel S K, Hughes D A and Slaughter A S (2015). Water resources management in the context of future climate and development changes: a South African case study *Journal of Water and Climate Change*. **8** (3) 772–786.

Marsalek J, Jiménez-Cisneros, B E, Malmquist, P A, Karamouz, M, Goldenfum J, Chocat B. (2006). Urban water cycle processes and interactions. *IHP-VI Technical Documents in Hydrology No. 78*, UNESCO, Paris, 2006.

MCC (Mississauga City Council) (2016). *Understanding Your Stormwater Charge* [Accessed online 15th Sept2017]. Available from: http://www.mississauga.ca/portal/stormwater/charge

Mccartney M P and Arranz R (2007). *Evaluation of Historic, Current and Future Water Demand in the Olifants River Catchment, South Africa* (Research Reprot 118) (Colombo: International Water Management Institute)

Mehta V, Aslam O, Dale L, Miller N and Purkey D (2013). Scenario-based water resources planning for utilities in the Lake. *Physics and Chemistry of Earth* **61** 22-31.

Mitchell V G, Duncan H, Inman M, Rahilly M, Stewart J, Vieritz A, Holt P, Grant A, Fletcher T D, Coleman J, Maheepala S, Sharma A, Deletic A and Breen P (2007). State of the art review of integrated urban water models. In: *NovaTech (2007), Lyon France.*

Mockler E, Chun K, Sapriza G, Bruen M and Wheater H (2016a). Assessing the relative importance of parameter and forcing uncertainty and their interactions in conceptual hydrological model simulations. *Advances in Water Resources* **97** 299-313.

Mockler E, O'Loughlin, F and Bruen M (2016b). Understanding hydrological flow paths in conceptual catchment models using uncertainty and sensitivity analysis. *Computers and Geosciences* **90** 66–77.

Monteith J L (1965). Evaporation and environment *Symposium Society for Experimental Biology* **19** 205–24.

Moriasi D N, Arnold J G, Van Liew M W, Bingner R L, Harmel R D and Veith T L (2007). Modelling evaluation guidelines for systematic quantification of accuracy in watershed simulation. *American Society of Agricultural and Biological Engineers* **50** 885–900.

Muschalla, D, Schütze M., Schroeder K., Bach M, Blumensaat F, Klepiszewski K, Pabst M, Pressl A, Schindler N, Wiese J and Gruber G (2008). The HSG guideline document for modelling integrated urban wastewater systems. In: *11th Inter- national Conference on Urban Drainage. Edinburgh, Scotland, UK.*

MRC (2004). Decision Support Framework, Water Utilisation Project Component A: Final Report, vol. 11. Technical Reference Report, DSF 620 SWAT and IQQM Models. Phnom Penh, Cambodia (Cited in Bellin et al. 2016).

Nalbantis I, Efstratiadis A, Rozos E, Kopsiafti M and Koutsoyiannis D (2011). Holistic versus monomeric strategies for hydrological modelling of human-modified hydro-systems. *Hydrology and Earth System Sciences* **15** 743–758.

Neitsh, S L, Arnold J G, Kiniry J R, Williams J R (2011). Soil and Water Assessment Tool: Theoretical Documentation Version 2009. Tech. Rep. TR406-2011. Texas A&M University, Texas Water Resources Institute, College Station, Texas, 77843-2118. (Cited in Bellin et al. 2016).

Nolan P. (2015). *Ensemble of Regional Climate Model Projections for Ireland -Report Number: 159*, Report prepared for the Environmental protection Agency, Ireland

O'Loughlin F Bruen M and Wagener T (2013). Parameter sensitivity of a watershed-scale flood-forecasting model as a function of modelling time-step. *Hydrology Research* **44** 334–350. [Cited in Mockler et al. 2016a]

OPW (Office of Public Work) (2012a). *Eastern CFRAM Study: HA09 Inception Report* [Ref No.: IBE0600Rp0008_F02/Aug2012] (Report prepared by RPS group). [Accessed online 05 April 2016]. Available from: http://eastcfram.irish-surge-forecast.ie/wp content/uploads/2011/10/IBE0600Rp0008_HA09-Inception-Report_F02.pdf

OPW (Office of Public Work) (2012b). *Eastern CFRAM Study: Liffey Flood Controls and Flood Forecasting System Option* [Ref No.: IBE0600Rp0010] (Report prepared by RPS group). [Accessed online 05th April 2016]. Available from: http://www.opw.ie/en/media/Liffey%20Flood%20Controls%20and%20Flood%20Forecasting%20System%20Option%20report.pdf

OPW (Office of Public Work) (2016a). *Eastern CFRAM Study: HA09 Hydrology Report* [Ref No.: IBE0600Rp0015] (Report prepared by RPS group). [Accessed online 05th April 2016]. Available from: http://www.cfram.ie/otherprojects/IBE0600Rp0016_HA09%20Hydrology%20Report_F02.pdf

OPW (Office of Public Work) (2016b). *Eastern CFRAM Study: Stage 2 Radar Report* [Ref No.: IBE0600Rp0016] (Report prepared by RPS group). [Accessed online 05th April 2016]. Available from: http://www.opw.ie/en/media/Eastern%20CFRAM%20%20Analysis%20of%20Radar%20Rainfall%20Data.pdf

OPW (Office of Public Work) (2016c). *Eastern CFRAM Study: HA09 Hydraluics Report* [Ref No.: IBE0600Rp0027] (Report prepared by RPS group). [Accessed online 05th Jan 2017]. Available from: http://eastcfram.irish-surge-forecast.ie/wp-content/uploads/2011/10/Liffey-Hydraulics-Report-HA09.pdf

Renard B, Kavetski D, Kuczera G, Thyer M and Franks S (2010). Understanding predictive uncertainty in hydrologic modelling: The challenge of identifying input and structural errors. *Water Resources Research*. **46** W05521

Rodrigo D, Calva E J L and Cannan A (2012). *Total water management* (Cincinnati, OH: U.S Environmental Protection Agency)

Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M and Tarantola S (2010). Variance based sensitivity analysis of model output. Design and estimator of total sensitivity index. *Computer Physics Communications* **181** 259-270.

Schmitt T G and Huber W C (2005). The scope of integrated modeling – system boundaries, sub-systems, scales and disciplines. In: *the10th International Conference on Urban Drainage, 21-25 August 2005 Copenhagen, Denmark.*

SEI (Stockholm Environemmt Institute) (2015). *WEAP21: Water Evaluation And Planning user guide*. Available from https://www.weap21.org/

SEI (Stockholm Environemmt Institute) (2015). *WEAP21: Water Evaluation And Planning* [Software]

Seibert J. HBV light. Version 2. User's Manual. Stockholm; (2005).

Seibert J. and Vis M. (2012). Teaching hydrological modeling with a user-friendly catchment-runoff-model software package. *Hydrology and Earth System Sci*ences, **16** 3315–3325.

Shin M, Guillaume J, Croke B and Jakeman A (2013). Addressing ten questions about conceptual rainfall–runoff models with global sensitivity analyses in R. *Journal of Hydrology*. **503** 135–152

Simons M, Podger G, Cooke R, 1996 Iqqm– hydrologic modelling tool for water resource and salinity management. *Environmental Modelling Software* **11** 185-192 (Cited in Bellin *et al* 2016).

Singh G, (2012). *GIS in Water Resources Engineering* Delhi: SBS Publishers & Distributors PTV. LTD.

Sirkanthan S, Chiew F and Frost A (2007). *Stochastic Climate Library - User guide. CRC for Catchment Hydrology*, Australia. [Accessed online 01st Aug 2018] Available from: [https://toolkit.ewater.org.au/Tools/SCL].

Sitzenfrei R, Möderl M, and Rauch W (2013). Assessing the impact of transitions from centralised to decentralised water solutions on existing infrastructures – Integrated city-scale analysis with VIBe. *Water Research* **47** 7251–7263.

Steele-Dunne S, Lynch P, McGrath R, Semmler T, Wang S, Hanafin J and Nolan P (2008). The impacts of climate change on hydrology in Ireland. *Journal of Hydrology*. **325** 28–45.

Stibinger J, (2014). Examples of Determining the Hydraulic Conductivity of Soils: Theory and application of selected basic methods. Jan Evangelista Purkyně University Handbook on soil hydraulics [accessed on 20th July 2016] Available from: http://envimod.fzp.ujep.cz/sites/default/files/skripta/16e_final_tisk.pdf

Subramanya K (2005). *Engineering Hydrology, Fourth Edition* New Delhi: McGraw Hill Education.

Sun X Newham L Croke B and Norton J (2012). Three complementary methods for sensitivity analysis of a water quality model. *Environmental Modelling Software* **37**, 19–29 (Cited in Mockler et al. 2016a).

Tang Y, Reed P, Wagener T and van Werkhoven K (2007). Comparing sensitivity analysis methods to advance lumped watershed model identification and evaluation. *Hydrology Earth System Science* **11** 793–817 (Cited in Mockler et al. 2016a).

Tchobanoglous G and Schroeder E (1985) *Water Quality: Characteristics, modeling and modification*. Reading MA: Addison-Wesley Publishing Co. [cited in Yates et al. 2005]

Tedd P (2002). Reservoirs in a changing world. In the: *12th Conference of the The British Dam Society, 4-8 September 2002,* Trinity College Dublin: ICE Publishing

The Agricultural Institute (An Foras Talúntais) (1980). *Soil Associations of Ireland and their Land Use Potential: Explanatory Bulletin to Soil Map of Ireland* Dublin: Mount Salus Press Limited

Todini E (2009). Predictive uncertainty assessment in real time flood forecasting. in: P Baveye (Eds.) Uncertainties in Environmental Modelling and Consequences for Policy Making. Springer Netherlands, pp. 205-228 (Cited in Mockler et al. 2016a).

Tsoukalas I and Makropoulos C (2015). A Surrogate based optimisation approach for the development of uncertainty-aware reservoir operation rules: the case of Nestos Hydro-system. *Water Resources Management* **29** 4719-4734.

Urich C, Bach P, Sitzenfrei R, Kleidorfer M, McCarthy D, and Deletic A (2013). Modelling cities and water infrastructure dynamics. In: the *ICE - Engineering Sustainability, 16 October 2013,* ICE Publishing.

USACE (US Army Corps of Engineers) (2003). Hydrologic Engineering Center HEC-ResSim, Reservoir System Simulation User's Manual Version 2.0. CPD-82. Davis, CA: USACE (Cited Yates et al. 2005)

USDA (United States Department of Agriculture) n.d. Soil Survey: Saturated hydraulic conductivity (USDA: Natural Resources Conservation Services Soils) [Accessed online 10 June 2016). Available from: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/office/ssr10/tr/?cid=nrcs144p2_074846

Van Lennep E and Finn S (2008). *Green Roofs Over Dublin* – A Green Roof Policy Guidance Paper for Dublin (Dublin: Dublin City Council).

van Werkhoven K, Wagener T, Reed P and Tang Y (2008). Characterization of watershed model behavior across a hydro-climatic gradient. *Water Resources Research.* **44**. W01429 (Cited in Mockler et al. 2016a)

van Werkhoven K, Wagener T, Reed P and Tang Y (2009). Sensitivity-guided reduction of parametric dimensionality for multi-objective calibration of watershed models. *Advances in Water Resources*. **32** 1154–1169. (Cited in Mockler et al. 2016a).

Vojinovic Z and Seyoum S (2008). Integrated urban water systems modelling with a simplified surrogate modular approach. In *11th International Conference on Urban,* 2008, *Edinburgh, Scotland.*

Walker W, Harremoës P, Rotmans J, van der Sluijs J, van Asselt M, Janssen P, Krayer von Krauss M (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*. **4** 5–17. (Cited in Mockler et al. 2016a).

Ward S, Farmani R, Atkinson S, Butler D, Hargreaves A, Cheng V, Denman, S, Echenique M, (2012). Towards an integrated modelling framework for sustainable urban development. In: *9th International Conference on Urban Drainage Modelling (9UDM), Belgrade, Serbia*

Welsh W D *et al* (2013). An integrated modelling framework for regulated river systems. *Environmental Modelling Software.* **39** 81–102.

Wheater H, Bishop K and Beck M (1986). The identification of conceptual hydrological models for surface-water acidification. Hydrological Processes. **1** 89–109. (Cited in Mocker et al. 2016a)

Willuweit L and O'Sullivan J (2013). A decision support tool for sustainable planning of urban water systems: Presenting the Dynamic Urban Water Simulation Model. *Water Research, 47* 7206-22.

Willuweit L, O'Sullivan J and Shahumyan H (2016). Simulating the effects of climate change, economic and urban planning scenarios on urban runoff patterns of a metropolitan region. *Urban Water Journal, 13* 803-818.

Yang C, Chandler R, Isham V and Wheater H (2005). Spatial-temporal rainfall simulation using generalised linear models. *Water Resources Research* **41** (11).

Yates D, Sieber J, Meldrum J and Young C (2013a). A water resources model to explore the implications of energy alternatives in the southwestern US *Environmental Research Letter* **8** 045004.

Yates D, Meldrum J and Averyt K (2013b). The influnce of future electricity mix alternatives on southwestern US water resources. *Enivronmental Research Letter* **8** 045005.

Yates D, Sieber J, Purkey D, Huber-Lee A (2005). WEAP21 – a demand- , priority- , and preference-driven water planning model part 1 : model characteristics. *Water International.* **30** 487–500.

Yates D, Purkey D, Sieber J, Huber-Lee A, Galbriath H, West J, Herrod-Julius S, Young C, Joyce B and Rayej M (2009). Climate driven water resource model of the sacramento basin, California *J. Water Resources Planning and Management.* **135** 303–313.

Young C, Escobar-Arias M, Fernandes M, Joyce B, Kiparsky M, Mount J, Mehta V, Purkey D, Viers J, and Yates D (2009). Modeling the hydrology of climate change in California's Sierra Nevada for subwatershed scale adaptation. *Journal of the American Water Resources Association* **45** 1409–1423.

