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Potential influence of climate and land-use changes on green water security in a semi-arid catchment

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ABSTRACT

Temporal and spatial changes of green water (GW) security due to climate and land-use/land-cover (LULC) changes can be used to make the best decisions for sustainable GW management. In this study, simultaneous effects of climate and LULC changes on water resources in Kashafrood Basin were evaluated using the Soil and Water Assessment Tool (SWAT). A land change modeler was set up to monitor LULC, assess changes and make predictions. The MIROC-ESM model derived from Coupled Model Intercomparison Project Phase 5 under two representative concentration pathway (RCP) emission scenarios RCP2.6 and RCP8.5 was applied to evaluate the effects of climate change. Two indices of GW-Scarcity and GW-Vulnerability, representing GW-Security, were quantified using the GW-Footprint concept in Kashafrood Basin. The results show that the annual average of blue water was predicted to increase by 142–350%, and GW storage and the annual averages of GW flow were predicted to decrease by 12–65 and 8–20%, respectively, depending on emission scenarios and time. The GW-Security estimates in the entire basin suggest a better condition in the future by indicating 24–45 and 16–52% decreases in GW-Scarcity and GW-Vulnerability, representing scenarios and time.

Key words: green water security, land change modeler, land-use/land-cover change, MIROC-ESM, Soil and Water Assessment Tool

HIGHLIGHTS

- Land change modeler predicts a decline in agricultural area and a growth in urban and pasture areas.
- Blue water rises by 142–350% under the effect of climate and land-use changes.
- Green water (GW) storage and GW flow decrease by 12–65 and 8–20%, respectively.
- The condition of the basin in terms of GW-Security would improve in the future.
- GW-Scarcity and GW-Vulnerability escalate in southern and some western subbasins.

INTRODUCTION

Climate and land-use/land-cover (LULC) changes play a prominent role in altering the hydrological processes. Climate change influences the regional water balance by affecting precipitation and temperature, and LULC changes are directly linked to changes in evapotranspiration, interception and infiltration (Pan *et al.* 2017; Shao *et al.* 2018). Land degradation, soil erosion, desertification, urbanization, suburbanization, industrialization and poor management of environmental resources induce the LULC changes which decrease available water supplies (Briassoulis 2019). LULC change analysis indicates the qualitative and quantitative characteristics of LULC. This analysis reveals the forces or factors that directly or indirectly induce changes. Moreover, the prediction of LULC changes indicates the spatial and temporal levels of this analysis. A study of LULC changes can provide incentives to make policies for integrated water resources management and sustainable development. Additionally, Global Circulation Models (GCMs) can be used as one of the most reliable tools for climate projections in climate change assessment. Coupled Model Intercomparison Project Phase 5 (CMIP5), with improved capability of simulating climate change, provides numerous GCMs and has a smaller bias than CMIP3 (Jia *et al.* 2019). The Intergovernmental Panel of Climate Change (IPCC), in its Fifth Assessment Report

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(AR5), released four new greenhouse gas emission scenarios (called representative concentration pathways (RCPs) 2.6, 4.5, 6.0 and 8.5) based on their potential range of radiative forcing values (W/m^2) (Tan *et al.* 2017). Climate change mainly affects the amount of precipitation, while land-use change mainly influences soil water holding capacity and surface evapotranspiration. These changes in hydrological processes threaten the freshwater resources availability for human, irrigation and energy generation (Veettil & Mishra 2016). Water consumption is one of the stressors that expose 80% of world's population to the water security risk (Vörösmarty *et al.* 2010; Rodrigues *et al.* 2014). Approximately 1.8 billion people would encounter water scarcity by 2025 (WWAP 2012; Connor 2015). Thus, it is necessary to have a full perception of water resources components in a sustainable manner. Furthermore, awareness of the effects of climate and LULC changes on water resources can supply a theoretical basis for ecological water resource planning and local water resource management.

The freshwater cycle is classified into 'green' water (GW) and 'blue' water (BW) according to storage types in hydrological processes. BW is described as the total deep aquifer recharge and surface runoff stored in lakes, rivers and shallow aquifers. GW flow (GWF) is the actual evapotranspiration emitted to the atmosphere as a result of evaporation from water bodies and soil and transpiration from vegetation. GW storage (GWS) refers to the portion of precipitation that infiltrates the soil (Falkenmark & Rockström 2006; Rodrigues et al. 2014). GW resources play a significant role in sustaining the production and services in land ecosystems (Lyu et al. 2019). Considering the water balance in hydrological cycles, GW (consumed by evapotranspiration in grasslands, forests, wetlands and cultivated lands) and BW account for 65 and 35% of the total global precipitation, respectively. Moreover, GW contributes to over 80% of the global grain production (Liu et al. 2009). Although the availability of GW is much larger than BW, the allocation of GW is rarely considered. Competition over the consumption of the limited GWF between natural ecosystems and human economy for biomass production leads to GW-Scarcity. These tensions are intensified as the GW demand for biomass grows with the growth of population and increase of GW demands per capita (Schyns et al. 2019). Therefore, the scarcity and vulnerability assessments of GW resources can provide a useful basis for the future. The BW and GW consumed by human activities are defined as water footprints (Hoekstra 2003; Hoekstra et al. 2011). The BW-Footprint represents the consumption of BW sources for producing goods and services (e.g., industrial, domestic, irrigation and power production), while the GW-Footprint represents the consumption of GW in agricultural lands (e.g., evapotranspiration from cultivated land and pastures) (Hoekstra et al. 2011; Veettil & Mishra 2016).

