

## 02 – FUTURE WATER VULNERABILITY IN IRELAND: AN INTEGRATED WATER RESOURCES, CLIMATE AND LAND USE CHANGES MODEL

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### Abstract

Water resources management and policies need to consider the dynamic nature of any catchment's water balance, particularly in planning stage, to develop effective strategies for the future. The main goal of this research is to create an innovative and integrated environmental modelling tool (GEO-CWB) by applying Machine Learning Techniques to a Geographic Information system (GIS). The developed tool uses as test and validation case the trans-boundary Shannon river basin. Climate change projections for the Shannon River catchment are simulated and presented using GEO-CWB for several climate variables from multi-GCM ensembles for three future time intervals using a range of different Representative Concentration Pathways (RCPs). As part of the integrated environmental modelling approach, the future spatially distributed urban expansion scenarios and land use changes for Shannon river basin are simulated and presented based on realistic land cover change models and projected to several time intervals. This is achieved using a hybrid modelling technique combining a logistic regression and a cellular automata (CA) model for developing spatial patterns of urban expansion. The research presented here provides an appropriate methodology for long-term changes analysis in European trans-boundary river's water level and streamflow parameters after using a customized GIS-based algorithm to simplify the hydrological system. GEO-CWB provides an integrated GIS tool for modelling potential evapotranspiration on the catchment scale. The GEO-CWB tool has been developed to help and support water sector modellers, planners, and decision makers to simulate and predict future spatially distributed dynamic water balances using a GIS environment at a catchment scale in response to the future change in climate variables and land use. Several Machine Learning Techniques are applied on the outcomes of the GEO-CWB model for the Shannon River in order to model and predict the water level and streamflow parameters for some stations along the river for daily time steps.

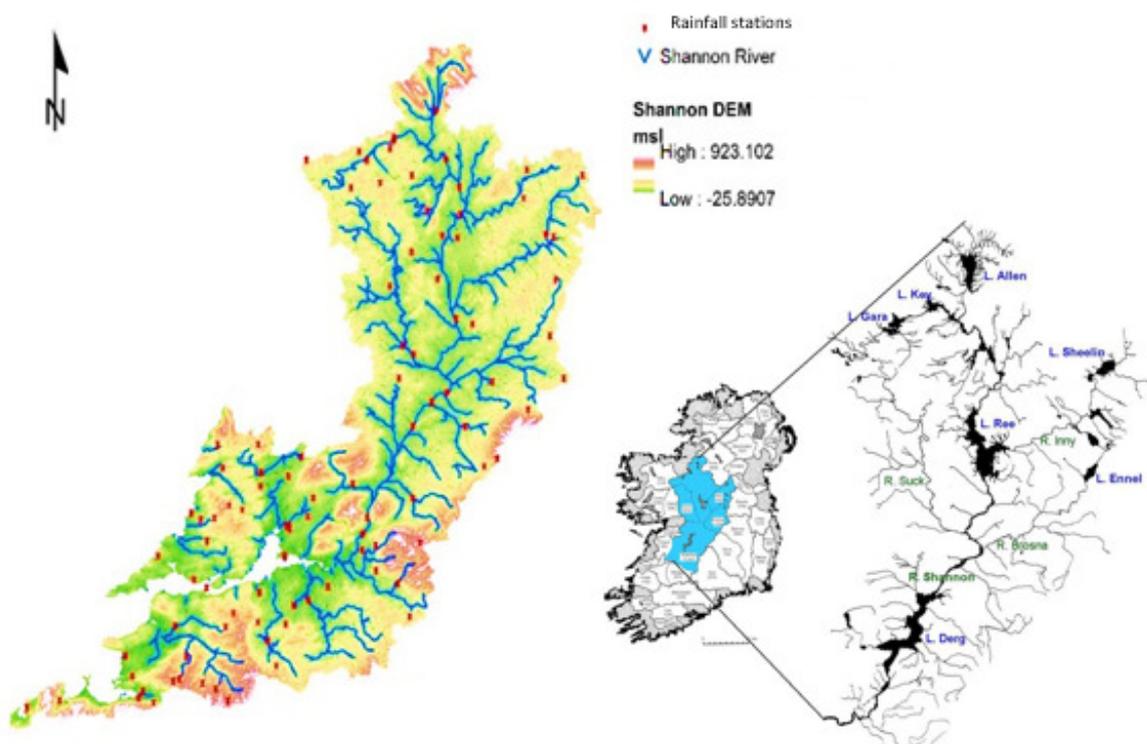
### 1. INTRODUCTION

Future management planning scenarios and policies for a specific catchment should integrate a dynamic water balance with future changes in climate variables and land use in a spatially distributed form. This integration allows decision makers and water resources modellers to predict climate change impacts and land use effects with more confidence in simulations for future scenarios or plans. Modelling and assisting the impacts of climate change effects on water resources is a fragmented and multi-stages process, which can be processed through several methods and techniques such as physical base models, statistical base models or/and machine learning techniques (Leavesley, 1994, Coppola Jr *et al.*, 2003, Grotch and MacCracken, 1991, Kim and Valdés, 2003, Dibike *et al.*, 2001, Berkhout *et al.*, 2002, Sweeney *et al.*, 2003, Change, 2007, Tripathi *et al.*, 2006, Chen *et al.*, 2006). As such, there is a scientific need to provide an integrated method which applies these techniques through geo-referenced spatially distributed calculation using a Geographic Information System (GIS) platform with the ability to validate and calibrate the results. This research project contributes to the scientific knowledge by addressing this need through an innovative and integrated tool and method. The designed method and the developed tool use as test and validation case the trans-boundary (Republic of Ireland and Northern Ireland) European Shannon river basin (figure 1). Surface freshwater, specifically lakes, reservoirs and rivers in addition to groundwater are the main water resources in Ireland. The water demands and threats to both surface water and groundwater resources have grown dramatically in recent years, fueled by the competing interests of urbanization, agriculture, industrial development and tourism, and compounding

the threats now posed by climate change (Irish, 2009, McGarrigle *et al.*, 2010). Furthermore, the disparity between demand and supply in Ireland due to the prominent location of water resources in the west while demand is greatest along the eastern seaboard is likely to increase with climate change (Sweeney *et al.*, 2003, Charlton *et al.*, 2006, Steele-Dunne *et al.*, 2008, Wilby *et al.*, 2006, Akhtar *et al.*, 2008, Kiely, 1999).

