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Modelling and dynamic water analysis for the ecosystem service in the Central Citarum watershed, Indonesia

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Abstract: Exploring the drivers of changes in ecosystem services is crucial to maintain ecosystem functionality, especially in the diverse Central Citarum watershed. This study utilises the integrated valuation of ecosystem service and trade-offs (InVEST) model and multiscale geographically weighted regression (MGWR) model to examine ecosystem services patterns from 2006 to 2018. The InVEST is a hydrological model to calculate water availability and evaluate benefits provided by nature through simulating alterations in the amount of water yields driven by land use/cover changes. Economic, topographic, climate, and vegetation factors are considered, with an emphasis on their essential components. The presence of a geographical link between dependent and explanatory variables was investigated using a multiscale geographic weighted regression model. The MGWR model is employed to analyse spatial impacts. The integration of both models simplified the process and enhanced its understanding. The findings reveal the following patterns: 1) decreasing land cover and increasing ecosystem services demand in the watershed, along with a decline in water yield, e.g. certain sub-districts encounter water scarcity, while others have abundant water resources; 2) the impact of natural factors on water yield shifts along vegetation > climate > topography (2006) changes to climate > vegetation > topography (2018).

Keywords: Citarum watershed, Indonesia, integrated valuation of ecosystem service and trade-offs (InVEST), multiscale geographically weighted regression (MGWR), water demand, water scarcity, water supply

INTRODUCTION

The understanding of seasonal and geographic variations in the temporal water resource distribution is crucial for sustainable water resource management. In Indonesia, unequal water resource allocation causes flooding in some areas during the rainy season, while others suffer from drought during the dry season. Available and consumable water supplies are limited, but the population and water-intensive sectors are growing, increasing water demand (Fulazzaky, 2014). This problem is aggravated by a reduced watershed capacity due to land change and pollution. Changes in land cover patterns have a direct impact on water retention, leading to reduced water availability at the turn of seasons. This leads to more severe floods and droughts

(Habibie *et al.*, 2020). The vulnerability of hydropower systems is determined primarily by the size of the basin and the capacity of surface water, as well as shallow and deep groundwater within the basin (Permatasari *et al.*, 2019).

In this decade, various models have been developed for analysing, mapping, predicting, and planning water use allocation in a region, such as the water evaluation and planning model (WEAP), irrigation water quality index (*IWQI*), optimally pruned learning machine (OP-ELM), dynamic evolving neural-fuzzy inference system (DENFIS), multivariate adaptive regression spline (MARS), and integrated valuation of ecosystem service and trade-offs (InVEST) (Khafaji *et al.*, 2022; Nivesh *et al.*, 2022; Adnan *et al.*, 2023; Nahib *et al.*, 2023). However, most of the models are used for specific purposes in agriculture or homogenous characteristics of climate zones. The model for tropical zones, like Indonesia, is still rarely developed because various of sub-climatic zones and various land use and land cover (LULC). However, the InVEST is a hydrological model that can be used to calculate water availability and evaluate the benefits provided by nature through simulating alterations in the amount of water yields driven by land use/cover changes (Geng *et al.*, 2014).

Climate change can significantly affect water balance of a specific area because of precipitation and temperature changes. Furthermore, the LULC change also can have a considerable impact on the water balance, resulting in significant physical impacts (Ojeda Olivares *et al.*, 2019). The expansion of urban and agricultural areas may have a negative impact on water resources, such as changes in overland flow patterns and other negative long-term implications. Agricultural land is expected to shrink as farms are abandoned and urbanisation spreads into rural areas.

Prior studies of the LULC in the Central Citarum watershed determined that the paddy field area declined (4.00%), natural forest (23.75%), and plantation (2.38%) between 2006 and 2018. Moreover, residential area increased (13.84%), dry agricultural land expanded (20.40%), and dry land mixed farming areas increased (12.26%). In a study by Nahib *et al.* (2021), the InVEST simulation suggested that changes in the LULC had a direct influence on the water yield (*WY*) in a specific area. The data demonstrated that changes in the LULC can result in a *WY* drop. The study is part of a larger research project, and the combination of the model with the MWGR is an extension of previous research that solely used the InVEST model in the same area (Nahib *et al.*, 2021). The validation of modelling results with observation data showed Pearson correlation of 0.9885, a root-mean-square error (*RMSE*) value of 0.70, p value of 0.0005, and significance of 0.0000. These results indicate that the InVEST modelling for the *WY* can be used to predict the actual *WY* conditions in the Citarum River basin.

The multiscale geographically weighted regression (MGWR) is a spatial regression technique that analyses spatial correlations between variables at various scales. The MGWR extends beyond the typical geographically weighted regression (GWR) by including various bandwidths, each of which corresponds to a distinct scale of study. This method recognises that the intensity and form of spatial linkages can change across geographic scales, allowing for a more nuanced understanding of these relationships; it is particularly effective in situations where spatial correlations between variables are complex and varied.

The key sectors that rely on basin water resources are agriculture, drinking water, animal husbandry, and industries. It is critical to manage water resources wisely and efficiently, ensuring equal allocation across the many sectors (Nivesh *et al.*, 2022). Furthermore, a study by (Wei *et al.*, 2022) explains that land use and precipitation can affect runoff and water yield spatially in a watershed region. For example, converting paddy fields to dry land will increase runoff and sediment yield, thus causing soil erosion.

Ecosystem services (ES) refer to advantages that individuals gain from ecosystems, such as provision, regulation, support, and cultural services (Bai *et al.*, 2022). In the past few years, there has been a notable rise in the integration of ecosystem services, specifically those related to water resources, into global decision-making processes (Cabral *et al.*, 2021). In many parts of the world, water scarcity is a major constraint on socio-economic development and a threat to livelihoods (Zhang, Hoekstra and Mathews, 2013; Liu *et al.*, 2017). Therefore, it is important to solve the water stress problem (Uche *et al.*, 2015; Wang *et al.*, 2021).

The Central Citarum watershed is a vital reservoir for water supply to many activities in the Java Island, especially in West Java, such as agriculture, industries, businesses, and households. The Central Citarum Watershed borders the Purwakarta, Bandung, Bekasi, and Majalengka districts. Currently, these districts saw strong growth, especially in urban residential and industrial areas. The rapid growth is expected to have a significant impact on the current water balance in the region. However, scientific research has failed to explain the tropical complex process in the Central Citarum Watershed so that many stakeholders do not understand the process. Currently, the complex process will worsen because of uncertainties in climate change that transform patterns of annual temperatures and rainfall in regions with mixed climate conditions (Al-Ghobari and Dewidar, 2021).

This study has integrated the InVEST model and the MGWR model to simplify complex interaction of climate, socio-economic, ecological processes in tropical areas and to fill the understanding gap. Based on above reasons, this study aimed to: 1) examine supply-demand ratio (*SDR*) and water scarcity index (*WSI*) in 2006–2018; 2) reveal mechanisms of spatial response to factors affecting ES. Through the integration of the InVEST and MGWR models, this study strives to bridge the knowledge gap by simplifying these interactions and providing a clearer understanding of mechanisms that can guide sustainable water management strategies in the region and similar tropical ecosystems.

MATERIALS AND METHODS

STUDY AREA

This research was conducted in the main Citarum Watershed, which consists of 17 sub-watersheds of 227,016 ha in 2022. These watersheds include Cilawan, Cipada, Cibalagung, Cihalang, Cikaleo, Citarum108 and Citarum58, Cimang, Cibreal, Cisokan, Cikidang, Chipatunjang, Cimurah, Cisubah, Cibungur and Cibodas. The research area is located in West Java and is divided into the following five administrative regions: Bandung Regency, Purwakarta Regency, Sumedang Regency, Cianjur Regency, and the Bogor Regency. As seen in Figure 1, it is located between 107°22'50.606"–107°56'46.297" E and 6°45'40.112"–7°14'27.018" S.