Younger P (2009). Groundwater in the Environment: an Introduction. Blakcwell, London (cited in Mockler *et al* 2016a)

Younger P M, Freer J and Beven K J. (2009). Detecting the effects of spatial variability of rainfall on hydro- logical modelling within an uncertainty analysis framework. *Hydrological Processes* **23** 1988–2003.

Zagona E, Fulp T, Shane R, Magee T and Goranflo H (2001). RiverWare: A generalized tool for complex reservoir systems modeling. *Journal of the American Water Resources Association* **37** 913-29 (Cited in Bellin *et al* 2016 and Yates *et al* 2005)

Appendix A.1: Information on Liffey reservoirs operations provided through personal communication with ESB

Mohammed,

Please see below responses in red to your previous request.

Best Regards,
Cathal

Cathal Smith | Supervising Engineer | Turlough Hill & Liffey Stations | 72226 | 01 2137231 | M: +353 87 9704701 | www.esbi.ie

ESB International, Stephen Court, 18/21 St. Stephen's Green, Dublin 2, Ireland.

Dear Cathal,

Thanks for your email, my updated request was as below.

I am emailing you to seek your kind support again for the PhD project "Development of Integrated Urban Water Management Model for Dublin City" through providing additional information in relation to the Liffey Scheme Reservoirs and the Hydropower stations. These include;

(i) Volume elevation curves for the following reservoirs: Golden Falls and Lexilip Storage curves attached.

(ii) Monthly reservoir storage data / monthly-observed volumes for Pollaphuca, Golden Falls and Lexilip for each month. Hourly water level data attached for Golden Falls and Leixlip and daily water level attached for Pollaphuca. You can use this level data to translate it to the equivalent storage information you require.

(iii) The percentage of month that each hydropower is in operation for each of the Reservoirs; Pollaphuca, Golden Falls and Lexilip. (i.e. total number of hours the hydropower is in operation per month) I'm not sure if this information is of much use to your hydraulic model as if the dams are spilling water through the spillways this information would not be captured by the percentage of the time that the turbines are running. I've sent you the average daily discharge figures for the 3 dams which should be enough for your modelling purposes.

(iv) Target monthly or annually hydropower production (MWH) for each of the three stations; Pollaphuca, Golden Falls and Lexilip We do not have target production levels as it's based on the water levels in the reservoirs which is completely dependent on the availability of water in the system.

We highly appreciate if you please indicate to us whether you will be able to provide us with such information, or other data which may be helpful for estimating the above.

Should you require further details, please feel free to contact me
Mohammed Yassin

Appendix B.1: Formal Data Request to Irish Water

Irish Water
Colvill House, Talbot Street, Dublin 1
Dublin 1

Attention: Innovation & Technology Department

Re: Possibility to facilitate access to data for the PhD Project 'Development of Integrated Urban Water Management Model for Dublin City'

My name is Mohammed Yassin, and I am a PhD student at Dublin Institute of Technology, working on the project of 'Development of Integrated Urban Water Management Model for Dublin City. I am writing this letter to introduce you to the project, and to seek your kind support through facilitating access to some data required for the project.

The PhD project aims to develop an Integrated Urban Water Management Model for Dublin City, through which different alternatives, proposed to manage urban water resources system in Dublin, will be assessed and evaluated under future scenarios of climate change, population, and economic growth projections. The project intends to provide a predictive tool as well as technical information for stakeholders involved in the Water Resource Planning and Management to support the design of an optimum water management strategy. [For further information on the project please refer to the attached proposal (Ref: Research Proposal) and to the schematic framework and project activities (Ref: Schematic Framework and timeline)]

I am currently in the process of collecting data to develop the mathematical model, and at this stage, some data of interest to the project have been found to be not publically available. These include;

- Geo-referenced data for water supply infrastructure in Dublin Region, including reservoirs, water treatment plants and major water mains
- Geo-referenced data for water supply zones, and district metred areas (DMAs) within the Dublin City administrative areas.
- Water Flow data for DMAs of Dublin City Water Supply Zones [in particular DMAs of Water Supply Zones (1) and (3).
- Geo-referenced data for foul catchments and storm water / river catchments as in the Greater Dublin Drainage Strategic Study
- Georeferenced data for drainage networks and major sewer trunks running through Dublin Drainage Study Area
- Wastewater flows data, in particular for areas or catchments of Dublin City, for example, the following catchment; City Centre / Docklands, Grand Canal, and Rathmines & Pembroke Sewerage

It is highly appreciated if you please indicate to us whether such data are available within your organisation. We also value your guidance to what sources we may approach in case you know that data are available somewhere else (i.e. a partner council)

Should there are certain procedures we need to follow with regard to accessing data from your organisation, please feel free to advise us with them
Please feel free to contact us shall you require any additional information
I look forward to hearing from you

Yours truly,
Mohammed Yassin
c.c.: Dr. Ahmed Elssidig Nasr

Appendix B.2: Formal Data Request to ESB

Electricity Supply Board (ESB)
Stephen Court, 18/21 St. Stephen's Green,
Dublin 2

Re: Possibility to facilitate access to data for the PhD Project 'Development of Integrated Urban Water Management Model for Dublin City'

My name is Mohammed Yassin, and I am a PhD student at Dublin Institute of Technology under the research project titled above. I am writing this letter to introduce you to this project, and to seek your kind support through facilitating access to some hydrometric data, which are essential to the project.

The PhD project aims to develop an Integrated Urban Water Management Model for Dublin City, through which different alternatives, proposed to manage urban water resources system in Dublin, will be assessed and evaluated under future scenarios of climate change, population, and economic growth projections. The project intends to provide a predictive tool as well as technical information for stakeholders involved in the Water Resource Planning and Management to support an optimum design of a water management strategy. [Please refer to the attached documents for further information on the project.

The project has identified a number of hydrometric stations in interest to the project, and which are being operated and managed through ESB. I am therefore writing this letter to seek the possibility of your kind support in providing access to hydrometric data of the following stations for the Year 2012 and beyond;

Station Number	Station Name	Water Body	Station Status	Catchment Area
09032	POLLAPHOUCA	LIFFEY	Active	317.6 km2
09007	GOLDEN FALLS	LIFFEY	Inactive	324.60 km2
09022	LEIXLIP STATION	LIFFEY	Active	848.10 km2
09013	STRAFFAN D/S	LIFFEY	Active	678.10 km2

Should there are certain procedures we need to follow with regard to requesting or accessing data from your organisation, please feel free to advise us with them

Please feel free to contact us shall you require any additional information

Your assistance is highly appreciated

I look forward to hearing from you
Yours truly,
Mohammed Yassin
c.c.: Dr. Ahmed Elssidig Nasr

Appendix C.1: Data status table for rainfall stations located within or close to the Liffey and Dublin bay catchment.

Station No.	Station Name
2415	GLEN IMAAL (FOR.STN.)
1420	GLENMACNASS
2420	OLDBRIDGE (OAKVIEW)
3223	GLENBRIDE LODGE
3823	BALLYMORE EUSTACE D.C.W.W.
8623	BLESSINGTON (HEMPSTOWN)
8423	NAAS (OSBERSTOWN)
5323	NAAS (C.B.S.)
9323	SALLINS (KERDIFFSTOWN)
8823	STRAFFAN (TURNINGS)
7923	BRITTAS (GLENARANEEN)
8123	CELBRIDGE (ARDRASS HOUSE)
7214	Lullymore_Nature_Centre
5631	ENFIELD (NEWCASTLE HOUSE)
3723	Casement
1923	GLENASMOLE D.C.W.W.
5623	GLENASMOLE (SUPT'S LODGE)
5523	GLENASMOLE (CASTLEKELLY)
1332	MALAHIDE CASTLE
3524	BALLYEDMONDUFF HOUSE
175	PHOENIX PARK
1823	DUBLIN (GLASNEVIN)
9223	DUN LAOGHAIRE
7523	DUBLIN (SIMMONSCOURT)
3923	DUBLIN (MERRION SQUARE)
2523	DUBLIN (RINGSEND)
532	Dublin_Airport
2931	WARRENSTOWN
2532	DUNSHAUGHLIN (LAGORE)
2432	RATOATH
2632	FAIRYHOUSE RACECOURSE

Include Temp. , Grass Temp., 10cm soil temp

Include Temp. , Grass Temp., 10cm soil temp., Mean CBL pressure

Include Temp, Grass Temp, Wind Speed and Direction, Highest Guest, PET, Evap., Soil Moisture Deficit well, moderate and poorly

Available as monthly only

Appendix C.2: Area weighted monthly time series rainfall data for each river sub-basin used to drive the Dublin-WEAP model

Mon	Year	UL1	ML1	ML2	ML3	ML4	ML5	ML6	ML7	RW1	LL1	LL2	DD1	DD2
Jan	2012	121.2	91.9	76.0	77.5	73.5	71.9	84.5	68.3	75.8	69.6	74.7	95.4	77.8
Feb	2012	46.4	32.7	24.8	26.6	23.5	19.5	31.8	19.8	22.9	21.0	23.9	33.4	24.2
Mar	2012	32.0	24.6	25.9	22.4	26.8	17.4	25.5	19.6	22.0	28.4	28.3	29.7	19.4
Apr	2012	188.7	117.9	111.7	125.1	111.3	88.8	134.9	102.7	101.4	99.1	109.3	150.8	107.0
May	2012	83.0	53.1	45.6	49.8	43.3	54.4	61.4	57.1	56.7	64.6	70.3	97.8	77.8
Jun	2012	249.2	172.9	165.7	165.3	163.4	140.6	175.8	138.3	147.9	173.2	184.1	228.7	216.5
Jul	2012	140.7	107.2	121.3	121.7	123.1	113.6	125.6	127.1	122.8	105.6	116.4	141.0	119.1
Aug	2012	148.5	139.9	101.2	106.1	97.0	93.6	106.7	78.7	86.9	72.9	79.6	115.3	98.4
Sep	2012	131.9	99.5	78.0	84.0	75.2	68.8	95.8	75.3	74.2	89.5	99.7	131.2	110.4
Oct	2012	109.3	87.9	82.7	82.9	81.2	71.3	87.1	68.4	71.5	80.9	88.6	127.5	93.6
Nov	2012	147.0	120.9	87.1	96.0	82.8	76.4	104.6	73.1	71.8	77.9	89.6	129.1	99.1
Dec	2012	103.1	64.6	60.4	62.0	58.8	58.7	65.4	55.5	62.9	49.7	52.8	91.1	60.7
Jan	2013	121.9	91.2	72.2	74.3	68.5	74.8	76.2	76.1	85.7	77.1	73.1	99.0	95.2
Feb	2013	91.1	57.3	50.6	48.3	49.7	46.4	58.2	44.0	45.5	48.2	53.3	73.8	58.4
Mar	2013	134.5	46.6	37.9	40.8	37.0	43.9	55.4	46.4	46.2	80.1	77.2	140.2	126.2
Apr	2013	68.7	59.9	55.2	56.9	54.1	49.0	58.0	44.7	48.6	48.3	50.5	49.2	42.6
May	2013	79.2	47.9	47.2	47.0	46.9	49.3	54.6	47.3	48.3	49.5	56.3	80.1	60.5
Jun	2013	59.8	45.3	37.5	38.9	35.4	39.1	43.1	40.4	48.8	44.9	45.7	55.0	38.7
Jul	2013	45.4	53.2	42.8	49.4	41.0	47.3	48.9	40.9	47.9	54.6	48.6	53.0	66.2
Aug	2013	68.2	68.6	52.2	47.4	51.2	62.4	56.9	57.1	50.7	53.9	54.7	61.2	45.7
Sep	2013	79.0	63.3	48.9	49.1	46.7	36.8	51.3	48.5	52.7	37.5	43.2	66.7	48.1
Oct	2013	189.0	144.6	117.6	113.3	111.7	91.1	110.0	81.5	110.7	99.0	104.0	152.4	124.8
Nov	2013	45.3	33.6	33.6	34.2	33.0	30.0	36.4	27.4	33.2	23.7	26.4	29.4	23.5
Dec	2013	182.2	148.1	126.4	126.9	122.8	107.0	121.9	110.7	115.8	100.7	112.7	147.2	113.9
Jan	2014	173.4	140.8	124.5	124.8	121.8	108.5	119.3	110.4	112.0	106.2	113.0	160.5	129.2
Feb	2014	264.4	181.5	133.9	132.1	130.1	102.4	137.3	93.4	92.2	113.7	133.0	267.9	161.8
Mar	2014	98.0	75.7	62.8	64.9	61.3	61.9	67.4	56.6	60.2	58.3	63.8	92.3	67.7
Apr	2014	68.7	47.4	35.8	38.0	33.0	28.7	40.0	40.9	40.2	39.2	42.9	71.8	56.4
May	2014	136.0	89.3	94.8	103.8	93.4	88.3	114.5	85.2	86.5	92.1	111.1	172.3	121.2
Jun	2014	51.0	53.9	32.8	33.9	28.7	33.6	39.5	27.4	32.8	31.9	34.7	35.7	39.5
Jul	2014	68.4	41.6	27.2	31.5	24.7	38.1	50.8	34.9	35.9	43.9	58.1	60.4	45.7
Aug	2014	170.4	104.6	104.0	107.1	104.2	110.7	128.4	116.2	124.6	145.3	150.5	173.1	164.4
Sep	2014	13.6	21.1	8.7	8.1	6.9	6.5	7.5	6.4	22.1	14.1	11.7	10.2	8.5
Oct	2014	164.2	137.5	122.2	113.0	123.2	90.5	108.7	100.1	95.7	87.3	94.8	140.7	123.9
Nov	2014	203.3	140.5	132.7	130.4	132.2	124.1	141.9	119.0	128.8	150.7	156.3	180.9	168.1
Dec	2014	118.8	85.5	75.7	81.5	74.9	67.6	88.7	65.2	70.1	68.6	77.0	112.3	76.8
Jan	2015	97.8	70.1	72.8	65.6	72.4	63.2	69.9	64.0	68.2	64.7	72.9	95.4	68.7
Feb	2015	61.7	41.9	38.5	40.4	37.0	34.8	42.7	33.7	37.3	30.6	35.4	52.0	36.7
Mar	2015	79.7	64.1	61.8	60.0	60.6	56.2	60.6	55.3	62.9	59.0	61.1	74.6	58.7
Apr	2015	59.7	37.2	63.6	59.0	69.2	51.3	58.4	51.5	52.6	55.8	60.1	61.3	49.2
May	2015	121.5	87.9	91.3	98.2	88.8	83.8	92.9	80.5	89.7	99.7	98.7	121.0	98.6
Jun	2015	35.2	26.6	22.3	20.0	21.0	15.1	21.4	19.2	21.7	15.3	18.6	27.1	19.0