This paper illustrates the modelling stages for the developed GIS-based integrated model (GEO-CWB) and gives an overview of the used techniques and methods (figure 2). GEO-CWB applies Machine Learning Techniques to a Geographic Information system (GIS), which allow the scientific community, modellers, planners and decision makers to study the impact of climate and land use changes on water resources. The main simulation steps, figure 2, for GEO-CWB are:

- Climate change modelling and projection.
- Land use scenarios modelling and projection.
- Hydrological system simplifying algorithm and long-term variation analysis for historical data such as water level and streamflow.
- Future dynamical spatially distributed water balance projection.
- Using Machine Learning Techniques to model and predict water level and streamflow regime.



**Figure 1:** Shannon River catchment location map.

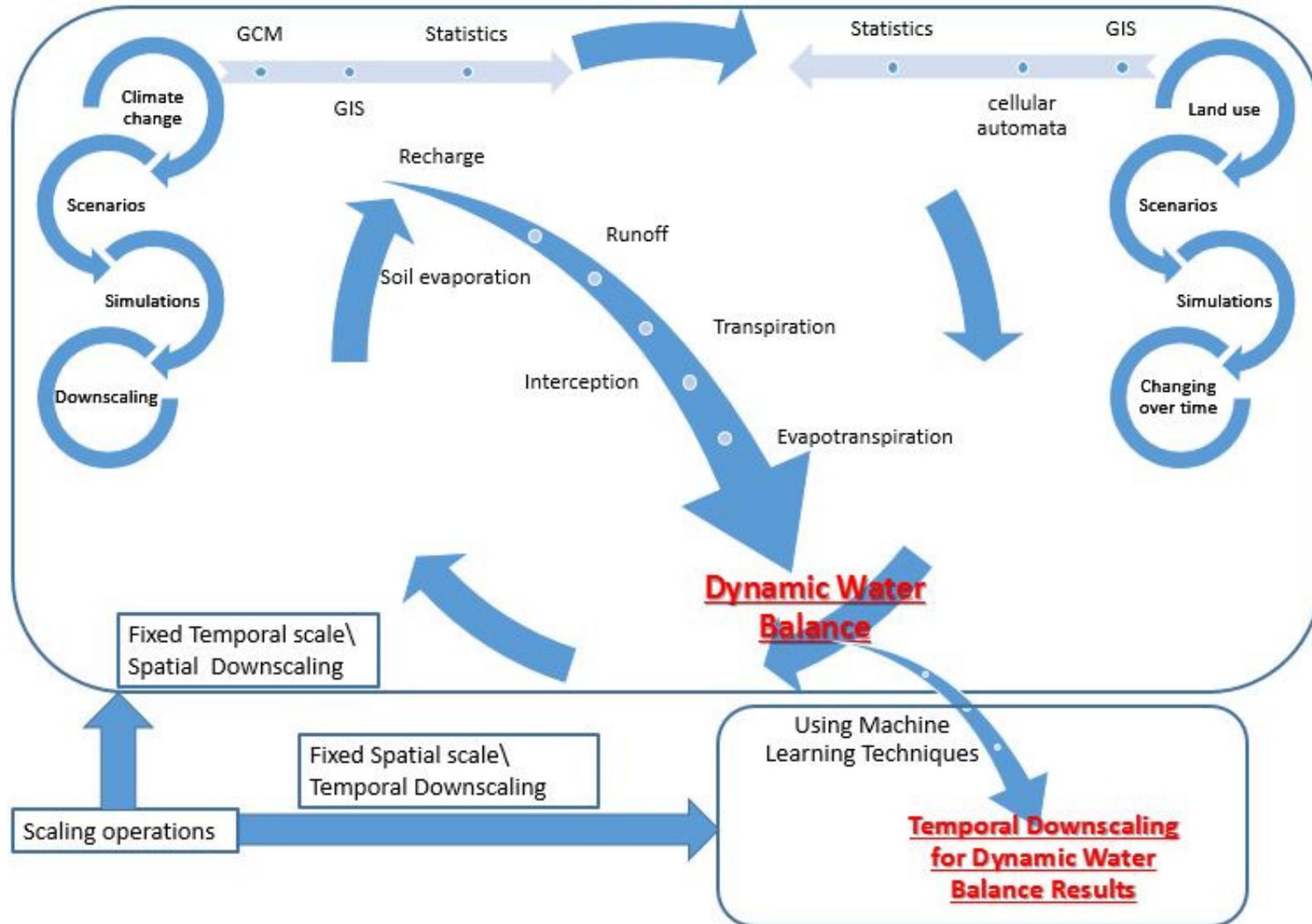


Figure 2: GEO-CWB general framework.

## 2. CLIMATE CHANGE MODELLING AND PROJECTION USING GEO-CWB

General circulation models (GCMs), which are the tools for estimating future climate scenarios, run on a very coarse scale, so the output from GCMs needs to be downscaled to obtain a finer spatial resolution. This section presents the innovative use of a Geographical Information System (GIS) as a downscaling environment, which was presented for the first time in (Gharbia *et al.*, 2016b). The section aims to present GIS platform as a downscaling environment through a suggested algorithm, which applies statistical downscaling models to multidimensional GCM-Ensembles simulations, see table 1. Applying such algorithm on GIS platform provides a wide range of output formats for the datasets, which can be used in most of the impact models without any extra effort in formatting the output datasets.

