



Spatially Explicit Systematic Conservation Planning Based on Multi-Ecosystem Services in an Urban Tropical Watershed: A Case Study of the Citarum Watershed, Indonesia

Suprajaka Suprajaka^{1*}, Darmawan Listya Cahya^{1,2}, Aphrodita Puspateja¹, Surya Kurniawan³, Wa Ode Nurhaidar¹, Ghefra Rizkan Gaffara^{3,4}, Rizka Windiastuti⁵, Ati Rahadiati⁶, Bono Pranoto^{2,7}, Irmadi Nahib^{2,7}

¹ Urban and Regional Planning Study Program, Faculty of Engineering, Universitas Esa Unggul, Jakarta Barat 11510, Indonesia

² Research Center for Limnology and Water Resources, National Research and Innovation Agency of Indonesia (BRIN), Bogor 16911, Indonesia

³ Survey and Mapping Study Program, Faculty of Engineering, Universitas Esa Unggul, Jakarta Barat 11510, Indonesia

⁴ Environmental Engineering Department, Faculty of Civil and Environmental Engineering, Institut Teknologi Bandung, Bandung 40132, Indonesia

⁵ Research Center for Geoinformatics, National Research and Innovation Agency of Indonesia (BRIN), Bogor 16911, Indonesia

⁶ Research Center for Ecology, National Research and Innovation Agency of Indonesia (BRIN), Bogor 16911, Indonesia

⁷ Study Program of Natural Resources and Environmental Management Science (NREMS), Graduate School, IPB University, Bogor 16143, Indonesia

Corresponding Author Email: suprajaka-cu@esaunggul.ac.id

Copyright: ©2026 The authors. This article is published by IETA and is licensed under the CC BY 4.0 license (<http://creativecommons.org/licenses/by/4.0/>).

<https://doi.org/10.18280/ijstdp.210810>

ABSTRACT

Received: 28 April 2026

Revised: 2 August 2026

Accepted: 10 August 2026

Available online: 31 August 2026

Keywords:

conservation prioritization, ecosystem service trade-offs, landscape-scale analysis, Marxan optimization, multi-ecosystem services, spatial prioritization, Systematic Conservation Planning, tropical watershed management

Watersheds are complex socio-ecological systems that provide multiple ecosystem services (ES) essential for human well-being. However, rapid land-use change and intensive human activities have increasingly degraded watershed functions in many tropical regions. This study develops a spatially explicit Systematic Conservation Planning (SCP) framework based on multiple ES to support conservation planning in the Citarum Watershed, Indonesia, one of the country's most critical watersheds. Three key ES, namely water yield (WY), sediment retention (SR), and carbon storage (CS), were quantified for 2010 and 2020 using the InVEST model. Global and local spatial autocorrelation analyses were then applied to identify spatial synergies and trade-offs among ES. The resulting ES layers were integrated into the Marxan model to identify priority conservation areas under two planning scenarios: (A) incorporating existing protected areas, and (B) excluding them. Spatial similarity between scenarios was evaluated using Jensen–Shannon Divergence (JSD) and overlay analysis. The results show that between 2010 and 2020, the watershed experienced a reduction in WY (–15.08%) and CS (–7.16%), while SR increased (+12.46%). WY, SR, and CS also showed strong spatial associations, particularly in upstream and midstream areas, although localized trade-offs remained in areas experiencing strong land-use pressure. Scenario A produced more compact and spatially connected conservation areas, achieving 29.21% conservation coverage with lower additional land allocation requirements. In contrast, Scenario B required broader spatial expansion to achieve comparable conservation targets. The two scenarios showed substantial spatial divergence, reflected by a high JSD value of 0.78. These findings indicate that integrating existing protected areas can improve spatial efficiency and ecological connectivity, while excluding them may provide opportunities for identifying alternative conservation zones. This study contributes to the development of SCP by explicitly incorporating spatially overlapping ES beyond conventional habitat- or species-based approaches. Overall, the proposed framework provides a flexible and spatially explicit basis for watershed-scale conservation planning and supports national and global biodiversity targets, including the "30 by 30" initiative.

1. INTRODUCTION

Watersheds are widely recognized as complex socio-ecological systems that integrate hydrological processes, ecological functions, and human activities within a defined spatial unit [1]. As fundamental units for natural resource

management, their structure and function are shaped by continuous interactions between biophysical processes and anthropogenic pressures [2]. However, increasing land-use intensification, rapid urban expansion, and the discharge of domestic and industrial waste have significantly disrupted watershed systems worldwide. These pressures have resulted

in water pollution, ecosystem degradation, and growing risks to human health [3]. More importantly, they have reduced the capacity of watersheds to sustain essential ecosystem services (ES), particularly in regions experiencing rapid socio-economic development and increasing competition for land resources.

ES, defined as the benefits that ecosystems provide to human societies, are fundamental to sustaining human well-being and supporting long-term development [4]. However, prevailing development pathways often prioritize short-term economic gains over ecological sustainability, accelerating the degradation of ES globally. This has resulted in declining ecosystem functionality, increased vulnerability to hydrometeorological hazards, and heightened risks of natural disasters [5]. At the watershed scale, such degradation often leads to the emergence of critical systems in which ecological thresholds are exceeded and resilience is compromised. Without appropriate management, these conditions can trigger cascading environmental, economic, and social impacts. Consequently, integrative and spatially explicit approaches are required to balance ecological sustainability with socio-economic demands [6].

In Indonesia, watershed degradation has become a major environmental issue, reflected in declining water quality, land degradation, increased flooding, and reduced ecosystem resilience [7]. A total of 108 watersheds have been classified as critical and prioritized for restoration [8]. Among these, the Citarum Watershed is one of the most degraded systems due to rapid land-use change, industrial pressures, and high population density. These interacting pressures make it an important case for studying ecosystem service dynamics and conservation planning in human-dominated landscapes.

An understanding of the spatial distribution and interactions among ES is essential for effective watershed management. Many studies have used correlation-based approaches to identify trade-offs and synergies among ES [9]. However, these approaches are often limited to aggregated analyses and fail to capture spatial heterogeneity. Recent developments suggest that integrating correlation analysis with bivariate local spatial autocorrelation can improve the detection of ES interactions at multiple scales, providing a more detailed understanding of trade-offs and synergies [9]. Despite these developments, their application in conservation planning is still quite limited.

