The impact of land use and land cover change on groundwater recharge in northwestern Bangladesh

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ABSTRACT

Groundwater recharge is affected by various anthropogenic activities, land use and land cover (LULC) change among these. The long-term temporal and seasonal changes in LULC have a substantial influence on groundwater flow dynamics. Therefore, assessment of the impacts of LULC changes on recharge is necessary for the sustainable management of groundwater resources. The objective of this study is to examine the effects of LULC changes on groundwater recharge in the northwestern part of Bangladesh. Spatially distributed monthly groundwater recharge was simulated using a semi-physically based water balance model. Long-term temporal LULC change analysis was conducted using LULC maps from 2006 to 2016, while wet and dry LULC maps were used to examine seasonal changes. The results show that the impervious built-up area has increased by 80.3%, whereas vegetated land cover has decreased by 16.4% over the study period. As a result, groundwater recharge in 2016 has decreased compared to the level seen in 2006. However, the decrease in recharge due to long-term temporal LULC changes is very small at the basin scale (2.6 mm/year), although the impact on regional level is larger (17.1 mm/year) due to urbanization. Seasonal LULC variations also affect recharge due to the higher potential for dry seasonal LULC compared to the wet seasonal LULC, a substantial difference (20.6 mm/year). The results reveal important information about the groundwater system and its response to land cover changes in northwestern Bangladesh.

1. Introduction

Groundwater is the water in saturated zones underneath the soil surface. It is the Earth's mostaccessed freshwater source (Lall et al., 2020). Groundwater recharge is "the rate at which aquifers are replenished" and is a key factor in groundwater sustainability (Ajami, 2021). Recharge can be greatly affected by climate change and anthropogenic activities (Wang et al., 2018). One of the most important anthropogenic interventions is changes in land use and land cover (LULC). LULC represents the naturally and artificially distributed features on the Earth's surface, such as forest vegetation, water bodies and human structures (Mahmon et al., 2015). Changes in LULC affect groundwater by modifying the pattern of water balance components (Poelmans et al., 2010; Sun et al., 2018; Wang et al., 2019).

Over the past few decades, human created variations in land use have affected hydrological components, such as recharge and runoff (Ansari et al., 2016). These variations in land surface can occur over a long period, spanning years and decades (long-term temporal changes), or covering shorter time cycles (seasonal changes) (Verbesselt et al., 2010; Vogelmann et al., 2016). The long-term temporal changes are primarily caused by developments such as agricultural expansion, urbanization, desertification, the decline of forests, etc. (Vogelmann et al., 2016). Agricultural expansion is a dominant cause of the extensive changes in LULC which have an influence on the underlying groundwater zone (Scanlon et al., 2005). Groundwater-fed irrigated agriculture can have detrimental effect on groundwater, including a reduction in recharge and declination of water table (Han et al., 2017; Mojid et al., 2019). Rapid urbanization is another serious concern for water resources (Zare et al., 2016). Increased impervious surfaces created by urbanization, such as roofs or roads, can reduce the natural infiltration, decreasing the volume of water reaching the water table (Zhu and Li, 2014). This leads not only to a reduction in groundwater recharge but also to more flood

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incidents generated from additional surface runoff (Zhang et al., 2018; Astuti et al., 2019). Numerous studies have shown how urbanization has led to a decline in regional groundwater recharge (Dams et al., 2013; Zomlot et al., 2017; Wen et al., 2019; Adhikari et al., 2020; Ghimire et al., 2021). However, urbanization can also decrease the amount of vegetation, leading to less evapotranspiration in certain regions, possibly resulting in increased recharge (Minnig et al., 2018). These types of diverse behaviors make predicting recharge at different locations and varying climates challenging. Hence, understanding the response of groundwater systems to changing LULC is necessary to properly manage this resource. Seasonal LULC variations are also mostly linked to vegetation or water body changes as a response to the annual cycles of climate and related characteristics (Vogelmann et al., 2016). These short-term changes in LULC can also affect hydrological processes. An increase or decrease in certain land cover classes, such as water bodies and forest vegetation, can alter groundwater recharge and other hydrological components by affecting interception and infiltration processes (Baker and Miller, 2013; Kuroda et al., 2017). The water table has been observed to fluctuate with seasonal changes (Kirimi et al., 2018). Hence, the increase or decrease of such land cover might have implications on groundwater recharge. However, unlike in the case of long-term temporal LULC changes, there has been little study examining the impact of short-term seasonal LULC changes on groundwater recharge, making more research necessary in this particular area.

Although many researchers around the world have been working on land use change and its impact on groundwater recharge, as far as the author is aware, very little study has been conducted on this issue in the context of Bangladesh. Groundwater is the primary, and often the only, safe source of drinking, industry and agricultural water in Bangladesh, as surface water is scarce and inconsistent (Qureshi et al., 2015; Mustafa et al., 2017). In particular, the use of groundwater is higher in the northwestern region compared to other regions of the country (Shahid and Hazarika, 2010). For example, the amount of groundwater irrigation is 11 km^3 in the northwestern region compared to around 14 km^3 for all the remaining regions combined (CSIRO et al., 2014). However, this precious resource is under constant threats of overexploitation and pollution in this region. Notably in the last decade, this areahas seen a substantial decline in the water table with 35 out of 36 groundwater monitoring wells in Rajshahi District showing falling water table trends, threatening the sustainability of irrigation water use (Jahan et al., 2010; Mustafa et al., 2019; Mojid et al., 2019). Due to excessive and inefficient use, the water table has fallen and depleted beyond an exploitable depth in some part of the northwestern region of Bangladesh (Habiba et al., 2012). The reason behind the declining northwestern water table and the role of anthropogenic factors, such as climate change, in the decline is currently unclear (Mojid et al., 2019). Recently, Mustafa et al. (2017) reported that groundwater levels in the area decreased by almost 5 m between 1979 and 2007 and inferred that climate change was not a significant factor in the groundwater level drop. They also examined the influence of land cover changes between 1990 and 2010 on groundwater recharge and found that the effects were not significant at the large basin scale. However, they identified land cover changes due to urbanization as one of the influencing factors for groundwater drought and depletion, along with groundwater abstraction, and outlined the importance of further study at the regional level. Urbanization dominated land use change has been observed to have a significant influence on groundwater recharge, even greater than climate change in a few studies (Ghimire et al., 2021). In recent decades, rapid economic growth and unprecedented urbanization have caused significant changes in LULC patterns. Shi et al. (2018) reported that the LULC change in recent decades is significantly higher than in previous decades. Dey et al. (2021) found a 15% increase in urbanized settlements in Rajshahi city between 2000 and 2020 and predicted a 30% increase in urbanization by 2040, compared to the city in 2000. Mojid and Mainuddin (2021) suggested that increased urbanization might have an effect on declining groundwater recharge. However, the effect of this unprecedented urbanization

in recent years on the groundwater system of northwestern Bangladesh is still unknown but is thought to be important for ensuring the sustainable management of the overexploited aquifer. Moreover, identification of the effects of regional land cover changes, considering spatial, long-term temporal and seasonal effects, is vital. Huq et al. (2019) reported that land use and land cover in southern Bangladesh significantly change between the dry and wet seasons because of the non-uniform rainfall distribution of the tropical climate. However, the details of seasonal land cover changes in the northwestern part of Bangladesh and their effect on the groundwater system are still largely unknown. To the best of the authors' knowledge, limited study has been done so far on seasonal land cover changes and their effect on groundwater recharge in northwestern Bangladesh. Hence, the reliable assessment of human induced land use change and its influence on groundwater recharge is necessary for understanding groundwater flow dynamics.

The integration of long-term temporal and seasonal inconsistencies in land cover is important for estimating groundwater recharge, considering the sensitivity of recharge to varying land types (Dragoni and Sukhija, 2008). Recharge is also dependent on a spatially varied climate as well as hydrogeological factors like rainfall, soil and topography (Batelaan and De Smedt, 2007). Thus, consideration of the spatially distributed physical characteristics of a basin is important for recharge computation to increase the reliability of the simulated value (Gebremeskel and Kebede, 2017). To achieve this, a number of hydrological models have been developed based on concepts such as water balance and water table fluctuation (Ahmadi et al., 2012). WetSpass (Water and Energy Transfer between Soil, Plants and Atmosphere under a quasi-Steady State) is a widely used spatially distributed water balance model (Batelaan and De Smedt, 2001). It has been successfully applied across the world in different climates (Pan et al., 2011; Dams et al., 2013; Zomlot et al., 2015; Armanuos et al., 2016; Gebremeskel and Kebede, 2017; Salem et al., 2019). The original model can only support seasonal temporal resolution. To implement monthly support, WetSpass-M was developed (Abdollahi et al., 2017), which has been used previously in northwestern Bangladesh (Mustafa et al., 2017, 2018, 2019, 2020).