Water security is described as 'capacity to maintain a reliable access to sufficient quantity and good quality of water for livelihood, socio-economic development and human well-being, to ensure protection against water-related disasters and water-borne pollution in order to conserve ecosystems' (UN Water 2013; Marttunen *et al.* 2019). Similar to integrated water resources management, water security suggests a paradigmatic approach toward water systems analysis that covers quantity and quality concerns including water availability and hazards. In the absence of an integrated framing in water security, the greater environmental objectives can be excluded (Cook & Bakker 2012). In water resources discipline-based definition, GW-Security is calculated as a ratio of consumed water to available water (Rodrigues *et al.* 2014; Veettil & Mishra 2016). This ratio is employed to specify the geographic hotspots under water stress (Hoekstra *et al.* 2011; Rodrigues *et al.* 2014). The assessment of GW-Security is a research prerequisite and can contribute to universal analysis of environmental health, food security, poverty and human and economic developments (Hoekstra *et al.* 2011).

Due to poor water resources management, significant levels of water scarcity already exist in Iran. In addition to climate change and LULC changes, some important issues in agricultural policy, which are directly related to water security, are aiming to achieve food self-sufficiency in the country, heavy dependence on irrigation, mismatch between the geographic distribution of water availability and the spatial cropping pattern, low water-use efficiency and a small share of rain-fed agriculture (Karandish & Hoekstra 2017). Kashafrood River, as the longest river in the northeast of Iran, is the main source of surface water supply in Mashhad, which is the major city located within Kashafrood River Basin. Extreme dry events have caused water scarcity and contamination in Kashafrood Basin (Afshar *et al.* 2017). Most of the studies on water resources components in Kashafrood Basin have mainly focused on the projected climate variations, ignoring the future LULC variability (Sayari *et al.* 2013; Afshar *et al.* 2018). A comparison of the simultaneous effects of climate and LULC changes and the effect of climate change can reveal the prominent role of LULC changes in water resources projection.

Given that climate and LULC changes directly affect water balance and water resources components, it is desirable to study their effects on water resources and GW-Security considering the LULC changes. Hence,

the objectives of the present study are (a) building a land change modeler (LCM) model, analyzing the changes and predicting the future LULC maps; (b) investigating the spatiotemporal distribution of BW, GWS and GWF in Kashafrood Basin under the proposed scenarios and (c) quantifying the GW-Security and the spatial distribution of GW-Security based on water scarcity and vulnerability. This is known to be the first study that has investigated the effects of climate and LULC changes on water resources components in Kashafrood Basin simultaneously and has assessed water security focusing on GW in the future. The spatiotemporal LULC changes were also analyzed to develop better policies for water resources management. The understanding of variation of freshwater resources, GW-Security and LULC changes in Kashafrood Basin in the future can help policymakers to manage the basin more sustainably.

MATERIALS AND METHODS

Case study and data description

This study was done in Kashafrood Basin ($35^{\circ}40'-36^{\circ}3'N$, $58^{\circ}2'-60^{\circ}8'E$) located in the northeast of Iran. The altitude of the study area is from 391 m in the southeast to 3,234 m in the northwest (Figure 1). This basin, with a total area of 16,750 km², covers major cities such as Mashhad (the second most populous city in Iran), Quchan and Chenaran. It has a semi-arid and cold climate with low annual precipitation and high evapotranspiration rate in summer. The climate data for study area within 1992–2017 are mean precipitation of 340 mm/year, mean annual temperature of 13.6 °C, maximum recorded temperature of 20.6 °C and minimum recorded temperature of 7.1 °C (Afshar *et al.* 2017). The predominant LULC type in the basin in 2017 was



Figure 1 | Location of the study area.



Figure 2 | LULC map of 2017.

pasture, followed by irrigated farmland, rain-fed land, forest, residential areas, barren lands and water bodies (Figure 2). The main crops cultivated in Kashafrood Basin are wheat (spring and winter), barley and sugar beet according to Khorasan Razavi agricultural landscape report.