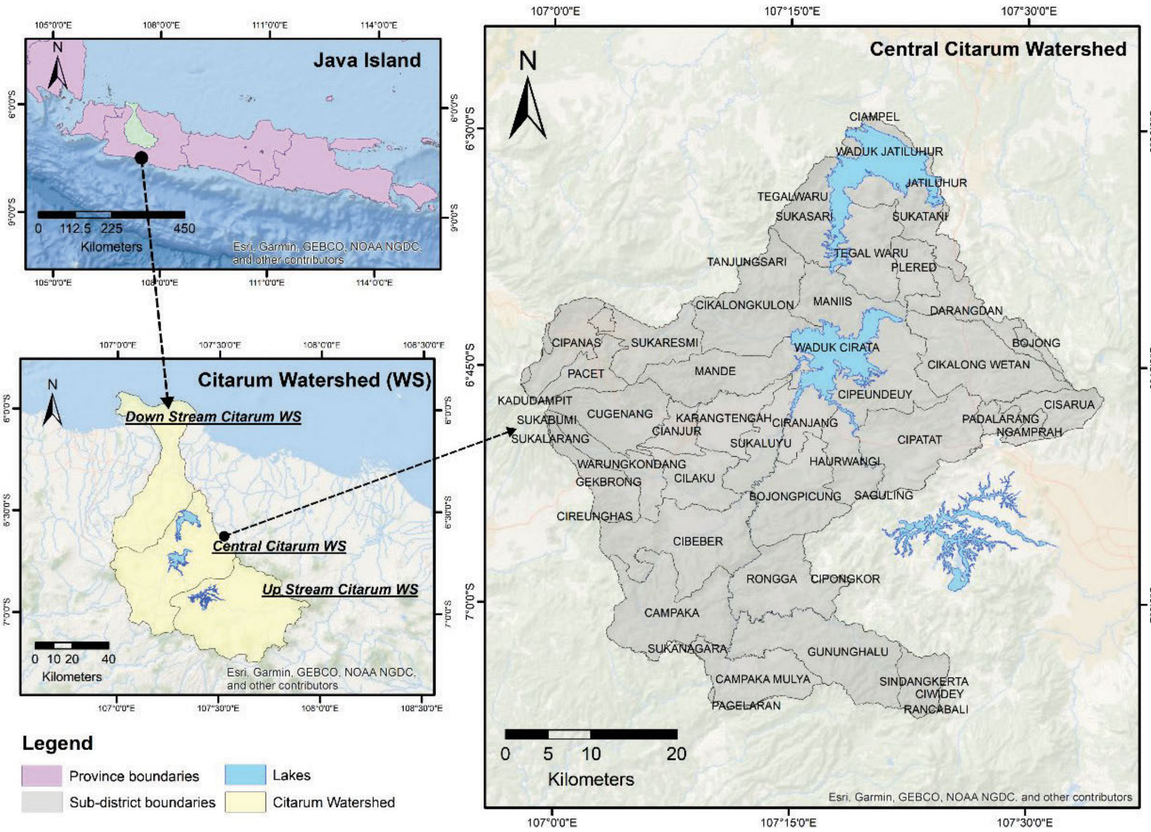

Fig. 1. Study area; source: own elaboration

STUDY METHODS

The information was analysed using the InVEST tool and the geographic information system (GIS). In order to use the InVEST, the original data were transformed into a gridded format with a resolution of 30 m and aligned with the WGS84 reference system. Table 1 shows types and sources of data variables.

Driving factors behind the change in water yield

According to previous research by Zhang *et al.* (2021), the study makes use of four key data elements: climate, topography, soil, socio-economic factors, and vegetation (Tab. 2). Using zoning statistics, grid data such as land cover/use, climate, and socio-economic characteristics are investigated and aggregated. These aggregated statistics are then used at each of the 17 sub-catchment levels.

The research is divided into three sections, as shown in Figure 2.

The first stage comprises the development of the water yield model with the InVEST model. This entails analysing the *SDR* utilising geographical and temporal data and measuring oscillations in water yield in the Central Citarum sub-watershed in 2006–2018.

The second stage is the selection of the driving factor behind water yield. Factors affecting water production in the watershed include *P*, *ET*avg, *ETo*, *Root1*, *Root2*, *Kc*, *PAWC*, *Elv*, *slope*, *GRDI*,

Table 1. Variable and data source

Variable	Data	Processing	Source
Land cover	satellite imagery 30×30 m resolution	supervised classification	Houska (2012)
Precipitation	annual precipitation data for 2000 – 2020	numerical/table data, with location coordinates, a spline interpolation technique	BMKG (2022)
Average annual reference evapotranspiration	temperature data	a spline interpolation technique	BMKG (2022)
Root restricting layer depth	map of the soil type of 1: 100,000	extraction and resampling, conversion polygon to raster	Sulaeman *et al.* (2013)
Plant available water content	percentage of clay and sand		FAO (2022)
Biophysical table	root depth and crop coefficients	extraction and resampling matrix (.csv)	FAO (2022)
Water demand	water consumption		BPS (2022)

Source: own elaboration.

Table 2. Description of potential driving factors

Type	Factor
Climate	average precipitation (P in mm, X_1), average evapotranspiration ($ETavg$, in mm X_2), evapotranspiration (ETo in mm, X_3)
Vegetation	root restricting layer depth ($Root1$, X_4), the maximum root depth for vegetated each land use and land cover class ($Root2$, X_5), plant evapotranspiration coefficient (Kc, X_6)
Soil	plant available water content ($PAWC$, X_7)
Topography	elevation (Elv, X_8), slope ($slope$, X_9)
Socio-economic data[1]	total gross regional domestic income ($GRDI$ in rupiah, X_{10}), total population density (POP in person, X_{11})

[1] The source of socio-economic data, gross regional domestic income and population density from BPS West Java, the Republic of Indonesia (BPS, 2022).
Source: own elaboration.

Figure 2 displays a study flowchart outlining data inputs required for the InVEST model. The phrase "water yield" refers to the amount of water that flows across a certain terrain in this model. Water yield volume and average rate are computed at the sub-catchment level using the water balancing method.

Detailed methods and techniques for calculating water yields using the InVEST model are provided in "Supplementary material".

Water yield service (supply and demand)

To figure out how much people want and need ecosystem services (ES) in various areas, information from various sources, such as remote sensing, land surveys, and GIS, must be combined. The distributed InVEST model, which allows for detailed water calculations, was utilised to simulate and represent the distribution of ES related to water supply across the landscape. The InVEST is an annual study aimed at measuring ES across the landscape in real-time (Vigerstol and Aukema, 2011).

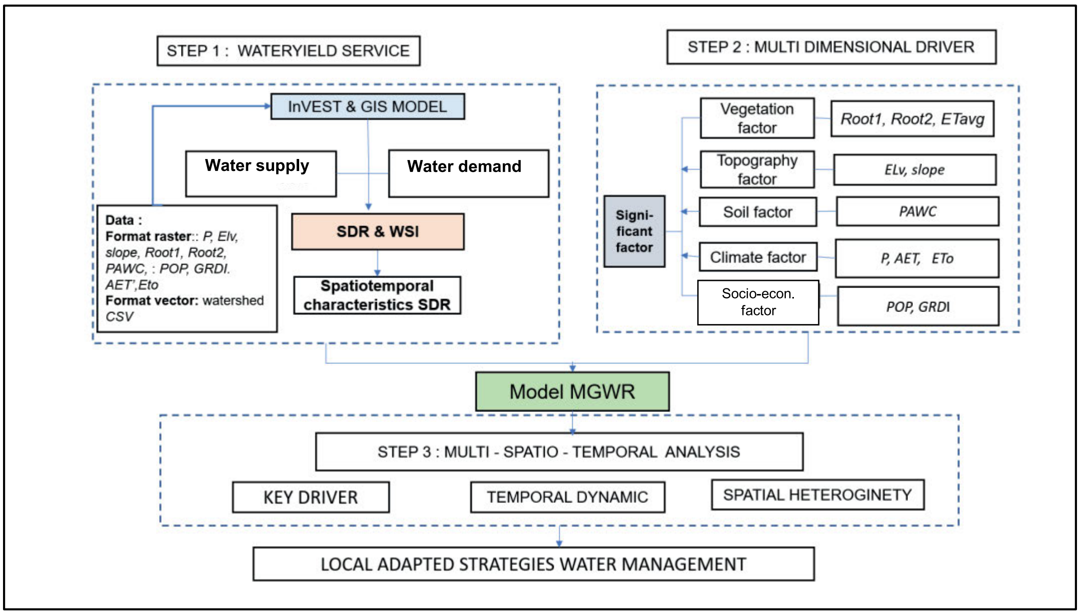

Fig. 2. Flowchart research model; *P, Elv, slope, Root1, Root2, POP, GRDI, ETavg, Eto, Kc*, as in Tab. 1, *SDR* = synthesis of supply-demand ratio, *WSI* = water scarcity index, MGWR = multiscale geographically weighted regression; source: own elaboration

and *POP*. It is necessary to make sure that the factors providing explanation to certain phenomena are not too closely related. This is done by analysing their variance inflation factor (*VIF*) values. We removed factors with *VIF* values >10. This indicates a multicollinearity effect between variables (Nahib *et al.*, 2023).

The third stage applies the MGWR techniques to investigate the spatial response mechanisms that affect ecosystem services.

The determination of water yield using the InVEST model

The data processing in this study consists of using the InVEST model to calculate water availability in the Central Citarum Watershed. It serves as a tool for mapping and valuing natural goods and services that contribute to and benefit human well-being.

Water scarcity occurs when the available water resources are insufficient to meet the water demand (*WD*) in a particular location. It denotes a mismatch between water availability and water demand (Vörösmarty *et al.*, 2000). The local excess or lack of potable water services can be assessed by comparing Wyoming service provision to *WD* needs. According to Boithias *et al.* (2014), calculations can be using Equation (1).

$$SDR = \frac{WS_i}{WD_i} \tag{1}$$

where: SDR = ratio of available water supply to demand, WS_i = water supply in watershed i-th, WD_i = water demand in watershed i-th.