Mon	Year	UL1	ML1	ML2	ML3	ML4	ML5	ML6	ML7	RW1	LL1	LL2	DD1	DD2
Jul	2015	106.1	80.4	55.3	57.5	50.1	47.5	67.8	46.7	56.2	65.7	67.7	95.0	85.9
Aug	2015	101.3	82.5	80.0	84.0	77.9	84.0	85.6	75.4	85.8	82.7	78.4	87.3	81.2
Sep	2015	50.7	28.8	39.6	45.4	39.6	36.4	44.2	28.1	37.6	33.4	33.8	49.7	45.3
Oct	2015	83.2	60.8	40.4	40.7	37.5	38.5	42.7	34.1	38.9	44.1	45.8	70.3	56.8
Nov	2015	186.8	161.0	136.8	137.6	131.0	120.5	141.1	129.6	140.1	115.9	127.7	178.4	127.8
Dec	2015	326.5	259.2	198.0	207.1	190.0	194.4	217.4	186.9	188.1	204.9	218.1	286.4	235.6

Appendix C.3: Monthly average temperature and wind speed as applied for each river sub-basin in the WEAP-Dublin model

Mon	Year	T(C)	Ws m/s
Jan	2012	4.9	7.1
Feb	2012	4.6	5.4
Mar	2012	9.6	4.5
Apr	2012	6.0	5.3
May	2012	9.6	4.1
Jun	2012	14.2	4.6
Jul	2012	14.7	4.4
Aug	2012	14.9	4.7
Sep	2012	11.6	5.6
Oct	2012	7.0	4.6
Nov	2012	5.8	5.5
Dec	2012	5.2	6.0
Jan	2013	4.7	5.6
Feb	2013	4.7	5.0
Mar	2013	3.5	5.4
Apr	2013	5.8	6.2
May	2013	10.1	5.7
Jun	2013	13.3	4.6
Jul	2013	18.2	3.5
Aug	2013	15.4	4.7
Sep	2013	13.5	4.7
Oct	2013	10.8	5.3
Nov	2013	5.6	4.9
Dec	2013	7.2	7.6
Jan	2014	5.7	6.5
Feb	2014	5.5	8.1
Mar	2014	6.3	5.9
Apr	2014	8.5	4.7
May	2014	11.9	4.7
Jun	2014	14.3	3.4
Jul	2014	15.4	4.2
Aug	2014	13.1	5.4
Sep	2014	13.1	3.1
Oct	2014	9.6	5.8
Nov	2014	6.3	4.4
Dec	2014	4.4	6.8

Mon	Year	T(C)	Ws m/s
Jan	2015	4.6	7.5
Feb	2015	3.0	5.3
Mar	2015	5.1	6.3
Apr	2015	8.0	4.5
May	2015	10.1	6.1
Jun	2015	13.6	5.1
Jul	2015	14.0	5.1
Aug	2015	14.2	4.4
Sep	2015	11.5	4.0
Oct	2015	9.1	4.0
Nov	2015	7.6	6.8
Dec	2015	7.1	7.8

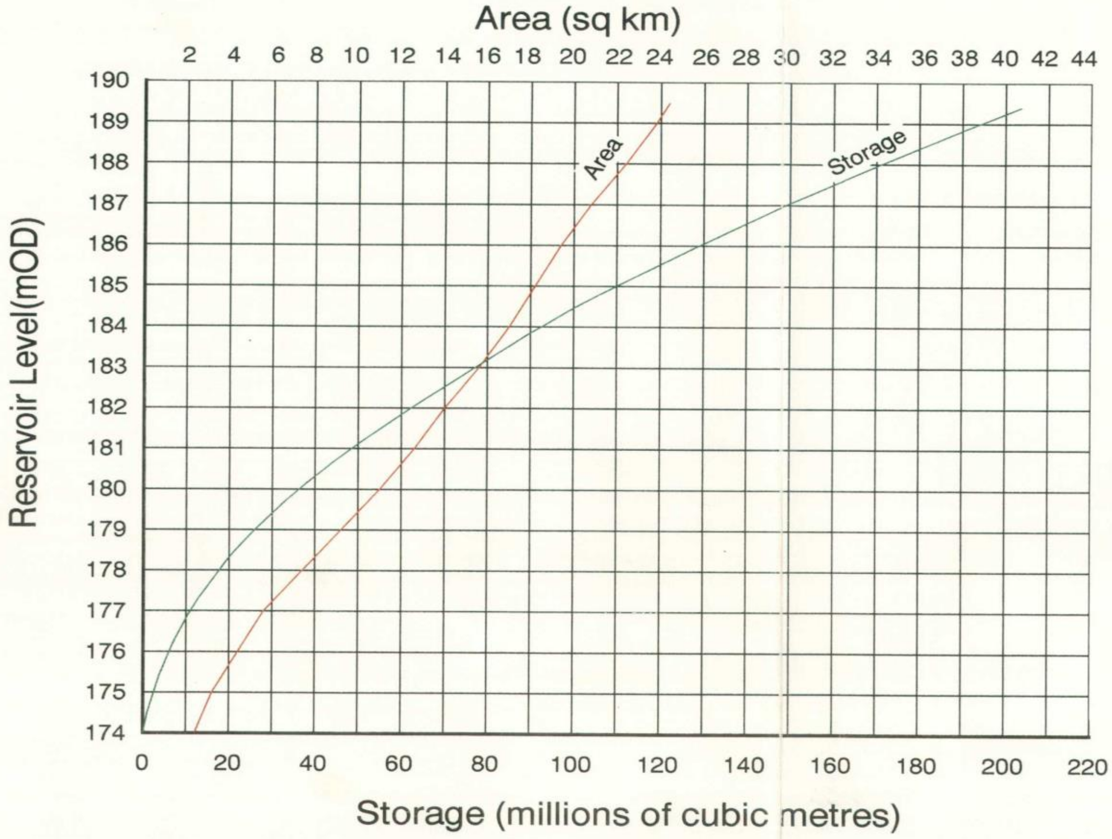
Appendix D.1: Estimated number of households per each supply zone, based on analysis of census data

	2011			2016			Annual	2012
	HU Nr.	**Vacant Nr.**	**PPOCC Nr.**	**HU Nr.**	**Vacant Nr.**	**PPOCC Nr.**	***R***	**HH**
Zone 1								
Dublin City	100896	11226	87743	102309	9913	92396	0.010	88654
Kildare County	49215	3300	39965	51184	2653	48531	0.040	41548
South Dublin	89295	4541	82916	92510	3410	89100	0.014	84117
Wicklow County	668	100	550	688	84	604	0.019	560
Sum	240074	19167	211174	246691	16060	230631		214879
Zone 2								
Dublin City	48146	3402	43415	48820	3004	45816	0.011	43885
Fingal	102793	7204	93150	107316	5799	101517	0.017	94766
Kildare County	19620	1220	17902	20405	981	19424	0.016	18197
Meath County	8006	471	7348	8270	403	7867	0.014	7449
Sum	178565	12297	161815	184811	10187	174624		164297
Zone 3								
Dublin City	6619	324	5702	6712	286	6426	0.024	5840
Sum	6619	324	5702	6712	286	6426		5840
Zone 4								
Dublin City	11499	582	10647	11660	514	11146	0.009	10745
Sum	11499	582	10647	11660	514	11146		10745
Zone 5								
Dublin City	24497	3012	20556	24840	2660	22180	0.015	20871
Sum	24497	3012	20556	24840	2660	22180		20871
Zone 6								
Dublin City	49956	6092	41857	50655	5379	45276	0.016	42519
Dan Laghaire	85896	6616	76351	88559	6616	83438	0.018	77719
Wicklow County	30001	2120	27123	30901	2120	29116	0.014	27510
Sum	165853	14828	145331	170115	14828	157830		147748

Where HU is total housing units; vacant is vacant houses; PPOCC is permanent occupied properties; r is annual growth rate of household; HH is estimate of household number

PPOCC=HU-Vacant; $r = (PPOCC_{2016} / PPOCC_{2011})^{1/5}$; $HH_{2012\text{-}2015} = PPOCC_{2011}(1+ r)^{n}$

Appendix D.2 : Volume-elevation curve for Phollaphuca reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)



Water Level mOD	Storage $10^6 m^3$	Water Level mOD	Storage $10^6 m^3$	Water Level mOD	Storage $10^6 m^3$
174.0	0.0	179.0	26.0	184.0	92.6
174.1	0.2	179.1	27.0	184.1	94.2
174.2	0.4	179.2	28.0	184.2	95.8
174.3	0.6	179.3	29.0	184.3	97.4
174.4	0.8	179.4	30.0	184.4	99.0
174.5	1.0	179.5	31.0	184.5	100.7
174.6	1.3	179.6	32.0	184.6	102.3
174.7	1.6	179.7	33.0	184.7	104.3
174.8	1.9	179.8	34.1	184.8	106.1
174.9	2.2	179.9	35.2	184.9	108.0
175.0	2.5	180.0	36.3	185.0	109.9
175.1	2.8	180.1	37.4	185.1	111.8
175.2	3.1	180.2	38.6	185.2	113.7
175.3	3.4	180.3	39.8	185.3	115.6
175.4	3.7	180.4	41.0	185.4	117.5
175.5	4.1	180.5	42.2	185.5	119.4
175.6	4.5	180.6	43.4	185.6	121.3
175.7	4.9	180.7	44.6	185.7	123.2
175.8	5.3	180.8	45.9	185.8	125.1
175.9	5.7	180.9	47.2	185.9	127.0
176.0	6.1	181.0	48.5	186.0	129.0
176.1	6.5	181.1	49.8	186.1	131.0
176.2	6.9	181.2	51.1	186.2	133.0
176.3	7.4	181.3	52.5	186.3	135.0
176.4	7.9	181.4	53.9	186.4	137.0
176.5	8.4	181.5	55.3	186.5	139.0
176.6	8.9	181.6	56.7	186.6	141.0
176.7	9.4	181.7	58.1	186.7	143.0
176.8	9.9	181.8	59.5	186.8	145.0
176.9	10.4	181.9	60.9	186.9	147.0
177.0	11.0	182.0	62.3	187.0	149.1
177.1	11.6	182.1	63.7	187.1	151.2
177.2	12.2	182.2	65.2	187.2	153.4
177.3	12.8	182.3	66.7	187.3	155.6
177.4	13.5	182.4	68.2	187.4	157.8
177.5	14.2	182.5	69.7	187.5	160.0
177.6	14.9	182.6	71.2	187.6	162.2
177.7	15.6	182.7	72.7	187.7	164.4
177.8	16.3	182.8	74.2	187.8	166.6
177.9	17.0	182.9	75.7	187.9	168.8
178.0	17.7	183.0	77.2	188.0	171.0
178.1	18.4	183.1	78.7	188.1	173.3
178.2	19.1	183.2	80.2	188.2	175.6
178.3	19.9	183.3	81.7	188.3	177.9
178.4	20.7	183.4	83.2	188.4	180.2
178.5	21.5	183.5	84.7	188.5	182.5
178.6	22.4	183.6	86.2	188.6	184.8
178.7	23.3	183.7	87.7	188.7	189.4
178.8	24.2	183.8	89.2	188.8	189.4
178.9	25.1	183.9	90.8	188.9	191.7
				189.0	194.1
				189.1	196.5
				189.2	198.9
				189.3	201.3
				189.4	203.7
				189.5	206.1

FIGURE 3 : POLLAPHUCA RESERVOIR - AREA & STORAGE CURVES

Revision of February 2006

Appendix D.3 : Volume-elevation curve for Golden Falls reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)