The use of such models requires spatially distributed input data in raster form. The resolution of the input data can play a key role in analyses (Arnone et al., 2016) as the degree of raster data detail is dependent on the raster resolution. A number of studies have found that raster cell resolution can be a significant determinant for model performance, using inputs including land use and land cover, soil and digital elevation models (DEM) (Jantz and Goetz, 2005; Ménard and Marceau, 2005; Samat, 2006; Chaplot, 2014; Yang et al., 2014; Zhang et al., 2014; Jin et al., 2015; Tan et al., 2015; López-Vicente and Álvarez, 2018; Fan et al., 2021). At the same time, the resolution of input data affects the accuracy of input variables, possibly leading to various degrees of uncertainty (Zhang et al., 2014; Gires et al., 2015). This issue can be explained through the concept of the modifiable areal unit problem, which discusses "the variation in results that can often be obtained when data for one set of areal units are progressively aggregated into fewer and larger units for analysis" (Openshaw, 1983). Land use classes are often small in size (such as urban and rural built-up areas) and, as such, detailed spatial data from high resolution maps is required for precise information on the physical characteristics of that land use class (Díaz-Pacheco et al., 2018). At a broader resolution, a small land use unit might be absent, leading to lower accuracy in result prediction than in its finer counterpart (Cama et al., 2016). The inaccuracies resulting from low detailed spatial data can cause the misinterpretation and incorrect analysis of terrain information included in the raster inputs. Inputs with incorrect information may, in turn, create uncertainties in model-predicted results. For example, the misclassification of land cover can lead to incorrect parameterization of the land classes, resulting in inaccurate recharge estimation (Zomlot et al., 2017). High resolution can also be advantageous since it can be modified into a lower resolution if necessary. Even though researchers have recognized the
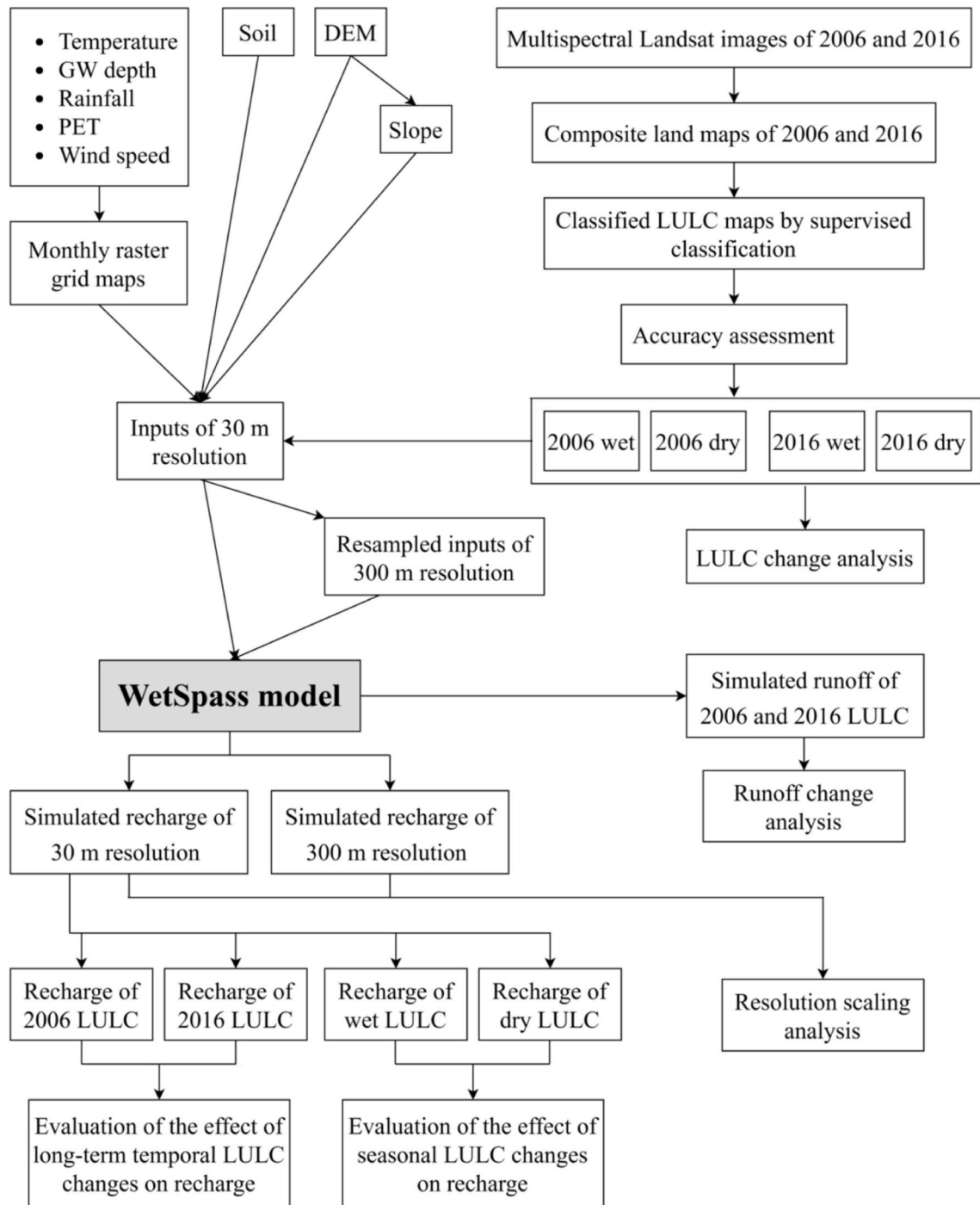
Fig. 1. Conceptual methodology of the study; GW: groundwater; PET: potential evapotranspiration (reference evapotranspiration for the study); DEM: digital elevation model; LULC: land use and land cover.

value of resolution in modeling (Ménard and Marceau, 2005; van Delden et al., 2011), specific studies inferring the influence of inputs at different spatial resolutions in groundwater recharge simulation are still lacking.

On the other hand, finer resolutions do not always lead to the best modeling performance (Ménard and Marceau, 2005; Lee et al., 2010; Ye et al., 2011; Yang et al., 2014; Arnone et al., 2016; Díaz-Pacheco et al., 2018). Increased computational load can be an issue with finer resolution data (Maleika, 2015). At a higher resolution, the number of cells to process increases, raising the amount of computational analysis needed and, thus, the time requirement, whereas lower raster resolution requires less computational power, albeit at the cost of model accuracy

(Calder and Mayer, 2003). The lower resolution of rasters also improves the model execution period due to the decreased quantity of data (Munoth and Goyal, 2019). Overall, the comparison between high and low resolution of raster data creates a dilemma of prioritizing result accuracy against computational requirements. In fields such as policy planning, this is important, as results are often needed in a short time without the sufficient availability of powerful computing hardware. Hence, more research is needed to address the computational requirement and desired degree of accuracy in modeling considering the study objectives and applications.

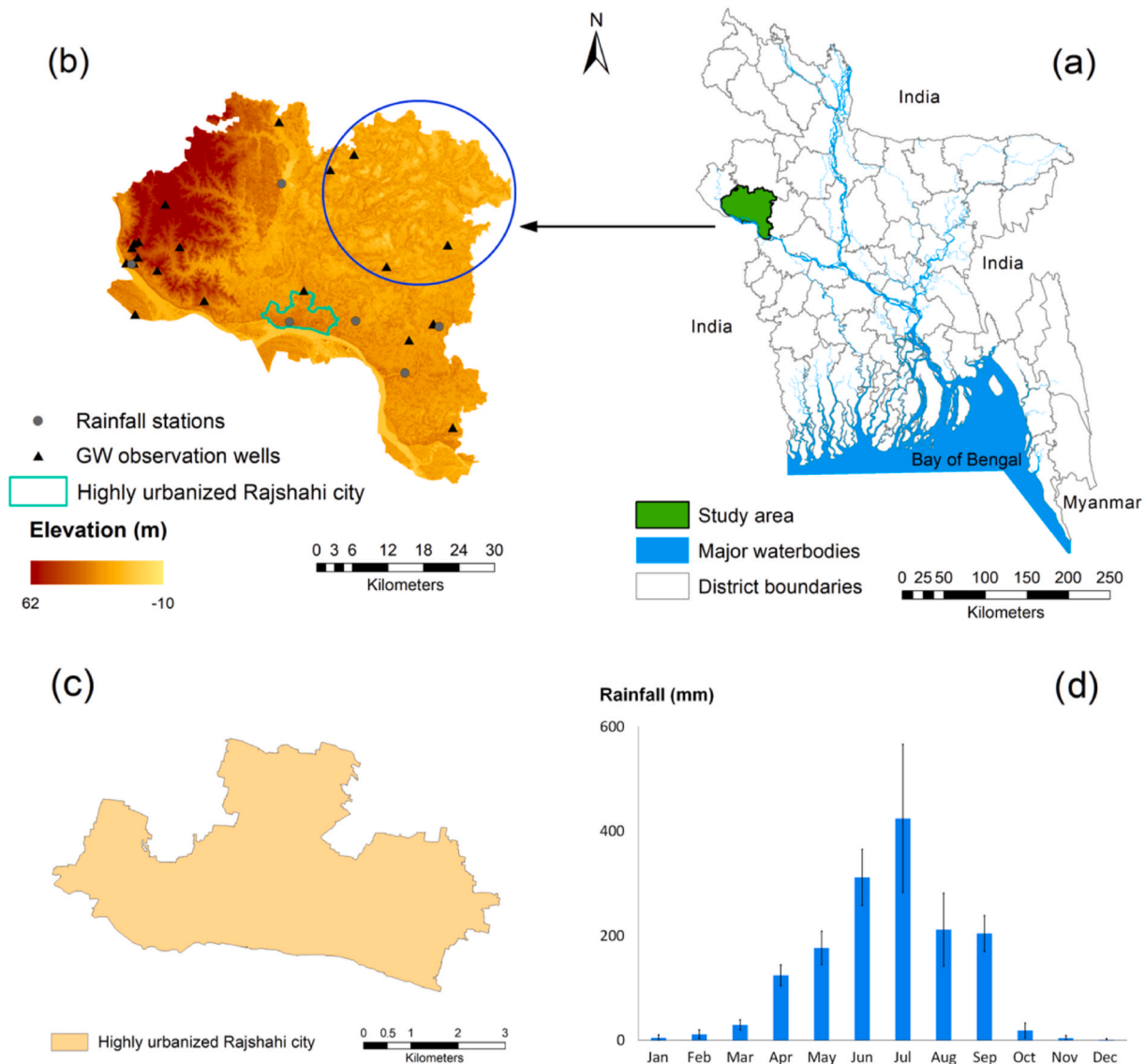The general aim of this study is to examine the effects of land use and

Fig. 2. Study area: (a) location of the study area in Bangladesh, (b) elevation map with rainfall stations marked with black circles, groundwater observation wells marked with triangles and the wetland area (northeast part) marked by the blue circle, (c) the highly urbanized Rajshahi city and (d) monthly rainfall distribution from 2006 to 2016 (bars showing average; error lines showing spatial range); GW: groundwater. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

land cover changes on groundwater recharge in northwestern Bangladesh, comparing LULC changes between 2006 and 2016 for long-term temporal changes and between wet and dry for seasonal changes. To achieve this, the water balance model WetSpass-M was used to simulate spatially distributed groundwater recharge under different LULC conditions. In doing this, the specific objectives are to (1) identify and quantify the changes in different land cover types over the study period using remote sensing data, (2) assess the relation of groundwater recharge with rainfall, soil texture and land cover class and (3) analyze the influence of long-term temporal and seasonal LULC changes on groundwater recharge. In addition, the scaling effect of different spatial resolutions on groundwater recharge simulation will be evaluated using inputs at different resolutions. The findings of the study will be useful for strategy and policy planning regarding land and water resource management in the northwestern part of Bangladesh and beyond.

2. Methodology

The methodology applied to evaluate the effects of LULC changes on groundwater recharge in the study area is shown in Fig. 1. First, spatially distributed raster map inputs of 30 m resolution were prepared. These are raster of hydrometeorological data (rainfall, temperature, wind speed, potential evapotranspiration: PET), DEM, slope, soil texture and groundwater depth. The inputs of 30 m resolution were resampled into a 300 m resolution. Next, LULC maps for 2006 and 2016 were prepared from collected multispectral Landsat images using remote sensing. After that, the input maps were used to compute monthly spatially distributed groundwater recharge using the water balance model WetSpass. In the next step, the recharges for 2006 and 2016 LULC were compared to analyze the influence of long-term temporal land cover changes. Similarly, the recharges for wet and dry season LULC were compared to analyze the influence of seasonal land cover changes. Then, the runoff sets for 2006 and 2016 were examined to study the effects of urbanization focused land cover changes between 2006 and 2016. Finally, the simulated recharge sets of both the 30 m and 300 m resolutions were compared to analyze the scaling effect.
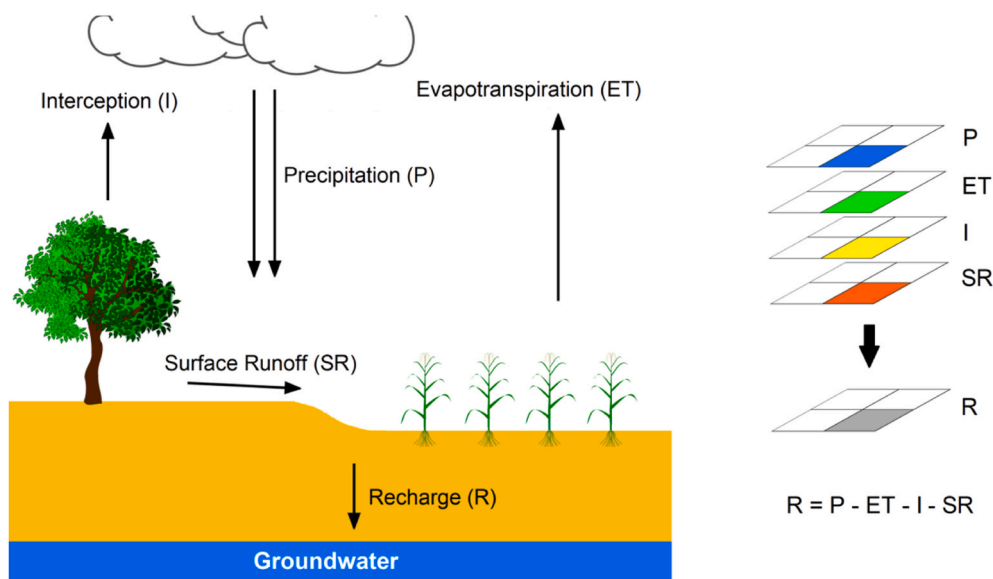
Fig. 3. Water balance components and recharge computation for a cell.