Surplus occurs when supply exceeds demand, whereas deficit when demand exceeds supply. By measuring the amount of water available and how much is consumed, the research can determine the *SDR* for the entire Citarum sub-watershed. A common dividing line between a surplus and a deficit *SDR* is achieved when supply equals or exceeds demand.

The difference between water supply (*WS*) and water demand (*WD*) was evaluated using the *D*-ratio, which compares *WS* and *WD*. The purpose of the analysis was to identify potential conflicts or discrepancies between the two variables. Additionally, the relationship between water availability and water demand can be further investigated using the water scarcity index (*WSI*) (Khan *et al.*, 2020; Zou and Mao, 2021) based on Equation (2).

$$WSI = \log \frac{WS_i}{WD_i} \tag{2}$$

A definition of *WSI* > 0 indicates that *WS* exceeds *WD* (i.e., water surplus), conversely, *WS* is less than *WD* (i.e., water deficit). In order to better understand the value of the *WSI*, define the regional *WS* and *WD* situation, and identify the spatiotemporal variation characteristics, the *WSI* is divided into four groups: scarcity (<–0.5), depletion (from –0.5 to 0), adequate (from 0 to 0.5), abundant (>0.5).

Spatiotemporal characteristics of the supply demand ratio (*SDR*)

According to Tobler's first law of geography, all phenomena are interconnected but the strength of their relationships lessens as the distance between them expands. In other words, things that are near together have a stronger association than things that are far apart. Geographical autocorrelation quantifies the degree of geographic relationship between geographical objects and the attribute values associated with them (Zhao *et al.*, 2021). Moran's *I* is the equation used to calculate the spatial autocorrelation of the Central Citarum sub-watershed contribution to regional demand for ES. Moran's *I* is classified as global Moran's *I* or local Moran's *I*. Global Moran's *I* is used to examine the overall geographical distribution of *SDR* in the sub-watersheds of Central Citarum and to evaluate if *SDR* demonstrates a spatial clustering pattern. Local Moran's *I* helps to determine the type and location of spatial clustering (Bai *et al.*, 2022). Below are the formulas for determining Moran's *I*.

Global Moran's *I*:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})^2} \tag{3a}$$

Local Moran's *I*:

$$I = \frac{n^2}{\sum_i \sum_j W_{ij}} \cdot \frac{(x_i - \bar{x}) \sum_j W_{ij}(x_j - \bar{x})}{\sum_j (x_j - \bar{x})^2} \tag{3b}$$

The quantity of space-related unit samples in the research region is denoted by *n* in these calculations, x_i and x_j indicate the characteristics of spatial units *i* and *j*, in that order, whereas *x* represents the mean value of the attribute across all spatial units. The weight matrix, represented by the sum W_{ij}, illustrates the correlation between each spatial unit *i* and spatial unit *j* within the study area. Moran's *I* and spatial association (LISA) were used to examine the worldwide and nearby linkage autocorrelation of the *SDR* for ecological services among the sub-district clusters of Central Citarum. The *Z*-score and *p*-value are used to determine whether global autocorrelation is positive or negative. Moreover, positive or negative Moran's *I* influences whether global autocorrelation appears dispersed or consolidated. A positive Moran's *I* value signifies a positive spatial correlation, with larger values indicating a clearer spatial correlation and emphasising the examined item's global dispersion. A Moran's *I* value of 0 indicates a random geographical distribution of items studied. The majority of the local autocorrelation research was done in ArcGIS with a cluster and outlier analysis, namely Anselin local Moran's *I*, which provides attribute correlations between research regions.

Multiple linear regression (MLR)

The MLR analysis was implemented to determine the correlation between the dependent variable *SDR* and independent variables (*P*, *ET*avg, *ETo*, *Root1*, *Root2*, *Kc*, *Elv*, *slope*, *PAWC*, *GRDI*, *POP*, and total population). The R studio program was utilised for the analysis. The primary objective in obtaining an appropriate regression model was to pick the essential variables, eliminate insignificant variables, and verify that the independent factors do not exhibit multicollinearity by examining the value of the *VIF*. The tolerance value can be used to determine the approach to testing multicollinearity. The *VIF* limit is ten and the limit tolerance is 0.10.

In order to verify that the sample utilised was typically distributed, a significance test was performed. It examines the distribution of the sample and compares it with the standard distribution to identify if the data show notable deviation from what is considered normal.

The research carried out Kolmogorov–Smirnov (K–S) and Shapiro–Wilk tests to evaluate if the data followed a normal distribution. After that, they employed variable ranking to determine the most important variable in the model by examining its impact on the overall results. The impact was measured by comparing the difference in the residual sum of square (*RSS*) values between the MLR findings with and without the variable under consideration (*RSSj*).

Considering contribution percentage amounts are relative, the combined total of different values that act as general indicators was 100. The calculation for the rate of contribution (*CR*) is presented as follows:

$$CR\,(\%)\; j = \frac{RSSj - RSSi}{RSSj} 100\% \tag{4}$$

This research developed a basic framework (framework A) to investigate the outcomes of assessing forces on water output. The framework can be described as follows:

$$\text{Model}A : Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{ij} X_i + \varepsilon \tag{5}$$

where: *Y* = *SDR* at the district level, X_i = independent factor from 2006 to 2018, βi = coefficient of the model, β_0 stands for the intercept, and ε = residual term.

Variable *X* is as follows: the average precipitation (*P* in mm, X_1), average evapotranspiration (*ET*avg, X_2), evapotranspiration (*ETo* in mm, X_3), root restricting layer depth (*Root1*, X_4), maximum root depth for vegetated each land use and land cover (*LULC*, X_5) class (*Root2*, X_6), plant evapotranspiration coefficient

(Kc, X_7), plant available water content ($PAWC$, X_8), elevation (Elv, X_9), slope ($slope$, X_{10}), total gross regional domestic income ($GRDI$, in rupiah, X_{11}), and total population density (POP, in person, X_{12}).

Geographically weighted regression (GWR)

The state of the SES is influenced by multiple interrelated elements, encompassing biophysical aspects (weather patterns, land use, terrain), socio-economic factors, and the integration of socio-economic factors within the surrounding environment. When spatial influence is considered, GWR approaches "can uncover correlations between dependent index planetary variables" (Fang *et al.*, 2021). Numerous preceding research endeavours employed the GWR technique to replicate the spatial pattern model correlation connecting plant life and precipitation and to acquire knowledge about the determining factor of the water production ecosystem service (Zhang *et al.*, 2021). GWR enhances the conventional regression approach by assessing the estimation of localised instead of universal parameters (Fotheringham, Yang and Kang, 2017) framework present the GWR model:

$$y_i = \beta_{0(u_i,v_i)} + \sum_k \beta_{k(u_i,v_i)} x_{ik} + \varepsilon_i \tag{6}$$

where: (u_i, v_i) specifies the i-th point's coordinates, k = the observed value.

The GWR model performs independent regression on each data point and limits the inclusion of data points in the regression analysis based on specific proximity to the observed place by considering the location of the dependent variable into account. As an outcome, the estimated parameters will become localised and change depending on location.

This research employed adaptable and unchanging kernels for bandwidth computation. The effectiveness of three models, namely ordinary least squares (OLS), unchanging geographically weighted regression (UGWR), and adaptable geographically weighted regression (AGWR), was evaluated by assessing their quality through correlation coefficient (r) and RSS.

Multiscale geographically weighted regression

The existence of geographic associations between dependent and explanatory variables was examined using MGWR models. The model is based on adaptive bandwidth selection, explores key factors at multiple spatial scales, and is currently the best version of the GWR model (Shen *et al.*, 2020). The MGWR model is expressed as follows:

$$y_i = \sum_{j=1}^{n} a_j x_{ij} + \sum_{j=n+1}^{n} \beta_j(\mu_i, \gamma_i) x_{ij} + {}_i \tag{7}$$

where: n = number of driving factor.

In this research, a search for bandwidth is conducted utilising a golden ratio exploration and a Gaussian model. Optimal bandwidth is determined using AICc (Fotheringham, Yang and Kang, 2017), where y is the dependent variable (including different kinds of ecosystem services and total ecosystem service); (μ_i, y_i) is the spatial location of the i-th sample; $\beta_{0(u_i,v_i)}$ is the intercept; n is the number of driving factors; x_{ij} is the independent variables (including climatic, vegetation factors, soil, topographic, and social-factor); β_j (μ_i, y_i) represents the regression coefficient of the i-th sample for the j-th driving factors; and ε_i is the error term.

RESULTS

ECOSYSTEM SERVICES SUPPLY

Water balance-based approaches were used to estimate water yield in 2006 and 2018. To perform these estimations, the InVEST hydrological model, in particular, requires a small number of input data variables (Adiningrum, 2016). The advantage of the InVEST model in this study is that water content estimations can be performed in fields with restricted data availability.