A key challenge lies in the implementation of conservation strategies. While ES are more recognized in policy frameworks, conservation areas remain insufficient and are often not aligned well with ES distributions. In the Citarum Watershed, only about 10% (69,054 ha) of the area is protected, far below the national requirement of at least 30% [10] and the global "30 by 30" biodiversity target [11]. This gap highlights a misalignment between policy goals and spatial planning practice. Achieving the target of about 208,000 hectares of conservation coverage requires a systematic and spatially explicit planning strategy that integrates multiple ES, particularly in crowded areas where trade-offs between conservation and development are unavoidable.

Systematic Conservation Planning (SCP) is a structured framework that aims to optimize conservation outcomes by integrating ecological value, threats, and implementation costs [12]. However, most SCP applications focus on habitat or species-based targets and operate under the assumption of spatial independence among conservation features. This

assumption does not reflect the interconnected nature of ES, which are often exhibit spatial overlap. As a result, existing approaches may fail to describe trade-offs and synergies among multiple ES [13].

This limitation highlights a significant research gap, especially in human-dominated watersheds such as the Citarum. Even with recent progress in SCP, bringing spatially overlapping ES into a multi-objective optimization framework is still underdeveloped, particularly in socio-ecologically complex watersheds [12]. Existing studies have generally focused on individual ES, biodiversity features, or hotspot-based approaches, with limited attention to the spatial interactions among multiple ES and their implications for conservation planning.

This study contributes to the development of ecosystem service-based SCP by integrating spatial ecosystem service interactions into conservation prioritization at the watershed scale. Unlike previous studies that primarily focused on biodiversity representation or single ES, this study combines multi-ecosystem service modeling, spatial autocorrelation analysis, and Marxan-based optimization within a unified planning framework. Specifically, the study integrates water yield (WY), sediment retention (SR), and carbon storage (CS) with bivariate Local Indicators of Spatial Association (LISA) to identify spatial synergies and localized trade-offs among ES. In addition, the study applies Jensen–Shannon Divergence (JSD) analysis to evaluate spatial divergence between alternative conservation scenarios. By incorporating ecosystem service interactions, spatial complementarity, and scenario-based optimization simultaneously, this study provides a more spatially explicit and ecologically integrated framework for watershed conservation planning in tropical socio-ecological systems.

The research objectives for this study include: (i) examining spatial patterns of WY, SR, and CS in 2010 and 2020; (ii) using spatial autocorrelation analysis to assess trade-offs and synergies among ES (iii) developing conservation models through SCP in two scenarios; and (iv) measuring spatial similarity through JSD and spatial overlay analysis.

2. MATERIALS AND METHODS

2.1 Study area

This study focuses on spatial modeling of ecosystem service-based conservation areas in the Citarum River Basin in West Java Province, as shown in Figure 1. The Citarum River Basin in West Java Province, covering approximately 690,000 ha, is undergoing rapid change and faces significant development pressures.

The watershed is located between 5°54'11" and 7°15'3" S latitude, and between 106°56'31" and 107°58'33" E longitude. Its pronounced elevation gradient influences climatic variability, hydrological processes, and land-use patterns across the watershed. The region's topography is varied, with hills and volcanic formations among its topography. Variations in slope can be found at the base (5 to 15%), on mountain slopes (15 to 30%), and at the peaks (30 to 90%)

The area experiences a dry climate every three months, with an average annual rainfall of 2,358 millimeters. Three major dams, Saguling, Cirata, and Jatiluhur, are located along the Citarum River, which flows through the watershed and plays an essential role in freshwater supply, agriculture, and

electricity generation in West Java. The region has varied topography, including hills and volcanic formations. Slope variations ranging from 5-15% in the lower areas, 15-30% on mountain slopes, and 30-90% at the peaks.

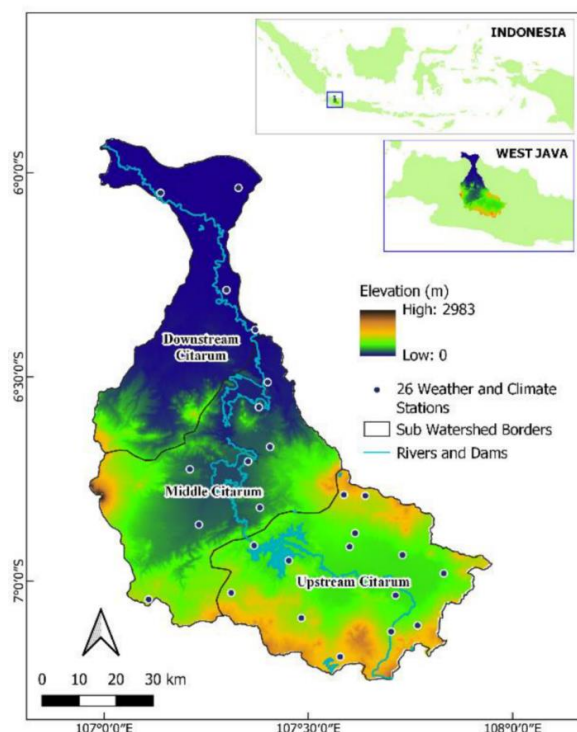


Figure 1. Research location of the Citarum Watershed, West Java Province, Indonesia

The Citarum Watershed is divided into three geomorphological regions: upstream, midstream, and downstream. The upstream region consists of mountainous volcanic terrain at elevations ranging from 750 to 2,600 m above sea level [14]. This sub-watershed is dominated by Latosol, Andosol, and Regosol soils [15], with an average annual rainfall of approximately 4,000 mm and a minimum temperature of 15.3 °C. The midstream region is also located within volcanic formations, with elevations ranging from 200 to 800 m above sea level, annual rainfall between 1,000 and 4,000 mm, and temperatures ranging from 15.3 °C to 27 °C. The downstream region is a flat lowland area at elevations of 1 to 200 m above sea level. This area is characterized by Alluvial, Entisol, and Inceptisol soils [15], with average annual rainfall of around 1,000 mm and a minimum temperature of 27 °C.

2.2 Data sources

This study used ecosystem service maps, land use and land cover (LULC) data, climatic variables, soil data, and conservation-area information to assess ecosystem service dynamics and support conservation planning in the Citarum Watershed. Multi-temporal LULC maps for 2010 and 2020 were derived from Landsat 5 TM and Landsat 8 OLI/TIRS imagery (path/row 122/65; 30 m spatial resolution) obtained from the USGS EarthExplorer platform. The images were classified using a supervised Random Forest algorithm to generate LULC maps at a spatial resolution of 30 m × 30 m.