2.1. Study area

The study area was selected due to its high groundwater dependency for agricultural and domestic purposes and consequently high rate of abstraction. The district of Rajshahi, shown in Fig. 2a and Fig. 2b, was chosen. Lying on the alluvial plains of the river Padma, it is part of the northwestern Barind region of Bangladesh. It is located between 24.12° and 24.72° north and 88.28° and 88.97° east. The average annual rainfall varied between 1350 mm and 1450 mm from 2006 to 2016, but this is unevenly distributed throughout the district. Rainfall is irregular over the months as well, with the highest rainfall in July (424.7 mm) and the lowest in December (1.3 mm), as shown in Fig. 2d. The average annual temperature from 2006 to 2016 was 25.8 °C, varying from 11.6 °C in winter to 35.9 °C in summer.

Geographically, Rajshahi is situated within the Barind tract, which is around 23 m above the mean sea level. The elevation varies from 23 to 62 m above mean sea level (Fig. 2b). The area comprises Barind land and Ganges floodplain, with several types of soil texture, including sand, silty loam, loam and clay loam. A large part of the region is covered by partially impervious clay-silt aquitard, characterized by a single or several layers of aquifer system (Jahan et al., 2007) with low rates of infiltration (Adham et al., 2010). The Rajshahi city area (Fig. 2c) has two layers in the aquifer system. The upper layer is made of clay and silty clay, followed by a composite layer of fine to coarse sand below (Haque et al., 2012). The region is also thought to have a potential aquifer system for the development of groundwater at greater depths (Ferozur et al., 2019). Rainfall acts as the principal source of recharge in the study area (Mojid et al., 2019).

The area is primarily dominated by agriculture. Groundwater abstraction for agriculture is high, particularly in the dry season. During the rainy season, the aquifer is not usually fully replenished. As a result, the groundwater level is declining at a high rate and has not returned to its original level after 2002–2004 (Jahan et al., 2015). The wetland region in the northeast part of the study area (marked with a blue circle in Fig. 2b) periodically dries up during the dry months of winter and is used for agricultural purposes (Hossain et al., 2009).

2.2. Model description

WetSpass is a semi-distributed physically-based water balance model which can simulate seasonal groundwater recharge (Batelaan and De Smedt, 2001, 2007). It has been applied for land use impact analysis on

groundwater recharge in numerous studies (Pan et al., 2011; Gebere et al., 2016; Zomlot et al., 2017; Mustafa et al., 2017). WetSpass-M is the version of the original model which supports monthly calculation (Abdollahi et al., 2017). In this study, WetSpass-M was used to simulate spatially distributed monthly groundwater recharge. This model takes raster maps of various hydrological and meteorological components as inputs (Fig. 1). Each raster cell is split into four subdivisions, namely open water, vegetated, bare soil and impervious, to consider the heterogeneity of land cover. Groundwater recharge of the whole cell is then estimated from the water balance of each subdivision. From the following water balance equation, groundwater recharge is computed as a residual for each raster cell,

$$R = P - ET - I - SR$$

where, R is groundwater recharge, P is precipitation, ET is evapotranspiration, I is interception and SR is surface runoff. WetSpass calculates interception as a fraction of precipitation depending on land use; surface runoff based on a number of factors including land use, slope, soil texture etc.; and evapotranspiration from the sum of evaporation and transpiration for each cell. Finally, groundwater recharge is obtained from the remaining water balance.

Fig. 3 depicts a simplified representation of the water balance components and the estimation of recharge from these components for a raster cell.

2.3. Land use and land cover classification

2.3.1. Data and classification

The United States Geological Survey (USGS) managed Landsat program has been a reliable source of remotely sensed Earth terrain data. Numerous land use impact analysis studies have used Landsat images (Prabhakar and Tiwari, 2015; Zhang et al., 2017; Patra et al., 2018; Wen et al., 2019; Chemura et al., 2020). Multispectral images of USGS Landsat 5 Thematic Mapper (LT05) and Landsat 8 Operational Land Imager (LC08) programs were obtained for 2006 and 2016 LULC, respectively. The month of October was chosen. The reason for choosing this (post-monsoon) month was because of its minimal cloud coverage and the sufficient amount of water remaining on water bodies before the drying period started in the winter. The images were collected from a USGS Global Visualization Viewer or GloVis (https://glovis.usgs.gov; last accessed on 19 June 2021) for the respective years. The visible bands (blue, green, red), near infrared and the two shortwave infrared

Table 1
Land cover classes and their description.

Land cover class	Description
Built-up	City centers, airports, highways, residential area, semi-urban area.
Vegetated	Croplands, woods and smaller forests.
Bare soil	Exposed soil, dunes and beaches, excavated areas.
Open water	Rivers, lakes, ponds.
Flooded land	Seasonal wetlands, low-lying marshes.

Table 2
Model inputs, their sources, the period of collected and processed data and the spatial resolution of each input for the primary analysis. PET: potential evapotranspiration; DEM: digital elevation model; SRTM: Shuttle Radar Topography Mission; USGS: United States Geological Survey; BMDA: Barind Multipurpose Development Authority; BWDB: Bangladesh Water Development Board; BMD: Bangladesh Meteorological Department; WARPO: Water Resources Planning Organization; SRDI: Soil Resource Development Institute.

Inputs	Source	Collected temporal period	Processed temporal period	Spatial resolution
Groundwater depth	BMDA, BWDB	Weekly	Monthly average	30 m
Rainfall	BMD, BWDB	Daily	Monthly sum	30 m
Temperature	BMD	Daily	Monthly average	30 m
PET	Calculated from Temperature	Daily	Monthly sum	30 m
Wind speed	BMD	Daily	Monthly average	30 m
No. of rainy days	Observed rainfall	Daily	Monthly sum	–
DEM	SRTM	Static raster map	Static raster map	30 m
Land use	USGS	2006 and 2016	2006 and 2016	30 m
Slope	Processed from DEM	Static raster map	Static raster map	30 m
Soil	SRDI	Static raster map	Static raster map	30 m

bands were considered (bands 1, 2, 3, 4, 5 and 7 for LT05 and bands 2, 3, 4, 5, 6 and 7 for LC08) for this study. The satellite images were arranged together into composite maps for both 2006 LT05 and 2016 LC08. The composite maps were clipped with the study area shapefile. A training sample was generated for a total of 5 land cover classes, as shown in Table 1. Maximum Likelihood Supervised Classification was performed on the clipped composite maps, based on the training sample, to produce 2006 and 2016 LULC maps with the desired classes. Two more LULC maps for 2006 and 2016 were prepared by clipping the classified LULC maps with the highly urbanized Rajshahi city area. This procedure was carried out in order to observe whether intense urbanization had a greater influence of LULC changes on recharge.

Land use change analyses were based on two different categories, using long-term temporal and seasonal land covers. The long-term temporal changes were investigated between 2006 and 2016 in two steps. In the first step, the whole study area was considered in a basin scale analysis. The last step only took the Rajshahi city area into account for a regional scale study of urbanization dominated LULC changes and effects on recharge. The seasonal study used wet (May–October) and dry (November–April) type LULC for the whole basin, representing the wet and dry season, respectively. The classified land cover with the 5 classes mentioned (Table 1) was considered as the wet LULC. In the wet season, the "Flooded land" areas in the wetland usually stay inundated. However, during the dry season, this land mostly dries out and is used for agricultural practices. Hence, the dry season LULC had 4 classes with "Flooded land" converting into "Vegetated" area. For simplicity, all of the "Flooded land" was converted into "Vegetated" area during the dry season (November–April).

2.4. Accuracy assessment

The accuracy of the LULC maps was assessed using kappa statistical analysis (Viera and Garrett, 2005) on 2 sets of the 2006 and 2016 classified (wet) LULC maps. Each set included a reference and a simulated/predicted land class map. The Kappa index was used to show the agreement level between the reference and simulated land class maps. 50 random points were generated in ArcGIS and each point was assigned a reference land class using the true color composite of the red, green and blue bands for the evaluation.
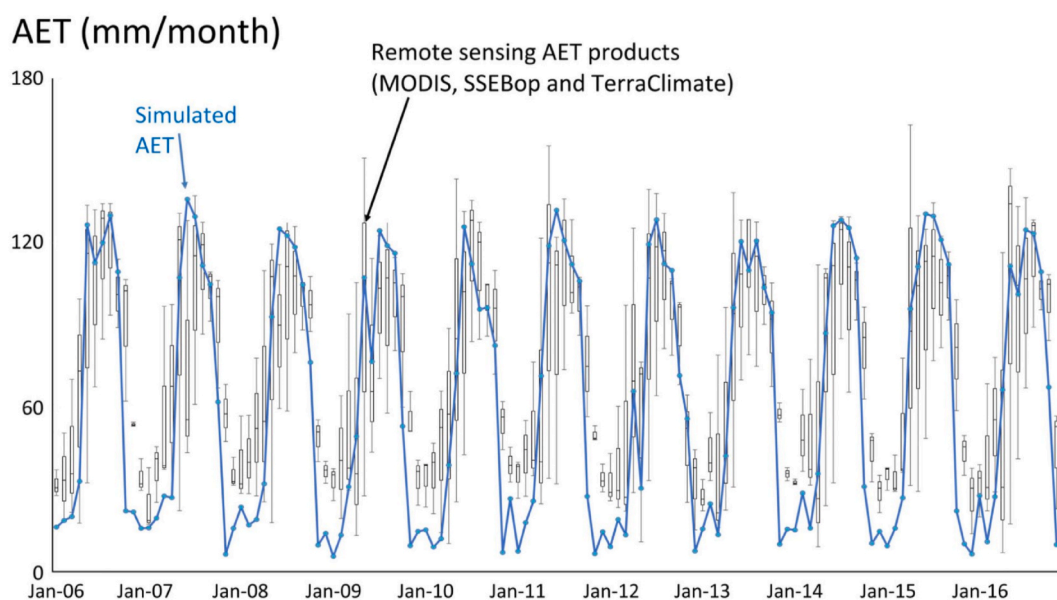