The water yield in the InVEST model is calculated from the part of precipitation that remains after evapotranspiration, i.e. "the amount of water that does not evaporate into the atmosphere" (Fuadi *et al.*, 2016). The calculation results show that the water yield in 2006 was $3.715 \cdot 10^6$ $m^3 \cdot y^{-1}$, while in 2018, it decreased to $3.270 \cdot 10^6$ $m^3 \cdot y^{-1}$. The exact evapotranspiration value under limited water conditions is "potential evapotranspiration (EAT)" (Habibie *et al.*, 2020b). The results of this study illustrated that the Cilawang sub-watershed had the maximum water yield of 1.590 $m^3 \cdot ha^{-1} \cdot y^{-1}$ in 2006, with a utilisation ratio of 36%, and this sub-watershed is the most complex if compared to others. Meanwhile, the Citarum sub-watershed has a water output of 58.1 $m^3 \cdot ha^{-1} \cdot y^{-1}$, with a maximum utilisation ratio of 74%. In 2018, the highest water yield remained in the Cilawang sub-watershed, 1.544 $m^3 \cdot ha^{-1} \cdot y^{-1}$, with a water utilisation ratio of 37%. The Cibodas sub-watershed generates 32 $m^3 \cdot ha^{-1} \cdot y^{-1}$ of water, with the maximum water utilisation ratio increasing from 64% to 77%.

Figures 3a and 4a depict the availability of water products. According to data analysis, the total water yield value of Central Citarum dropped by 11.93% from 2006 to 2018, while water use has increased by 32.12% or 2.67% per year. The area witnessed a rise in open land of 41,793.30 ha (51.66%), plantation 3,510.00 ha (16.89%), virgin forest decline of 11,584.80 ha (48.35%), and plantation forest 39,171.60 ha (42.93%). Rainfall, on the other hand, has increased gradually between 2006 and 2018. Meanwhile, the number of towns and industries that demand water has been increasing. This issue must be considered while managing the Central Citarum watershed to provide a sustainable water supply.

ECOSYSTEM SERVICES DEMAND

According to the InVEST model, the Cirameuwah sub-watershed recorded the highest water consumption in 2006, namely 7,836 $m^3 \cdot ha^{-1} \cdot y^{-1}$, and 10,178 m^3 in 2018, as the area is part of the less developed Purwakarta Regency. On the other hand, the water consumption of the Cikariu water catchment was 6.17 $m^3 \cdot ha^{-1} \cdot y^{-1}$ in 2006 but reached 7.94 $m^3 \cdot ha^{-1} \cdot y^{-1}$ in 2018, with a yield value of 28,351 $m^3 \cdot ha^{-1} \cdot y^{-1}$ in 2006. Figures 3b and 4b include maps of domestic agricultural water demand in 2006 and 2018. Table 3 displays the supply, demand, and supply-demand ratio in the Central Citarum sub-watersheds for 2006 and 2018, taking into account their administrative boundaries. The Cimanggu sub-watershed had a reserve order that was nearly

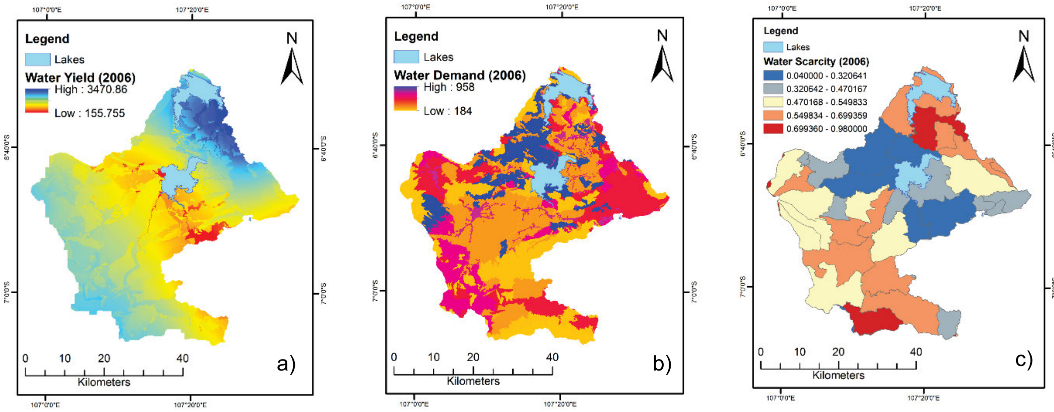

Fig. 3. Spatial distribution of: a) water yield, b) water demand, c) water scarcity in 2006; source: own study

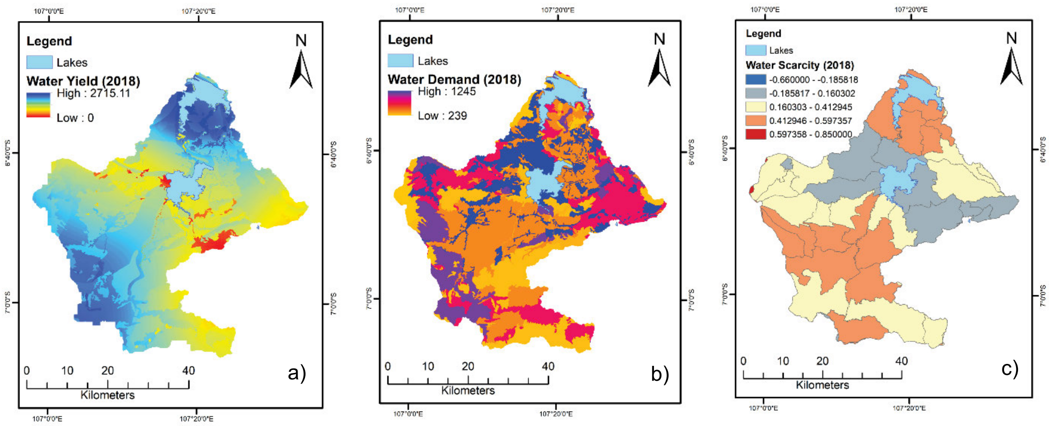

Fig. 4. Spatial distribution of: a) water yield, b) water demand, c) water scarcity in 2018; source: own study

Table 3. Water scarcity index (*WSI*) in 2006 and 2018

Year	Sub-district having *WSI* value							
	<–0.5		from –0.5 to 0		from 0 to 0.5		>0.5	
	n	%	*n*	%	*n*	%	*n*	%
2006	0	0	0	0	23	44.2	29	55.7
2018	0	0	8	15.3	34	67.0	10	19.2

Explanation: n = number of sub-districts.
Source: own study.

equal to the Citarum58 sub-watershed in 2006. However, the Cimanggu sub-watershed achieved a supply-demand ratio of 9.61 $m^3 \cdot ha^{-1} \cdot y^{-1}$ in 2018. Furthermore, the water supply in the Citarum58 sub-watershed fell dramatically to 4.85 $m^3 \cdot ha^{-1} \cdot y^{-1}$.

The relationship analysis of rainfall values and water availability in each sub-watershed shows that each sub-watershed has its own water availability and water demand outcomes. In 2006, high rainfall enhanced water availability in nearly all sub-watersheds. Despite the fact that water demand only covers domestic and agricultural water needs, supplies began to decline in a number of sub-watersheds in 2018. However, other water needs, such as those of animal husbandry, fisheries, and other industries, have yet to be analysed or investigated. High rainfall can, in fact, increase the amount of water in the area. However, it is important to note that water consumption in the region is anticipated to increase due to the presence of built-up land cover, which includes activities generating demand for water.

Due to an unavoidable rise in demand for water from all sub-watersheds, water stocks will be exhausted. This is the most common cause of drought in a certain area. Water yield increased in 2018, with Cibodas 2.89 $m^3 \cdot ha^{-1} \cdot y^{-1}$, Cikidang 3.61 $m^3 \cdot ha^{-1} \cdot y^{-1}$, and Cimurah 1.19 $m^3 \cdot ha^{-1} \cdot y^{-1}$, all increasing by 2.5%. When precipitation decreases (dry season) and water demand remains constant, available water production decreases as well. The understanding of the situation is very important for effective management of water yield. For example, an area may need dams and reservoirs to accommodate water during the wet season and supply it during the dry season. The need for water in irrigated rice fields involves evapotranspiration, water loss caused by percolation and seepage, and initial watering to saturate the soil. In contrast, the water lost through seepage to crops other than lowland rice does not help to meet the irrigation water needs (Sahin and Hall, 1996).

WATER SCARCITY OF ECOSYSTEM SERVICES

The Central Citarum sub-watersheds contain 23 sub-districts, each having a *WSI* index of 0–0.5 and 29 with a *WSI* value of >0.5 (Tab. 3). According to the *WSI*, water supplies in the Central Citarum watershed were still adequate in 2006 and 2018.

In 2006 and 2018, detail information regarding *WY*, *WD*, and *WSI* is based data from sub-districts and for the Central

Citarum Watershed, the data are provided in "Supplementary materials" (Tab. S1).