**Table 1:** Multi-GCM ensembles models details.

GCM	Institution	Resolution
CSIRO-MK3.0	CSIRO, Australia	175km * 175km
MIROC-H	Centre for Climate Research, Japan	100km * 100km
HADGEM1	Hadley Centre, UK	125km * 125km
NCAR-CCSM	National Centre for Atmospheric Research, USA	125km * 125km
CanESM2	Canadian Climate Centre, Canada	128km * 128km

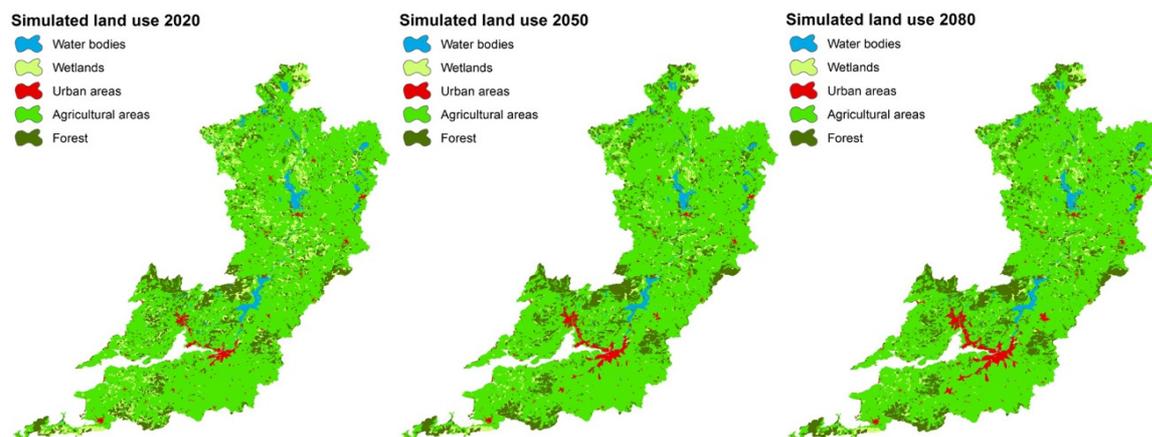
Climate change projections for the Shannon River catchment in Ireland were developed for several climate variables from multi-GCM ensembles for three future time intervals forcing by different Representative Concentration Pathways (RCP): all these processes are implemented in a GIS platform through designed and developed GIS-based algorithm. Statistical downscaling methods were used in the projection process after a particular verification and performance evaluation using several techniques such as Taylor diagram for each GCM-ensembles within independent sub-periods. The established statistical relationships were used to predict the response of the future climate from simulated climate model changes of the coarse scale variables. Significant changes in temperature, precipitation, wind speed, solar radiation, and relative humidity were projected at a very fine spatial scale. It was concluded that the main source of uncertainty was related to the GCMs simulation and selection. In addition, it was obvious to conclude that GIS platform is an efficient tool for spatial downscaling using raster data forms. The details and results from the climate change modelling part in GEO-CWB were published in the following papers (Gharbia *et al.*, 2016b, Gharbia *et al.*, 2016c).

## 3. LAND USE SCENARIOS MODELLING AND PROJECTION USING GEO-CWB

This stage investigates the spatiotemporally varying effects of urbanization using a combined method of CA and GIS rasterization for the River Shannon Basin area as a support tool for city planners, economists, urban ecologists and resource managers to help them establish decision-making strategies and planning towards urban sustainable development. The results generated from Cellular Automata model, see table 2 and figures 3-5, indicated that the historical urban growth patterns in the River Shannon Basin area, in considerable part, be affected by distance to district centres, distance to roads, slope, neighbourhood effect, population density, and environmental factors with relatively high levels of explanation of the spatial variability. The optimal factors and the relative importance of the driving factors varied over time, thus, providing a valuable insight into the urban growth process. The developed model for Shannon catchment has been calibrated, validated, and used for predicting the future land use scenarios for the future time intervals 2020, 2050 and 2080. By involving natural and socioeconomic variables, the developed CA model had proved to be able to reproduce the historical urban growth process and assess the consequence of future urban growth. The details, calibration, and validation process and results from the land use modelling part in GEO-CWB were published in the following paper (Gharbia *et al.*, 2016a).