Fig. 4. Comparison of simulated AET (blue line) and remote sensing AET (box plots) from 2006 to 2016; AET: actual evapotranspiration. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
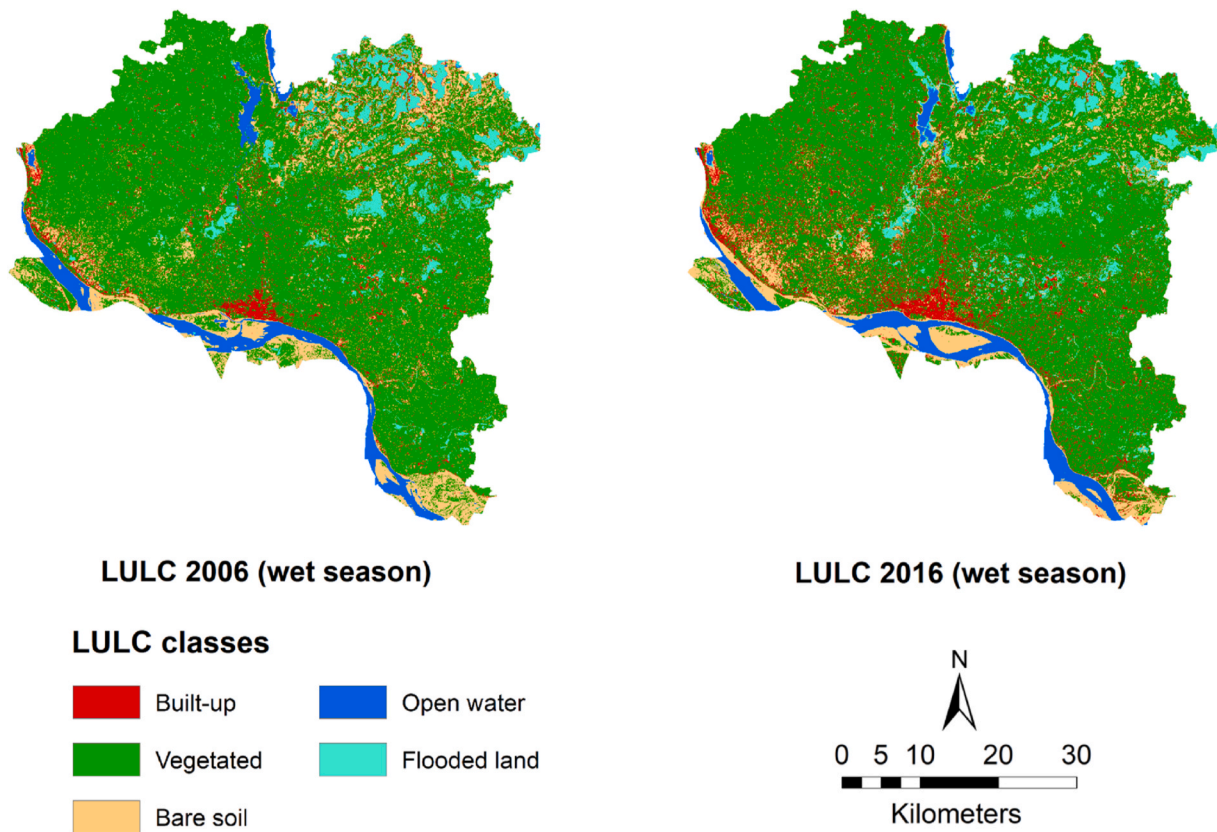
Fig. 5. LULC maps for 2006 and 2016 (wet season) with 5 land classes; LULC: land use and land cover.
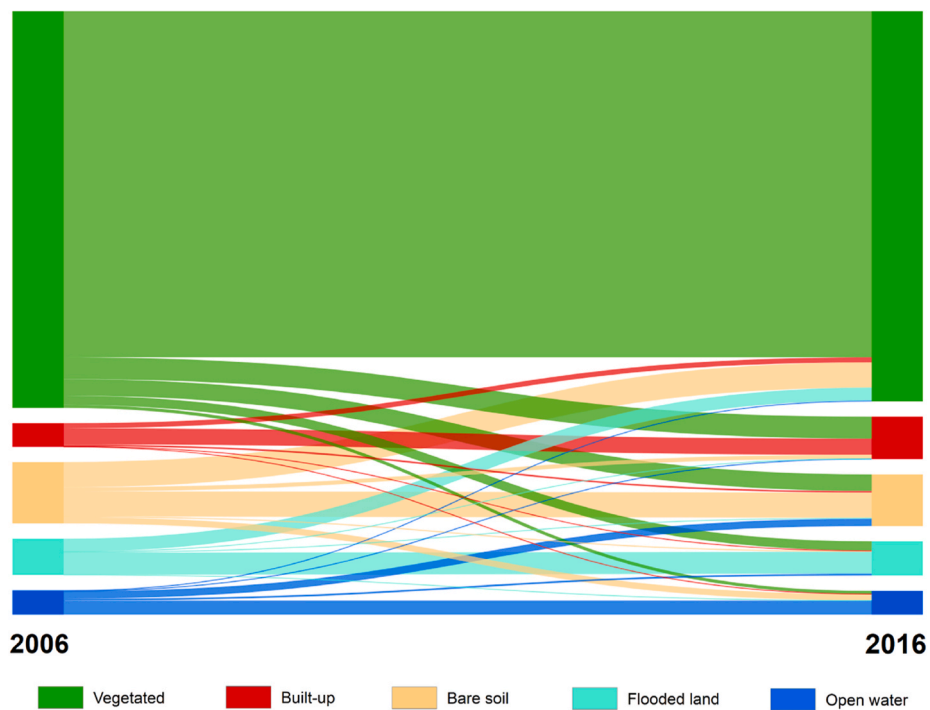

Fig. 6. Areal changes for all 5 land classes between 2006 and 2016; wet LULC maps.

2.5. Model inputs

WetSpass takes raster maps of hydrometeorological components like groundwater depth, rainfall, temperature, PET and wind speed as inputs (Table 2). Data for these components were collected from various sources for a period of 11 years (2006–2016). Groundwater depth data was collected from the Barind Multipurpose Development Authority (BMDA) and the Bangladesh Water Development Board (BWDB).

Table 3

Changes in land use and cover in Rajshahi over the study period (positive change represents addition, while negative change represents reduction); unit: area in Hectare.

LULC types	Area (ha)		Change
	2006	2016	
Built-up	10,578 (4.3%)	19,045 (7.8%)	8467 (3.5%)
Vegetated	178,422 (73.2%)	175,517 (72%)	−2905 (−1.2%)
Bare soil	27,564 (11.3%)	23,174 (9.5%)	−4390 (−1.8%)
Open water	10,941 (4.5%)	10,679 (4.4%)	−262 (−0.1%)
Flooded land	16,257 (6.7%)	15,347 (6.3%)	−910 (−0.4%)
Total	243,762 (100%)	243,762 (100%)	–

Climate data (rainfall, maximum and minimum temperatures, wind speed), recorded by the Bangladesh Meteorological Department (BMD) and BWDB, was collected from the Water Resources Planning Organization (WARPO). In this study, reference evapotranspiration (ET_0) was considered as potential evapotranspiration (PET). ET_0 was calculated from maximum and minimum temperatures using "ET_0 Calculator" software which uses the FAO Penman-Monteith formula (FAO, 2009). WARPO supplied the Soil Resource Development Institute (SRDI) developed soil texture map as a shapefile, which was converted into raster to use in the model. The Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) of 30 m resolution was used as the elevation model. The slope map was prepared from this DEM.

All of the inputs were at a 30 m resolution for the LULC impact analysis. The data was processed in order to prepare raster maps for the model. Inverse Distance Weighting (IDW) was used for interpolation because of its good performance and relative simplicity compared to other methods like Kriging (Hodam et al., 2017). The ArcMap Model Builder was used to automate the whole raster building process from the input data for a total of 132 months from 2006 to 2016. Each of the land
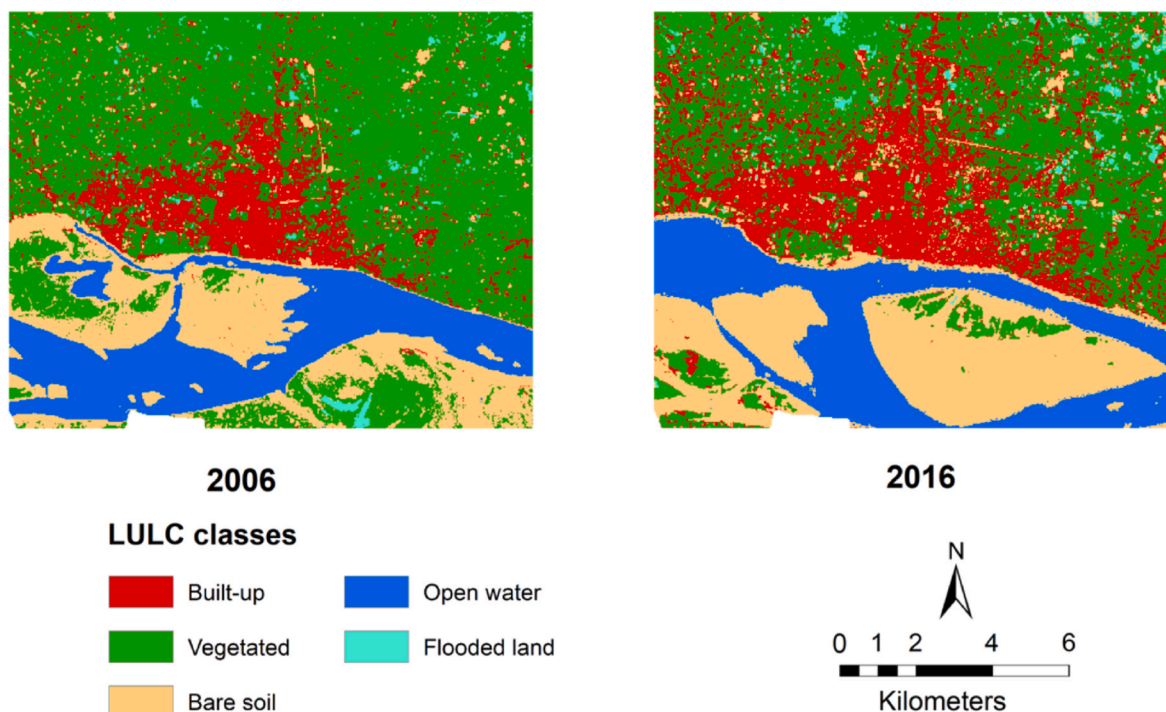

Fig. 7. Expansion of Rajshahi city urban area and changes in the adjacent Padma River due to meandering between 2006 and 2016.
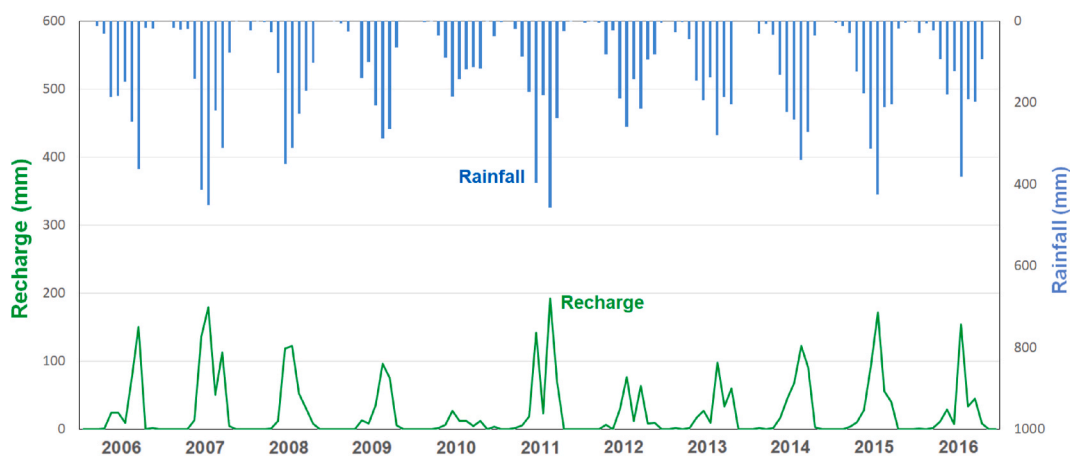