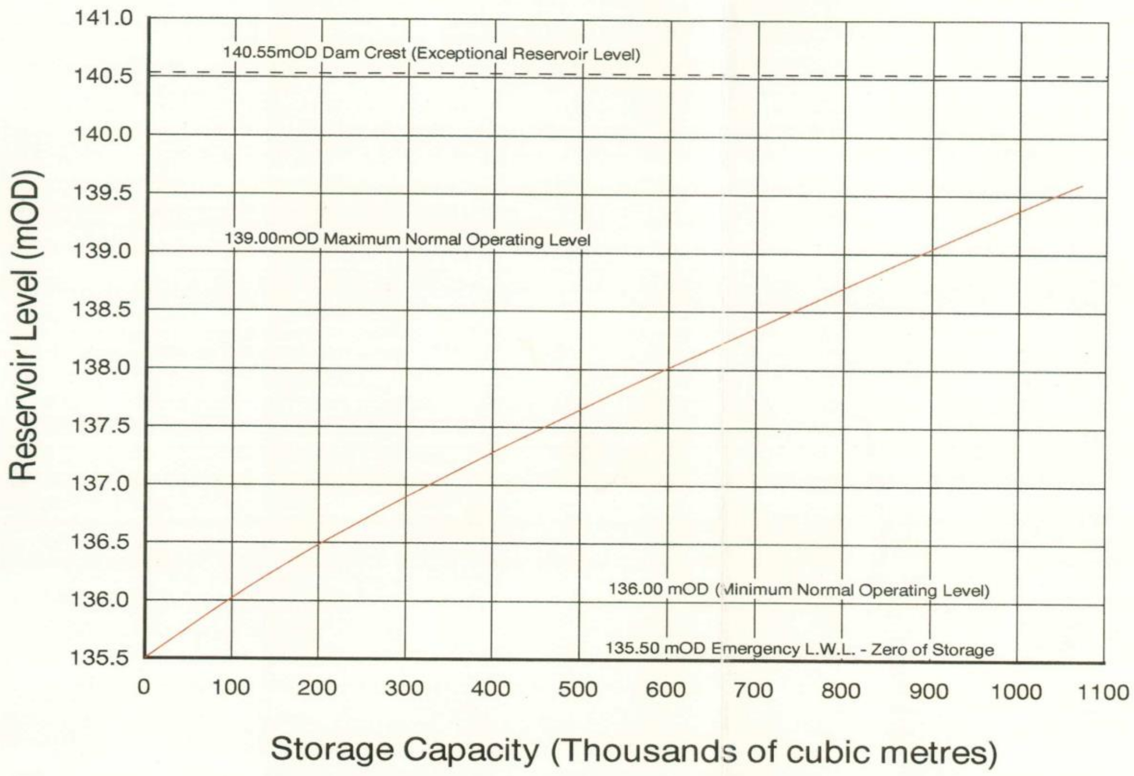
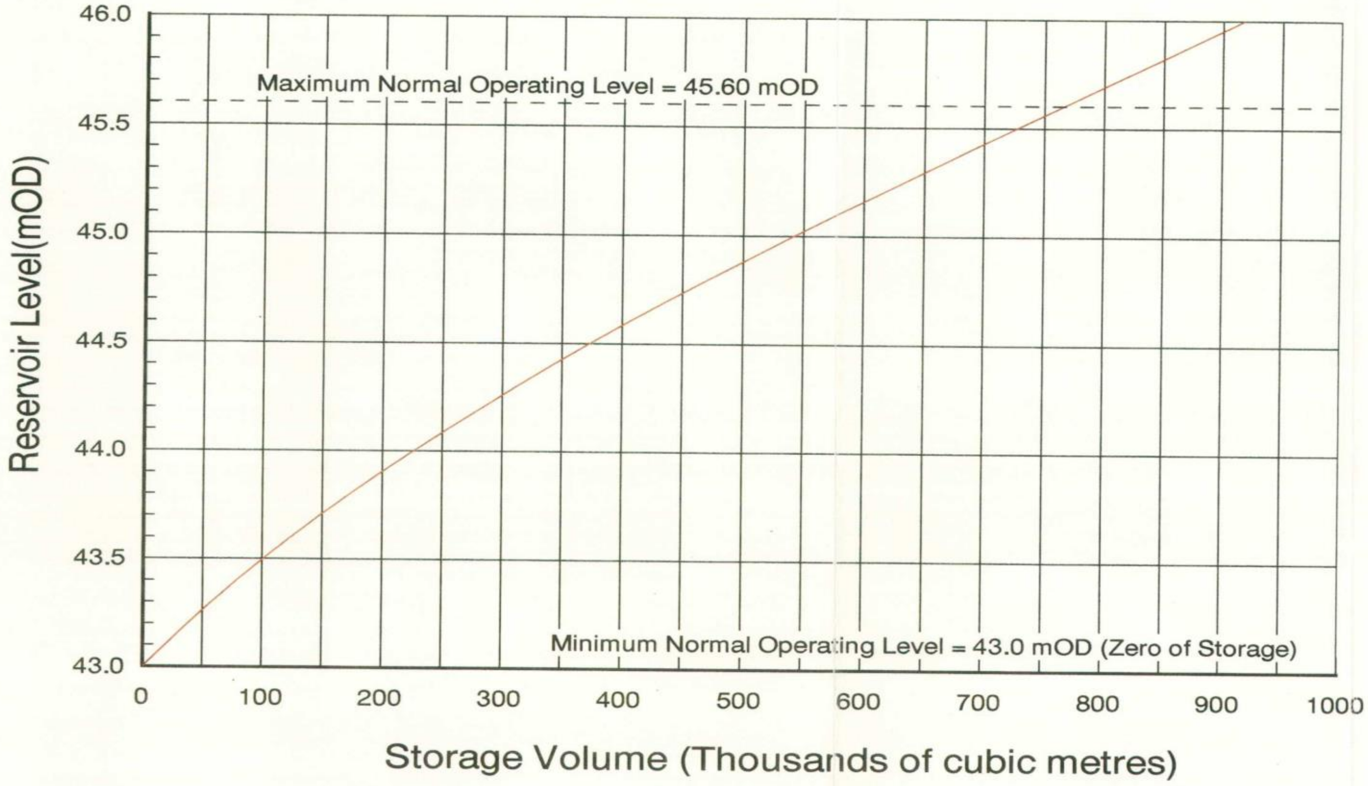


FIGURE 9 : GOLDEN FALLS RESERVOIR - STORAGE CURVE

Water Level mOD	Storage 10^3 m^3	Equiv to 1 cm rise
135.5	zero	
135.6	19	1.9
135.7	38	1.9
135.8	57	1.9
135.9	76	1.9
136.0	96	2.0
136.1	116	2.0
136.2	137	2.1
136.3	159	2.2
136.4	181	2.2
136.5	204	2.3
136.6	228	2.4
136.7	252	2.4
136.8	276	2.4
136.9	301	2.5
137.0	327	2.6
137.1	353	2.6
137.2	379	2.6
137.3	405	2.6
137.4	432	2.7
137.5	459	2.7
137.6	486	2.7
137.7	513	2.7
137.8	540	2.7
137.9	568	2.8
138.0	596	2.8
138.1	625	2.9
138.2	654	2.9
138.3	683	2.9
138.4	712	2.9
138.5	741	2.9
138.6	770	2.9
138.7	799	2.9
138.8	828	2.9
138.9	857	2.9
139.0	887	3.0
139.1	917	3.0
139.2	947	3.0
139.3	978	3.1
139.4	1009	3.1
139.5	1040	3.1
139.6	1072	3.2

Revision of February 2006

Appendix D.4 : Volume-elevation curve for Lexilip reservoir. Source: Personal contact with ESB (Turlough Hill and Liffey Stations)



Water Level mOD	Storage $m^3 \times 10^3$	Equiv to 1 cm rise
43.0	0	1.9
43.1	19	1.9
43.2	38	2.0
43.3	58	2.1
43.4	79	2.2
43.5	101	2.3
43.6	124	2.4
43.7	148	2.5
43.8	173	2.6
43.9	199	2.7
44.0	226	2.8
44.1	254	2.9
44.2	283	3.0 2.9
44.3	312 313	3.1
44.4	342	3.2
44.5	373	3.3
44.6	405	3.4
44.7	438	3.5
44.8	472	3.5
44.9	507	3.5
45.0	542	3.6
45.1	578	3.7
45.2	615	3.7
45.3	652	3.7
45.4	689	3.8
45.5	727	3.8
45.6	765	3.8

FIGURE 17 : LEIXLIP RESERVOIR : STORAGE CURVE

Revision of February 2006

Appendix E.1: Python code linking the water evaluation and planning software (WEAP21) with the statistical parameter optimisation tool (SPOTPY) for parameter uncertainty analysis.

<u>Code 1</u>

```
# This code provides an example of linking SPOTPY with WEAP21. The code represents a python setup that contains assumed parameter distributions and ranges, call for the modelling software (WEAP21) to perform simulations, read of calibration data and evaluation of objective functions

#
# Python packages used in the code
#
import random
import win32com.client
import pythoncom
import pandas as pd
import numpy as np
import spotpy


#
# SPOTPY setup
#

class spotpy_setup(object):

    # Assuming parameter distributions and ranges

    def __init__(self):
        self.params =
[spotpy.parameter.Uniform('kc_NI',0.70,2.50,0.10,1.30),

spotpy.parameter.Uniform('kc_p',0.35,0.90,0.05,0.80),

spotpy.parameter.Uniform('kc_f',0.80,3.60,0.10,3.55),

spotpy.parameter.Uniform('swc_NI',500,1000,50,885),

spotpy.parameter.Uniform('swc_p',200,500,50,235),

spotpy.parameter.Uniform('swc_f',100,700,50,650),
                        spotpy.parameter.Uniform('dwc',100,
400,50,100),

spotpy.parameter.Uniform('rrf_NI',2.5,5,0.05,3),

spotpy.parameter.Uniform('rrf_p',2,4,0.05,3.20),

spotpy.parameter.Uniform('rrf_f',5,10,0.05,6.79),

spotpy.parameter.Uniform('rzc_NI',500,1000,50,500),
```

```
spotpy.parameter.Uniform('rzc_p',500,1000,50,950),

spotpy.parameter.Uniform('rzc_f',10,500,50,100),

spotpy.parameter.Uniform('dc',500,1000,50,950),

spotpy.parameter.Uniform('pfd_NI',0.7,0.95,0.05,0.80),

spotpy.parameter.Uniform('pfd_p',0.40,0.95, 0.05,0.80),
                       spotpy.parameter.Uniform('pfd_f',0.40,
0.75, 0.05, 0.60)]

    #
    # Generating random parameter sets for use in WEAP21
    #
    def parameters(self):
        return spotpy.parameter.generate(self.params)

    #
    # Calling WEAP21 software and passing parameter sets
    #
    def simulation(self, vector):
        pythoncom.CoInitialize()
        WEAP = win32com.client.Dispatch("WEAP.WEAPApplication")
        WEAP.Verbose = 1
        WEAP.Visible = True
        WEAP.ActiveArea="Dublin"
        WEAP.Versions("Ryewater seperate").Revert
        WEAP.ActiveScenario = WEAP.Scenarios("RyeWater")
        WEAP.View ="Data"
        WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Kc").Expression=vector
[0]
        WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Kc").Expression=vector[1]
        WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Kc").Expression=vector[2]
        WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Soil Water
Capacity").Expression=vector[3]
        WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Soil Water
Capacity").Expression=vector[4]
        WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Soil Water
Capacity").Expression=vector[5]
        WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Deep Water
Capacity").Expression=vector[6]
        WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Runoff Resistance
Factor").Expression=vector[7]
        WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Runoff Resistance
Factor").Expression=vector[8]
```

```
        WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Runoff Resistance
Factor").Expression=vector[9]
        WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Root Zone
Conductivity").Expression=vector[10]
        WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Root Zone
Conductivity").Expression=vector[11]
        WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Root Zone
Conductivity").Expression = vector[12]
        WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Deep Conductivity").Expression =
vector[13]
        WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Preferred Flow
Direction").Expression = vector[14]
        WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Preferred Flow
Direction").Expression = vector[15]
        WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Preferred Flow
Direction").Expression = vector[16]
        WEAP.LoadFavorite("Observed and Modeled Streamflow")
        filename =
"c:\Ryewater_simulations\simulated"+str(vector[0])+".csv"
        WEAP.ExportResults(filename, IncludeTitle=False,
IncludeColTitles=True, ForceTranspose=True)
        data = pd.read_csv("c:\Ryewater_simulations\simulated"
+ str(vector[0]) + ".csv")
        data_array = np.array(data)
        simulated = data_array[:, 2]
        simulated = simulated[:-1]
        return simulated


    #
    # reading evaluation/calibration data
    #
    def evaluation(self):
        data=pd.read_csv("c:\Ryewater_simulations\Flows.csv")
        data_array = np.array(data)
        observed = data_array[:,1]
        observed = observed[:-1]
        return observed
    #
    # assessing model performance using different
      objective functions
    #
    def objectivefunction(self,simulation,evaluation):
        indexes=[]
        for i,value in enumerate(evaluation):
            if not value==0:
```

```
                indexes.append(i)

        sub_evaluation=evaluation[indexes]
        sub_simulation=simulation[indexes]
        sub_objectivefunction1=
spotpy.objectivefunctions.nashsutcliffe(sub_evaluation,sub_simu
lation)
        sub_objectivefunction2 =
spotpy.objectivefunctions.lognashsutcliffe(np.float64(sub_evalu
ation), np.float64(sub_simulation))

sub_objectivefunction3=spotpy.objectivefunctions.bias(sub_evalu
ation,sub_simulation)

sub_objectivefunction4=spotpy.objectivefunctions.rsr(sub_evalua
tion,sub_simulation)
        return
[sub_objectivefunction1,sub_objectivefunction2,sub_objectivefun
ction3,sub_objectivefunction4]
```

Code 2

```
# This code provides an example of the SPOTPY sampler file
which executes the setup file above by using a sampling
algorithm and number of parameter sets.
import spotpy
from spotpy import analyser
from spotpy_setup_Ryewater_objfuns import spotpy_setup


results=[]
spotpy_setup=spotpy_setup()# identifying spotpy setup file
rep=10000                  # number of repetitions or samples
sampler=spotpy.algorithms.lhs(spotpy_setup,dbname='c:\Sampling
results\Rlhhs_Four functions_2000',dbformat='csv') path to
where the database containing simulated data and
evaluation results are saved
sampler.sample(rep)
results.append(sampler.getdata())
```