Topographic information was obtained from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model

(DEM) provided by the United States Geological Survey (USGS). Watershed boundaries were compiled from maps provided by the College of Forestry, Environment and Resources Management, Ministry of Environment and Forestry of the Republic of Indonesia, and the Citarum Ciliwung River Basin Center, and were further processed through digital watershed delineation using the DEM.

Climate data, including rainfall and temperature records, were obtained from the Indonesian Agency for Meteorology, Climatology and Geophysics (BMKG), and the Citarum Ciliwung River Basin Center. Spatial climate surfaces were generated using spline interpolation. Evapotranspiration data were obtained from the WorldClim database and processed using the same interpolation approach. Soil data, including soil texture, organic matter content, and effective rooting depth, were obtained from the Citarum Ciliwung River Basin Center and converted from polygon to raster format through extraction and resampling procedures.

These datasets were used to model WY, SR, and CS. CS was estimated using Indonesian land-cover carbon pool values. Detailed information on the datasets, processing procedures, and data formats is provided Appendix 1. Data processing, and spatial analysis were conducted using several software tools, including GeoDa, ArcGIS 10.8 and Marxan [16-18].

2.3 Research methodology

The InVEST model was used to simulate three ES, namely WY, SR, and CS. Spatial relationship pattern analysis was then applied to identify the spatial distribution, trade-offs, and synergies among the ES. SCP was subsequently employed to delineate conservation zones in the Citarum Watershed. The conceptual framework of Ecosystem Service-based SCP is presented in Figure 2.

Multiple ecosystem service modeling. This stage focused on the quantification and spatial mapping of ecosystem services across the Citarum Watershed. The InVEST model was used to simulate three key ES, namely WY, SR, and CS, for 2010 and 2020. These services represent important hydrological, geomorphological, and climate-regulating functions related to watershed sustainability. The outputs were generated as spatially explicit raster layers, which provided a biophysical basis for subsequent spatial analysis and conservation planning. This stage established the ecological foundation of the study by identifying the magnitude and spatial distribution of ecosystem service provision.

Although the InVEST model provides a practical framework for ecosystem service assessment, the outputs remain subject to uncertainty due to input data limitations, parameter assumptions, and model simplifications [17]. Therefore, the consistency and plausibility of the modeled ecosystem service outputs were assessed using several complementary approaches.

For WY, modeled outputs were qualitatively compared with available hydrological observations from runoff monitoring stations located at the watershed outlet as a general plausibility check. However, due to the limited availability of consistent long-term field measurements, comprehensive field-based validation could not be fully conducted. For SR and CS, direct field validation was not possible because in situ observational datasets were unavailable.

To provide a quantitative assessment of model consistency, a benchmarking exercise was conducted by comparing the

modeled ecosystem service values with previously published estimates for the same watershed reported by the study [19]. This benchmarking analysis was performed at the sub-watershed level using the following statistical indicators:

1. Root Mean Square Error (RMSE), calculated as the square root of the average squared differences between the modeled values and the study values [19], expressed in the same units as each ecosystem service;
2. Coefficient of determination (R^2), used to evaluate the degree of linear correspondence between the modeled outputs and the reference dataset;
3. Percent deviation, calculated as: Percent Deviation = $(|Modeled - Reference| / Reference) \times 100\%$.

It is important to note that this benchmarking exercise represents a model-to-model comparison and consistency assessment rather than true field validation. Therefore, the resulting statistical metrics primarily reflect the degree of agreement between datasets generated using similar methodological frameworks and input sources. Future studies should incorporate field-based measurements and independent observational datasets to improve the robustness and empirical reliability of ecosystem service assessments.

The modeling was carried out using InVEST version 3.14.8, specifically the Annual Water Yield (AWY), Sediment Delivery Ratio (SDR), and CS modules. The WY module estimates the spatial distribution of WY based on the water

balance principle. In this approach, WY is defined as the portion of precipitation remaining after plant transpiration and surface evaporation within each grid cell. The model assumes that the remaining water eventually reaches the watershed outlet through surface and subsurface runoff. The WY estimation incorporates several factors, including precipitation, potential evapotranspiration, root system characteristics, and soil depth. The model outputs were further adjusted using observed runoff data from hydrological stations located at the basin outlet. The final WY values for each grid were calculated using the algorithms outlined in Eqs. (1) and (2) [17].

$$Y_{xj} = (1 - AET_{xj}/P_x) \times P_x \quad (1)$$

$$\frac{AET(x)}{P(x)} = \frac{I + w_x R_{xj}}{I + w_x R_{xj} + I/R_{xj}} \quad (2)$$

where, Y_{xj} represents the WY of grid cell x with land-use type j ($m^3 \cdot hm^{-2}$), AET_{xj} represents the annual actual evapotranspiration of grid cell x with land-use type j (mm), P_x represents the annual average precipitation of grid cell x (mm), R_{xj} represents the dryness index of grid cell x with land-use type j , and w_x represents the available water content for vegetation.