The used databases are satellite data, digital elevation model (DEM), geographical data (roads, cities and towns), soil-type data, meteorological data, hydrological data and the future climate data. DEM data, received from the National Cartographic Center of Iran (NCC), were used to generate the digital river network and to delineate the basin into subbasin design. The soil property map was also gained from the Range and Watershed Department (RWD) of Khorasan Razavi. Meteorological data (including daily precipitation and temperature data from 1992 to 2011) were attained from Iran Meteorological Organization (IMO). The monthly runoff data records at five gauging stations (Sar Asiab Shandiz, Zire Band Golestan, Golestan Jaghargh, Hesar Dehbar and Kartian) were collected from Water Resource Management Company (IWRMC). The datasets required to project the future land use were the land-use maps for previous years and the variables affecting land-use changes. Remote sensing was employed to prepare land-use maps. Landsat satellite images from Landsat Thematic Mapper (LTM) in 1987, Enhanced Thematic Mapper (ETM⁺) in 2002 and Operational Land Imager (OLI) in 2017 were acquired from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). Image preprocessing, including radiometric and atmospheric corrections, image mosaicking and image cutting, was performed to obtain accurate classification. Using the maximum-likelihood method, the basin was classified into seven land-use types: pasture (PAST), agricultural land-generic (AGRL), winter wheat (WWHT), forest (FRSE), urban area (URBN), range-brush (RNGB) and water body (WATR). Google Earth and field investigations were applied to examine the accuracy of interpreted images, which helped in preparing the LULC maps for 1987, 2002 and 2017. The geographical data obtained from NCC were applied to prepare the affective variables (distance to road and distance to urban area) by ArcGIS.

Soil and Water Assessment Tool model and simulation setup

The Soil and Water Assessment Tool (SWAT) model was employed to simulate the water resources components. The SWAT model, which is a semi-physically-based, semi-distributed and basin-scale model, is widely applied for water quantity assessment in many countries. For example, it was used in the studies conducted in the United States (Veettil & Mishra 2016), Brazil (Rodrigues et al. 2014), India (Gosain et al. 2011), China (Zang & Liu 2013; Zhu et al. 2018) and Iran (Faramarzi 2010; Afshar et al. 2018). In SWAT, a basin can be divided into several subbasins according to the DEM data. Each subbasin can also be divided into different hydrologic response units (HRUs), which contain identical land-use types, slope characteristics and soil types (Arnold et al. 2012). Kashafrood Basin was divided into 217 subbasins and 635 HRUs. The surface flow was estimated by the Soil Conservation Service (SCS) curve number method, and the potential evapotranspiration was calculated by the Hargreaves method. Hydrological variables, such as runoff and evapotranspiration, were obtained from each subbasin. The Sequential Uncertainty Fitting program algorithm (SUFI-2) in SWAT-CUP interface was utilized to optimize, validate, calibrate and render uncertainty analysis of the model parameters. In SUFI-2, parameter uncertainty applies to all sources of uncertainty including uncertainty in conceptual model, measured data, driving variables and parameters (Abbaspour 2011). In this study, determination coefficient (R^2) and Nash–Sutcliffe efficiency (NSE) were utilized to assess the model performance. P-factor and r-factor were also applied in uncertainty analysis. P-factor is percentage of the measured data bracketed by 95% predictive uncertainty band, and rfactor is the mean width of the band (Abbaspour et al. 2004). SWAT performance analysis was done within 19 years from 1992 to 2011. For model evaluation, the dataset of 1992-2011 was divided into calibration period (1992-2000) and validation period (2001-2011). A warm up period (1992-1995) was chosen to achieve a steady state for modeling.

Land change modeler

The LCM for ecological sustainability was designed for the analysis of land-cover changes and the projection of the future land-use maps. The basic principle in this model is to evaluate the trend of changes from one land-use class to another, considering the influence of several variables such as roads, slope and aspect. Generally, LCM predicts a land-use pattern based on the previous change trend. This model was selected because of its efficiency in land-use change prediction (Pickard *et al.* 2017; Anand *et al.* 2018). LCM is a Cellular Automata and Markov-Chain-based built-in module at TerrSet IDRISI and contains the tools for analyzing land-cover change, identifying class transition potential and modeling several transitions at one time to predict the land-use maps. The change

analysis tool was applied to recognize the class changes within 1987–2002. This tool assesses the transition among land-use classes in a selected time. Considering the sophisticated land-use changes in Kashafrood Basin, dominant transitions were specified (transitions below 1 km² were neglected) and classified into two sub-models: (1) transitions to urban area (AGRL to URBN, PAST to URBN and WWHT to URBN) that directly considers the growth of urbanization and (2) other transitions (AGRL to PAST, FRSE to PAST, PAST to AGRL, PAST to RNGB and WWHT to PAST). Driver variables were tested, and the variables with Cramer's coefficient of higher than 0.1 were selected. Distance to roads and distance to urban area were selected for the first sub-model, while DEM, slope and aspect were selected for the second sub-model. Modelling of transitions at one time in LCM was performed by multi-layer perceptron artificial neural network. A hard modeling process, which relies on the predictions with particular change classifications based on a class designation competitive model identical to a multi-objective decision process, was employed (Armenteras *et al.* 2019). In the present study, the prediction of land-use change was validated by a comparison of the reference map and the prediction map of 2017. The percentage of area differences in land-use classes was less than 8%. Considering this level of agreement, the model was found eligible to predict the changes for 2032, 2062 and 2092 (Saifullah *et al.* 2017).