Code 3

```
# This code provides an example of using SPOTPY "analyser" for
analysing results of the previous Latin Hyper Cube simulations

# Python packages
import spotpy
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from spotpy_setup_Ryewater_objfuns import spotpy_setup
import seaborn as sns
```

```
spotpy_setup=spotpy_setup()

# reading the database of resulting Latin Hyper Cube
simulations
results_mod=pd.read_csv('c:\Sampling results\RLHS_Four
functions_10000_narrowed.csv')
fields=[word for word in results_mod.head(0) if
word.startswith('sim')]


results=spotpy.analyser.load_csv_results('c:\Sampling
results\RLHS_Four functions_10000_narrowed')

# reading observation data
observation_data=pd.read_csv("c:\Ryewater_simulations\Flows_tes
t.csv")
observation_array = np.array(observation_data)
evaluation=observation_array[:,1]
evaluation=evaluation[:-1]

# Example of setting criteria for the behavioural parameter set
or models
results_above_threeshold=results[np.where((results['like1']>=0.
50) &(results['like2']>=0.40 & (results['like3']<=10)&
(results['like3']>=-10 & (results['like4']<=0.70))]

# plot parameter interactions and parameter uncertainty  for
behavioural parameter sets
spotpy.analyser.get_best_parameterset(results)
spotpy.analyser.plot_parameterInteraction(results_above_threesh
old)
plt.show()


# Further analysis for each individual performance metric
results_above_threeshold_NSE=results[np.where(results['like1']>
=0.50)]
results_above_threeshold_logNSE=results[np.where(results['like2
']>=0.40)]
results_below_threeshold_bias=results[np.where((results['like3'
]<=10) & (results['like3']>=-10))]
results_below_threeshold_rsr=results[np.where(results['like4']<
=0.70)]

#print(results_above_threeshold_NSE)
print('NSE')
print(len(results_above_threeshold_NSE))
print(np.median(results_above_threeshold_NSE['like1']))
print(np.min(results_above_threeshold_NSE['like1']))
print(np.max(results_above_threeshold_NSE['like1']))

#print(results_above_threeshold_logNSE)
print('LogNSE')
print(len(results_above_threeshold_logNSE))
print(np.median(results_above_threeshold_logNSE['like2']))
print(np.min(results_above_threeshold_logNSE['like2']))
```

```
print(np.max(results_above_threeshold_logNSE['like2']))

#print(results_below_threeshold_bias)
print('bias')
print(len(results_below_threeshold_bias))
print(np.median(results_below_threeshold_bias['like3']))
print(np.min(results_below_threeshold_bias['like3']))
print(np.max(results_below_threeshold_bias['like3']))

#print(results_below_threeshold_rsr)
print('rsr')
print(len(results_below_threeshold_rsr))
print(np.median(results_below_threeshold_rsr['like4']))
print(np.min(results_below_threeshold_rsr['like4']))
print(np.max(results_below_threeshold_rsr['like4']))


# plotting correlations between different values of different
objective functions for best performing models

sort_NSE=np.sort(results,order='like1')
best_NSE_100=sort_NSE[-100:-1]
print("\n","\n",best_NSE_100)

plt.subplot(2,2,1)
plt.scatter(best_NSE_100['like1'],best_NSE_100['like2'],s=15,co
lor='black',alpha=0.50)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.xlabel('NSE',fontsize=12)
plt.ylabel('logNSE',fontsize=12)

plt.subplot(2,2,2)
plt.scatter(best_NSE_100['like1'],best_NSE_100['like3'],s=15,co
lor='black',alpha=0.50)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.xlabel('NSE',fontsize=12)
plt.ylabel('%bias',fontsize=12)

plt.subplot(2,2,3)
plt.scatter(best_NSE_100['like1'],best_NSE_100['like4'],s=15,co
lor='black',alpha=0.50)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.xlabel('NSE',fontsize=12)
plt.ylabel('RSR',fontsize=12)

plt.tight_layout()
plt.show()
```

Code 4

```
# This provides an example of plotting uncertainties in
modelled flows resulting from uncertainties of WEAP21
parameters

import spotpy
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from spotpy_setup_Ryewater import spotpy_setup

spotpy_setup=spotpy_setup()

# a step for Identifying the location of simulated data in the
SPOTPY database results_mod=pd.read_csv('c:\Sampling
results\RLHS_Four functions_10000_narrowed.csv')
fields=[word for word in results_mod.head(0) if
word.startswith('sim')]

# Loading results or the relevant SPOTPY database

results=spotpy.analyser.load_csv_results('c:\Sampling
results\RLHS_Four functions_10000_narrowed')


# reading the observed data from an appropriate file
observation_data=pd.read_csv("c:\Ryewater_simulations\Flows_tes
t.csv")
observation_array = np.array(observation_data)
evaluation=observation_array[:,1]
evaluation=evaluation[:-1]
months=observation_array[:,0]
months=months[:-1]
months_list=[]
for month in months:
    months_list.append(month)


# Calculating quantiles of simulated data at each time step and
plotting resulting quantiles
fig=plt.figure(figsize=(12,6))
ax=plt.subplot(1,1,1)
q1,q25,q50,q75,q99=[],[],[],[],[]
for field in fields:
    q1.append(np.percentile(results[field],1))
    q25.append(np.percentile(results[field],25))
    q50.append(np.percentile(results[field],50))
    q75.append(np.percentile(results[field],75))
    q99.append(np.percentile(results[field],99))

ax.plot(q1,color='red',linestyle='solid',linewidth=0.50)
ax.plot(q25,color='red',linestyle='solid',linewidth=0.50)
```

```
ax.plot(q50,color='white',linestyle='solid',linewidth=0.50)
ax.plot(q75,color='blue',linestyle='solid',linewidth=0.50)
ax.plot(q99,color='blue',linestyle='solid',linewidth=0.50)

ax.fill_between(np.arange(0,432,1),list(q1),list(q25),facecolor
s='red',linewidth=0,label='1st - 25th',alpha=0.45)
ax.fill_between(np.arange(0,432,1),list(q25),list(q75),facecolo
rs='white',linewidth=0,label='25th - 75th',alpha=0.45)
ax.fill_between(np.arange(0,432,1),list(q75),list(q99),facecolo
rs='blue',linewidth=0,label='75th - 99th',alpha=0.45)

ax.plot(evaluation,color='black',linewidth=0.65,label='observed
',linestyle='solid',marker='d',markersize=2.50)
ax.set_xlim(0,432)
ax.set_xticklabels([months[0],months[50],months[100],months[150
],months[200],months[250],months[300],months[350],months[400]],
fontsize=12)
ax.set_ylim(0,12)
ax.tick_params(axis='y', labelsize=12)
ax.set_ylabel('Flow  (cms)',fontsize=13)
ax.legend()
plt.show()
```

Appendix E.2: Calculation of first order and total order sensitivity indices of the Sobol's method for parameters of the WEAP21 model of Ryewater using SALib python library

```
# This python code provides an example of using SALib library
for calculating first order sensitivity indices (S1) and total
order sensitivity indices (TSI)for parameters of a WEAP21 model
of Ryewater; The code also prepares statistical summaries of
calculated sensitivity indices

from SALib.analyze import sobol
import pandas as pd
import numpy as np
import statistics

# define the model inputs using a dictionary
problem={'num_vars':17,'names':['Kc_NI','Kc_p','Kc_f','SWC_NI',
'SWC_p','SWC_f','dwc','rrf_NI','rrf_p','rrf_f','rzc_NI','rzc_p'
,'rzc_f','dc','pdf_NI','pdf_p','pdf_f'],'bounds':[[0.70,2.50],[
0.35,0.90],[0.80,3.70],[500,1000],[100,400],[100,700],[100,400]
,[1.50,4],[2,3.50],[4,9],[700,1000],[700,1000],[0.10,500],[600,
1200],[0.70,0.95],[0.40,0.95],[0.40,0.75]]}

# read the database which contains the ensemble of flow
simulations or the output variance that will undergo a
sensivity analysis
simulations_data=pd.read_csv("c:\For sensitivity\For
sensitivity_narrowed.csv")
simulations_array=np.array(simulations_data)

# Create lists to hold calculated sensitivity indices S1 and
TSI as well as corresponding 95% confidence bounds at each
month during the study period
S1s_Kc_NI=[]
STs_Kc_NI=[]
S1conf_Kc_NI=[]
STconf_Kc_NI=[]

S1s_Kc_p=[]
STs_Kc_p=[]
S1conf_Kc_p=[]
STconf_Kc_p=[]

S1s_Kc_f=[]
STs_Kc_f=[]
S1conf_Kc_f=[]
STconf_Kc_f=[]


S1s_SWC_NI=[]
STs_SWC_NI=[]
S1conf_SWC_NI=[]
STconf_SWC_NI=[]
```

```
S1s_SWC_p=[]
STs_SWC_p=[]
S1conf_SWC_p=[]
STconf_SWC_p=[]

S1s_SWC_f=[]
STs_SWC_f=[]
S1conf_SWC_f=[]
STconf_SWC_f=[]

S1s_dwc=[]
STs_dwc=[]
S1conf_dwc=[]
STconf_dwc=[]

S1s_rrf_NI=[]
STs_rrf_NI=[]
S1conf_rrf_NI=[]
STconf_rrf_NI=[]

S1s_rrf_p=[]
STs_rrf_p=[]
S1conf_rrf_p=[]
STconf_rrf_p=[]

S1s_rrf_f=[]
STs_rrf_f=[]
S1conf_rrf_f=[]
STconf_rrf_f=[]

S1s_rzc_NI=[]
STs_rzc_NI=[]
S1conf_rzc_NI=[]
STconf_rzc_NI=[]

S1s_rzc_p=[]
STs_rzc_p=[]
S1conf_rzc_p=[]
STconf_rzc_p=[]

S1s_rzc_f=[]
STs_rzc_f=[]
S1conf_rzc_f=[]
STconf_rzc_f=[]

S1s_dc=[]
STs_dc=[]
S1conf_dc=[]
STconf_dc=[]

S1s_pdf_NI=[]
STs_pdf_NI=[]
S1conf_pdf_NI=[]
STconf_pdf_NI=[]

S1s_pdf_p=[]
```

```
STs_pdf_p=[]
S1conf_pdf_p=[]
STconf_pdf_p=[]

S1s_pdf_f=[]
STs_pdf_f=[]
S1conf_pdf_f=[]
STconf_pdf_f=[]

# perform sensitivity analysis for simulated flows at each time
step using the sobol method
for i in range(simulations_array.shape[1]):
    simulated=simulations_array[:,i]

Si=sobol.analyze(problem,simulated,calc_second_order=True,print
_to_console=False)

    S1s_Kc_NI.append(Si['S1'][0])
    STs_Kc_NI.append(Si['ST'][0])
    S1conf_Kc_NI.append(Si['S1_conf'][0])
    STconf_Kc_NI.append(Si['ST_conf'][0])

    S1s_Kc_p.append(Si['S1'][1])
    STs_Kc_p.append(Si['ST'][1])
    S1conf_Kc_p.append(Si['S1_conf'][1])
    STconf_Kc_p.append(Si['ST_conf'][1])

    S1s_Kc_f.append(Si['S1'][2])
    STs_Kc_f.append(Si['ST'][2])
    S1conf_Kc_f.append(Si['S1_conf'][2])
    STconf_Kc_f.append(Si['ST_conf'][2])

    S1s_SWC_NI.append(Si['S1'][3])
    STs_SWC_NI.append(Si['ST'][3])
    S1conf_SWC_NI.append(Si['S1_conf'][3])
    STconf_SWC_NI.append(Si['ST_conf'][3])

    S1s_SWC_p.append(Si['S1'][4])
    STs_SWC_p.append(Si['ST'][4])
    S1conf_SWC_p.append(Si['S1_conf'][4])
    STconf_SWC_p.append(Si['ST_conf'][4])

    S1s_SWC_f.append(Si['S1'][5])
    STs_SWC_f.append(Si['ST'][5])
    S1conf_SWC_f.append(Si['S1_conf'][5])
    STconf_SWC_f.append(Si['ST_conf'][5])

    S1s_dwc.append(Si['S1'][6])
    STs_dwc.append(Si['ST'][6])
    S1conf_dwc.append(Si['S1_conf'][6])
    STconf_dwc.append(Si['ST_conf'][6])

    S1s_rrf_NI.append(Si['S1'][7])
    STs_rrf_NI.append(Si['ST'][7])
    S1conf_rrf_NI.append(Si['S1_conf'][7])
    STconf_rrf_NI.append(Si['ST_conf'][7])
```

```
    S1s_rrf_p.append(Si['S1'][8])
    STs_rrf_p.append(Si['ST'][8])
    S1conf_rrf_p.append(Si['S1_conf'][8])
    STconf_rrf_p.append(Si['ST_conf'][8])

    S1s_rrf_f.append(Si['S1'][9])
    STs_rrf_f.append(Si['ST'][9])
    S1conf_rrf_f.append(Si['S1_conf'][9])
    STconf_rrf_f.append(Si['ST_conf'][9])

    S1s_rzc_NI.append(Si['S1'][10])
    STs_rzc_NI.append(Si['ST'][10])
    S1conf_rzc_NI.append(Si['S1_conf'][10])
    STconf_rzc_NI.append(Si['ST_conf'][10])

    S1s_rzc_p.append(Si['S1'][11])
    STs_rzc_p.append(Si['ST'][11])
    S1conf_rzc_p.append(Si['S1_conf'][11])
    STconf_rzc_p.append(Si['ST_conf'][11])

    S1s_rzc_f.append(Si['S1'][12])
    STs_rzc_f.append(Si['ST'][12])
    S1conf_rzc_f.append(Si['S1_conf'][12])
    STconf_rzc_f.append(Si['ST_conf'][12])

    S1s_dc.append(Si['S1'][13])
    STs_dc.append(Si['ST'][13])
    S1conf_dc.append(Si['S1_conf'][13])
    STconf_dc.append(Si['ST_conf'][13])

    S1s_pdf_NI.append(Si['S1'][14])
    STs_pdf_NI.append(Si['ST'][14])
    S1conf_pdf_NI.append(Si['S1_conf'][14])
    STconf_pdf_NI.append(Si['S1_conf'][14])

    S1s_pdf_p.append(Si['S1'][15])
    STs_pdf_p.append(Si['ST'][15])
    S1conf_pdf_p.append(Si['ST'][15])
    STconf_pdf_p.append(Si['ST'][15])

    S1s_pdf_f.append(Si['S1'][16])
    STs_pdf_f.append(Si['ST'][16])
    S1conf_pdf_f.append(Si['ST'][16])
    STconf_pdf_f.append(Si['ST'][16])

# prepare and print statistical summaries for sensitivity
indices S1 and TSI for each parameter

print('Mean S1_Kc_NI: ',statistics.mean(S1s_Kc_NI),' Std:
',statistics.stdev(S1s_Kc_NI))
print('Mean ST_Kc_NI: ',statistics.mean(STs_Kc_NI),' Std:
',statistics.stdev(STs_Kc_NI))
print('Mean S1confKc_NI: ',statistics.mean(S1conf_Kc_NI))
print('Mean STconfKC_NI: ',statistics.mean(STconf_Kc_NI))
print('\n')
```

```
print('Mean S1_Kc_p: ',statistics.mean(S1s_Kc_p),' Std:
',statistics.stdev(S1s_Kc_p))
print('Mean ST_Kc_p: ',statistics.mean(STs_Kc_p),' Std:
',statistics.stdev(STs_Kc_p))
print('Mean S1confKc_p: ',statistics.mean(S1conf_Kc_p))
print('Mean STconfKC_p: ',statistics.mean(STconf_Kc_p))
print('\n')

print('Mean S1_Kc_f: ',statistics.mean(S1s_Kc_f),' Std:
',statistics.stdev(S1s_Kc_f))
print('Mean ST_Kc_f: ',statistics.mean(STs_Kc_f),' Std:
',statistics.stdev(STs_Kc_f))
print('Mean S1confKc_f: ',statistics.mean(S1conf_Kc_f))
print('Mean STconfKC_f: ',statistics.mean(STconf_Kc_f))
print('\n')

print('Mean S1_SWC_NI: ',statistics.mean(S1s_SWC_NI),' Std:
',statistics.stdev(S1s_SWC_NI))
print('Mean ST_SWC_NI: ',statistics.mean(STs_SWC_NI),' Std:
',statistics.stdev(STs_SWC_NI))
print('Mean S1confSWC_NI: ',statistics.mean(S1conf_SWC_NI))
print('Mean STconfSWC_NI: ',statistics.mean(STconf_SWC_NI))
print('\n')

print('Mean S1_SWC_p: ',statistics.mean(S1s_SWC_p),' Std:
',statistics.stdev(S1s_SWC_p))
print('Mean ST_SWC_p: ',statistics.mean(STs_SWC_p),' Std:
',statistics.stdev(STs_SWC_p))
print('Mean S1confSWC_P: ',statistics.mean(S1conf_SWC_p))
print('Mean STconfSWC_P: ',statistics.mean(STconf_SWC_p))
print('\n')

print('Mean S1_SWC_f: ',statistics.mean(S1s_SWC_f),' Std:
',statistics.stdev(S1s_SWC_f))
print('Mean ST_SWC_f: ',statistics.mean(STs_SWC_f),' Std:
',statistics.stdev(STs_SWC_f))
print('Mean S1confSWC_f: ',statistics.mean(S1conf_SWC_f))
print('Mean STconfSWC_f: ',statistics.mean(STconf_SWC_f))
print('\n')

print('Mean S1_dwc: ',statistics.mean(S1s_dwc),' Std:
',statistics.stdev(S1s_dwc))
print('Mean ST_dwc: ',statistics.mean(STs_dwc),' Std:
',statistics.stdev(STs_dwc))
print('Mean S1conf_dwc: ',statistics.mean(S1conf_dwc))
print('Mean STconf_dwc: ',statistics.mean(STconf_dwc))
print('\n')

print('Mean S1_rrf_NI: ',statistics.mean(S1s_rrf_NI),' Std:
',statistics.stdev(S1s_rrf_NI))
print('Mean ST_rrf_NI: ',statistics.mean(STs_rrf_NI),' Std:
',statistics.stdev(STs_rrf_NI))
print('Mean S1conf_rrf_NI: ',statistics.mean(S1conf_rrf_NI))
print('Mean STconf_rrf_NI: ',statistics.mean(STconf_rrf_NI))
print('\n')
```

```
print('Mean S1_rrf_p: ',statistics.mean(S1s_rrf_p),' Std:
',statistics.stdev(S1s_rrf_p))
print('Mean ST_rrf_p: ',statistics.mean(STs_rrf_p),' Std:
',statistics.stdev(STs_rrf_p))
print('Mean S1conf_rrf_p: ',statistics.mean(S1conf_rrf_p))
print('Mean STconf_rrf_p: ',statistics.mean(STconf_rrf_p))
print('\n')

print('Mean S1_rrf_f: ',statistics.mean(S1s_rrf_f),' Std:
',statistics.stdev(S1s_rrf_f))
print('Mean ST_rrf_f: ',statistics.mean(STs_rrf_f),' Std:
',statistics.stdev(STs_rrf_f))
print('Mean S1conf_rrf_f: ',statistics.mean(S1conf_rrf_p))
print('Mean STconf_rrf_f: ',statistics.mean(STconf_rrf_p))
print('\n')

print('Mean S1_rzc_NI: ',statistics.mean(S1s_rzc_NI),' Std:
',statistics.stdev(S1s_rzc_NI))
print('Mean ST_rzc_NI: ',statistics.mean(STs_rzc_NI),' Std:
',statistics.stdev(STs_rzc_NI))
print('Mean S1conf_rzc_NI: ',statistics.mean(S1conf_rzc_NI))
print('Mean STconf_rzc_NI: ',statistics.mean(STconf_rzc_NI))
print('\n')

print('Mean S1_rzc_p: ',statistics.mean(S1s_rzc_p),' Std:
',statistics.stdev(S1s_rzc_p))
print('Mean ST_rzc_p: ',statistics.mean(STs_rzc_p),' Std:
',statistics.stdev(STs_rzc_p))
print('Mean S1conf_rzc_p: ',statistics.mean(S1conf_rzc_p))
print('Mean STconf_rzc_p: ',statistics.mean(STconf_rzc_p))
print('\n')

print('Mean S1_rzc_f: ',statistics.mean(S1s_rzc_f),' Std:
',statistics.stdev(S1s_rzc_f))
print('Mean ST_rzc_f: ',statistics.mean(STs_rzc_f),' Std:
',statistics.stdev(STs_rzc_f))
print('Mean S1conf_rzc_f: ',statistics.mean(S1conf_rzc_f))
print('Mean STconf_rzc_f: ',statistics.mean(STconf_rzc_f))
print('\n')

print('Mean S1_dc: ',statistics.mean(S1s_dc),' Std:
',statistics.stdev(S1s_dc))
print('Mean ST_dc: ',statistics.mean(STs_dc),' Std:
',statistics.stdev(STs_dc))
print('Mean S1conf_dc: ',statistics.mean(S1conf_dc))
print('Mean STconf_dc: ',statistics.mean(STconf_dc))
print('\n')

print('Mean S1_pdf_NI: ',statistics.mean(S1s_pdf_NI),' Std:
',statistics.stdev(S1s_pdf_NI))
print('Mean ST_pdf_NI: ',statistics.mean(STs_pdf_NI),' Std:
',statistics.stdev(STs_pdf_NI))
print('Mean S1conf_pdf_NI: ',statistics.mean(S1conf_pdf_NI))
print('Mean STconf_pdf_NI: ',statistics.mean(STconf_pdf_NI))
print('\n')
```

```
print('Mean S1_pdf_p: ',statistics.mean(S1s_pdf_p),' Std:
',statistics.stdev(S1s_pdf_p))
print('Mean ST_pdf_p: ',statistics.mean(STs_pdf_p),' Std:
',statistics.stdev(STs_pdf_p))
print('Mean S1conf_pdf_p: ',statistics.mean(S1conf_pdf_p))
print('Mean STconf_pdf_p: ',statistics.mean(STconf_pdf_p))
print('\n')

print('Mean S1_pdf_f: ',statistics.mean(S1s_pdf_f),' Std:
',statistics.stdev(S1s_pdf_f))
print('Mean ST_pdf_f: ',statistics.mean(STs_pdf_f),' Std:
',statistics.stdev(STs_pdf_f))
print('Mean S1conf_pdf_f: ',statistics.mean(S1conf_pdf_f))
print('Mean STconf_pdf_f: ',statistics.mean(STconf_pdf_f))
```