Fig. 8. A similarly patterned time series of monthly rainfall and groundwater recharge (blue bars indicate monthly rainfall and the green line represents monthly recharge). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
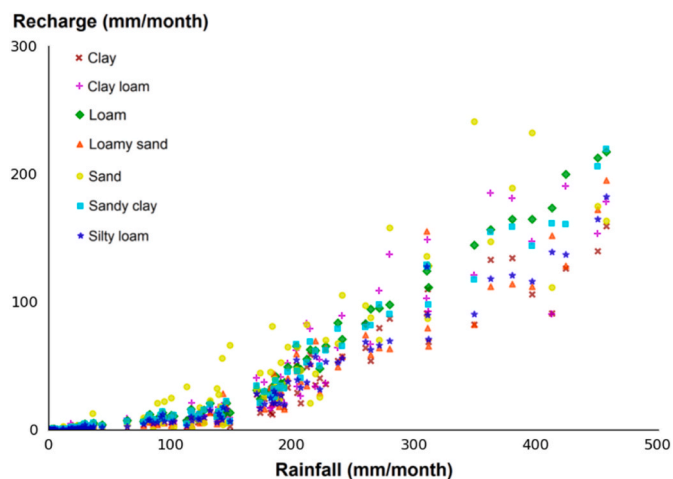
Fig. 9. Monthly recharge as a function of monthly rainfall for each soil texture. This shows the highest rainfall induced recharge in sand.
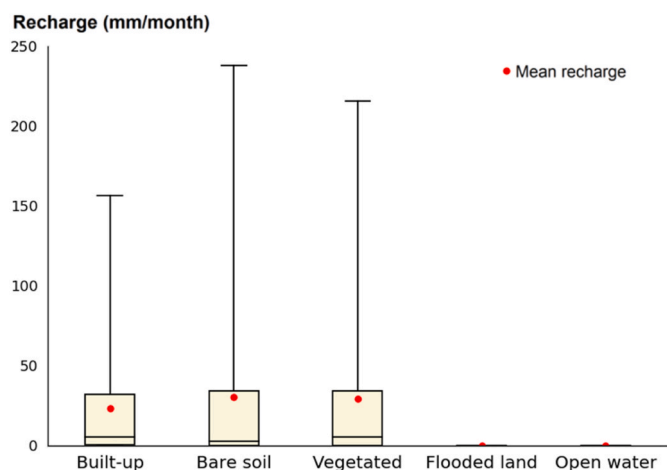

Fig. 10. Monthly recharge for each LULC class using the 2006 LULC map (box plots), including mean values (red dots). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

use maps (2006, 2016, wet, dry) were used to simulate groundwater recharge from the 132 sets of monthly inputs.

2.6. Model tuning

In situ river discharge and actual evapotranspiration (AET) data were not available in the study area. So, the model performance was evaluated using data from two different sources, (i) available remote sensing AET products and (ii) available groundwater recharge data by studies covering the same area. Weerasinghe et al. (2020) recommended remote sensing AET products as an alternative to observed data in data-scarce areas. In this study, three widely used remote sensing AET products, namely the Moderate Resolution Imaging Spectroradiometer MOD16 algorithm (MODIS; Mu et al., 2007, 2011), Simplified Surface Energy Balance model (SSEBop; Senay et al., 2013) and TerraClimate (Abatzoglou et al., 2018), were used to evaluate the simulated results. The remote sensing AET products varied in range compared to simulated evapotranspiration, as shown in Fig. 4. However, the simulated AET was in strong agreement with the remote sensing AET products. The seasonal AET variation was also appropriately captured by the simulated AET series. This shows the good simulation capacity of the model. After the comparison with remote sensing AET data, simulated recharge was then

compared with the available data on groundwater recharge from studies covering the same area (details in the Simulated groundwater recharge section).

2.7. LULC impact assessment

The impact analysis of LULC changes was performed in 3 steps using 3 different scenarios. The first scenario focused on the impact of long-term temporal LULC changes on the basin scale. For this, the simulated recharges for both 2006 and 2016 LULC over the whole study area were compared. The second scenario analyzed the long-term temporal LULC changes on a regional scale based on the highly urbanized Rajshahi city area. Similarly to the basin scale analysis, recharges for 2006 and 2016 LULC were compared considering only the Rajshahi city area instead of the whole study area. The impact of seasonal LULC changes was then assessed in the third scenario. At this step, the simulated recharges over the whole study area for wet and dry LULC were compared. Similarly, runoff sets for 2006 and 2016 LULC were compared, once considering the whole study area and then considering only Rajshahi city.

2.8. Effect of resolution scaling

The input maps were resampled into 300 m resolution to analyze the effects of different resolutions of input on the results. All of the modeling and analytical procedures were repeated with the resampled maps. The results were then compared with those from the 30 m resolution. During the simulation processes, the times needed to complete the simulation of the whole 132 months for the LULC impact assessment scenarios were recorded for inputs of both a 30 m and 300 m resolution. The recorded times of the corresponding scenarios at both a 30 m and 300 m resolution were compared to examine the difference in computational time requirement for the simulation of both resolutions.

2.9. Data analysis, visualization, and computation

For data analyses and plotting, Python modules NumPy, Pandas and Matplotlib were used. GIS applications (ArcGIS 10.5 and QGIS 3.6) and Python module Rasterio were used for geospatial analysis, land cover classification and mapping. The Mann–Whitney *U* test and Kruskal-Wallis H test were performed to check the statistical significance of the results using Python module SciPy. The images were prepared using Microsoft Excel 2010 and the GNU Image Manipulation Program (GIMP). The flowchart was drawn using the online diagram editor Draw. io (https://app.diagrams.net; last accessed on 19 June 2021) and the Sankey diagram (Fig. 6) was produced on SankeyMATIC (https://sankeymatic.com/; last accessed on 29 September 2021). The modeling simulations were performed on a computer with a 3.70 GHz processor and 8 GB RAM.

3. Results and discussion

3.1. Changes in LULC between 2006 and 2016

The LULC maps for 2006 and 2016 for the wet season are shown in Fig. 5. The Kappa coefficients of the maps were 0.86 and 0.82 for the respective maps. As both Kappa indices were over 0.8, the land classification was adequately accurate (Wen et al., 2019). They revealed an increase of built-up area within the study period, amounting to 8481ha (an increase of 80.3%). For the other LULC types, all reduced in total size with bare soil decreasing the most (by 16.4%) by 2016. The remaining vegetated, open water and flooded land areas also declined in size. The water bodies, namely open water and flooded area, saw a slight decrease of 2.2% and 4.6%, respectively. Table 3 shows the changes in area between land cover maps between 2006 and 2016. In the case of the LULC maps for the dry seasons, the flooded land was fully converted into
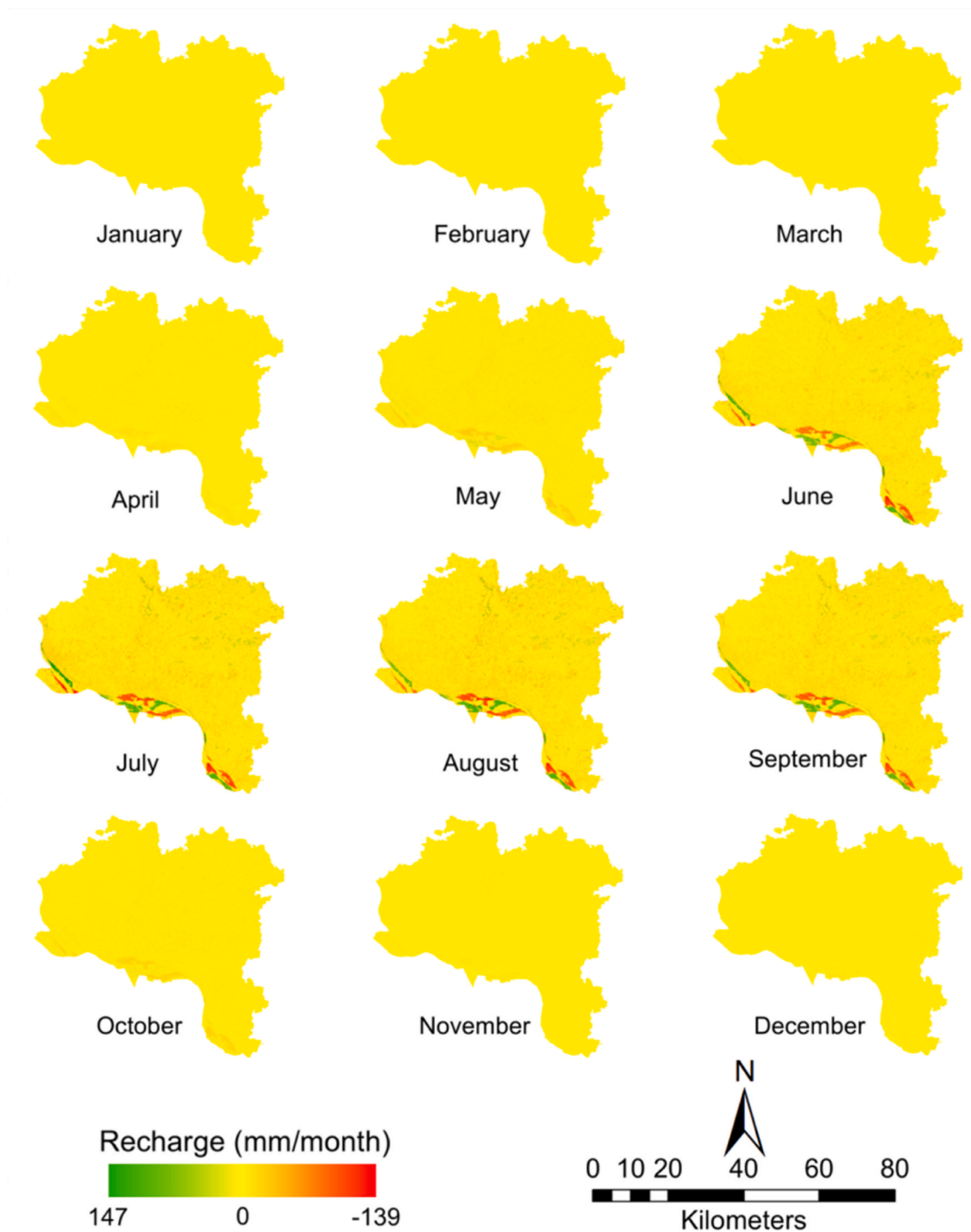
Fig. 11. Spatial distribution of monthly average changes in groundwater recharge over 11 years due to variations in long-term temporal LULC.

vegetated land as agriculture is usually practiced on dried up wetlands and other low-lying regions.