Description of the scenarios for climate and LULC changes

To survey the simultaneous effects of climate and LULC changes on hydrological components, four time intervals were considered: historical period (1992-2013), near future (2014-2042), intermediate future (2043-2071) and distant future (2072-2100). MIROC-ESM is a Japanese earth system model derived from the CMIP5 to project the climate conditions. Among 14 GCMs, MIROC-ESM has shown a good performance in reproducing the observed climatology in Kashafrood Basin (Afshar et al. 2018). The bias-corrected spatial disaggregation (BCSD) method was used to downscale the MIROC-ESM model data. Details of this method have been presented by Afshar et al. (2018) and Jafarzadeh et al. (2019). After downscaling the climate data and predicting the future land-use maps by LCM, appropriate climatic and land-use data were prepared for each time period. LULC maps of 2002, 2032, 2062 and 2092 were related to historical, near future, intermediate future and distant future periods, respectively. RCPs were labeled based on their radiative forcing level by 2100. Furthermore, the lowest level (RCP2.6) and the highest level (RCP8.5) of radiative forcing were considered to investigate the highest impact and the lowest impact of climate change on water resources. Low representative RCP2.6 scenario is shown to be technically feasible, by participation of all countries in the world in the short run. It can be referred to the broadening participation of the Organization for Economic Cooperation and Development (OECD) countries (Van Vuuren et al. 2010). RCP8.5 follows the pathway of a continuously rising radiative forcing and targets 8.5 W/m² in 2100 with a further enhanced residual circulation and significant CH₄ increases. In addition, by selecting these two scenarios, the results of this study can be compared with a similar study in Kashafrood Basin conducted by Afshar et al. (2018).

In other words, six statuses for the future scenarios and one historical scenario were examined to analyze the long-term values of water resources and GW-Security. Figure 3 shows a schema of the SWAT model used for assessing water resource components and GW-Security in Kashafrood Basin.

Quantification of GW-Security

Vulnerability and scarcity indices were applied to assess GW-Security in the basin. GW-Scarcity indicator was measured as the ratio of GW-Footprint to GW-Availability (Hoekstra *et al.* 2011; Veettil & Mishra 2016). Actual evapotranspiration represents the GW-Footprint. As already depicted, the Hargreaves method was selected for simulating evapotranspiration at the HRU spatial scale. GW-Availability is the amount of available water for sustainable crop growth and can be calculated by subtracting the wilting point from the total soil moisture in the root zone. Wilting point is the minimum soil moisture content at which crop sustainability no longer exists (Rodrigues *et al.* 2014; Veettil & Mishra 2016). Therefore, the initial soil water content obtained from the HRU output files represents the GW-Availability. Closeness of the mean water use to the physical water availability threshold can be represented by the water scarcity indicator (Rodrigues *et al.* 2014). GW-Scarcity can be calculated by the following equation:

 $GW - Scarcity_{(x,t)} = \frac{GW - Footprint_{(x,t)}}{GW - Availability_{(x,t)}}$

(1)



Figure 3 | Schematic flowchart of the used SWAT model.

where GW-Availability_(x,t) is the amount of initial soil water content in zone 'x' within the period 't', and GW-Footprint_(x,t) is the GW consumed in zone 'x' during period 't'.

The GW-Vulnerability indicator can be described as the susceptibility of agricultural water consumption under drought-like conditions or low soil water content (Padowski & Jawitz 2012). Thus, GW-Vulnerability is measured as the ratio of GW-Footprint to the historical low GW-Availability (the 30th percentile). GW-Vulnerability is calculated by the following equation:

$$GW - Vulnerability_{(x,t)} = \frac{GW - Footprint_{(x,t)}}{GW - Availability_{(P30)(x,t)}}$$
(2)

where GW-Availability_{(P30)(x,t)} is the historical low volume of soil water content at zone 'x' during the period 't', which exceeds 70% of the time, expressed by the 30th percentile of the records.

RESULTS AND DISCUSSION

LULC change analysis and prediction

Figure 4 shows the LULC maps predicted for 2032, 2062 and 2092 by the LCM model. The relative areas in each LULC class for the historical and the future periods are presented in Table 1.

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Figure 4 | LULC maps predicted for the future.

LULC areas in the historical

Table 1 | LULC areas in the historical and future periods and change percent in the future in Kashafrood Basin

LULC	period (km ²)			LULC areas in the future (km ²)			Change percent (%)		
	1987	2002	2017	2032	2062	2092	2002-2032	2032-2062	2062–2092
AGLR	4,803	4,724	4,626	4,591	4,468	4,354	-0.79	-0.73	-0.68
FRSE	517	491	474	445	404	368	-0.27	-0.24	-0.21
PAST	8,554	8,607	8,644	8,709	8,803	8,886	0.60	0.56	0.49
RNGB	81	89	122	98	108	117	0.05	0.05	0.05
URBN	186	240	326	348	452	553	0.64	0.62	0.60
WATR	1	2	6	2	2	2	0	0	0
WWHT	2,608	2,598	2,547	2,553	2,510	2,468	-0.26	-0.25	-0.25