A water scarcity map with a value slightly higher than one indicates that water management efforts are required to maintain sustainable water supply. Figures 3c and 4c contain more information, including specifics on sub-district areas and water scarcity distribution patterns across watersheds and sub-watersheds. Figure 3c illustrates the scarcity index in 2006, which includes 23 sub-districts in the á0; 0.5) category and 29 sub-districts in the >0.5 category. Compared to the baseline conditions in 2018, the stress level increased slightly, from an average *WSI* of 0.5304 or >0.5 category changes to 0.3221 or ⟨0; 0.5) category.

Increasing population density has placed a significant strain on long-term development, and to ensure optimal and sustained absorption of demand, population pressure in the Citarum Watershed should be controlled according to the ecosystem capacity (Rajput and Sinha, 2020). In this study, a country segmentation survey was conducted to determine populations at and below the watershed level. District units were found to be consistent with sub-watershed boundaries. Therefore, the population of every district was computed by extracting the district's population and finding a correspondence for it with the population of the underwater catchment. The population density was determined by dividing the population ($n \cdot ha^{-1}$) by the area.

As shown in Figure 4c, water depletion (*WSI* < 0) affected eight sub-districts (15%), including Cipeundeuy, Sukanagara, Saguling, Cireunghas, Cikalong Kulon, Haurwangi, Manis, and Mande. In contrast, 35 sub-districts have *WSIs* ranging from 0 to 0.5, and 10 sub-districts with *WSI* > 0.5 or adequate water levels.

SPATIOTEMPORAL CHARACTERISTICS OF THE ECOSYSTEM SERVICES SUPPLY DEMAND RATIO

GeoDa is an open-source software tool that specialises in processing spatial data. GeoDa is not a complete geographic information system, but it provides functionality for exploring and visualising geographic data. It serves as a valuable tool for analysing spatial datasets and extracting insights. In 2006-2018, the local Moran index was developed using GeoDa to analyse the spatial relationship between supply and demand for *WY* services in the Central Citarum basin (Tab. 4, Fig. 5).

Table 4 examines the global and local autocorrelation of *SDR* ES among Central Citarum sub-district clusters using the Moran's *I* and the spatially associated local index (LISA). Between 2006 and 2018, the Moran's *I* values were 0.344 and 0.346, respectively, indicating a significant positive geographic correlation of *SDR*. These results demonstrate the importance of geographical clusters. Moreover, the modest increase in the Moran's *I* in 2018 indicates the increasing importance of spatial clustering of this *SDR* within the watershed.

According to Table 4, the global Moran's *I* was 0.344 in 2006 and 0.368 in 2018. In 2006 and 2018, positive *Z*-scores of 10.2678 and 12.430 were obtained, all with *p*-values of <0.001. These results indicate that there is a significant spatial relationship (Thadewald and Büning, 2007) between water supply availability and demand in the Central Citarum Watershed. Additionally, all components passed the 1% significance test, indicating a meaningful correlation.

Figure 6 shows that there has been a change in the water supply-demand balance in several sub-districts, including the Pacet Sub-district with a change from High-Low in 2006 to Not Significant in 2018. Manis Sub-district with a change from High-High in 2006 to Low-High in 2018 and, in a similar vein, the Gununghalu District where Not Significant in 2006 became High-High in 2018.

Table 4. Global Moran's (Moran's *I*) in the Central Citarum Watershed in 2006–2018

Year	Moran's *I*	*Z* value	*p*-value
2006	0.344	10.2678	<0.001
2018	0.346	12.4305	<0.001

Source: own study.

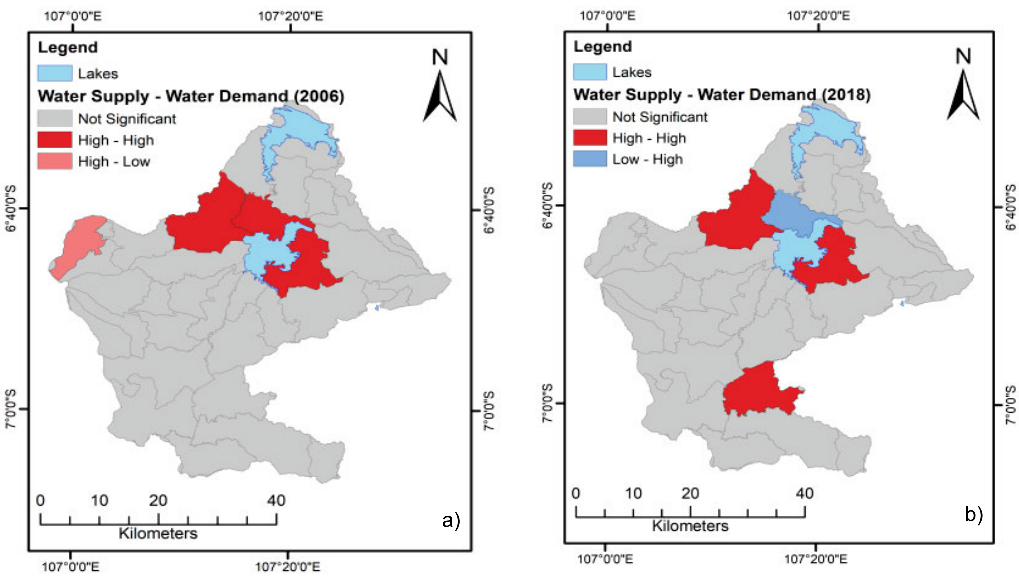

Fig. 5. Global Moran index of water yield service in the Central Citarum Watershed in: a) 2006, b) 2018; source: own study

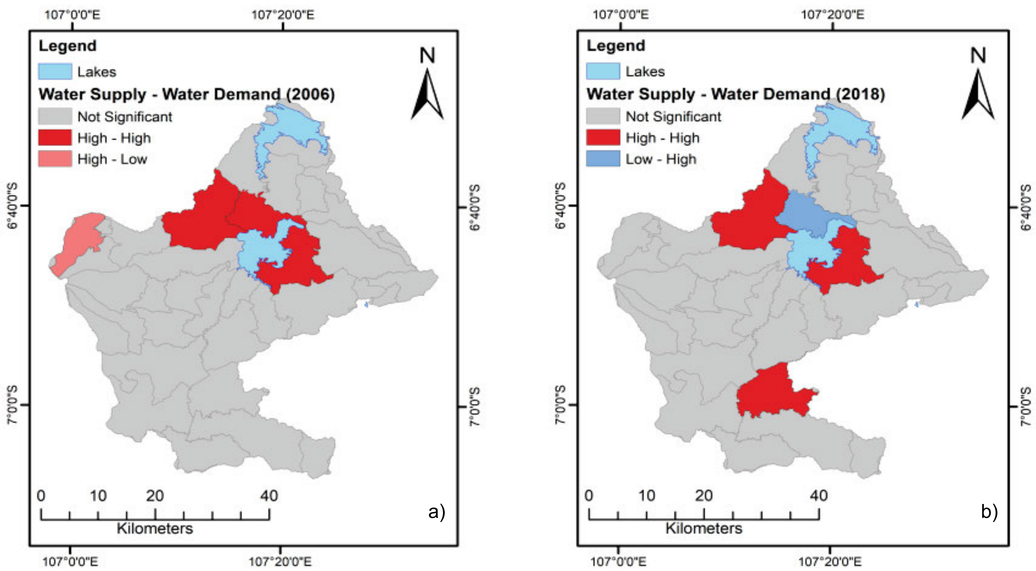

Fig. 6. Spatial matching of supply and demand of water yield service in the Central Citarum Watershed in: a) 2006, b) 2018; source: own study

This indicates that the arrangement of *WY* in space exhibits a favourable spatial connection within the research region. The occurrence of geographic clustering is evident, meeting necessary conditions to utilise the MGWR and GWR models.

The multicollinearity test demonstrates the tolerance value or the *VIF* based on a stepwise regression analysis. This suggests the *VIP* value of all independent variables is less than ten and the tolerance value is more than 0.10, indicating that no multicollinearity exists as shown in Table 5.

Table 5. The variance inflation factor (*VIF*) related to independent variables in 2006 and 2018

Year	*VIF* for										
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
2006	2.13	1.42	1.24	3.12	1.51	1.52	4.84	4.69	4.16	1.74	1.64
2018	1.62	1.49	1.68	3.34	1.58	1.76	5.65	8.25	5.86	1.43	1.83

Explanations X_1 = *P*, X_2 = *ET*avg, X_3 = *ETo*, X_4 = *Root1*, X_5 = *Root2*, X_6 = *Kc*, X_7 = *PAWC*, X_8 = *Elv*, X_9 = *slope*, X_{10} =*POP*, X_{11} = *GRDI* as in Tab. 2.
Source: own study.

DRIVING FACTORS FOR WATER YIELD CHANGE

The outcome of the OLS fitting revealed that the *VIF* of every factor was below 10. This signifies the absence of variable redundancy and any multiple linear correlations among the elements. Concurrently, the findings by Jarque-Bera indicate that the residuals did not adhere to the normal distribution, indicating a one-sided model fitting. To enhance the accuracy of the fitting, it is advisable to incorporate the GWR model.