All LULC transformations between 2006 and 2016 are shown in Fig. 6. In general, most of the LULC from 2006 remained the same in 2016. The highest change was observed in the conversion of 9821ha of the vegetated area into built-up zones due to urbanization. Considerable transformations between vegetated, bare soil and open water areas were also observed. These can be explained by the meandering actions of the river Padma. Old sandbars sank while newer sandbars emerged due to the meandering of Padma. This natural action was mostly responsible for the changes between the LULC classes. This was also true for the

transitions on sandbars, as some agriculture is practiced there. The changes caused by the meandering of the river Padma through Rajshahi city are shown in Fig. 7. One notable part was the conversion of built-up area into vegetated area. This may be due to population migration to urban regions, caused by a hope for higher income and a better quality of life. UN-Habitat (2012) also reported that about 3 million people were estimated to move into cities every week globally. The mass movement of people to cities was associated with the enhanced well-being of people (IOM (International Organization for Migration) 2015). Seto (2011) showed that the significant rise in the urban population in the Ganges-Brahmaputra delta over the past 20 years was due to the high
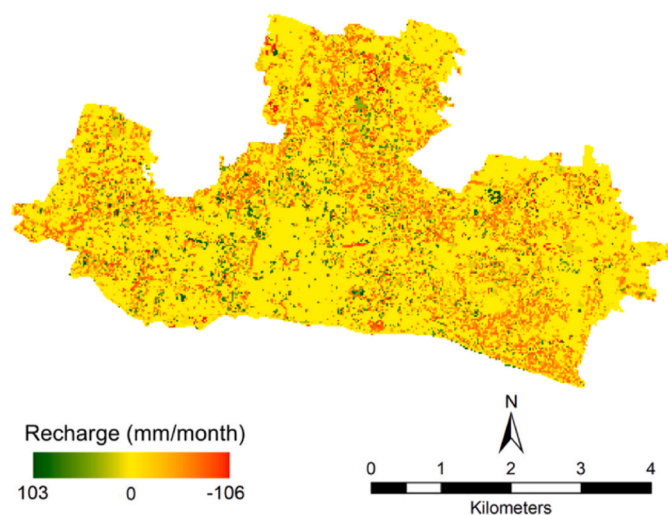
Fig. 12. Spatial distribution changes in recharge (July) in Rajshahi city.

economic, demographic and political inequalities between societies. As a result of this migration, rural and semi-urban zones are often abandoned and converted into agricultural lands and smaller woods.

3.2. Simulated groundwater recharge

Monthly groundwater recharge, considering the LULC map of 2006 (wet) along with rainfall, is shown in Fig. 8. It revealed that the trend of recharge was similar to that of rainfall. In the wet months (May to October), recharge was very high because of high rainfall. Conversely, recharge rates dropped during the dry season (November to April). Monthly recharge varied between 0.2 mm (January) and 80.9 mm (July), averaging 26.8 mm/month over all 12 months. Annual simulated recharge was observed to range from 215 mm to 512.5 mm. The average annual recharge was 321.2 mm. This is similar to the findings of Shamsudduha et al. (2011), who reported annual recharge values varying from 250 mm to 600 mm in the same region. Mustafa et al. (2017) also found annual recharge between 230 mm and 660 mm in northwestern Bangladesh. The recharge was also spatially varied over the study area.

Fig. 9 presents the relationship between rainfall and recharge on different soil textures. The average recharge was highest in sand (28 mm/month), closely followed by loam (26.1 mm/month). Clay soil had the lowest value amongst all the soil types (18.1 mm/month). This was because recharge is closely related with the permeability of soil textures. Coarser soil textures, such as sand or loam, were observed to have higher recharge due to their higher permeability compared to finer textures, such as clay (Tafasca et al., 2019). Recharge was also found to be close to zero when rainfall was ≤50 mm. Zomlot et al. (2015) found comparable results in loam dominated Flanders, in Belgium, with high recharge in sand and low recharge in clay type soils.

Groundwater recharge was strongly correlated with land cover classes, as shown in Fig. 10. Bare soil and the vegetated area both had high average monthly recharge, with 30.5 mm and 29.2 mm, respectively. The built-up area, characterized by both fully and partially impervious lands with vegetation, was observed to have a 23 mm annual average recharge. WetSpass-M assigned no recharge for water surface covers (both flooded land and open water classes). This was because the model assumed that rainfall-induced recharge on water surface covers was negligible compared to the recharge from the water body itself (Batelaan and De Smedt, 2007). As the recharge in this study was only sourced from rainfall, there was zero recharge in the flooded land and open water LULC classes. Mustafa et al. (2017) reported similar findings for recharge using the same WetSpass model in northwestern

Bangladesh.

3.3. The impact of LULC changes on spatially distributed groundwater recharge

3.3.1. The impact of long-term temporal LULC changes

The annual average groundwater recharges were 322.5 mm and 319.9 mm for the 2006 and 2016 land covers, respectively. Similarly, monthly recharge for 2016 land cover dropped to 26.7 mm from its 26.9 mm level in 2006. The recharge was high in the months of June, July, August and September. Contrarily, little to almost zero recharge was observed during the dry period (November–April). Overall, the recharge in the basin decreased by 2.6 mm/year from changes in long-term temporal land use and land cover. This was caused by the difference in the rate of recharge for 2006 and 2016 land covers. The monthly spatially varied differences between 2006 and 2016 over the study area are mapped in Fig. 11. The variation due to long-term temporal LULC changes was found to be statistically insignificant (p > 0.05; 95% confidence level). The changes were small over the whole basin. This insignificant change in recharge was primarily caused by the expansion of built-up areas (8467ha; 3.5% in total). Reduction in the vegetated area (2905ha; 1.2% in total) also played a part in decreasing recharge. The decrease in vegetation cover led to reduced evapotranspiration. This raised surface runoff in 2016 LULC compared to 2006. The increase in surface sealing through urbanization lowered infiltration and increased runoff from the water balance in the 2016 LULC, resulting in lower recharge. However, the growth in built-up and fall in vegetated land cover types was still too small, considering the whole study area (243762ha), to influence recharge by a large margin. Mustafa et al. (2017) reported similar small changes in recharge due to the long-term temporal LULC changes between 1990 and 2010 in northwest Bangladesh.

The regional scale study involved the highly urbanized Rajshahi city area which saw a 815ha increase in built-up land (increase by 55%). Recharge here declined by about 17.1 mm/year or 1.4 mm/month from 2006 to 2016. Fig. 12 shows the spatially varied changes (July average) in recharge in the urbanized area. Though the change was higher in the city area compared to the basin as a whole, the difference in recharge between 2006 and 2016 was not significant (p > 0.05; 95% confidence level). The reason behind this change was the heavy increase in the built-up area as a result of rapid urbanization. Vegetated areas with high recharge were converted into built-up zones. Consequently, the overall recharge in urbanized Rajshahi city considerably decreased. Similarly, Adhikari et al. (2020) and Ghimire et al. (2021) found a similar reduction in recharge under medium and high urbanization scenarios in Vietnam and Thailand, respectively. However, Minnig et al. (2018) observed increased groundwater recharge in Dübendorf, Switzerland, even with the effects of urbanization. They inferred the reduced evapotranspiration rate caused by urban growth as the primary factor responsible. This agreement and disagreement might be attributed to climatic characteristics, particularly temperature and associated evapotranspiration. Temperature was a major influential factor in determining evapotranspiration from water balance (Pan et al., 2011). Switzerland, as a significantly colder region compared to Bangladesh, witnessed enough reduction in evapotranspiration to result in increasing recharge. Contrarily, Thailand and Vietnam have similar temperatures to Bangladesh and, as a result, the decrease in evapotranspiration was lower and was too insufficient to considerably affect recharge in these regions.

The monthly average changes in groundwater recharge differed considerably with spatial variation. The dry months presented very small differences. For the most part, wet months were similar. However, they revealed significant distinctions when spatial variation was considered. July showed the highest change for both basin and regional scale. These were caused by changes in land cover type over the study period. Specifically, the areas adjacent to the River Padma saw
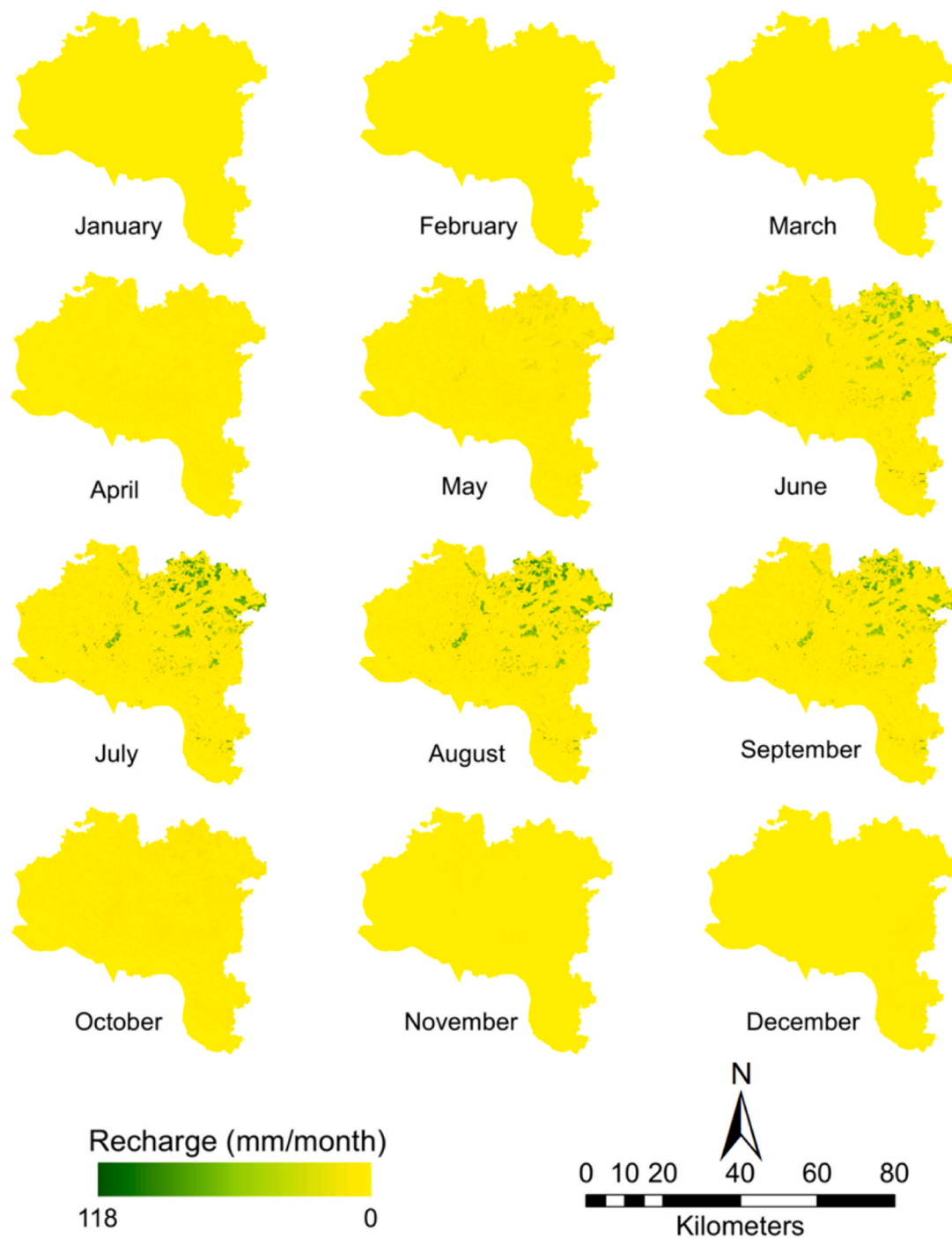
Fig. 13. Spatial distribution of the monthly average changes in groundwater recharge over 11 years due to variations in seasonal LULC.

substantial changes in recharge. Padma meandered greatly over the 11 years of the study period, transforming open water areas with zero recharge into sandbars of bare soil with maximum recharge and vice versa. As a result, this particular area was associated with the greatest long-term temporal change in groundwater recharge rate. For the remaining region, the smaller decreases were caused by the increase in built-up zones. The wetland region at the northeast showed increases, mostly due to the transformation of flooded lands into vegetated areas.