**Table 2:** Land Cover transition matrix of River Shannon Basin area (Gharbia et al., 2016a).

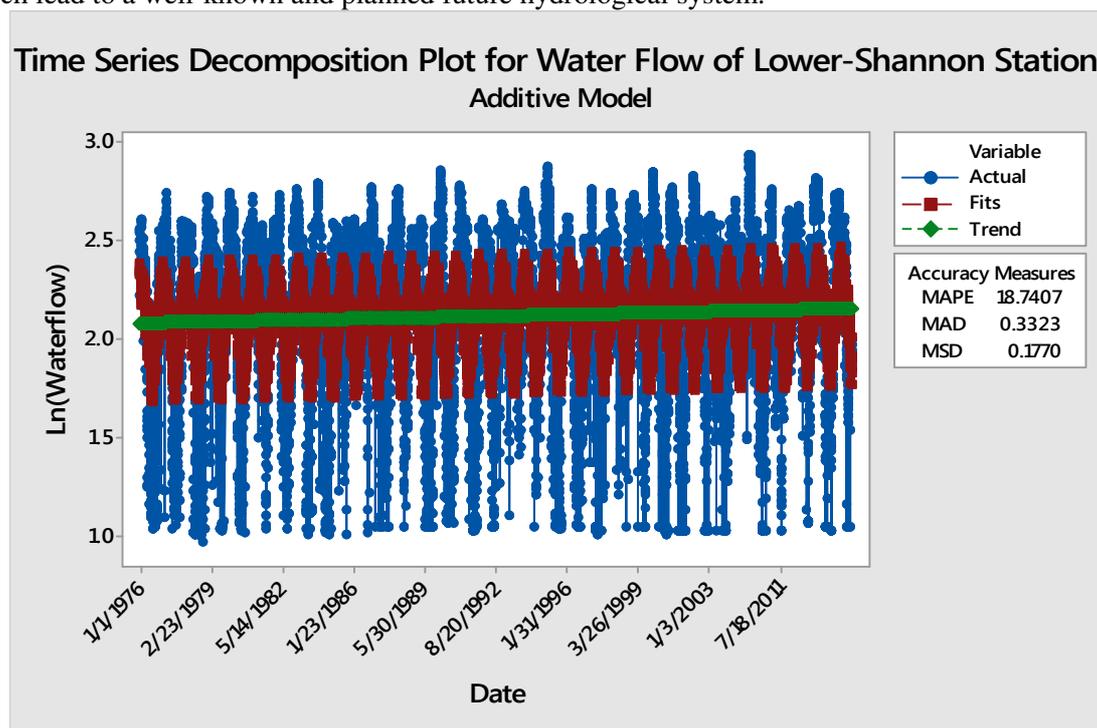
Land Cover Classes	km <sup>2</sup>	percent
<b>Change 2012 to 2020</b>		
Water bodies	-1.71	-0.39%
Wetlands	-208.45	-11.51%
Urban area	28.53	9.75%
Agricultural	110.99	0.82%
Forest	70.64	3.11%
<b>Change 2012 to 2050</b>		
Water bodies	-81.7	-18.58%
Wetlands	-941.21	-51.99%
Urban area	136.38	46.59%
Agricultural	553.59	4.08%
Forest	332.94	14.66%
<b>Change 2012 to 2080</b>		
Water bodies	-90.11	-20.50%
Wetlands	-1024.5	-56.59%
Urban area	244.05	83.37%
Agricultural	456.42	3.37%
Forest	414.13	18.23%

**Figure 3-5:** Cellular Automata (CA) predicted land cover for 2020, 2050 and 2080 (Gharbia et al., 2016a).

#### 4. HYDROLOGICAL SYSTEM SIMPLIFYING ALGORITHM AND LONG-TERM VARIATION ANALYSIS

This stage uses the integration of GIS-based systematic algorithms and time series statistical decomposition method for hydrological parameters' long-term variation analysis. In order to assess the long-term variation for a large and complicated system, the system need to be simplified or structured in a way that it can be introduced to a statistical model (Gharbia et al., 2015b). The suggested method has been used to identify the long-term variations in multi-time scales water level and streamflow regime over a 40-year period from 1975 to 2016. After running the developed GIS algorithm and design the simplified system, normality, independency and homogeneity assumptions are tested in preliminary data analysis stage. The results of the hydrological data tests illustrate that the streamflow and water level data could be taken as homogeneous, independent and normally distributed data for the simplified and structured hydrological system. Long-term changes analysis has been done for the water flow and water level time series data sets through statistical decomposition method, which examines both the seasonal and the trend components of each input time series, as an example figure 6 shows the statistical decomposition analysis for the water flow of Lower-Shannon hydrometric station. The results show that this variation analysis will be extremely helpful in studying and predicting the effects of climate changes on water level and streamflow for the applied Shannon River, since, it can provide a solid

ground for future daily water level and streamflow predictions using Machine Learning Techniques, which lead to a well-known and planned future hydrological system.



**Figure 6:** Time series decomposition plot for the Ln (water flow) transformed water flow time series of Lower-Shannon hydrometric station.