Although geographical detectors are utilised to identify primary variables regulating supply and demand for the ES in the Central Citarum region, they are unable to describe the influence of each element on the *SDR* in each sub-district. The in-detector factor coefficients with explanatory powers greater than 0.3 were chosen for additional research in order to duplicate patterns of direction, strength of influence, and spatiotemporal oscillations. Using the OLS and MGWR models, this research investigated the effect of geographical dispersion on the supply-demand relationship. Table 6 compares the R^2 and adjusted values as well as results of running the two models. The R^2 of the MGWR model is significantly more than 0.9 and much greater than that of the OLS models. Furthermore, the *AICc* and sum of squared residual values of the MGWR model are substantially lower compared to that of the OLS model. This shows higher accuracy and explanatory power. As a result, the MGWR model is utilised in the study to examine the mechanism behind supply and demand for ES in the Citarum sub-watershed.

Table 6. Comparative analysis of the multiscale geographically weighted regression (MGWR) and ordinary least squares/geographically weighted regression (OLS/GWR)

Year	Model	R^2	adj. R^2	*AIC*	*AICc*
2006	OLS	0.726	0.637	94.990	108.365
	GWR	0.876	0.795	100.152	106.318
	MGWR	0.946	0.899	40.368	85.738
2018	OLS	0.676	0.591	105.823	116.490
	GWR	0.739	0.650	110.593	124.793
	MGWR	0.724	0.622	103.872	116.080

Explanations: R^2 = regression coefficient, adj. R^2 = adjusted regression coefficient, *AIC* = Akaike information criterion, *AICc* = corrected Akaike information criterion.
Source: own study.

To assess the model's complexity, a number of explanatory and diagnostic variables in effective degrees of freedom is applied. By matching each environmental explanatory variable with its spatial scale, the MGWR can more accurately estimate coefficients in the local regression model. The better the model matches the data, the higher the R^2 and adjusted R^2 values. Simpler models have fewer parameters and a higher effective degree of freedom.

According to these findings, GWR models can account for location-specific and more targeted functions of pertinent elements affecting water production alterations, while the OLS solely generates universal coefficients for every explanatory factor (Nahib *et al.*, 2023). Moreover, the MGWR model represents a progression from the GWR model, accommodating dynamic spatial connections by incorporating ideal ranges of various independent factors, effectively addressing the aforementioned issue (Li and Fotheringham, 2020).

According to the results shown in Figure 5, the nearby spatial regression framework utilising the MGWR could offer a more accurate picture of how influential factors affect the *WY*.

This local R^2 mapping can be used to identify whether a particular location requires extra elucidating elements for a more comprehensive grasp of the fundamental workings that have their impact on the *WY*.

According to Figure 7, the western region, which includes Tanjungsari, Cikalongkulon, Sukaresmi, Mande, Cipanas, and Pacet, as well as the southern region, which includes Sindang Kerta and Ciwedey, have higher local R^2 values than the central and northern regions, which include Ciranjang, Haurwangi, Bojongpicung, Manis, Tegalwaru, and Sukasari Selatan. These places are mostly in the medium (yellow) to high (red) value range. The local R^2 values, on average, show a moderate (0.7) to high (0.9) association. The variance in R^2 values between locations illustrates the influence of location-specific heterogeneity, which influences water formation.

Based on the MGWR output, a visual analysis of the correlation coefficients for each driver was performed using the ArcGIS spatial distribution engine, as shown in Figures 8, 9, and Table 7.

MAIN TRIGGER IDENTIFICATION AND SPATIAL CHARACTERISTICS

The research area was evenly divided into 52 sample points representing 52 sub-district administrative areas to encourage water yield or water scarcity analysis. Based on Table 8, the MGWR has a larger R^2 of 22.0 and 48.0% higher than the 2006 and 2018 global regression models. In addition, the residual

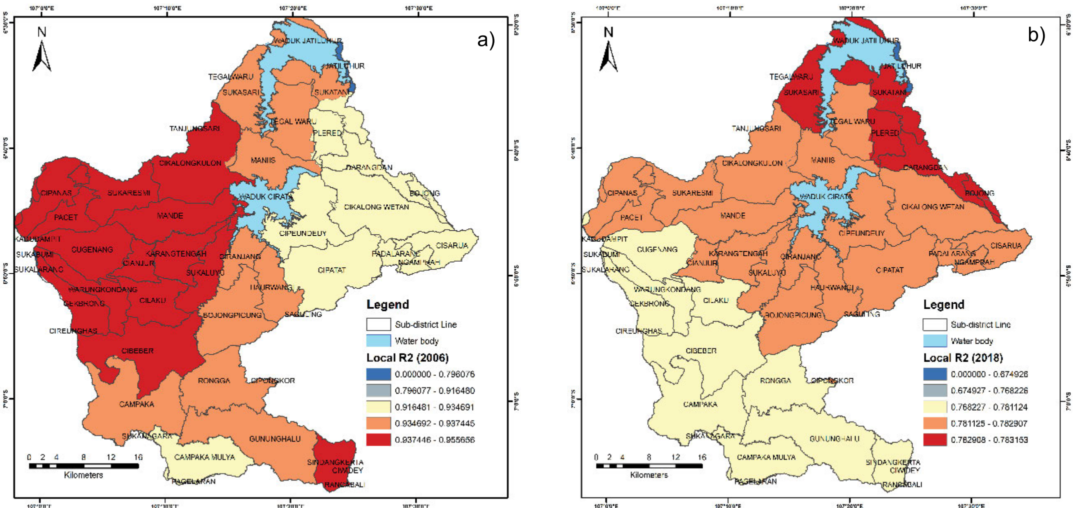

Fig. 7. Local regression coefficient (R^2) spatial distribution of the fitting results in the MGWR model; source: own study

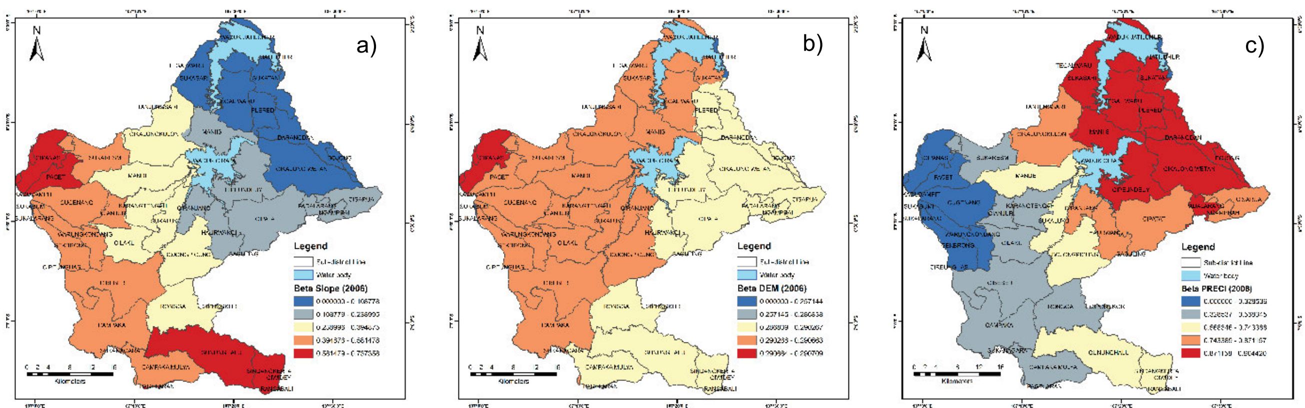

Fig. 8. Multiscale geographically weighted regression coefficients between supply-demand ratio and driving factors in 2006: a) distribution of beta slope, b) distribution of beta Elv, c) distribution of beta precipitation; source: own study

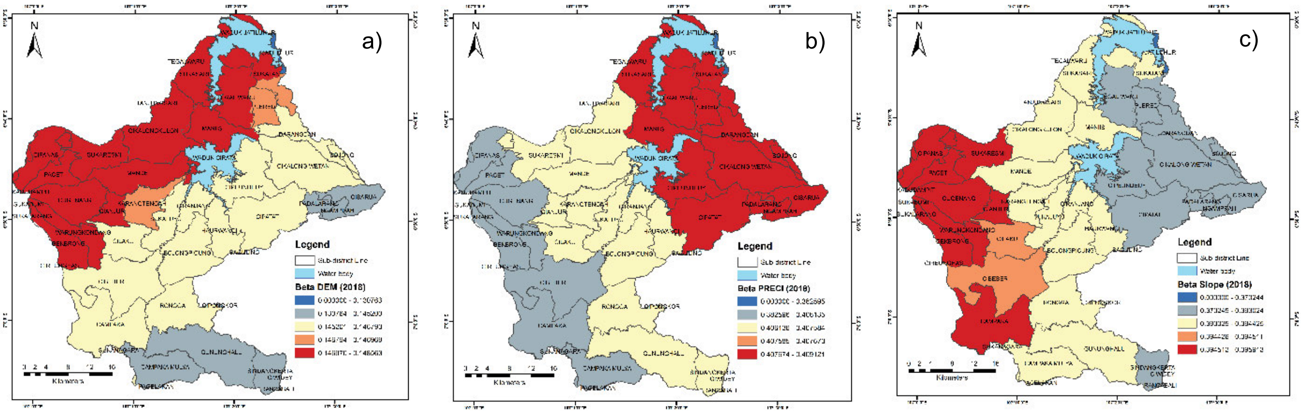

Fig. 9. Multiscale geographically weighted regression coefficients between supply-demand ratio and driving factors in 2018: a) distribution of beta slope, b) distribution of beta Elv, c) distribution of beta precipitation; source: own study