Appendix E.3: R code for fitting spatial GLM model for Ryewater sub-catchment to simulate multiple rainfall sequences

```
# read csv files of data, sites and region
Ryewater.data=read.csv("Ryewater.data.csv")
Ryewater.sites=read.csv("Ryewater.sites.csv")
rownames(Ryewater.sites)=c('  DU','  FA','  CA','  EN','  CE','
ST')
Ryewater.sites
Ryewater.regions=read.csv("Ryewater.regions.csv")

# write data in an appropriate format
write.GLCdata(Ryewater.data,file="Ryewater.dat")

# define site information (containing region, eastings and
northings)
Ryewater.siteinfo<-
make.siteinfo(Ryewater.sites,site.names=1,region.col=2,attr.nam
es=c("Eastings (inches from left of 299000\" wide
map)","Northings (inches from bottom of 254000\" high
map)"),regions=Ryewater.regions)
Ryewater.siteinfo

# Trivial rainfall occurrence model
Model0.Init<-read.modeldef("Model0_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo)
Model0.Init
Model0.fitted<-GLCfit("logisitic",siteinfo =
Ryewater.siteinfo,model.def = Model0.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 0 )
Model0.fitted
summary(Model0.fitted)
if (dev.cur()==1) x11(width = 8,height = 6)
par(mfrow=c(2,2))
plot(Model0.fitted,which.plots =1:2)

# Occurrence model with seasonality
write.modeldef(Model0.fitted,file = "Model1_Init.def")
Model1.Init<-read.modeldef("Model1_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo)
Model1.Init
Model1.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model1.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 0)
Model1.fitted
anova(Model0.fitted,Model1.fitted)
summary(Model1.fitted,tables=NULL)


# Rainfall occurrence - accounting for autocorrelation
write.modeldef(Model1.fitted,file = "Model2_Init.def")
```

```
Model2.Init<-read.modeldef("Model2_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names = "Rainfall")
Model2.Init
Model2.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 0)

Model2.Init<-read.modeldef("Model2_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names = "Rainfall")
Model2a.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 1)
Model2a.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)

write.modeldef(Model2a.fitted,file="Model2b_Init.def")
Model2b.Init<-read.modeldef("Model2b_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names = "Rainfall")
Model2b.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2b.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
anova(Model2a.fitted,Model2b.fitted)
write.modeldef(Model2b.fitted,file="Model2c_Init.def")
Model2c.Init<-read.modeldef("Model2c_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model2c.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2c.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
write.modeldef(Model2c.fitted,file="Model2d_Init.def")
Model2d.Init<-read.modeldef("Model2d_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model2d.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2d.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
anova(Model2a.fitted,Model2b.fitted,Model2c.fitted,Model2d.fitt
ed)
Model4.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model2d.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
summary(Model4.fitted,tables=NULL)
plot(Model4.fitted,which.plots = 1:2)

# Rainfall occurrence - interactions
write.modeldef(Model4.fitted,file="Model5_Init.def")
Model5.Init<-read.modeldef("Model5_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model5.Init
```

```
Model5.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model5.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
anova(Model4.fitted,Model5.fitted)
Model5.fitted
Model5.Init<-read.modeldef("Model5_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model5.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model5.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
anova(Model4.fitted,Model5.fitted)

# Rainfall occurrence - site effects
par(mfrow=c(1,1))
plot(Model5.fitted,which.plots = 3)
write.modeldef(Model5.fitted,file="Model6_Init.def")
Model6.Init<-read.modeldef("Model6_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model6.Init
Model6.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model6.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
anova(Model5.fitted,Model6.fitted)

# Rainfall occurrence - inter-site dependence
write.modeldef(Model6.fitted,file="Model7_Init.def")
Model7.Init<-read.modeldef("Model7_Init.def",model.type =
"logistic",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Model7.fitted<-GLCfit("logistic",siteinfo =
Ryewater.siteinfo,model.def = Model7.Init,data.file =
"Ryewater.dat",diagnostics = 1, nprev.required = 4)
Model7.fitted

# Modelling rainfall intensity
write.modeldef(Model7.fitted,file="Ryewater.IntensityModel.Init
ial.def")
Ryewater.IntensityModel.Initial<-
read.modeldef("Ryewater.IntensityModel.Initial.def",model.type
= "gamma",siteinfo = Ryewater.siteinfo,var.names =
"Rainfall",oldGlimClim.warning=FALSE)
Intensity.fitted<-GLCfit("gamma",siteinfo =
Ryewater.siteinfo,model.def = Ryewater.IntensityModel.Initial,
data.file = "Ryewater.dat",nprev.required = 0,diagnostics =
2,cor.file = "IntensityCorrelations.dat",resid.file =
"IntensityResids.dat")
par(mfrow=c(1,2))
plot(Intensity.fitted,which.plots = 4:5)
```

```
# Simulations
set.seed(2000)
sim<-
GLCsim(list(Occurrence=Model7.fitted,Intensity=Intensity.fitted
),nsim=100,start=200501,end=201512,impute.until =
200412,which.regions = 0:1,simdir = "./SimFiles",file.prefix =
"SimDemo")
Obs<-
GLCsim(list(Occurrence=Model7.fitted,Intensity=Intensity.fitted
),nsim=20,start=200501,end=201512,which.regions = 0:1,simdir =
"./SimFiles",file.prefix = "Imputation")
seasons <- list(3:5,6:8,9:11,c(12,1,2))
sim.summary<-summary(sim,season.defs = seasons,thresholds =
0,which.regions = 0)
obs.summary<-summary(Obs,season.defs = seasons,thresholds =
0,which.regions = 0)
sim.summary
par(mfrow=c(2,5))
plot(sim.summary,imputation = obs.summary,which.sites =
NULL,which.timescales = "daily")
par(mfrow=c(2,2))
plot(sim.summary,imputation = obs.summary,which.sites =
NULL,which.timescales = "monthly",colours.sim = "colour")
```