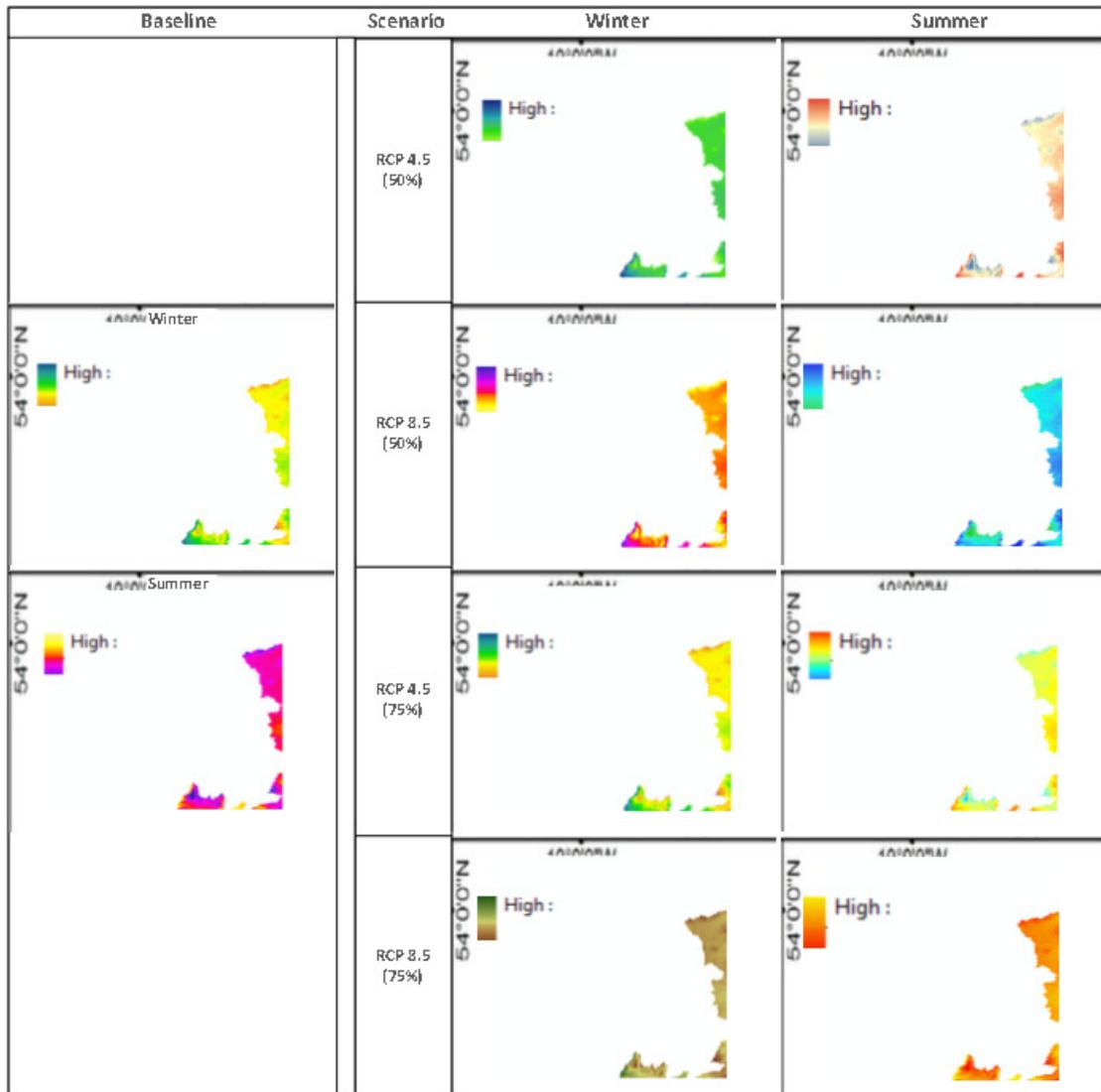
## 5. POTENTIAL EVAPOTRANSPIRATION SIMULATION USING GEO-CWB

Water balance modelling requires the spatial estimation of potential evapotranspiration (PET). PET is a complex non-linear hydrological process comprised of direct evaporation of moisture from the earth's surface and the transpiration of moisture within the leaves of plants. Due to complex interactions between meteorological and site-specific factors, PET is extremely difficult to quantify for a given location. Due to the nature of PET, its rate can vary significantly over a relatively short distance, thus the application of PET data related to another location can induce significant error. Consequently, to produce the reliable PET data required for the study region PET is modelled throughout the area within a Geographic Information System (GIS). In this stage of GEO-CWB, six temperature based PET equations are applied to long-term mean monthly data for the region; those equations are:

- Blaney-Criddle (Allen and Pruitt, 1986).
- Kharrufa (Kharrufa, 1985).
- Hargreaves and Samani (Hargreaves and Samani, 1982).
- Oudin (Oudin et al., 2010).
- Thornthwaite (Thornthwaite and Mather, 1957)
- Hamon (Hamon, 1961)

For each method, 12 monthly raster maps are created with a 50m<sup>2</sup> cell size representing PET throughout the Shannon catchment within the GIS. In order to evaluate the accuracy of the models, short-term mean monthly PET data is sourced from Met Éireann for four synoptic weather stations in the study area. From the comparison of the results with this data the Hamon method is found to be the most accurate with a mean  $R^2 = 0.888$ , RMSE = 8.6mm, MAPE = 16.5% and MAD = 6.5mm. Hamon method is applied to evaluate the possible effect of future climate change on PET rates. Climate change projections are completed for mean monthly temperature, from multi-GCM ensembles for three future time intervals (2020, 2050 and 2080) using a range of different Representative Concentration Pathways (RCPs) producing four scenarios for each time interval, resulted from climate change stage. Seasonal

results (April-September, October-March) are compared to baseline results to evaluate the impact of climate change, as an example figure 7 shows the simulated PET for the climatic period the 2080s compared to the baseline period for different RCPs.



**Figure 7:** Seasonal PET baseline and projections for 2080 according to different RCP.

## 6. FUTURE DYNAMICAL SPATIALLY DISTRIBUTED WATER BALANCE PROJECTION USING GEO-CWB

This stage presents the dynamical spatially distributed water balance calculation in GEO-CWB by integrating the climate and land use changes. This stage uses a wide range of input parameters and grids, including seasonally climate variables and changes, land use/land cover and its seasonal parameters and future changes, seasonal groundwater depth, soil properties, topography, and slope. GEO-CWB gives a wide range of seasonally and yearly gridded outputs layers as surface runoff, recharge, interception, evapotranspiration, soil evaporation, transpiration including total uncertainties or error in the water balance. In this stage, all the results from the previous stages have been used as input data for the calculation process. The simplified flowchart for this stage is presented in figure 9. As an example for the results, recharge is one of the simulated parameters in this stage, see figure 8, and the simulations show that the average annual recharge for the Shannon catchment is increased by 7.12% under the climatic scenario RCP 8.5 (75%) and the climatic period 2080s.