Table 7. Mean statistics of multiscale geographically weighted regression coefficients between water yield and driving factors

Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
2006	0.626	–0.171	0.299	–0.173	0.139	–0.143	0.114	0.290	0.355	–0.131	0.060
2018	0.407	–0.032	0.088	–0.329	0.336	–0.020	–0.046	0.146	0.394	0.113	–0.066

Explanations X_1 = *P*, X_2 = *ET*avg, X_3 = *ETo*, X_4 = *Root1*, X_5 = *Root2*, X_6 = *Kc*, X_7 = *PAWC*, X_8 = *Elv*, X_9 = *slope*, X_{10} =*POP*, X_{11} = *GRDI* as in Tab. 2.
Source: own study.

Table 8. Driving factor of supply-demand ratio base on ordinary least squares (OLS) and multiscale geographically weighted regression (MGWR)

Driving factor		2006				2018			
		β	*p*-value	contributor rate (%)		*β*	*p*-value	contributor rate (%)	
		accuracy of model (%)		OLS	MGWR	accuracy of model (%)		OLS	MGWR
Climate factors	X_1	0.443	0.003	18.50	9.27	0.440	0.000	8.2	1.5
	X_2	–0.265	0.005	19.04	4.20	–0.060	0.534	10.2	8.8
	X_3	0.018	0.916	0.75	16.68	0.116	0.258	9.2	5.6
Subtotal		0.265	0.924	38.29	30.15	0.496	0.792	28.392	15.9
Vegetation factors	X_4	–0.177	0.246	11.61	10.39	–0.334	0.044	8.2	9.58
	X_5	0.218	0.048	5.51	13.96	0.301	0.004	11.9	8,81
	X_6	0.090	0.417	5.78	13.80	0.034	0.735	11.1	8.38
Subtotal		2.093	0.711	22.9	38.15	0.001	0.783	31.2	26.77
Soil factors	X_7	0.140	0.470	7.10	2.16	-0.042	0.841	5.2	5.99
Subtotal		0.140	0.470	7.10	2.16	-0.42	0.841	5.2	5.99
Topography	X_8	0.396	0.099	9.61	5.35	0.163	0.507	10.6	5.0
	X_9	0.354	0.104	6.73	13.50	0.406	0.059	6.7	13.5
Subtotal		0.750	0.203	16.34	18.85	0.569	0.566	17.3	18.50
Socioeconomic factors	X_{10}	0.030	0.819	4.57	3.82	0.117	0.198	10.8	3.2
	X_{11}	0.241	0.173	8.06	1.29	–0.034	0.725	8.7	1.4
Subtotal		0.271	0,992	12.63	5.11	0.113	0.923	19.5	4.6

Explanations: *slope*, *Elv*, *ETo*, *ET*avg, *P*, *PAWC*, *Root1*, *Root2*, *Kc*, *GRDI*, *POP* as in Table. 2.
Source: own study.

squared values and *AICc* from the outcomes of the regression exhibit a noteworthy decrease compared to the OLS model, showing a decrease of 22.62 and 4.10%. Consequently, this suggests that the MGWR model is a better fit in comparison to the OLS model.

According on the findings from the MGWR inspection, distinct spatial variations are clearly visible between the elements. In particular, the interaction between social and financial factors emerged as an important determinant, especially between population density and regional gross domestic income. Based on Table 8, *P*, *slope*, *Elv*, *PAWC*, and *Roots* are the dominant factors that influence water availability. Precipitation, vegetation, slope and elevation were all positively correlated in 2006 and 2018 with water availability. Residential land in rural areas and population density in 2018 have a negative correlation. Furthermore, elevation, vegetation, precipitation and soil (*PAWC*) are considered to be the main driving factors, all of which are positively correlated with water availability services in 2006 and 2018. However, the gross regional domestic income (*GRDI*) related to the agricultural land area shows a negative correlation in 2018.

In the Central Citarum Watershed, water yield data revealed a 11.97% decrease in water discharge during a 12-year period, from $3,715{\cdot}10^6$ $m^3{\cdot}y^{-1}$ in 2006 to $3,270{\cdot}10^6$ $m^3{\cdot}y^{-1}$ in 2018, due to an increase in area built up, decreased forest land cover, and various slope classes.

Furthermore, results of the MGWR model analysis are used to find the relationship between independent variables and the *WY* as the primary controlling factor for water yield and water scarcity. Based on the contribution rate formula, contribution rates obtained are climate > vegetation > topography > soil > socio-economic factors), where in 2006: vegetation (38%), climate (30%), and topography (24%). The contributions in 2018 were climate (38%), vegetation (26%), and topography (20%). Significant positive relationships between climate, vegetation, and topography in the MGWR model are consistent with $R^2 = 0.946$ in 2006 and $R^2 = 0.724$ in 2018.

The GWR model considerable positive relationship between vegetation, climate, and topography is consistent with prior studies that indicated elevation to be an important factor determining soil moisture dispersion. Elevation was determined to be the most important variable influencing soil moisture change in the China's semi-arid Loess Plateau region by Li *et al.* (2021) and Barnard *et al.* (2021). Similarly, elevation was a crucial determinant of soil moisture patterns in China's Inner Mongolia drylands.

DISCUSSION

WATER YIELD SERVICES

The Central Citarum watershed has a strong supply-demand balance for water yield services. The Central Citarum's sub-watersheds include significant amounts of wet and dry agricultural crops, so food services are ample, but the area of land available for the ecosystem use is relatively small. Thus, there are few regulatory and cultural services. Furthermore, the distribution of natural resources in watersheds is uneven, resulting in variable degrees of urbanisation; as a result, supply and demand for ES are regionally varied. Natural environmental and social factors influence the supply and demand for the ES in the watershed (Zhang, Zhang and Zhao, 2020). Changes in water yields are clearly influenced more by climatic factors than by changes in land use. While environmental variables such as climate, soil, and watershed elevation have an impact on the supply-demand relationship for the ES, societal factors are the most effective in influencing the evolution of ecosystem interactions. As indicated by the growing urbanisation of the district, there is a supply-demand mismatch, resulting in large changes in land use. This has a dramatic influence on the ES and contributes to the deterioration of ecosystem soils.

This discovery is likely to be replicated at different sizes and offers an improved and scientifically valid foundation for the management of the ES. The availability of detailed information on ecological resources and socio-economic development vary. Administrative areas and sub-watersheds encounter a dynamic interplay between supply and demand for the ES. The understanding of the spatial and temporal transfers of the ES, as well as scientifically structured linkages, would help watershed managers to manage their resources more effectively.

Overall, these findings indicate that climate, vegetation, topography, and soil can impact water yield patterns and dynamics in different places and situations. This finding is in line with previous research, namely (1) it can show spatial differentiation of ES drivers in Central Citarum, resulting in a more reasonable resource allocation for regional ecological conservation (Lautenbach *et al.*, 2011; Peng *et al.*, 2019), (2) it should be possible to reflect the trajectory of ES changes and their characteristics at different scales in the region to show mechanisms of evolutionary influence and identify dominant factors (Renard, Rhemtulla and Bennett, 2015). The MGWR models utilised in this analysis provide more evidence of these factors' impact on the study area. It may have significant implications for water management and conservation efforts.

According to Figure 6, spatial characteristics of supply and demand of *WY* Service in 2006 indicates high supply-high demand (*HH*), high supply-low demand (*HL*), and in 2018 low supply-high demand (*LH*). Then, the strategies and actions for the Central Citarum watershed management are proposed as shown in Table 9.

A driving factor behind water yield change

To investigate the pattern of fluctuations in water demand and supply in the Central Citarum sub-watersheds, observations and multi-year analysis are required. The purpose of this study is to identify influential factors and then apply the MGWR model to investigate the relationship between geographical variables and their related heterogeneity. The MGWR model is superior to the GWR model because it incorporates changes in a geographical scale into the analysis (Fotheringham, Yang and Kang, 2017). Since the global OLS regression method only filters at a global scale, it may cause losses if it ignores many factors with smaller effects. In addition, the MGWR is a more reasonable method than the GWR (Rong *et al.*, 2022) which uses adaptive bandwidth, namely a smaller bandwidth if the data points are dense and a larger bandwidth if the data points are dense, that can better balance standards with deviations and biases. Further discussion of the influence of climate, vegetation, topography, soil, and socio-economic factors is shown below.