Appendix E.4: Python code for generating an ensemble of simulated flows for Ryewater catchment using WEAP21 modelling software by combining rainfall sequences produced from the GLM with the best performing parameter sets of the Latin Hyper Cube sampling.

```
# import packages
import random
import win32com.client
import pythoncom
import pandas as pd
import numpy as np
import spotpy

# reading the output file of 10,000 latin hyber cube sampling
of parameters for Ryewater catchment
results=spotpy.analyser.load_csv_results('c:\Sampling
results\RLHS_Four functions_10000_narrowed')

# ranking models on the basis of the NSE statitic and
extracting the best 100 performing models
results_above_threshold_NSE=results[np.where(results['like1']>0
.50)]
results_above_threshold_NSE_sort=np.sort(results_above_threshol
d_NSE,order='like1')
print(results_above_threshold_NSE_sort['like1'][-1])
best_model_runs_NSE=results_above_threshold_NSE_sort[-100:]

# iterating through the behavioural models and running each
using the stochastic rainfall data
for i in range(len(best_model_runs_NSE)):
    WEAP = win32com.client.Dispatch("WEAP.WEAPApplication")
    WEAP.Verbose = 1
    WEAP.Visible = True
    WEAP.ActiveArea="Dublin"
    WEAP.Versions("Ryewater seperate_from 2005").Revert
    WEAP.ActiveScenario = WEAP.Scenarios("RyeWater")
    WEAP.View ="Data"
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Kc").Expression =
best_model_runs_NSE['parkc_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Kc").Expression =
best_model_runs_NSE['parkc_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Kc").Expression =
best_model_runs_NSE['parkc_f'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_f'][i]
```

```
    WEAP.Branch("Demand Sites and 
Catchments\W9").Variables("Deep Water Capacity").Expression = 
best_model_runs_NSE['pardwc'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\lnonirrigated").Variables("Runoff Resistance 
Factor").Expression = best_model_runs_NSE['parrrf_NI'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Pasture").Variables("Runoff Resistance 
Factor").Expression = best_model_runs_NSE['parrrf_p'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Forest").Variables("Runoff Resistance 
Factor").Expression = best_model_runs_NSE['parrrf_f'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\lnonirrigated").Variables("Root Zone 
Conductivity").Expression = best_model_runs_NSE['parrzc_NI'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Pasture").Variables("Root Zone 
Conductivity").Expression = best_model_runs_NSE['parrzc_p'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Forest").Variables("Root Zone 
Conductivity").Expression = best_model_runs_NSE['parrzc_f'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9").Variables("Deep Conductivity").Expression = 
best_model_runs_NSE['pardc'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\lnonirrigated").Variables("Preferred Flow 
Direction").Expression = best_model_runs_NSE['parpfd_NI'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Pasture").Variables("Preferred Flow 
Direction").Expression = best_model_runs_NSE['parpfd_p'][i]
    WEAP.Branch("Demand Sites and 
Catchments\W9\Forest").Variables("Preferred Flow 
Direction").Expression = best_model_runs_NSE['parpfd_p'][i]
    count=1
    # running each behavioural model using the stochastic 
rainfall data generated by GLM framework
    for x in range (101):
        Rainfall_expression="ReadFromFile(C:\Stochastic 
Rainfall Monthly\All stochastic rainfall 
data.csv,"+str(count)+")"
        WEAP.Branch("Demand Sites and 
Catchments\W9").Variables("Precipitation").Expression=Rainfall_
expression
        WEAP.LoadFavorite("Observed and Modeled Streamflow")
        filename = "c:\Rainfall 
simulations\simulated_Mod"+str(i)+"_seq"+str(count)+".csv"
        WEAP.ExportResults(filename, IncludeTitle=False, 
IncludeColTitles=True, ForceTranspose=True)
        count+=1
```

Appendix E.5: Python code for generating an ensemble of simulated flows for Ryewater sub-catchment by combining the behavioural models of WEAP21 from the Latin Hyper Cube sampling algorithms, stochastic rainfall sequences from the SCL software, and stochastic temperature sequences from the SCL software

```
# import packages
import random
import win32com.client
import pythoncom
import pandas as pd
import numpy as np
import spotpy

# reading the output file of 10,000 latin hyber cube sampling
of parameters for Ryewater catchment
results=spotpy.analyser.load_csv_results('c:\Sampling
results\RLHS_Four functions_10000_narrowed')

# ranking models on the basis of the NSE statistic and
extracting the best 10 performing models
results_above_threshold_NSE=results[np.where(results['like1']>0
.50)]
results_above_threshold_NSE_sort=np.sort(results_above_threshol
d_NSE,order='like1')
print(results_above_threshold_NSE_sort['like1'][-1])
best_model_runs_NSE=results_above_threshold_NSE_sort[-10:]

# iterating through the behavioural models and running each
using the stochastic rainfall data
for i in range(len(best_model_runs_NSE)):
    WEAP = win32com.client.Dispatch("WEAP.WEAPApplication")
    WEAP.Verbose = 1
    WEAP.Visible = True
    WEAP.ActiveArea="Dublin"
    WEAP.Versions("Ryewater seperate").Revert
    WEAP.ActiveScenario = WEAP.Scenarios("RyeWater")
    WEAP.View ="Data"
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Kc").Expression =
best_model_runs_NSE['parkc_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Kc").Expression =
best_model_runs_NSE['parkc_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Kc").Expression =
best_model_runs_NSE['parkc_f'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Soil Water
Capacity").Expression = best_model_runs_NSE['parswc_f'][i]
```

```
    WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Deep Water Capacity").Expression =
best_model_runs_NSE['pardwc'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Runoff Resistance
Factor").Expression = best_model_runs_NSE['parrrf_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Runoff Resistance
Factor").Expression = best_model_runs_NSE['parrrf_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Runoff Resistance
Factor").Expression = best_model_runs_NSE['parrrf_f'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Root Zone
Conductivity").Expression = best_model_runs_NSE['parrzc_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Root Zone
Conductivity").Expression = best_model_runs_NSE['parrzc_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Root Zone
Conductivity").Expression = best_model_runs_NSE['parrzc_f'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Deep Conductivity").Expression =
best_model_runs_NSE['pardc'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\lnonirrigated").Variables("Preferred Flow
Direction").Expression = best_model_runs_NSE['parpfd_NI'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Pasture").Variables("Preferred Flow
Direction").Expression = best_model_runs_NSE['parpfd_p'][i]
    WEAP.Branch("Demand Sites and
Catchments\W9\Forest").Variables("Preferred Flow
Direction").Expression = best_model_runs_NSE['parpfd_p'][i]

    # running each behavioural model using the 100 stochastic
temperature data

    count_t=1
    for temp in range(99):
        Temperature_expression="ReadFromFile(C:\All combined
simulations\Stochastic
temperature_adjusted.csv,"+str(count_t)+")"
        WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Temperature").Expression=Temperature
_expression

    # running each combination of behavioural model and
temperature sequence using the 100 stochastic rainfall data
        count_r=1
        for rain in range(99):
            Rainfall_expression = "ReadFromFile(C:\All combined
simulations\All stochastic rainfall data-SCL.csv," +
str(count_r) + ")"
            WEAP.Branch("Demand Sites and
Catchments\W9").Variables("Precipitation").Expression =
Rainfall_expression
```

```
            WEAP.LoadFavorite("Observed and Modeled 
Streamflow")
            filename = "c:\All combined 
simulations\simulated_Mod" + str(i) 
+"_Temp"+str(count_t)+"_Rain"+str(count_r)+".csv"
            WEAP.ExportResults(filename, IncludeTitle=False, 
IncludeColTitles=True, ForceTranspose=True)
            count_r += 1

        count_t += 1

    print("Finished Model ",i)
```

Appendix E.6: Python code for running HBV-light multiple times using different parameter sets, changing daily simulations into monthly simulations, and generating ensemble of simulated flows for the catchment

```
"""

This code first runs the HBV-light model for Ryewater 100 times using
parameter sets generated from the Gap calibration; then all resulting
simulations of daily discharges are converted into monthly discharges

"""

import os
import pandas as pd
import numpy as np
from shutil import copyfile
import matplotlib.pyplot as plt


# running the HBV-light model 100 times using different parameter
sets

j=1
while j<=100:
    os.system('"C:/Program Files (x86)/HBV-light/HBV-light-CLI.exe"
Run c:/RyewaterM SingleRun Results /p:GAP_Parameter_'+str(j)+'.xml')

copyfile('c:\RyewaterM\Results\Results.txt','c:\RyewaterM\All_Outputs
\Results_'+str(j)+'.txt')

copyfile('c:\RyewaterM\Results\Summary.txt','c:\RyewaterM\All_Outputs
\Summary_'+str(j)+'.txt')
    j+=1

# converting daily discharges into monthly discharges

years=[str(1980+yr) for yr in range(34) ]
months=['01','02','03','04','05','06','07','08','09','10','11','12']
yyyymm=[years[y]+months[m] for y in range(len(years)) for m in
range(len(months))]
conversion_factor=((211.30*10**3)/(60*60*24))

simulated_dict={}

seq=1
while seq<=100:

df=pd.read_table('c:\RyewaterM\All_Outputs\Results_'+str(seq)+'.txt',
header=0)
    data=np.array(df)


    Qavg=[]
    for i in range(len(yyyymm)):
        if i<(len(yyyymm)-1):

Qavg.append((np.mean(data[np.where((data[:,0]>int(yyyymm[i]+'00')) &
(data[:,0]<int(yyyymm[i+1]+'00')))][:,1]))*conversion_factor)

        else:
```

```
            Qavg.append((np.mean(data[np.where(data[:, 0] >
int(yyyymm[i] + '00'))][:, 1]))*conversion_factor)
    simulated_dict['sim'+str(seq)]=Qavg
    seq+=1

data_frame=pd.DataFrame(simulated_dict,columns=['sim'+str(seq+1) for
seq in range(100)])
data_frame.to_csv("c:\RyewaterM\All_Outputs\For_Drawing_All_HBV_simul
ations.csv")


# converting daily discharges into monthly discharges

results=pd.read_csv("c:\RyewaterM\All_Outputs\combination\For_drawing
_HBV_simulations.csv")
fields=[word for word in results.head(0) if word.startswith('sim')]

observation_data=pd.read_csv("c:\Ryewater_simulations\Flows_HBV.csv")
observation_array = np.array(observation_data)
evaluation=observation_array[:,1]
evaluation=evaluation[:-1]
months_drawing=observation_array[:,0]
months_drawing=months_drawing[:-1]
months_list=[]
for month in months_drawing:
    months_list.append(month)

fig=plt.figure(figsize=(12,6))
ax=plt.subplot(1,1,1)
q1,q25,q50,q75,q99=[],[],[],[],[]
for field in fields:
    q1.append(np.percentile(results[field],1))
    q25.append(np.percentile(results[field],25))
    q50.append(np.percentile(results[field],50))
    q75.append(np.percentile(results[field],75))
    q99.append(np.percentile(results[field],99))

ax.plot(q1,color='red',linestyle='solid',linewidth=0.50)
ax.plot(q25,color='red',linestyle='solid',linewidth=0.50)
ax.plot(q50,color='white',linestyle='solid',linewidth=0.50)
ax.plot(q75,color='blue',linestyle='solid',linewidth=0.50)
ax.plot(q99,color='blue',linestyle='solid',linewidth=0.50)

ax.fill_between(np.arange(0,408,1),list(q1),list(q25),facecolors='red
',linewidth=0,label='1st - 25th',alpha=0.45)
ax.fill_between(np.arange(0,408,1),list(q25),list(q75),facecolors='wh
ite',linewidth=0,label='25th - 75th',alpha=0.45)
ax.fill_between(np.arange(0,408,1),list(q75),list(q99),facecolors='bl
ue',linewidth=0,label='75th - 99th',alpha=0.45)

ax.plot(evaluation,color='black',linewidth=0.65,label='observed',line
style='solid',marker='d',markersize=2.50)
ax.set_xlim(0,408)
ax.set_xticklabels([months[0],months[50],months[100],months[150],mont
hs[200],months[250],months[300],months[350],months[400]],fontsize=12)
ax.set_ylim(0,12)
ax.tick_params(axis='y', labelsize=12)
ax.set_ylabel('Flow  (cms)',fontsize=13)
ax.legend()
plt.show()
```

Appendix F.1 Historic rainfall data used for the urban catchment to run the model for future simulations. The rainfall data represent the average of historic rainfall observations at rainfall stations: 532, 1723, 1823, 2523, 3727, 3923, and 9223

Historic Year	Simulation Year	Month	Rainfall (mm)
1982	2020	1	46.7
1982	2020	2	26.8
1982	2020	3	50.7
1982	2020	4	13.6
1982	2020	5	46.6
1982	2020	6	103.4
1982	2020	7	7.6
1982	2020	8	64.0
1982	2020	9	86.2
1982	2020	10	96.3
1982	2020	11	121.5
1982	2020	12	75.3
1983	2021	1	59.5
1983	2021	2	41.3
1983	2021	3	61.4
1983	2021	4	73.9
1983	2021	5	86.7
1983	2021	6	40.9
1983	2021	7	25.4
1983	2021	8	47.6
1983	2021	9	81.6
1983	2021	10	48.0
1983	2021	11	17.5
1983	2021	12	115.3
1984	2022	1	92.0
1984	2022	2	55.6
1984	2022	3	58.3
1984	2022	4	26.3
1984	2022	5	31.9
1984	2022	6	37.2
1984	2022	7	22.4
1985	2023	8	124.8
1985	2023	9	33.6
1985	2023	10	22.1
1985	2023	11	31.8
1985	2023	12	71.5
1986	2024	1	103.2
1986	2024	2	11.5
1986	2024	3	57.9
1986	2024	4	49.5
1986	2024	5	63.3
1986	2024	6	86.4
1986	2024	7	54.6
1986	2024	8	155.6
1986	2024	9	2.3
1986	2024	10	52.4
1986	2024	11	89.4
1986	2024	12	74.2
1987	2025	1	33.0
1987	2025	2	32.0
1987	2025	3	50.3
1987	2025	4	73.8
1987	2025	5	24.4
1987	2025	6	93.3
1987	2025	7	33.8
1987	2025	8	71.8
1987	2025	9	68.7
1987	2025	10	124.5
1987	2025	11	43.0
1987	2025	12	38.2
1988	2026	1	106.6
1988	2026	2	35.5
1988	2026	3	85.4
1988	2026	4	24.7
1988	2026	5	75.7
1988	2026	6	34.7
1988	2026	7	85.7
1988	2026	8	56.9
1988	2026	9	37.5
1988	2026	10	70.4
1988	2026	11	19.4
1988	2026	12	38.6
1989	2027	1	29.3
1989	2027	2	40.9
1989	2027	3	53.5
1989	2027	4	70.3
1989	2027	5	26.7
1989	2027	6	63.4
1989	2027	7	9.4
1989	2027	8	86.5
1989	2027	9	34.9
1989	2027	10	63.4