4. The impact of seasonal LULC changes

The average groundwater recharges were 309.8 mm/year and 330 mm/year for wet and dry land covers, respectively. Wet LULC produced an average recharge of 27.5 mm/month, compared to 25.8 mm/month for dry LULC. High recharge was observed in the months of June, July, August and September. Conversely, the recharge was almost zero during the dry period months (November–April). In general, the recharge in the basin increased by 20.6 mm/year with changes in seasonal land use and land cover. This meant that if the other governing variables, like rainfall, were the same, dry seasonal LULC would yield higher recharge
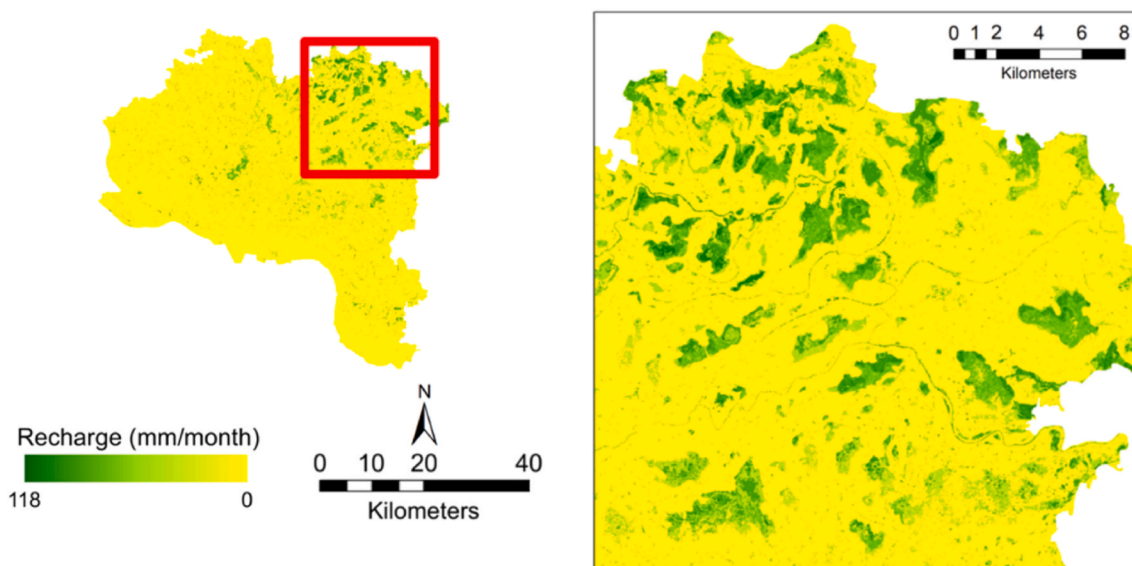
Fig. 14. Spatial distribution changes in recharge (July) in the wetland region.
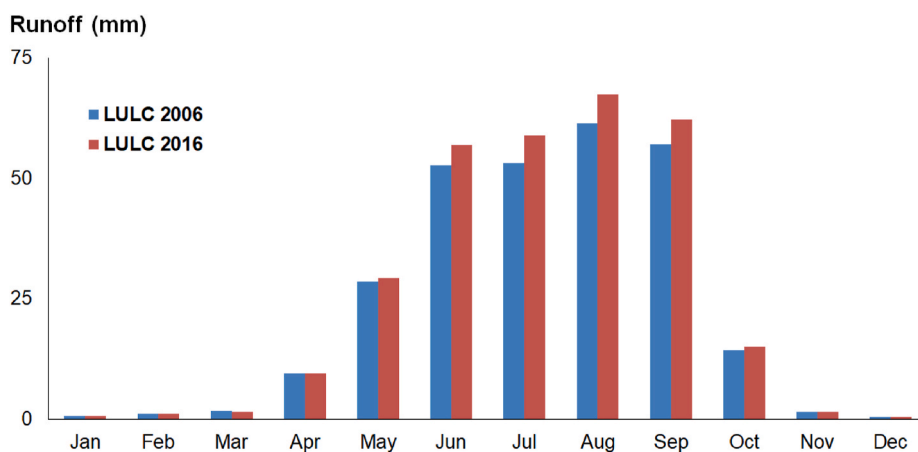

Fig. 15. Monthly average surface runoff for 2006 and 2016 LULCs in Rajshahi city; blue bars represent surface runoff for 2006 LULC, red bars represent surface runoff for 2016 LULC. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
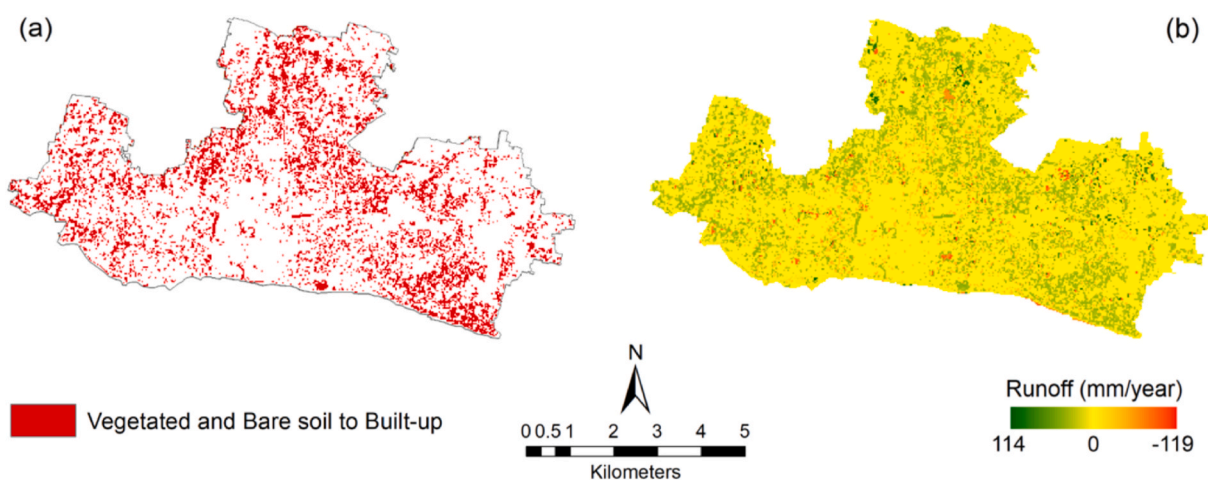

Fig. 16. Rajshahi city: (a) the transformation of vegetated and bare soil areas in 2006 into built-up areas in 2016 and (b) changes in runoff (July).
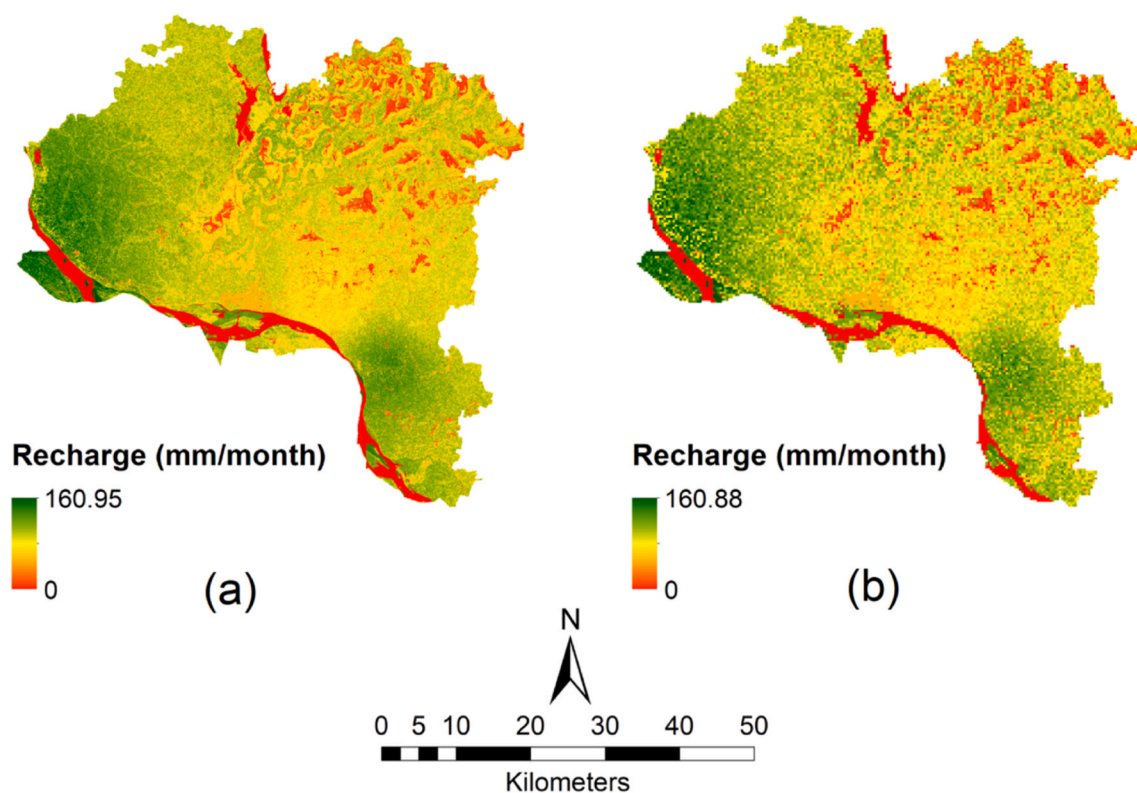
Fig. 17. Spatially distributed average recharge (July) maps at (a) 30 m and (b) 300 m resolutions.

compared to wet seasonal LULC. In other words, dry seasonal LULC had a higher potential for recharge than that of wet from the same rainfall. During the wet season, flooded lands were complete water bodies and thus the flooded land class was in a fully saturated condition. Due to this complete soil saturation condition, water could not infiltrate through this land cover and instead became surface runoff (Rahmati et al., 2018). The rate of evaporation was also considerably higher from the saturated surface for wet season LULC, raising the quantity of evapotranspiration. During the dry season, however, flooded lands transformed into vegetated land cover which was not fully saturated. Furthermore, vegetation covers improves infiltration by delaying surface runoff (Song et al., 2021). Hence, the vegetated land class allowed a substantial quantity of infiltration compared to the zero infiltration in flooded land. In addition, lower evaporation from vegetated land cover for dry season LULC kept the overall evapotranspiration lower than that for wet season LULC. Less water was attributed to the evapotranspiration and runoff components of the water budget for dry season LULC. This resulted in higher recharge for dry season LULC. The difference in recharge due to seasonal LULC changes was statistically insignificant ($p > 0.05$; 95% confidence level). However, the effects of seasonal LULC changes were high at the basin-scale, unlike the long-term temporal changes. This happened due to the conversion of approximately 16000ha (6.5% of the total area) of flooded land into vegetated area. As explained, there was no recharge for the flooded land class. In contrast, recharge for vegetated cover was quite high, as shown in Fig. 10. Thus, the rate of recharge increased due to the decrease in water bodies. Dissimilar results were found regarding water body associated recharge in the study by Kuroda et al. (2017), where the authors used observation wells for groundwater analysis. They concluded that surface water bodies like ponds contributed to groundwater recharge in suburban Hanoi, Vietnam by up to 120 mm/year from downward seepage. This difference in results was caused by the method of recharge estimation used in the current study. The WetSpass-M model, which was used in this study, considered rainfall as the only source in the water budget. Hence, this study interpreted rainfall-induced recharge as the actual recharge. Zero rainfall-induced

recharge was assigned by the model for the flooded land LULC class due to it being negligible compared to the recharge from water bodies (Batelaan and De Smedt, 2007). In general, seasonal LULC changes had a considerable influence on groundwater recharge. This information showed that dry season LULC can allow more water to convert into recharge from precipitation and other water sources above ground level, such as irrigation for agriculture during the dry season in the study area (Hossain et al., 2009).