Table 9. Management strategies and actions of the Central Citarum watershed management

Supply-demand status	Supply-demand matching type	Zone management	Regency and sub-district	Planning recommendations
Balance	high supply-high demand	conservation	Tanjungsari, Manis, Cikalongkulon, Sukaresmi, Cipendui	stringent measures to conserve the environment, endeavours to uphold the ability to provide water services in the region, and ensure the ecological condition remains intact
Deficit	low supply-high demand	improvement area	Cikalong wetan, Bojong, Cisarua, Cipatat	create a set of rules to manage the environment that concentrate on safeguarding water sources using a people-nature approach; enhance methods to protect and fix the natural balance, and employ advanced technology to manage the Citarum River, the primary water system
Surplus	high supply-low demand	preservation	Cipanas, Pacet, Sukaresmi	stringent environmental conservation measures, endeavours to preserve the capability of providing water production services in the region

Source: own study.

Climatic factors have the first order of 38.64% in influencing water yield in Central Citarum, especially rainfall. This area has a wet climate with rainfall of approximately 2,000–2,500 mm·y^{-1}.

Climate-related factors have a major influence on the supply-demand ratio of the water production service (Xue *et al.*, 2022). Areas with higher precipitation and lower temperatures tend to have a higher supply-demand ratio, indicating a better match between water supply and demand. In contrast, areas with lower precipitation and higher temperatures have a lower supply-demand ratio, indicating a deficit in water production and difficulty in meeting the demand. Consequently, rising temperatures associated with climate change can reduce water yield through increased evapotranspiration rates (Zhang *et al.*, 2021). The examination of 22 watersheds in the UK also revealed that water yields were highly responsive to rainfall variations, with a 10% increase in rainfall leading to a *WY* increase ranging from 11% to 27% (Redhead *et al.*, 2016). However, Redhead's study indicated that the *WY* did not exhibit significant sensitivity to evapotranspiration variations.

The influence of climate on water yield has been found to be more significant than land use/cover changes. Nahib *et al.* (2021) revealed that the alteration of rainfall had the most significant effect (14.06–27.53%) on water yield, followed by the evapotranspiration (10.97–23.86%) and LULC (10.29–12.96%). Similarly, a study conducted in the China's Qinghai Lake watershed reveals that the impact of land use changes is considerably smaller when compared to the influence of climate change, particularly changes in rainfall (Lian *et al.*, 2019).

Vegetation factor has the second order of 26.78% in influencing water yield. Field conditions indicate where a decrease in vegetation results in a decrease in water yield. Between 2006 and 2018, bare land increased by 51.66%, estate crop plantations increased by 16.89%, virgin forest decreased by 48.35% and plantation forests decreased by 42.93%.

However, the Central Citarum watershed has a strong supply-demand balance for the ES. The Central Citarum's sub-watersheds include a significant amount of wet and dry agricultural crops, resulting in quite a lot of food services, but the land available for the ecosystem use is relatively small, so there are few regulatory and cultural services. Changes in water yields are clearly affected by changes in land use. However, climate factors have a stronger influence.

In addition, the distribution of natural resources in watersheds is uneven, resulting in varying degrees of urbanisation; consequently, the supply and demand for the ES vary regionally. Natural environmental and social factors affect the supply and demand for the ES in the watershed (Zhang, Zhang and Zhao, 2020). As the number of urban building sites increased in the district, there is a supply-demand mismatch resulting in large changes in land use. This has dramatic effects on the ES and contributes to the destruction of soil ecosystems.

The topography factor has the third order in influencing water yield in the Central Citarum watershed (20.53%). The condition of the hilly area shows complex variations in elevation and slope.

The relationship between topography and water yield, encompassing both supply and demand, is a multifaceted and intricate topic that has been the subject of extensive research. The topographical features of a region can profoundly affect the availability and distribution of water resources, thereby influencing water yield. For example, the presence of a forest cover can alter evapotranspiration rates, which in turn can impact atmospheric moisture vapour, precipitation patterns, and water yield (Ellison, Futter and Bishop, 2012). When considering water demand, topography also plays a pivotal role. Regions with intricate topography, such as mountainous areas, may experience increased water demand due to its use for irrigation. The implementation of a plant-focused irrigation strategy that takes into account the dynamics of water supply and demand could significantly decrease water usage for irrigation while preserving crop yields (Zhang, Zhang and Zhao, 2020). Thus, while topography is undeniably a critical determinant of water yield and demand, it should be evaluated in combination with other environmental and human-induced factors.

Soil type effect on water yield is only 5.99%, especially *PAWC* plant available water content. The influence is almost the same as the socio-economic one (5.11%). There are about nine types of soil spread throughout the watershed. This condition certainly greatly affects the distribution of water yield, although it is not significant. Because the type of persistence from time to time will remain relatively unchanged, the influence on the socio-economic conditions will be stronger in the future.

Socio-economic factor has an effect of only 5.11%. However, the future population growth will increase water demand and increase built-up areas. This will certainly affect water yield conditions. The Central Citarum area has a wet climate, so the availability of water is still sufficient due to high rainfall. Unlike in arid and semi-arid regions, water scarcity is a significant obstacle to economic and social progress.

This problem is further exacerbated by the effects of climate change and human disturbances, leading to increased uncertainties about the availability and demand for water resources in these regions (Li *et al.*, 2021). Considering the influence of climate change, even regions currently deemed to have sufficient water resources may face challenges related to water scarcity, particularly in relation to intensive agricultural activities. To address this issue, it is crucial to gather data on anticipated water demand, along with its temporal and spatial variations. The data are crucial in developing robust water management strategies capable to tackle future concerns about water scarcity effectively (Fuhrer and Jasper, 2012).

Discovery

The main findings include climate > vegetation > topography > soil > socio-economic factors. The findings can then be replicated at different measures, offering a better and scientifically valid basis for the management of ES. Detailed information on ecological resources and socio-economic development is accessible at various scales. Between administrative spheres and sub-catchments, there is a dynamic interaction between supply and demand for ES. Understanding the spatial and temporal transfers of ES and establishing scientific linkages will help to manage the watershed more effectively.

Limitations of this study

While our study provides valuable insights, it is important to acknowledge its limitations. One of the primary constraints is that our analysis is based solely on annual water yield. This approach, while useful for providing a broad overview, does not account for seasonal variations in water yield. The latter can be significant, particularly in regions with distinct wet and dry seasons (Harris *et al.*, 2014).

Our study is limited based on annual water yield and may not fully capture the impacts of short-term climatic extremes, like sudden heavy rainfall (La-Niña) or prolonged droughts (El-Niño) in tropical area. These anomalies, exacerbated by global climate change, can introduce significant variability, potentially leading to the misunderstanding of data interpretation. A focused examination of long-period events in future research is essential to understand their true influence on water yield.

CONCLUSIONS

The calculated findings suggest that water yield declined by $-444 \cdot 10^6$ $m^3 \cdot y^{-1}$ (–11.97%) in 12 years, from $3.715 \cdot 10^6$ $m^3 \cdot y^{-1}$ in 2006 to $3.270 \cdot 10^6$ $m^3 \cdot y^{-1}$ in 2018. Water yield utilisation increased by 288.11 $m^3 \cdot y^{-1}$ between 2006 and 2018. Water demand is increasing at a rate of 1.49% each year. Some areas with water scarcity ($WSI < 0$) can be found in eight sub-districts (15%), including Cipeundeuy, Sukanagara, Saguling, Cireunghas, Cikalong Kulon Haurwangi, Manis, and Mande. In contrast, 35 sub-districts have the WSI ranging from 0 to 0.5, and 10 sub-districts have their $WSI > 0.5$ or exceptionally enjoy ample water. The results of changes in water yields demonstrate that based on the formula of contribution rate (the contribution rate obtained is climate > vegetation > topography > soil > socio-economic factors), where in the year of 2006 it was as follows: vegetation (38%), climate (30%), and topography (24%), while in the year 2018: climate (38%), vegetation (26%), and topography (20%). Significant positive relationships between climate, vegetation, and topography in the MGWR model are consistent with $R^2 = 0.946$ in 2006 and $R^2 = 0.724$ in 2018. Overall, these findings indicate that climatic, vegetation, topography, and soil can impact water yield patterns and dynamics in different places and under different situations. This finding is in line with previous research. It can show spatial differentiation of drivers for ecosystem services and it can be also applied to other tropical regions with some modifications to take into account specific factors unique to those areas. This study can provide guidance for assessing the sustainable use of water resources in various global regions. In addition, it also provides guidance in zoning water resource conservation areas.

SUPPLEMENTARY MATERIAL

Supplementary material to this article can be found online at https://www.jwld.pl/files/Supplementary_material_Suryanta.pdf.

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CONFLICT OF INTERESTS

All authors declare that they have no conflicts of interests.

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