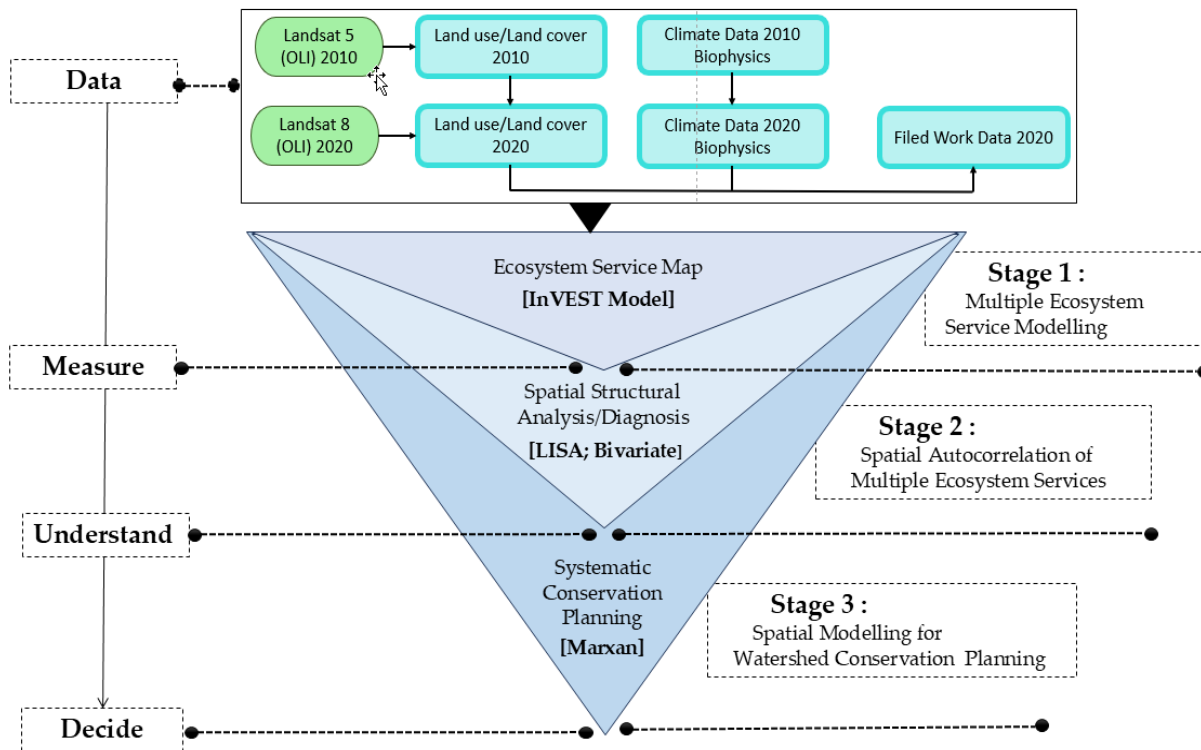


Figure 2. Conceptual framework of ecosystem service-based Systematic Conservation Planning (SCP) for the Citarum Watershed

SR was assessed using the SDR module in the InVEST model. In this approach, SR was calculated as the difference between potential soil erosion and sediment export for each pixel. Potential soil erosion was calculated using the RKLS factor, while actual soil erosion was estimated using the Universal Soil Loss Equation (USLE). The calculations are presented in Eqs. (3) to (6) [17].

$$RKLS_i = R_i \times K_i \times LS_i \quad (3)$$

$$USLE_i = R_i \times K_i \times LS_i \times C_i \times P_i \quad (4)$$

$$SR_i = RKLS_i - SED_i \quad (5)$$

$$SR_i = R_i \times K_i \times LS_i - (USLE_i \times SDR_i) \quad (6)$$

where, SR_i represents SR at pixel i , $RKLS_i$ denotes potential soil erosion, calculated from rainfall erosivity (R_i), soil erodibility (K_i), and slope length-steepness factors (LS_i); $USLE_i$ represents actual soil erosion after considering land-cover management (C_i) and conservation practice factors (P_i).

SDR_i represents the sediment delivery ratio, indicating the proportion of eroded soil transported from each pixel to the stream network, which reflects landscape connectivity and topographic conditions. Meanwhile, SED_i refers to sediment export, calculated as $USLE_i \times SDR_i$, representing the amount of soil effectively delivered to the river system.

CS was estimated using the InVEST CS module. CS within the landscape was calculated based on land-use data from different periods and their corresponding carbon pool values. Total carbon stock was computed as the sum of aboveground, belowground, soil, and dead organic matter carbon, as shown in Eq. (7) [20, 21]:

$$CS_{total} = CS_{above} + CS_{below} + CS_{soil} + CS_{dead} \quad (7)$$

where, total CS (CS_{total}) consists of aboveground carbon (CS_{above}), belowground carbon (CS_{below}), soil carbon (CS_{soil}), and carbon stored in dead organic matter (CS_{dead}). All values are expressed in $\text{ton} \cdot \text{ha}^{-1}$. The analytical procedures followed the guidelines described in the research [17].

The InVEST model outputs were validated by comparing the results with those reported in a previous study [19]. Due to the limited field observation data, model performance was evaluated using the RMSE, which measures the deviation between modeled and reference values. Lower RMSE values indicate better model performance.

Spatial autocorrelation of multiple ecosystem services. This stage examined the spatial structure and interaction patterns among ESs. Spatial autocorrelation analysis was applied to identify clustering patterns, spatial dependence, and potential synergies or trade-offs among ESs. Using spatial statistical approaches, the analysis assessed whether ESs were spatially clustered, dispersed, or randomly distributed. This step helped identify areas with overlapping or concentrated ES and provided important information for conservation prioritization.

The ecosystem service outputs, initially generated in raster format, were converted into vector format with a spatial resolution of $500 \text{ m} \times 500 \text{ m}$. The study area was then divided into planning units (PUs), resulting in a total of 28,302 PUs. Ecosystem service values for each PU were extracted using the zonal statistics tool in ArcGIS [22]. The values were subsequently standardized using Eq. (8):

$$ES_i = \frac{ES_{i,obs} - ES_{i,min}}{ES_{i,max} - ES_{i,min}} \quad (8)$$

where, $ES_{i,obs}$ represents the observed ecosystem service value, while $ES_{i,max}$ and $ES_{i,min}$ denote the maximum and minimum values, respectively. ES_i refers to the standardized value obtained from the normalization process.

Spatial autocorrelation analysis was conducted using GeoDa software. Univariate LISA was used to identify spatial patterns within individual ES, while bivariate analysis was applied to examine relationships between ES based on standardized values in each planning unit. Following the principles of Exploratory Spatial Data Analysis (ESDA), the analysis was used to detect spatial dependence, heterogeneity, and distribution patterns in the spatial data [23]. LISA and

multivariate Local Moran's I were further implemented to highlight areas with significant spatial autocorrelation. Global Moran's I and Local Moran's I were calculated for the entire study area using GeoDa 1.18 (<http://geodacenter.github.io>).

A first-order queen contiguity spatial weights matrix was used, where planning units sharing either a boundary or a vertex were considered neighbors. Binary weights were assigned and subsequently row-standardized so that the weights for each planning unit summed to one, minimizing the influence of unequal numbers of neighbors. The spatial weights matrix was generated in GeoDa 1.18. No isolated planning units (islands) were identified after planning-unit generation; therefore, no special treatment for zero-neighbor observations was required.

Interactions among ESs in the Citarum Watershed, including trade-offs and synergies, were examined using multivariate Global Moran's I to assess the presence and strength of spatial autocorrelation at the grid level [24]. The formulas for Global Moran's I and Local Moran's I are presented in Eqs. (9) and (10):

Global Moran's I:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})^2} \quad (9)$$

Local Moran's I:

$$I = \frac{n^2}{\sum_i \sum_j W_{ij}} \cdot \frac{(x_i - \bar{x}) \sum_j W_{ij} (x_j - \bar{x})}{\sum_j (x_j - \bar{x})^2} \quad (10)$$

In these equations, n represents the total number of spatial unit samples within the study area. The variables x_i and x_j denote the attribute values of spatial units i and j , respectively, while $\bar{x}$ refers to the mean attribute value across all units. The spatial weight matrix W_{ij} represents the spatial relationship between unit i and unit j , reflecting their relative spatial proximity. Moran's I and LISA were applied to evaluate both global and local autocorrelation of ecosystem service values across the planning units.