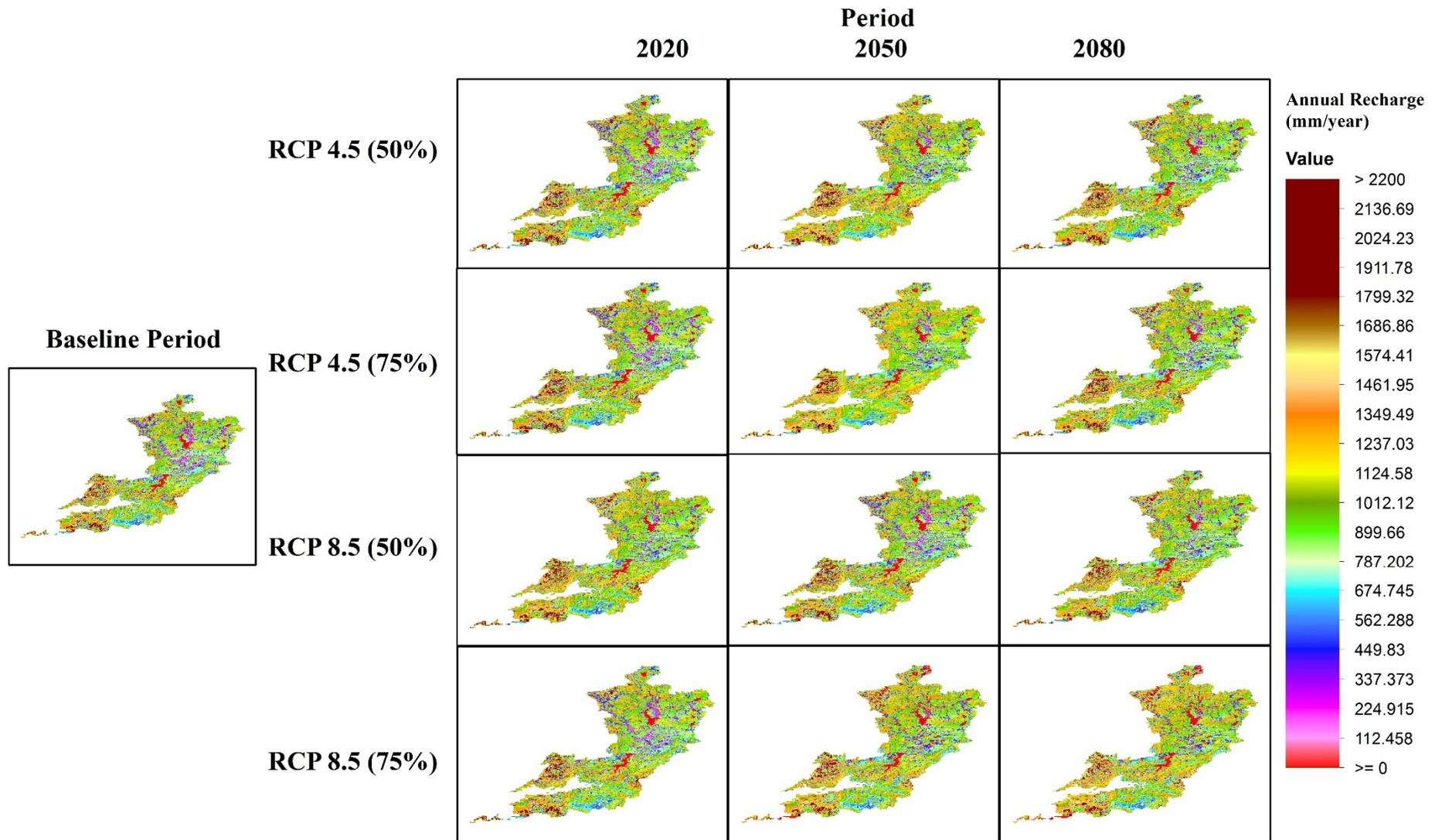


Figure 8: The average annual recharge for each climatic period simulated by GEO-CWB.