According to Table 1 and Figure 4, the AGRL LULC declines in the specified periods. Population growth, pressure of industry, water shortage, decline of agricultural productivity and change of rural lifestyles are among the factors affecting the AGRL class. FRSE LULC also has a declining trend, which can be due to the overexploitation of forests for timber and overgrazing in sub-mountain areas. However, the PAST LULC has an increasing trend. Since the pastures include dense, semi-dense and poor pastures, the conversion of other LULC classes to poor pastures due to the deforestation and reduction of water resources might be responsible for this trend. The RNGB land use covers a small area of the basin and its increase is likely due to conversion from poor pasture and largely due to drought and soil degradation in recent decades. According to the results, the URBN land use has an increasing trend, particularly due to population growth in residential areas. WATR in the study area is confined to the lake of dams and covers a very small area. Due to the water resources scarcity in recent decades, the government has adopted a dam-building policy. The construction of several dams in the area shows an increased water body in the historical LULC maps. After pasture and agricultural lands, the rain-fed area (WWHT) is the most abundant LULC in Kashafrood Basin. This land use has a gentle downward trend. Precipitation reduction, soil degradation and, in some areas, conversion to industrial areas are among the factors involved in the reduction of this LULC.

The 1987 and 2002 LULC layers were employed for the calibration of LCM as the observed data, while the 2017 classified LULC layer was applied for the verification of the simulated map for 2017. By analyzing LULC class changes in two time periods of 1987–2002 and 2002–2017, it could be concluded that the largest area change in the first period was a decline of AGRL class by 0.2% of the basin area. In the second period, the URBN class experienced the highest level of change with a 0.37% increase in the basin area. In both periods, the WATR class had the least change in the basin area due to its very small surface area. Therefore, its change was not taken into account in predicting the LULC maps. A comparison of the changes in the two periods implied that the intensity of changes was greater in the second period than in the first period. The simulation of LULC changes and the prediction of future LULC maps were carried based on the changes in the course of 1987–2002. Moreover, the decreasing or increasing trend of each LULC in future maps was repeated.

Simulation results of SWAT

The validation and calibration of the SWAT model were conducted with the SUFI-2 algorithm at five gauging stations in Kashafrood Basin. The goodness-of-fit between the simulated and observed flows was calculated (Table 2). The average R^2 values and NSE in both validation and calibration periods indicated that the SWAT model could satisfactorily simulate streamflow dynamics in Kashafrood Basin with an acceptable accuracy (Moriasi *et al.* 2007).

Spatial distribution of BW, GWF and GWS

For water resources management and planning in any region, it is essential to evaluate the spatial distribution of water resources components (BW and GW) affected by climate and LULC changes and subsequently identify the critical areas. To achieve a full understanding of water resources components, spatiotemporal distributions of mean annual temperature and annual precipitation under RCP2.6 and RCP8.5 were prepared (Figures 5 and 6). As shown in Figures 6 and 7, although the temperature will increase in future periods in the basin, it has a variable spatial distribution at the subsurface level. Furthermore, according to the RCP2.6 and RCP8.5 emission

 Table 2 | Goodness-of-fit statistics at five gauging stations (Afshar et al. 2018)

	Calibration results				Validation results			
Flow station	R ²	NSE	P-factor	r-factor	R ²	NSE	P-factor	<i>r</i> -factor
Sar Asiab Shandiz	0.72	0.71	0.57	1.1	0.65	0.64	0.56	0.96
Zire Band Golestan	0.66	0.65	0.58	1.29	0.84	0.83	0.65	0.92
Golestan Jaghargh	0.66	0.64	0.63	0.95	0.74	0.73	0.64	0.81
Hesar Dehbar	0.63	0.60	0.74	0.92	0.81	0.81	0.78	0.75
Kartian	0.68	0.63	0.66	0.90	0.87	0.87	0.67	0.58



Figure 5 | Spatiotemporal distribution of temperature.



Figure 6 | Spatiotemporal distribution of precipitation under RCP2.6 and RCP8.5.



Figure 7 | Spatial distribution of the water resources components in the historical period.

scenarios, precipitation will have a different trend in future periods. In a study conducted by Badou *et al.* (2018) on four subbasins of the Beninese part of the Niger River Basin, the effect of climate change on water resources components has been evaluated using three climatic models (HIRHAM5, RCSM and RCA4). A comparison of climate variables between historical and future periods suggests that rainfall will increase for HIRHAM5 and RCSM but shows mixed trends for RCA4. The mean temperature will also increase for HIRHAM5 and RCSM but decrease for RCA4.

As previously mentioned, four time periods were considered to evaluate the water resources components (historical period, near future, intermediate future and distant future), and two RCPs (RCP2.6 and RCP8.5) were applied to illustrate the climate change impacts in the future periods. Figure 7 displays the spatial distribution of the water resources components in the historical period.