The Z-score and p-value were used to assess whether global autocorrelation was positive or negative. The sign of Moran's I further indicates whether the spatial pattern is clustered or dispersed. A positive Moran's I value indicates positive spatial autocorrelation, meaning that similar values tend to cluster spatially, with higher values indicating stronger spatial relationship and clearer global clustering patterns. In contrast, a Moran's I value close to 0 suggests a random spatial distribution without a clear pattern. Local spatial autocorrelation analysis was conducted in GeoDa using Anselin Local Moran's I cluster and outlier analysis to identify spatial relationships among ES values across the study area.

To further examine trade-offs and synergies among ES, global and local bivariate Moran's I analyses (bivariate LISA) were applied. Global bivariate Moran's I measures the overall spatial correlation between two ES across the study area, whereas local bivariate Moran's I identifies spatial correlations within individual spatial units. The equations used in this study are presented in Eqs. (11) and (12) [25].

$$I_{eu} = \frac{N \sum_i \sum_{j \neq i}^N W_{ij} z_i^e z_j^u}{(N-1) \sum_i \sum_{j \neq i}^N W_{ij}} \quad (11)$$

$$I'_{eu} = z^e \sum_{j=1}^N W_{ij} \quad (12)$$

where, I_{eu} and I'_{eu} represent the global and local bivariate Moran's I values for ES, respectively; N is the total number of spatial units; W_{ij} is the spatial weight matrix describing the spatial relationship between spatial units i and j . The matrix was generated using queen contiguity weights to first-order neighboring units [25]. The variable z_i^e and z_j^u represent the standardized values of ES, ES_i and ES_j .

The values of I_{eu} and I'_{eu} range from -1 to 1. Positive values indicate positive spatial correlation, meaning that areas with high ecosystem service values tend to be surrounded by areas with similarly high values. Conversely, negative values indicate negative spatial correlation, where areas with high values are surrounded by areas with low values. Larger absolute values indicate stronger spatial relationships between ESs. Statistical significance was assessed using a permutation test with 999 permutations [26], and spatial correlations were considered significant at $p < 0.05$.

Bivariate LISA was used to visualize local spatial relationships through Moran's scatterplots, cluster maps, and significance maps. The four quadrants of bivariate LISA scatterplot represent four types of local spatial autocorrelation: high-high (HH), high-low (HL), low-high (LH), and low-low (LL). HH clusters indicate synergy, where high values of one ecosystem service are associated with high values of another service. HL and LH clusters represent trade-offs, where high values of one service are associated with low values of another. Meanwhile, LL clusters indicate areas where both ES are low, reflecting zones of ecological degradation or low ecosystem performance. Identifying these spatial interaction patterns helps distinguish areas with strong conservation synergies (HH) from areas with potential land-use conflicts (HL and LH).

Spatial modeling for watershed conservation planning. At this stage, ES information was translated into spatially explicit conservation priorities. The mapped ES layers were incorporated into a Marxan-based SCP framework as conservation features. Cost layers representing land-use constraints were also included to reflect implementation feasibility. Conservation targets were defined for each ecosystem service, and spatial optimization was performed to identify priority conservation areas that were both cost-efficient and spatially coherent. This process enabled ecosystem service information to be operationalized into conservation zoning within the Citarum Watershed. Three ecosystem service layers, namely WY, SR, and CS, were incorporated into the Marxan model as individual conservation features. In addition, the three layers were combined into a single integrated feature representing multi-ES, referred to as Aggregated Ecosystem Services (AES).

The conservation cost surface was developed based on the level of human disturbance associated with different land-use types and the total economic value of ES, which were converted into relative conservation costs. Conservation status was derived from the forest area map [27]. Detailed classifications of conservation costs and conservation status categories are presented in Tables 1 and 2.

Parameter calibration was conducted using the QMarxan platform. The primary parameters adjusted in the analysis included the Species Penalty Factor (SPF), Boundary Length Modifier (BLM), and the number of iterations and runs.

Calibration of SPF and BLM is essential to balance conservation target achievement and the spatial compactness of the resulting conservation network. This approach helps generate conservation solutions that are not only cost-efficient but also spatially connected and ecologically effective as expressed in Eqs. (13) and (14) [18, 28]:

Table 1. Conservation cost feature

No	Type of LULC	Value
1	Primary forest	1
2	Shrubland and bare land	5
3	Agriculture/plantation	10
4	Built-up area	15

Note: LULC = land use and land cover.

Table 2. Conservation status feature

No.	Forest Area Status	Value
1	Other land-use areas	0
2	Protected forest and conservation areas	2
3	Built-up areas	3
4	Production forest	3

$$Total\ Cost = basic\ cost + fragmentation\ penalty + unmet\ target\ penalty \quad (13)$$

$$Total\ Cost = \sum_{i=1}^n Cost + (BLM \times \sum Boundary) \sum_{i=1}^n (SPF \times penalty) \quad (14)$$

where, $\sum_{i=1}^n Cost$ represents the total costs of all planning unit derived from area or economic value. The term $BLM \times \sum Boundary$ represents the boundary length modifier component, which regulates the importance of maintaining compact conservation areas. Higher BLM values impose stronger penalties on fragmented solutions (those with long boundaries), thereby encouraging the formation of contiguous conservation areas. Meanwhile, $\sum_{i=1}^n (SPF \times Penalty)$ represents the penalty applied when conservation targets are not achieved. Higher SPF values indicate greater conservation priority for specific features.

During the data input process, penalties were assigned proportionally based on boundary length and the additional costs required to achieve unmet conservation targets. Increasing SPF values generally improve the likelihood of achieving conservation targets [29]. However, previous studies have noted that no fixed theoretical basis for determining optimal SPF values [30]. In practice, SPF values greater than 1 are commonly recommended, and some studies have used values up to 100 to ensure target achievement [29, 31].

To improve the robustness of the Marxan optimization, sensitivity analysis was conducted for key parameters, including SPF and BLM. Multiple parameter combinations were tested to evaluate their effects on spatial configuration, compactness, and conservation target achievement [32]. The results showed that conservation priorities remained relatively stable across a reasonable range of parameter values. In this study, the BLM value was set to 1. The ecosystem service protection targets evaluated in this study ranged from 20% to 50%. The 50% ecosystem service protection target was not intended to represent a direct land-area conservation target, but rather a precautionary conservation threshold used to identify spatial priorities capable of maintaining ecosystem service resilience under future environmental pressures. The final

conservation configuration generated under the 50% ecosystem service target produced approximately 28–30% conservation area coverage, which aligns with the global “30 by 30” conservation target under the Kunming–Montreal Global Biodiversity Framework. The use of a relatively high ecosystem service target was intended to increase spatial flexibility and improve the robustness of conservation prioritization in anticipation of future land-use change and ecological degradation.