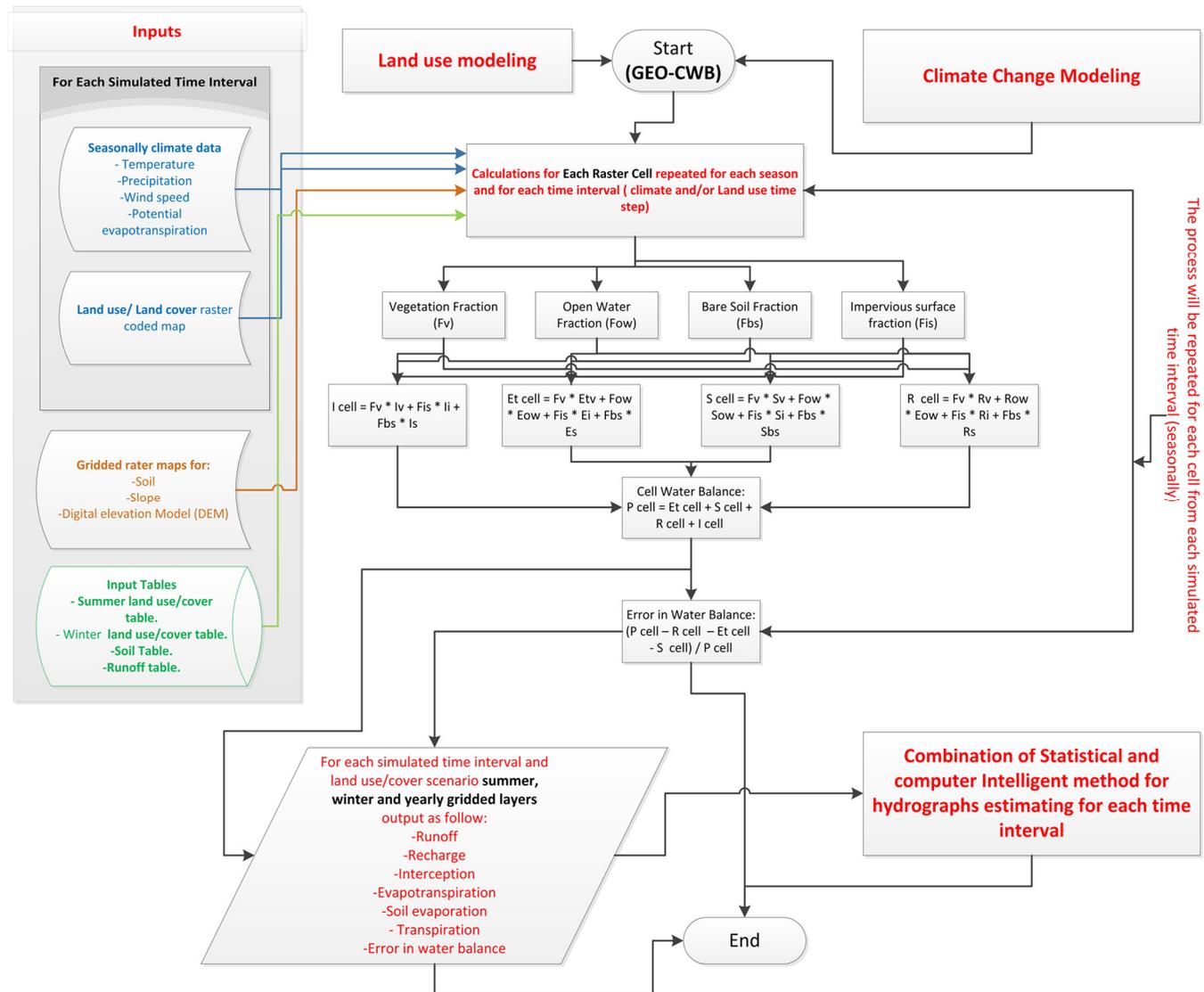


Figure 9: The simplified flowchart for the dynamical water balance stage in GEO-CWB (Gharbia et al., 2015a).

## 7. WATER VULNERABILITY PARAMETERS IN GEO-CWB

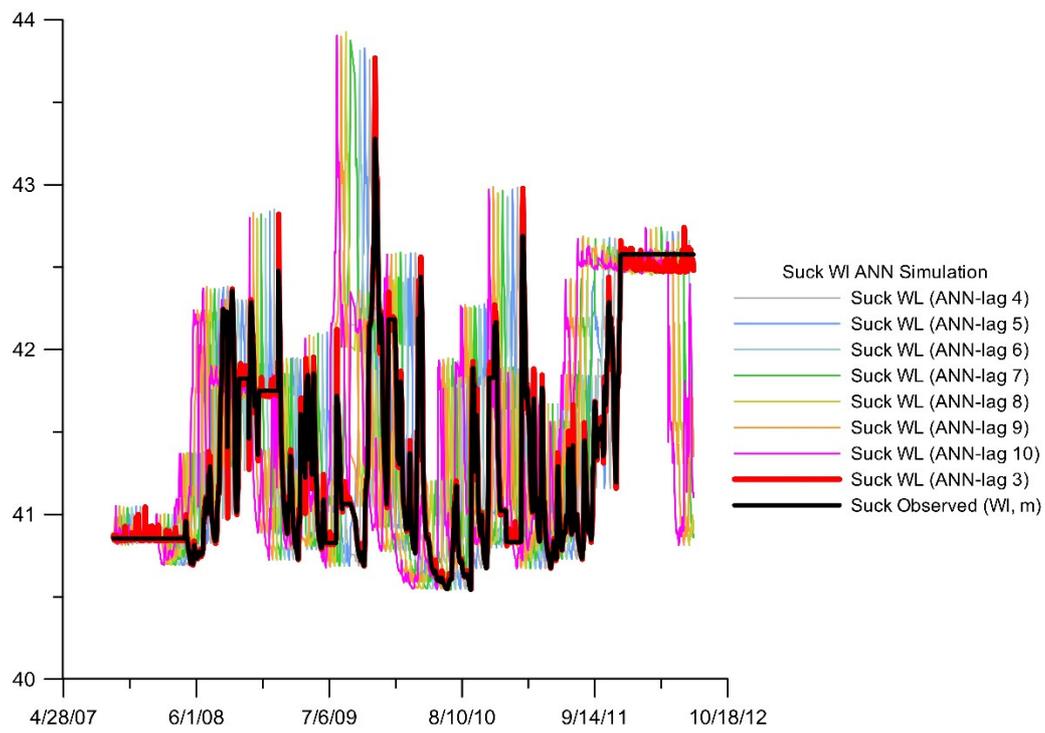
This Stage of GEO-CWB aims to produce some calculated parameters using the outputs from all the previous stages to assess the vulnerability to climate and land use changes for each climatic period and land use scenario. The calculated parameters are as following:

- The accumulated runoff volume in the rainy season is an indication of how much runoff water could be harvested every year during the rainy season.
- The safe yield groundwater abstraction rate expressed in (m<sup>3</sup>/d/ha).
- The water deficit for ideal crop growth, which can be estimated as the difference between the crop water requirement and the actual evapotranspiration.

As an example for this stage results, figure 11 shows the calculated accumulated runoff volume as results to the different climate change conditions and land use scenarios. For the illustrated annual accumulated runoff the baseline annual areal average accumulated runoff is 14.59m<sup>3</sup> as an average for all cells in the simulation domain, however, the areal average value for the accumulated runoff for the climatic period the 2080s forced by RCP 8.5 (75%) climatic scenario is 15.48, which means the average increase in the accumulated runoff is around 6%. However, the areal accumulated runoff average for the whole catchment is increased but hotspot areas spatial distribution is changed as results of climate and land use changes.

## 8. USING MACHINE LEARNING TECHNIQUES AND GEO-CWB FOR WATER LEVEL AND WATER LEVEL MODELLING

The last stage in the GEO-CWB is the using of the Machine Learning Techniques to the outputs from the previous stages in order to simulate the high-resolution temporal scale for the hydrological parameters such as water level and water flow. The GEO-CWB uses the following Machine Learning Techniques: (i) Wavelet (W), (ii) Support Vector Machine (SVM), (iii) Artificial Neural Network (ANN), (iv) Wavelet-Support Vector Machine (WSVM) and (v) Wavelet- Artificial Neural Network (WANN). The different methods are applied to the outcomes of the GEO-CWB model for the simplified and structured hydrological system for Shannon River in order to model and predict the water level and streamflow parameters for hydrometric stations along the river for daily time steps according to different climate change and land use scenarios and using different lag values for the input variables. As an Example for the results, figure 10 shows the observed and the simulated water level values for Suck hydrometric station using the ANN with different lag values, the figure shows that the model with lag (3) is performing the best.