The monthly, spatially varied differences between recharge for wet and dry seasonal LULCs are mapped in Fig. 13. Like the long-term temporal changes, the dry months presented very little change. For the most part, wet months were similar. However, significant differences were observed with spatial variation, with July showing the highest difference. These differences were caused by changes in land cover type due to seasonal change. The changes considering spatial variations were also highly notable. In particular, the northeastern region displayed substantial changes in groundwater recharge, as presented in Fig. 14 (for July). This section was mostly covered by flooded land with zero recharge during the wet season. However, in the dry season, the flooded lands were fully transformed into vegetated lands with a very high recharge rate. This caused a considerable increase in overall recharge between wet and dry season land covers. The remaining areas were unchanged and, as a result, there was no difference in recharge.

4.1. The impact of LULC change on surface runoff

Fig. 15 illustrates how runoff was unevenly distributed throughout the year, with a high quantity during the wet months but a lower amount during the dry months. The annual average surface runoff increased from 284.1 mm to 292.8 mm due to changes in LULC between 2006 and 2016 over the whole study area. Compared to the whole area, Rajshahi city witnessed an increase of 22.3 mm in annual average surface runoff, from 281.7 mm annual runoff to 304 mm from 2006 to 2016 LULCs. This increase in runoff was likely caused by urbanization. At the study area level, the built-up area expanded by 3.5% (8467ha), while the built-up
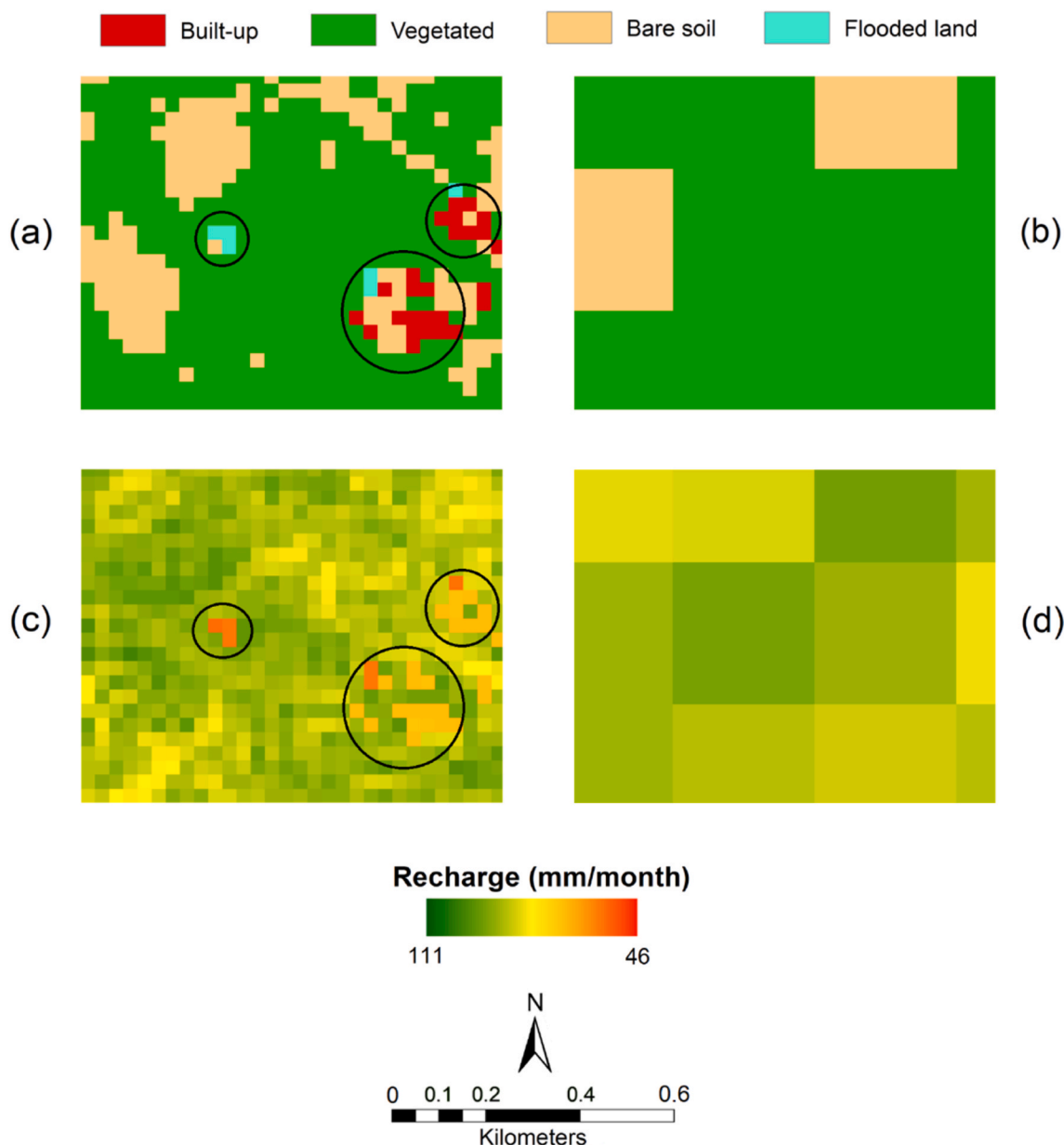
Fig. 18. Parts of maps of (a) LULC at a 30 m resolution, (b) LULC at a 300 m resolution, (c) recharge (average July) at a 30 m resolution and (d) recharge (average July) at a 300 m resolution (black circles indicating the zones of interest).

area of Rajshahi city expanded by 55% (815ha). Higher urbanization in the city resulted in a greater rise in surface runoff. Fig. 16a shows the transformation of vegetated and bare soil areas in 2006 into built-up area in 2016, and Fig. 16b shows the spatial variation in runoff from 2006 to 2016. These maps display an increase in runoff in zones where urbanization took over vegetated and bare soil areas. This result was in agreement with the study by Astuti et al. (2019) in Indonesia, with intense rainfall during the wet season but little rainfall during the dry season. They observed a 36 mm rise in average yearly surface runoff from 1995 to 2015 and pointed to concentrated urbanization as a major cause. Wakode et al. (2018) also showed that impermeabilization due to urbanization resulted in rainfall being mostly converted into surface runoff in Hyderabad, India. Zhang et al. (2018) also reported that areas with high urbanization become more prone to flooding.

4.2. The effect of spatial resolution difference

The above results were all produced with a 30 m raster resolution. The same procedures were all performed with rasters at 300 m resolution. Fig. 17 shows the average recharge maps for July at both 30 m and 300 m resolutions. The results show that the spatially distributed monthly average recharge at 30 m and 300 m resolutions were 26.76 mm/month and 26.77 mm/month. The difference was very small (0.01 mm/month). Considering computational time, it took an average of 193.4 minutes to simulate one-year of recharge at a 30 m resolution. On the other hand, simulation at 300 m raster only needed an average of 10.7 min to complete. Thus, simulation with the lower resolution (300 m) was approximately 18 times faster than that with the higher resolution (30 m). In brief, the differences in model output and results were very low but the difference in computational time was massive.

However, the LULC maps for the lower resolution had problems with accurately representing land classes. A raster grid cell of a map had only

one value within its own area. Thus, every 90000 m^2 area in a map at a 300 m resolution was completely homogeneous. In contrast, the smallest area of homogeneity was 900 m^2 in a map at a 30 m resolution. Regions smaller than 90000 m^2 might not be precisely included when represented in a 300 m resolution raster. Consequently, smaller areas of a certain class were mixed into other classes in the map at a lower resolution. This misclassification caused the incorrect computation of groundwater recharge in those areas. Similarly, Zomlot et al. (2017) observed incorrect approximations of recharge due to misrepresentation and overestimation of vegetated and built-up land classes. Fig. 18 shows some of the variance between maps at 30 m and 300 m resolution. The black circles point to the zones of interest. The small built-up and flooded land areas (marked with the circles) at a 30 m resolution (Fig. 18a) were not present at a 300 m resolution (Fig. 18b). These areas were grouped with bigger vegetated areas in the latter. This was clearly a misclassification of land cover. Both built-up and flooded land had much lower recharge rates than vegetated areas. As a result, recharge in these particular zones was inaccurately simulated in the 300 m resolution LULC map compared to at 30 m, as shown in Fig. 18d and c. Thus, the land heterogeneity was lost to some degree in the lower resolution recharge maps. Hence, studies requiring precision for smaller regions would need rasters at a higher resolution for proper representation.

5. Conclusions

This study assessed the influence of LULC changes on spatially distributed groundwater recharge in northwestern Bangladesh. All data was processed into rasters and used as input in the water balance model WetSpass to simulate monthly groundwater recharge.

From 2006 to 2016, Rajshahi had a huge increase in built-up areas. Impervious built-up zones almost doubled over the 11 years. The most notable land cover transformation was within the streamline of Padma River due to meandering.

From land cover change analysis, the recharge decreased from 2006 to 2016 LULC as a result of the increase in built-up areas. Most variations were detected in regions adjacent to the river, caused by transformation between bare soil and open water due to meandering. However, the change at the basin scale was very small (2.6 mm/year). The effects of LULC change were found to be considerably higher (17.1 mm/year) in the highly urbanized Rajshahi city area, primarily owing to urbanization. Seasonal LULC changes had a major impact on groundwater recharge. The LULC status during the dry season was found to have a higher potential for rainfall-induced recharge due to the conversion of flooded land into vegetated land cover. In the study area, recharge from rainfall increased by 20.6 mm/year with the dry LULC condition compared to the wet seasonal condition. In addition, a runoff analysis showed a 22.3 mm rise in generated surface runoff in Rajshahi city from 2006 to 2016 due to urbanization.

The resolution scaling analysis showed very little change in results at both 30 m and 300 m spatial resolution. The reduction in computational time in the 300 m simulation (an 18 times reduction on average) was noteworthy. However, the inputs of the 300 m resolution were not precisely representative of smaller areas. This led to misclassification of inputs like land cover and issues with predicting recharge in smaller sections. Therefore, using lower resolution maps for simulation can be recommended only when a quick investigation is required over precision analysis. Otherwise, maps at a higher resolution are recommended for the level of precision they offer.

Overall, long-term temporal LULC changes over the whole study area did not significantly influence groundwater recharge. However, the same LULC changes had a notable effect on the urbanization dominated Rajshahi city area. The changes in seasonal LULC also had a major impact on groundwater recharge in the study area. Furthermore, urbanized Rajshahi witnessed an increase in runoff which might lead to more flooding. These indicate that authorities should take urbanization into account when formulating new land and water management

policies, especially in the city of Rajshahi. Seasonal land cover change can also play an important role in water management planning. For example, artificial recharge schemes can be planned during the dry season, as the terrain will have higher potential for recharge. Finally, future research could focus on other possible influencing factors, including climate change, which might also affect groundwater dynamics. Research could also be done on detailed flood analysis for better disaster management. In addition, as RS data were used in this study for model calibration due to the lack of in-situ measurement, further studies could be conducted using in-situ measurement of variables used for model calibration.

Availability of data and material

The data used in this paper is summarized and presented in tables, figures, and references. The data is available from the authors upon request (syed.mustafa@abdn.ac.uk).

Credit author statement

Md Sifat Siddik: Conceptualization, Methodology, Formal analysis, Resources, Writing – original draft, Visualization. **Shibli Sadik Tulip:** Formal analysis, Resources, Writing – original draft, Visualization. **Atikur Rahman:** Writing – review & editing. **Md. Nazrul Islam:** Funding acquisition. **Ali Torabi Haghighi:** Writing – review & editing. **Syed Md Touhidul Mustafa:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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