Marxan employs a simulated annealing optimization algorithm, which increases the likelihood of generating near-optimal spatial configurations compared with conventional heuristic approaches [33]. The model identifies planning units with the high selection frequencies that can be prioritized for conservation, as well as areas that are consistently excluded from the solution [18]. Spatial weighting is an important component of the zoning process because it can reduce management costs and minimize potential land-use conflicts by reducing spatial overlap among competing land uses [34].

Each ES raster was incorporated into the Marxan model as a conservation feature. A conservation target equivalent to 30% of the total ES supply was defined for each service, reflecting Indonesia's conservation policy targets. Two planning scenarios were evaluated: (A) incorporating existing protected areas as locked-in units, and (B) excluding existing protected areas to represent a fresh planning approach. Four Marxan runs were conducted for each scenario, and the solution with the lowest total cost was selected as the optimal conservation configuration.

Spatial modeling of conservation areas under two planning scenarios. Conservation area modeling was conducted under two planning scenarios. In this study, the impacts of LULC change and climate change were not explicitly simulated using process-based ecosystem service models. The protection targets of 20%, 30%, 40%, and 50% refer to Marxan feature-representation targets rather than percentages of watershed area. Each target specifies the minimum proportion of the total amount of each ecosystem service (WY, SR, CS, and aggregated ES) that must be represented within the selected planning units. Because Marxan identifies the minimum-cost combination of planning units that satisfies these representation targets while maximizing spatial complementarity, the resulting conservation area is substantially smaller than the feature target itself. Consequently, achieving a 50% ecosystem service representation target required approximately 29% of the watershed area rather than 50% of the land area.

To assess the effectiveness of protected-area representation, two planning approaches were applied [27]. In scenario A, existing protected areas were fully integrated into the planning process, with all formally designated protected areas locked into the Marxan simulations. This scenario was designed to identify additional priority conservation areas beyond the current protected area network while retaining existing protected areas in the final conservation configuration. Retaining these areas in the output maps also enabled comparison between newly identified conservation priorities and the formally designated protected zones. In scenario B, existing protected areas were not enforced in the planning process. As a result, all planning units had an equal opportunity to be selected as conservation areas. This approach represents a fresh planning scenario without spatial constraints imposed by the current protected area network.

After running both scenarios, the selection frequency of

each planning unit across the 1,000 iterations was analyzed. Selection frequency was used as an indicator of irreplaceability, where planning units selected more frequently were considered more important for achieving conservation objectives. The classification of conservation priority levels followed [27, 35], as defined below:

- Priority I (>75%) – planning units with very high importance that form the core components of the conservation network.

- Priority II (50–75%) – planning units with considerable importance that should be considered for conservation designation.

- Priority III (25–50%) – planning units functioning as complementary areas to strengthen the conservation network.

- Priority IV (<25%) – planning units with lower conservation importance but still offering potential contributions to conservation efforts.

In this study, priority conservation areas were defined based on Priority I units, representing planning units with the highest conservation importance.

Spatial pattern similarity analysis of conservation areas. In this study, four levels of ES protection targets, namely 20%, 30%, 40%, and 50%, were evaluated, with each scenario executed using 1,000 iterations. To assess the effectiveness of protected-area representation under different planning scenarios, two main approaches were applied [27, 32].

To quantify the spatial similarity between Scenario A and Scenario B, JSD was calculated from the normalized probability distributions of planning-unit selection frequencies generated by Marxan. For each planning unit, the selection frequency obtained from 1,000 Marxan runs was divided by the sum of selection frequencies across all planning units, producing a probability distribution for each scenario (P for Scenario A and Q for Scenario B). Thus, the JSD compares the complete spatial distributions of planning-unit selection probabilities rather than binary conservation maps or total conservation area. A JSD value of 0 indicates identical spatial priority distributions, whereas a value approaching 1 indicates increasingly different conservation priorities.

This method was selected because it is symmetric, produces bounded values, and can be applied to distributions containing zero values [36]. Each planning unit (PU) was assigned a relative probability value based on its ES score, as expressed in Eq. (15):

$$= \frac{\text{Relative Probability}}{\text{ES value of PU}} \times 100\% \quad (15)$$

$$= \frac{\text{Maximum ES value across PUs}}{\text{Maximum ES value across PUs}} \times 100\%$$

The probability assigned to planning unit i was calculated as

$$p_i = \frac{SF_i}{\sum_{j=1}^n SF_j} \quad (16)$$

where, SF_i is the Marxan selection frequency obtained from 1,000 runs. The resulting normalized vector (p_i) was used as the input probability distribution for the JSD calculation. The selection frequency of each PU across all iterations was compiled to form a spatial probability distribution representing the likelihood of that unit being selected in an optimal conservation solution. The probability distributions from the two planning scenarios were then compared using the JSD approach. The Kullback–Leibler (KL) divergence used in the calculation is expressed in Eq. (17) [37]:

$$KL[P(x) \parallel Q(x)] = \sum_{x \in X} [P(x) \log \frac{P(x)}{Q(x)}] \quad (17)$$

where, $P(x)$ represents the probability distribution derived from one scenario, while $Q(x)$ represents the probability distribution from the alternative scenario. The term X denotes the set of all planning units within the study area, and $\log \frac{P(x)}{Q(x)}$ represents the logarithmic ratio used to measure the relative dissimilarity between the two distributions.

The JSD was then calculated using Eq. (18) [37]:

$$JSD(P(x) \parallel Q(x)) = \frac{1}{2} KL \left(P(x) \parallel \frac{P(x) + Q(x)}{2} \right) + \frac{1}{2} KL \left(Q(x) \parallel \frac{P(x) + Q(x)}{2} \right) \quad (18)$$

where, $JSD(P(x) \parallel Q(x))$ represents the Jensen–Shannon divergence between distributions P and Q , while $\frac{P(x) + Q(x)}{2}$ represents the mixed distribution M , defined as the average of the two distributions. The factor $\frac{1}{2}$ is used because the JSD is calculated as the average of the two KL divergence terms. The two KL terms measure the divergence of each distribution relative to the mixed distribution.