Historic Year	Simulation Year	Month	Rainfall (mm)	Historic Year	Simulation Year	Month	Rainfall (mm)
1989	2027	11	33.1	1993	2031	7	60.4
1989	2027	12	62.1	1993	2031	8	36.1
1990	2028	1	72.4	1993	2031	9	95.6
1990	2028	2	115.7	1993	2031	10	81.9
1990	2028	3	11.4	1993	2031	11	38.0
1990	2028	4	25.0	1993	2031	12	109.7
1990	2028	5	41.0	1994	2032	1	74.4
1990	2028	6	46.8	1994	2032	2	101.4
1990	2028	7	34.3	1994	2032	3	69.6
1990	2028	8	57.5	1994	2032	4	67.9
1990	2028	9	17.9	1994	2032	5	57.1
1990	2028	10	140.3	1994	2032	6	17.7
1990	2028	11	66.8	1994	2032	7	57.3
1990	2028	12	83.2	1994	2032	8	60.6
1991	2029	1	72.8	1994	2032	9	86.8
1991	2029	2	51.8	1994	2032	10	45.6
1991	2029	3	79.7	1994	2032	11	54.7
1991	2029	4	94.0	1994	2032	12	90.0
1991	2029	5	4.8	1995	2033	1	116.1
1991	2029	6	64.7	1995	2033	2	88.6
1991	2029	7	30.4	1995	2033	3	52.9
1991	2029	8	31.6	1995	2033	4	28.4
1991	2029	9	45.9	1995	2033	5	43.2
1991	2029	10	79.9	1995	2033	6	11.1
1991	2029	11	55.8	1995	2033	7	53.4
1991	2029	12	35.7	1995	2033	8	5.3
1992	2030	1	30.3	1995	2033	9	47.2
1992	2030	2	29.3	1995	2033	10	37.9
1992	2030	3	63.7	1995	2033	11	142.3
1992	2030	4	66.1	1995	2033	12	73.5
1992	2030	5	35.9	1996	2034	1	92.6
1992	2030	6	27.0	1996	2034	2	61.1
1992	2030	7	67.4	1996	2034	3	69.3
1992	2030	8	72.3	1996	2034	4	55.0
1992	2030	9	67.6	1996	2034	5	71.9
1992	2030	10	29.3	1996	2034	6	17.9
1992	2030	11	60.7	1996	2034	7	38.8
1992	2030	12	41.7	1996	2034	8	77.2
1993	2031	1	66.3	1996	2034	9	18.0
1993	2031	2	19.1	1996	2034	10	96.1
1993	2031	3	26.3	1996	2034	11	102.3
1993	2031	4	48.6	1996	2034	12	46.3
1993	2031	5	150.3	1997	2035	1	12.7
1993	2031	6	145.5	1997	2035	2	61.9

Historic Year	Simulation Year	Month	Rainfall (mm)	Historic Year	Simulation Year	Month	Rainfall (mm)
1997	2035	3	11.8	2000	2038	11	144.8
1997	2035	4	37.5	2000	2038	12	123.1
1997	2035	5	64.2	2001	2039	1	37.0
1997	2035	6	124.6	2001	2039	2	45.1
1997	2035	7	46.9	2001	2039	3	66.9
1997	2035	8	74.5	2001	2039	4	55.1
1997	2035	9	16.4	2001	2039	5	55.4
1997	2035	10	69.0	2001	2039	6	35.7
1997	2035	11	110.4	2001	2039	7	37.3
1997	2035	12	88.2	2001	2039	8	85.2
1998	2036	1	92.4	2001	2039	9	36.3
1998	2036	2	10.9	2001	2039	10	86.1
1998	2036	3	65.0	2001	2039	11	33.7
1998	2036	4	122.3	2001	2039	12	18.2
1998	2036	5	29.8	2002	2040	1	52.7
1998	2036	6	118.6	2002	2040	2	109.2
1998	2036	7	38.9	2002	2040	3	33.1
1998	2036	8	35.3	2002	2040	4	72.1
1998	2036	9	92.1	2002	2040	5	105.4
1998	2036	10	67.6	2002	2040	6	63.8
1998	2036	11	73.7	2002	2040	7	70.5
1998	2036	12	67.9	2002	2040	8	51.4
1999	2037	1	70.0	2002	2040	9	16.9
1999	2037	2	30.2	2002	2040	10	164.3
1999	2037	3	30.8	2002	2040	11	176.2
1999	2037	4	60.7	2002	2040	12	99.0
1999	2037	5	40.2	2003	2041	1	48.9
1999	2037	6	56.6	2003	2041	2	27.5
1999	2037	7	23.4	2003	2041	3	31.7
1999	2037	8	98.2	2003	2041	4	35.7
1999	2037	9	130.8	2003	2041	5	85.7
1999	2037	10	35.9	2003	2041	6	70.4
1999	2037	11	45.6	2003	2041	7	43.2
1999	2037	12	71.3	2003	2041	8	14.8
2000	2038	1	35.6	2003	2041	9	36.4
2000	2038	2	43.4	2003	2041	10	111.3
2000	2038	3	16.3	2003	2041	11	57.5
2000	2038	4	81.6	2003	2041	12	54.2
2000	2038	5	51.4	2004	2042	1	82.9
2000	2038	6	31.8	2004	2042	2	16.4
2000	2038	7	39.4	2004	2042	3	47.8
2000	2038	8	68.5	2004	2042	4	36.6
2000	2038	9	99.7	2004	2042	5	34.8
2000	2038	10	74.1	2004	2042	6	52.6

Historic Year	Simulation Year	Month	Rainfall (mm)	Historic Year	Simulation Year	Month	Rainfall (mm)
2004	2042	7	42.9	2008	2046	3	111.6
2004	2042	8	115.3	2008	2046	4	30.8
2004	2042	9	46.5	2008	2046	5	27.5
2004	2042	10	134.0	2008	2046	6	75.7
2004	2042	11	40.8	2008	2046	7	108.3
2004	2042	12	43.9	2008	2046	8	174.1
2005	2043	1	62.1	2008	2046	9	101.8
2005	2043	2	37.9	2008	2046	10	96.7
2005	2043	3	31.6	2008	2046	11	44.9
2005	2043	4	50.4	2008	2046	12	41.1
2005	2043	5	63.9	2009	2047	1	68.0
2005	2043	6	23.6	2009	2047	2	61.2
2005	2043	7	85.4	2009	2047	3	19.9
2005	2043	8	25.9	2009	2047	4	66.8
2005	2043	9	48.2	2009	2047	5	65.0
2005	2043	10	101.6	2009	2047	6	63.7
2005	2043	11	51.5	2009	2047	7	125.2
2005	2043	12	63.1	2009	2047	8	57.8
2006	2044	1	18.0	2009	2047	9	22.6
2006	2044	2	36.4	2009	2047	10	81.7
2006	2044	3	65.3	2009	2047	11	162.9
2006	2044	4	33.2	2009	2047	12	73.1
2006	2044	5	93.3	2010	2048	1	55.9
2006	2044	6	23.7	2010	2048	2	37.9
2006	2044	7	15.7	2010	2048	3	56.9
2006	2044	8	69.5	2010	2048	4	24.9
2006	2044	9	79.0	2010	2048	5	54.8
2006	2044	10	85.2	2010	2048	6	44.4
2006	2044	11	75.5	2010	2048	7	84.5
2006	2044	12	94.1	2010	2048	8	40.2
2007	2045	1	63.8	2010	2048	9	109.6
2007	2045	2	60.3	2010	2048	10	33.7
2007	2045	3	43.8	2010	2048	11	113.9
2007	2045	4	6.5	2010	2048	12	62.5
2007	2045	5	37.3	2011	2049	1	27.9
2007	2045	6	137.0	2011	2049	2	74.7
2007	2045	7	121.0	2011	2049	3	17.0
2007	2045	8	104.6	2011	2049	4	20.1
2007	2045	9	30.2	2011	2049	5	40.4
2007	2045	10	16.8	2011	2049	6	68.2
2007	2045	11	50.7	2011	2049	7	45.3
2007	2045	12	55.6	2011	2049	8	42.4
2008	2046	1	97.9	2011	2049	9	63.2
2008	2046	2	15.5	2011	2049	10	161.8

Historic Year	Simulation Year	Month	Rainfall (mm)
2011	2049	11	58.9
2011	2049	12	46.4
2012	2050	1	65.6
2012	2050	2	19.4
2012	2050	3	18.6
2012	2050	4	81.8
2012	2050	5	63.4
2012	2050	6	171.6
2012	2050	7	100.3
2012	2050	8	72.7
2012	2050	9	87.4
2012	2050	10	74.2
2012	2050	11	73.2
2012	2050	12	44.5

Historic Year	Simulation Year	Month	Rainfall (mm)

Appendix F.2 Automating the calculation of surface areas and rainfall routing parameters as time series input for the WEAP model to run future simulations (2016-2050).

	A	B	C	D	E
1					
2	Total Area	*At*	581.1	km2	
3					
4	Pervious	*Ap*	224.299	km2	
5			0.38599		
6		*Cp*	0.18		
7					
8	Impervious	*Ai*	336.448	km2	
9			0.578985		
10		*Ci*	0.95		
11					
12	Decentralised	*Ad*	20.354	km2	
13			0.035027		
14		*Cd*	0.03		
15					
16	*factorRain*		0.6545		
17					
18	*Ro(Adj)*		0.9482		
19	*Inf(Adj)*		0.052		
20					
21					
22	*Est. RRF*	*RRFp*	5.56		
23		*RRFi*	1.05		
24		*RRFd*	33.33		
25					

	A	B	C	D	E	F	G	H
1	Year	Uarea	Ap	Ai	Ad	Rf	Ro%	Inf%
2	2013	377.56	151.024	226.536	0.09075	0.642	0.9996	0.0004
3	2014	382.13	152.67	229.004	0.457	0.6424	0.9982	0.0019
4	2015	386.69	154.311	231.466	0.913	0.6428	0.9965	0.0036
5	2016	391.26	155.956	233.934	1.37	0.6433	0.9946	0.0053
6	2017	395.82	157.598	236.396	1.826	0.6437	0.993	0.007
7	2018	400.39	159.243	238.864	2.283	0.644	0.9915	0.0086
8	2019	404.95	160.885	241.327	2.739	0.6444	0.9899	0.0102
9	2020	409.51	162.526	243.789	3.195	0.6448	0.9883	0.0118
10	2021	414.08	164.172	246.257	3.652	0.6452	0.9867	0.0133
11	2022	418.64	165.813	248.719	4.108	0.6455	0.9853	0.0148
12	2023	423.21	167.458	251.187	4.565	0.6459	0.9837	0.0162
13	2024	427.77	169.1	253.649	5.021	0.6462	0.9824	0.0177
14	2025	432.34	170.745	256.117	5.478	0.6465	0.981	0.0191
15	2026	436.9	172.387	258.58	5.934	0.6469	0.9796	0.0204
16	2027	442.91	174.55	261.825	6.535	0.6473	0.9779	0.0222
17	2028	448.92	176.714	265.07	7.136	0.6477	0.9762	0.0239
18	2029	454.92	178.874	268.31	7.736	0.6481	0.9745	0.0255
19	2030	460.93	181.038	271.556	8.337	0.6485	0.9729	0.0271
20	2031	466.94	183.201	274.801	8.938	0.6489	0.9713	0.0287
21	2032	472.95	185.365	278.047	9.539	0.6492	0.9699	0.0302
22	2033	478.96	187.528	281.292	10.14	0.6496	0.9684	0.0317
23	2034	484.97	189.692	284.537	10.741	0.6499	0.967	0.0331
24	2035	490.97	191.852	287.777	11.341	0.6503	0.9655	0.0345
25	2036	496.98	194.016	291.023	11.942	0.6506	0.9642	0.0359
26	2037	502.99	196.179	294.268	12.543	0.6509	0.9629	0.0372
27	2038	509	198.343	297.514	13.144	0.6512	0.9616	0.0385

Excel **calculation** sheet for calculating *Ap*, *Ai*, *Ad*, *RainFactor*, *Ro(Adj)*, *Inf (Adj)* – as expressed in Equations (8.1) – (8.13).

Excel **output** sheet to prepare time series inputs of areas and routing parameters for the WEAP model to run future simulations 2013-2050.

```
Sub automateCalculation()
r = 2
For i = 1 To 38
    Calculation.Cells(2, 3) = Output.Cells(r, 2)
    Ad = (Output.Cells(r, 2) - Output.Cells(2, 2)) * 0.1
    Calculation.Cells(12, 3) = Ad
    Output.Cells(r, 3) = Calculation.Cells(4, 3)
    Output.Cells(r, 4) = Calculation.Cells(8, 3)
    Output.Cells(r, 5) = Calculation.Cells(12, 3)
    Output.Cells(r, 6) = Calculation.Cells(16, 3)
    Output.Cells(r, 7) = Calculation.Cells(18, 3)
    Output.Cells(r, 8) = Calculation.Cells(19, 3)

r = r + 1

Next

End Sub
```

Visual basic module to iterate calculations of areas and routing parameters for each year along the simulation period 2016-2050.

LIST OF PUBLICATIONS

Yassin M and Nasr A. (2019) Climate-driven water resources planning model for the Dublin Region. *Draft manuscript to be submitted shortly.*
Based on Chapters 3-6

Yassin M and Nasr A (2018) Assessment of potential water supply management scenarios for Dublin using the Water Evaluation and Planning software WEAP21. *In Proceedings of the 2018 Civil Engineering Research in Ireland Conference (CERI2018).*
Based on Chapters 8 and 9

Yassin M and Nasr A (2018). Development of Integrated Urban Water Management (IUWM) for Dublin [Abstract]. In the 28th Irish Environmental Researchers Colloquium (Environ2018), Cork, Ireland. Abstract nr. 60
Based on Chapter 3-6

Yassin M and Nasr A (2016). Development of Integrated Urban Water Management (IUWM) for Dublin. *Exhibited at the 17th Irish National Hydrology Conference, Athlone, Ireland* November 2016
Based on Chapters 3-6

LIST OF EMPLOYABILITY SKILLS AND DISCIPLINE SPECIFIC SKILL TRAINING

Employability skills modules

- Introduction to Programming (Python)
- Programming for GIS
- Research Methods
- Writing in Engineering and Science

Discipline specific modules

- Water Resources and Quality Management
- Geographical Information System
- Modern Applied Statistical Modelling (R software)