According to Figure 7, in the historical period, the BW content was less than 55 mm/year in all the subbasins, except for the northern subbasins and some central and western subbasins. The maximum BW content was observed at the northwestern subbasins, where Kashafrood River enters the basin, while the minimum BW content was recorded at the downstream subbasins in the south. The highest and the lowest levels of BW were 126 and 0.7 mm/year, respectively. Due to the precipitation pattern in the historical period, high precipitation in the northern and northwestern subbasins justifies the high BW content in the subbasins. The dominant forest land cover in some northern basins and the soil texture with higher sand percentages in the northern and northwestern subbasins are the factors that contribute to the increased BW content. GWF content, which represents the actual evapotranspiration, is greater in the north and northwest of the basin than in the southern half of the basin. The maximum and minimum values of GWF in the basin were 323 and 132 mm/year. Since the GWF content directly depends on vegetation, GWF levels were higher in the northern half of the basin, particularly in the areas covered with agricultural lands, pastures and forests, compared to the southern half of the basin. In the southern subbasin, due to less precipitation and lack of water for agriculture, the GWF level is lower. Therefore, the GWF level was less than 180 mm/year in the subbasins with a rain-fed land cover. GWS represents the soil moisture content and depends on the soil type and soil texture. As shown in Figure 7, the GWS content was higher in three parts of the basin, with the values greater than 100 mm/year. The high values of GWS in the relevant subbasins are justified by the soil texture (mainly with higher clay and silt percentages). However, the amount of GWS reached the lowest level in the southwestern part of the basin. The maximum and minimum amounts of GWS in the subbasins were 164 and 0.3 mm/year. Generally, the mean values of GWF, BW and GWS in the basin were, 204, 39.4 and 54.2 mm/year, respectively. Precipitation rate, as the most important factor in the whole basin, was 254.8 mm/year.

Quantification of future water resource components

The RCP2.6 and RCP8.5 scenarios were employed to estimate the effect of climate change on water resource components. Figures 8 and 9 illustrate the spatial distributions of GWF, BW and GWS in the near, intermediate and distant future under the RCP2.6 and RCP8.5 scenarios.

Referring to Figure 8, under the RCP2.6 scenario, the amount of BW would increase in the majority of the subbasins in the future rather than in the historical period. An increase of BW content would be greater in the northeastern and southeastern subbasins than in other subbasins. The main factor affecting the BW amount is precipitation. Moreover, the LULC conversion of agriculture to pasture (likely poor pasture) at the northeastern part and the conversion of rain-fed land use to poor pasture and barren lands at the southeastern part of the basin reduce infiltration and increase runoff, which in turn increases the BW content. The GWF content would generally decline in most subbasins in all three near future, intermediate future and distant future periods compared to the historical period. Subbasins in the southern part oriented toward the center of Kashafrood Basin show an intense GWF level decrease, which can be due to the agricultural LULC conversion to other LULC classes in the subbasins. The GWS level would be generally decreased in the majority of the subbasins in the three future periods. Such a decrease, however, would not occur in the subbasins with high silt content and high storage capacity. The severity of GWS decline, especially in the northern subbasins, appears to be lower in the intermediate future period than in other future periods. The mean annual levels of water components under the RCP2.6 scenario along with precipitation values in the whole basin discovered during different time periods are illustrated in Table 3.



Figure 8 | Spatial distribution of water resources in the future under the RCP2.6 scenario.

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Figure 9 | Spatial distribution of water resources in the future under the RCP8.5 emission scenario.

Water resource (mm/year)	Historical period (1992-2013)	Near future (2014–2042)	Intermediate future (2043–2071)	Distant future (2072–2100)	CV in time periods
BW	39.4	136.2	95.5	146.3	0.46
GWF	204	176.8	170.7	175.7	0.08
GWS	54.2	41.6	47.4	36.4	0.17
PR	254.8	322	274.1	331.3	0.12

Table 3 | Levels of water resources components in different time periods under the RCP2.6 emission scenario

BW, blue water; GWF, green water flow; GWS, green water storage; PR, precipitation; CV, coefficients of variation.

According to Table 3, under the RCP2.6 scenario, the amount of BW in the whole basin would be higher in the near future rather than in the historical period. The BW amount would also be greater in the intermediate future than in the historical period but lower than the BW amount in the near future. The amount of BW would be far greater in the distant future than in all the preceding periods. The GWF amount would be lower in the near future than in the historical period. The amount of GWF would be lower in the intermediate future than in the historical period and the near future. However, the GWF amount would be lower in the distant future than in the historical and near future periods but higher than the GWF amount in the intermediate future. The GWS amount would be lower in the near future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the GWS amount would be lower in the intermediate future than in the historical period. However, the near future. The amount of GWS would be lower in the intermediate future than in the historical period.

Figure 9 shows the increase of BW amount in all the future periods and the decrease of BW intensity over time periods under the RCP8.5 scenario. Due to the higher rate of precipitation in the northern half of the basin, the BW amount is higher in the northern subbasins than in the southern subbasins. Also, the conversion of agricultural and rain-fed LULCs to poor pasture LULC contributes to the increase of BW content in the southeastern

subbasins. In all the future periods, the GWF content would decline and this decline would be more severe in the southern subbasins due to the decrease of irrigated agricultural lands. The GWS content also declines in all the future periods. This decline is intensified in the southern subbasins and a few northeastern subbasins.