**Figure 10:** The observed and simulated water level for Suck hydrometric station using ANN.

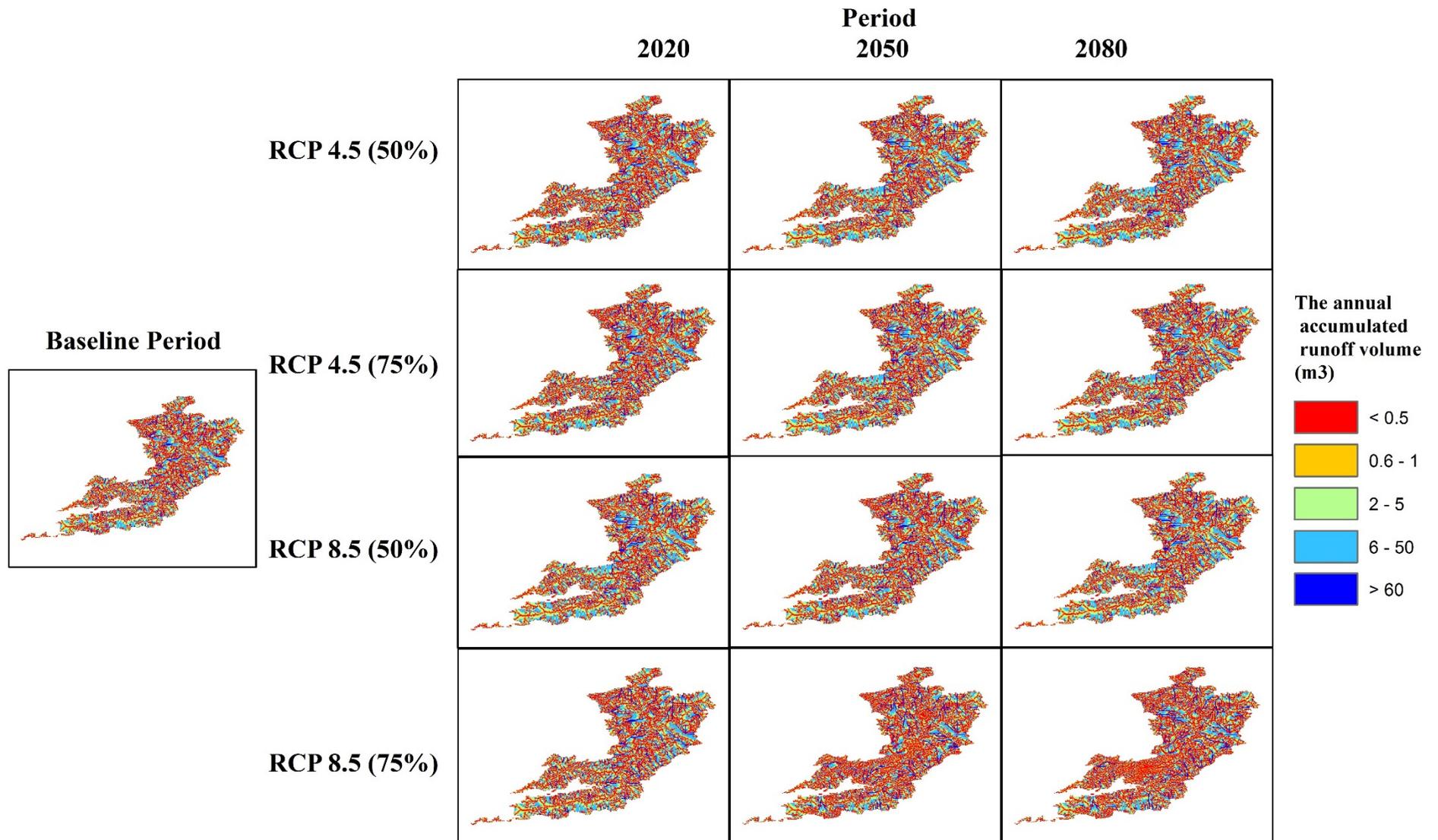


Figure 11: The annual accumulated runoff (m<sup>3</sup>) for each climatic period simulated by GEO-CWB.

## 9. CONCLUSIONS

This research is concerned with addressing gaps in the state of knowledge regarding the modelling and prediction of climate and land use changes and their impacts on water resources. The main goal of this research project is to create an innovative and integrated environmental modelling tool (GEO-CWB) to allow the scientific community, modellers, planners and decision makers to study the impact of climate and land use changes on water resources. This research shows the novelty of using an integrated physical Computer Learning Techniques to model the complicated hydrological systems under GIS platform.

The long-term trend analysis shows a significant increase (at the 95% confidence level) of streamflow in the Shannon River for the period of 1976–2015. Seasonal and annual streamflow analyses show consistency with the increasing trends. The results for the land use changes for the Shannon Basin area indicate an increase of urban area from 1.59% in 2012 to 2.92% in 2080, which is a total 244.05 km<sup>2</sup> of land will be converted into urban areas in 2080. That means the overall change percentage from 2012 to 2080 will be 83.37%. The majority of the urban area will come from the conversion of agricultural to urban areas; also, the small portion of the increase will be from converting wetlands and forest to an urban area. The urban expansion will be mainly around Limerick city, Ennis, Mullingar, Athlone, and Tipperary. The scale of increases in PET was found to vary depending on climate change scenario and year. The maximum mean increase in PET was as a result of the 75% RCP 8.5 scenario in 2080 which returned an increase of 75.9 mm annually. The results show that climate and land use changes have significant impacts on the dynamical water balance on both spatial and temporal scale.

These innovative methods and tools developed as part of this project and their integration with GIS represent an effective approach to study and predict the effects of climate and land use changes in a river basin because it can provide a solid ground for future daily hydrographs predictions, which lead to a well-known and planned future hydrological system.

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