The JSD values range from 0 to 1. A value close to 0 indicates that the two spatial distributions are highly similar, whereas a value close to 1 indicates substantial spatial differences. In this study, JSD values below 0.3 were interpreted as similar patterns, values between 0.3 and 0.6 as moderately different patterns, and values above 0.6 as significantly different patterns. This approach provides a

quantitative assessment of the stability and consistency of conservation area selection generated by the Marxan simulations [29]. In the final stage, the conservation-area maps from both scenarios were overlaid in ArcGIS. The overlay analysis was used to quantify the percentage overlapping conserved and non-conserved areas, enabling spatial comparison between the two planning scenarios.

3. RESULTS

3.1 Spatial characteristics of ecosystem services

The Random Forest (RF) classifier demonstrated strong classification performance across both study periods. For the 2010 Landsat image, the classification achieved an overall accuracy of 88.78% with a Kappa coefficient of 84.66%, while the 2020 Landsat image yielded an overall accuracy of 83.76% and a Kappa coefficient of 82.46%. Since both the overall accuracy and Kappa coefficient exceeded the commonly accepted threshold of 80%, the classification results can be considered reliable. Furthermore, all LULC classes attained Kappa values greater than 80%, further confirming the robustness of the classification and the reliability of the mapped categories [38]. Consequently, the generated LULC maps provide a dependable basis for subsequent ecosystem service assessments using the InVEST modeling framework.

The spatial distribution and changes of the three ESs in the Citarum Watershed over a decade, from 2010 to 2020, are presented in Figure 3, Tables 3 and 4. Meanwhile, the spatial changes in ESs between 2010 and 2020 are illustrated in Figure 4.

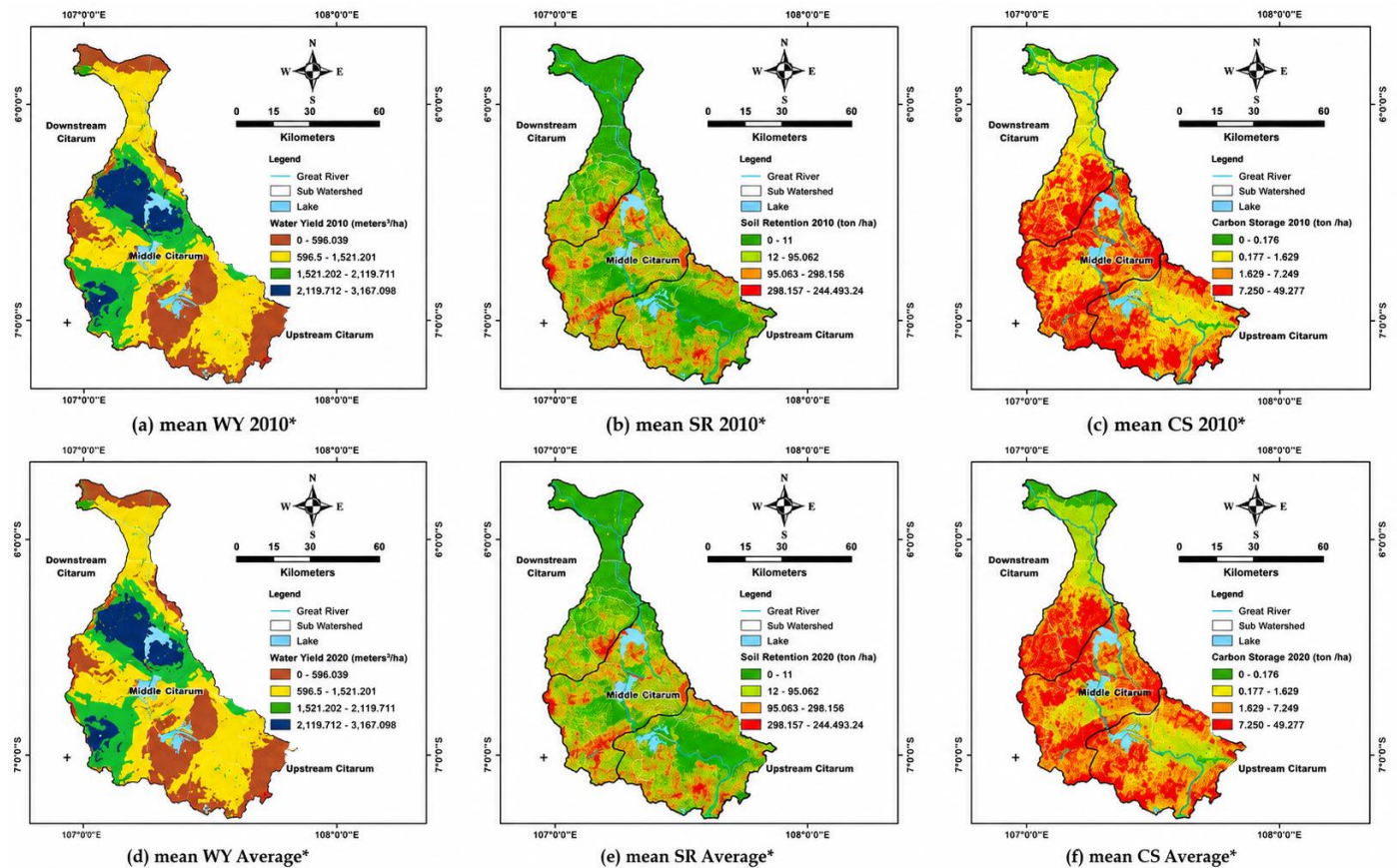


Figure 3. The distribution of ecosystem services (ES) in the Citarum Watershed for 2010 and 2020

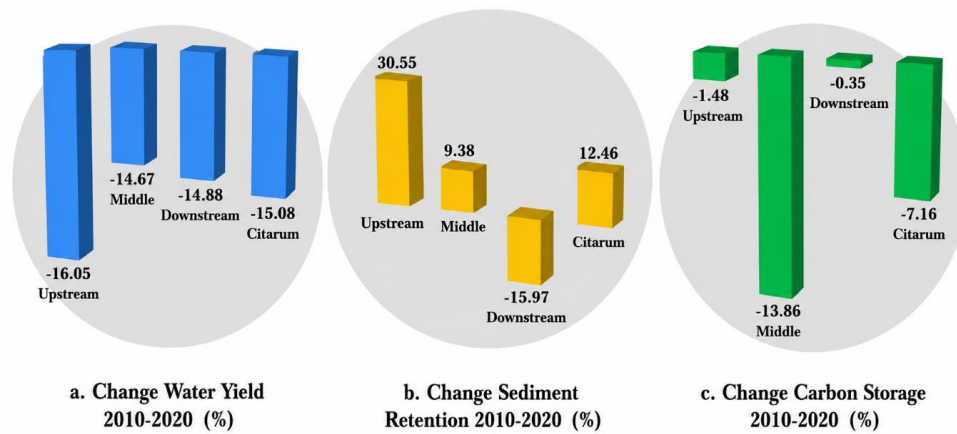


Figure 4. Changes in ESs from 2010-2020 at Citarum Watershed: (a) WY, (b) SR and (c) CS