According to Table 4, under the RCP8.5 scenario, the amount of BW in the whole basin would be higher in the near future than in the historical period. The BW amount would also be greater in the intermediate future than in the historical period but lower than the BW amount in the near future. The BW amount would be higher in the distant future than in the historical period but lower than the BW amount in the near and intermediate future periods. The amount of GWF would slightly decrease under both the RCP2.6 and RCP8.5 scenarios over all the future periods. The GWS content would be lower in the near future than in the historical period. The GWS content would also be lower in the intermediate future than in the historical period but higher than the GWS content in the near future. The GWS would be at its lowest level in the distant future, compared to the other periods. As shown in Tables 3 and 4, the coefficients of variation of BW under the RCP2.6 and RCP8.5 scenarios over the four time periods are 46 and 52%, respectively. These coefficients indicate the high intensity of BW changes in both emission scenarios over the time periods. The coefficients of variation of GWF under the RCP2.6 and RCP8.5 scenarios are 8 and 9%, respectively, showing the small change of GWF over the time periods. The coefficients of variation of GWS are 17 and 41%, respectively, indicating that the GWS changes are more severe in the RCP8.5 scenario than in the RCP2.6 scenario. Figure 10 shows the estimation of water resource components under the RCP2.6 and RCP8.5 emission scenarios. According to Figure 10, the BW amount estimated under the RCP8.5 scenario is significantly higher than the BW amount estimated under the RCP2.6 scenario for the near future and intermediate future periods. However, the BW amount estimated under the RCP8.5 scenario is lower than the BW amount estimated under RCP2.6 scenario for the distant future. There is no significant difference between the GWF estimates in the RCP2.6 and RCP8.5 scenarios. However, the RCP8.5 scenario shows a higher estimate in the near and intermediate future periods and a lower estimate in the distant future. Estimates of GWS level are greater in the RCP2.6 scenario than in the RCP8.5 scenario for all the future periods.

In a similar study conducted by Afshar *et al.* (2018) in Kashafrood Basin, they investigated only the effect of climate change on water resources components in the future periods using MIROC-ESM data. However, in this study, the effects of climate and LULC changes have been considered simultaneously. A comparison of the results obtained considering the effect of climate change along with the results obtained considering the effects of both climate and LULC changes has been presented in Table 5. Obviously, the BW levels are lower

Water resources (mm/ year)	Historical period (1992–2013)	Near future (2014–2042)	Intermediate future (2043–2071)	Distant future (2072–2100)	CV over time periods
BW	39.4	177.5	144.2	98.7	0.52
GWF	204	186.3	180	161.6	0.09
GWS	54.2	30.4	42.5	19	0.41
PR	254.8	375.1	331.8	265.5	0.18

Table 4 | Water resources components over time periods under the RCP8.5 emission scenario

BW, blue water; GWF, green water flow; GWS, green water storage; PR, precipitation; CV, coefficients of variation.





	Difference unde	er RCP2.6 (%)		Difference under RCP8.5 (%)			
Water resource	2014-2042	2043-2071	2072-2100	2014-2042	2043-2071	2072-2100	
BW	25.8	35.9	18.1	20.3	21.4	30.8	
GWF	-9.4	-9.1	-8.8	-9.7	-9.4	-8.0	
GWS	-29.6	-25.3	-25.7	-32.6	-33.3	-41.4	

Table 5 | Percentage of difference compared to situation with only climate change effects

and the GWF and GWS values are higher when only the effect of climate change on water resources is considered.

The assessment of the spatiotemporal trend of water resources components in the Ohio River Basin by Du *et al.* (2018) shows that despite the overall volumetric increase of both BW and GW in the entire basin, changes in their annual average values follow a distinctive spatial pattern. Furthermore, climate change in the Ohio River Basin is identified as being influential on BW, whereas land-use change increases GW remarkably, but is counterproductive on BW. In another study on the Weyb River basin in Ethiopia, Serur (2020) investigated the effects of climate change on water resources components. Results revealed a rise of BW and GW in the entire basin and in all the subbasins under different emission scenarios. Also at the subbasin level, the spatial variations of BW and GW-Availability are very high as compared to that of the entire basin analysis under all RCP scenarios. Xu & Wu (2018) estimated the County-Based GW Availability in the United States from effective rain using three different methods: Smith, U.S. Department of Agriculture – SCS (USDA-SCS) and the NHD plus V2 dataset. Their analysis illustrated that the fraction of GW resources availability varies significantly across regions. The water availability index for GW also depends on the precipitation pattern, crop type and spatially differentiated regions. However, the present study shows that the most important factors for BW are precipitation and LULC, while for GW, they are LULC and temperature.

GW-Security

GW-Security was evaluated by calculating GW-Scarcity and GW-Vulnerability. The impact of climate and LULC changes on GW-Security was assessed over four time periods (i.e., one historical and three future periods). Figure 11 displays the spatial distribution of GW-Vulnerability and GW-Scarcity in the historical period. Some central and southern subbasins in the study area faced high levels of GW-Scarcity (Figure 11). Higher temperature and agricultural LULC in the central subbasins induce higher evapotranspiration and consequently cause higher GW-Scarcity. Moreover, the soil texture with higher sand percentage in some of the southwestern subbasins is responsible for lower water availability and thereby higher GW-Scarcity. In the northern subbasins, despite the greater extent of agricultural LULC, GW-Scarcity is lower due to the higher altitude, lower temperatures and higher precipitation. The pattern of GW-Vulnerability is similar to that of GW-Scarcity. However, the vulnerability is more severe in the southeastern basins that have higher temperatures.



Figure 11 | Spatial distribution of GW-Security in the historical period.



Figure 12 | Spatial distribution of GW-Security in the future under RCP2.6 emission scenario.

Spatial distributions of GW-Vulnerability and GW-Scarcity under RCP2.6 scenario are shown in Figure 12. As can be seen in Figure 12, in most of the subbasins along the northeast to southeast direction and some southwestern subbasins, the GW-Scarcity is lower in the three future periods than in the historical period. An increase of precipitation and LULC conversion to pasture in the future would reduce GWF and increase GW-Availability in the mentioned subbasins. This can consequently lead to less GW-Scarcity. However, in the southern subbasins, GW-Scarcity would be intensified in the future due to lower precipitation and higher temperatures. Another factor is LULC change from forest to pasture, which reduces GWS and GW-Availability. Some central subbasins, with a higher rate of sand in their soil texture, have a higher GW-Scarcity, which is expected to be intensified in the near future. Vulnerability has a similar pattern in the future. Generally, the southern and western subbasins and a few central subbasins would be more vulnerable in the future, with a more severe vulnerability in the intermediate future. Spatial distributions of GW-Scarcity and GW-Vulnerability under the RCP8.5 scenario are shown in Figure 13. As can be seen in Figure 13, the GW-Scarcity in the majority of the subbasins would be lower in the near future than in the historical period. While in the intermediate and distant future periods, the GW-Scarcity would increase along the northwest to the southwest direction and in the southern subbasins, with an intensified



Figure 13 | Spatial distribution of GW-Security in the future under the RCP8.5 emission scenario.

	Historical period	RCP2.6			RCP8.5		
Water security indicator	1992-2013	2014-2042	2043-2071	2072-2100	2014-2042	2043-2071	2072-2100
Scarcity	7.94	5.30	5.57	5.34	4.31	5.24	6.02
Vulnerability	11.23	6.90	7.63	6.77	5.38	7.08	9.43

Table 6 | Water security indicators over time periods in Kashafrood Basin

value in the distant future. GW-Vulnerability in the majority of the subbasins would be lower in the near future than in other periods. However, in the intermediate future, the GW-Vulnerability would be greater in the southern and western subbasins and a few central subbasins compared to other subbasins. Moreover, a greater GW-Vulnerability would be seen in the southern basins in the distant future. As shown in Table 6, in both emission scenarios, water scarcity and vulnerability in the entire basin would be reduced in the future compared to the historical period.

In the Savannah Basin, Veettil & Mishra (2018) concluded that GW was more sensitive to changes in land-use pattern. In addition, the magnitude of various water security indicators is different within each county, suggesting that water scarcity is controlled by various factors within a region. The present study also shows that LULC plays an important role in the values of GW-Security indicators.

CONCLUSION

The SWAT model was employed to calculate the values of water resources components in Kashafrood Basin in the future. The climatic and LULC data for the future were prepared using the MIROC-ESM climatic model and the LCM model, respectively. The MIROC-ESM climatic model data downscaled by the BCSD method was applied to assess the effect of climate change on water resources in the basin under the RCP2.6 and RCP8.5 scenarios. After preparing the historical land-use maps using remote sensing, the LCM model was applied to project the future land-use maps focusing on urban growth. Moreover, the SWAT model was validated and calibrated to evaluate the effects of climate and LULC changes on water resource components. Finally, GW-Security in Kashafrood Basin was assessed using the GW-Vulnerability and GW-Scarcity indicators. According to the results, the main LULC changes in the basin in the future are agricultural, urban and pasture LULCs. Moreover, agricultural lands would be decreased, and urban areas and pasture would be increased in the future. The factors, including population growth, depletion of water resources and deforestation, were found to intensify the changes. Precipitation, as a climate variable, and LULC are the two factors affecting the BW amount in the basin. Compared to the historical period, the BW amount is estimated to be increased in the future, especially in the northern subbasins and in the near future. The GWF would be slightly lower in the future than in the historical period. GWS, which has a smaller share in water resources, will generally decline in the future. The increase of temperature and the reduction of soil permeability due to LULC changes are the most important reasons for the GWS decline. Generally, conditions of the basin would be improved in terms of GW-Scarcity and GW-Vulnerability over the future periods rather than the historical period. Given that vulnerability represents the worst condition of water availability, it was easier to identify the hotspots with higher risks through the spatial distribution of GW-Vulnerability. These hotspots can help the policymakers to adopt the best decisions for improving water conditions in vulnerable subbasins. However, it is suggested to apply a combined transition matrix from two periods in LCM to improve the LULC change trends, and employ other observational data such as evapotranspiration, soil moisture and deep recharge to calibrate the SWAT model in order to obtain accurate GW estimates in further studies. Since soil erosion is inevitable, changes in soil characteristics could be considered in SWAT modeling, and BW security could be evaluated. These constraints should be addressed in future works.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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