Table 3. Mean ecosystem service values in the Citarum Watershed (2010 and 2020)

ES	Unit	2010				2020			
		Upstream	Middle	Downstream	Citarum	Upstream	Middle	Downstream	Citarum
WY	m ³ ha ⁻¹	1,035.25	1,683.47	1,516.93	1,406.09	869.6	1,436.5	1,291.1	1,194.1
SR	tons ha ⁻¹	936.87	1,358.76	592.08	999.97	1,223	1,486	498	1,125
CS	tons ha ⁻¹	14.16	18.54	8.69	14.23	13.95	15.97	8.66	13.21

Note: ES = ecosystem services, WY = water yield, SR = sediment retention, CS = carbon storage.

Table 4. Total ecosystem service amounts in the Citarum Watershed (2010 and 2020)

ES	Unit	2010				2020			
		Upstream	Middle	Downstream	Citarum	Upstream	Middle	Downstream	Citarum
WY	×10 ⁶ m ³	2,540.63	4,231.79	2,944.83	9,709.02	2,134.10	3,611.00	2,506.50	8,245.00
SR	×10 ⁶ t	227.65	340.02	108.07	675.73	297.20	371.90	90.81	759.91
CS	×10 ⁶ t	38.57	51.74	18.69	109.12	38.01	44.57	18.62	101.31

Note: ES = ecosystem services, WY = water yield, SR = sediment retention, CS = carbon storage.

The spatial distribution of WY, SR, and CS exhibits clear upstream–midstream–downstream heterogeneity, with noticeable changes between 2010 and 2020. Overall, the results indicate declining hydrological and carbon-storage services, accompanied by localized improvements in SR, reflecting land-use-driven trade-offs across the watershed. In 2010, high WY values were concentrated in the transition zone between the middle and downstream regions, as well as in parts of the southwestern basin, whereas lower WY values were mainly observed in the eastern upstream headwaters. SR values were generally moderate to high, particularly in upstream and central mountainous areas associated with dense vegetation cover and steep slopes, while low SR values were found in several degraded areas. High CS values were mainly distributed in forested upstream and northern regions, whereas lower CS values occurred in agricultural and built-up areas in the middle and downstream regions.

By 2020, high-WY areas had contracted spatially, with the largest declines occurring in downstream areas and parts of the peripheral upstream region, indicating a basin-wide reduction in WY. SR showed a slight expansion of moderate-to-high values in parts of the upstream and middle watershed, suggesting improved erosion control, although decreases were still observed in downstream areas. Meanwhile, CS showed a reduction in high-carbon forest patches and an expansion of low-CS areas, particularly in the middle watershed, indicating forest conversion and increasing land-use intensification.

Overall, WY and CS declined between 2010 and 2020, whereas SR showed localized improvement, indicating ES trade-offs over time. Environmental degradation was more

pronounced in the middle and downstream regions, while upstream areas retained relatively higher ecological function. These patterns reflect the combined effects of urban expansion, agricultural pressure, and partial conservation efforts within the Citarum Watershed.

Tables 3 and 4 show a general decline in WY and CS across the Citarum Watershed between 2010 and 2020, while SR exhibited an increasing trend. Overall, the Citarum Watershed experienced reduced hydrological and carbon-regulation services despite improvements in SR, suggesting trade-offs among ESs driven by land-use change. Total WY decreased from $9,709.02 \times 10^6$ m³ in 2010 to $8,245.0 \times 10^6$ m³ in 2020, representing a decline of 15.08%. Declines occurred across all sub-watersheds, with the largest reduction observed in the downstream region, indicating increasing hydrological stress.

In contrast, total SR increased from 675.73×10^6 tons to 759.91×10^6 tons, representing an increase of 12.46%. The increase was mainly concentrated in the upstream and middle sub-watersheds, while SR slightly decreased in the downstream region, indicating spatial imbalance in erosion control. CS showed an overall decline from 109.12×10^6 tons in 2010 to 101.31×10^6 tons in 2020, equivalent to a decrease of 7.16%. This decline was mainly associated with forest conversion and land-use change, particularly in the middle sub-watershed. Overall, the ES dynamics indicate clear trade-offs among ESs. The watershed experienced declining hydrological and carbon-regulation functions alongside localized improvements in SR, reflecting uneven spatial responses of ESs to land-use change between 2010 and 2020.

To evaluate model consistency, the InVEST outputs were

benchmarked against the reference dataset reported by the research [19]. The benchmarking yielded RMSE values of $2.25 \times 10^6 \text{ m}^3 \text{ yr}^{-1}$ for WY, $18.67 \times 10^6 \text{ tons yr}^{-1}$ for SR, and $4.64 \times 10^6 \text{ tons yr}^{-1}$ for CS, with corresponding R^2 values of 0.98, 0.97, and 0.98, respectively. Throughout the manuscript, RMSE values are reported in absolute units ($\times 10^6$), whereas Appendix tables report the same values expressed directly in units of 10^6 . A summary of the benchmarking results for the ES models is presented in Appendix 2, while a summary of the main regression statistics is provided in Appendix 3.

Overall, the relatively low RMSE values and high R^2 coefficients indicate strong statistical consistency between the modeled ecosystem service estimates and previously published datasets for the Citarum Watershed. However, the validation procedure should be interpreted cautiously because the comparison was conducted against previously modeled datasets rather than independent field observations. Consequently, the benchmarking results indicate model

consistency and reproducibility rather than definitive predictive accuracy.

Future studies should incorporate field-based hydrological, sedimentation, and biomass observations to improve model calibration and validation. Integrating empirical monitoring data would strengthen confidence in ecosystem service estimation and improve the reliability of conservation planning outcomes.

Although climate change represents an important driver of watershed dynamics, this study primarily focused on the influence of land-use and land-cover change on ecosystem service distribution and conservation prioritization. Climate-related variables such as changing precipitation patterns and temperature variability were not explicitly incorporated into the modeling framework. Therefore, the results should be interpreted within the context of land-use-driven ecosystem service dynamics rather than as projections of future climate impacts.

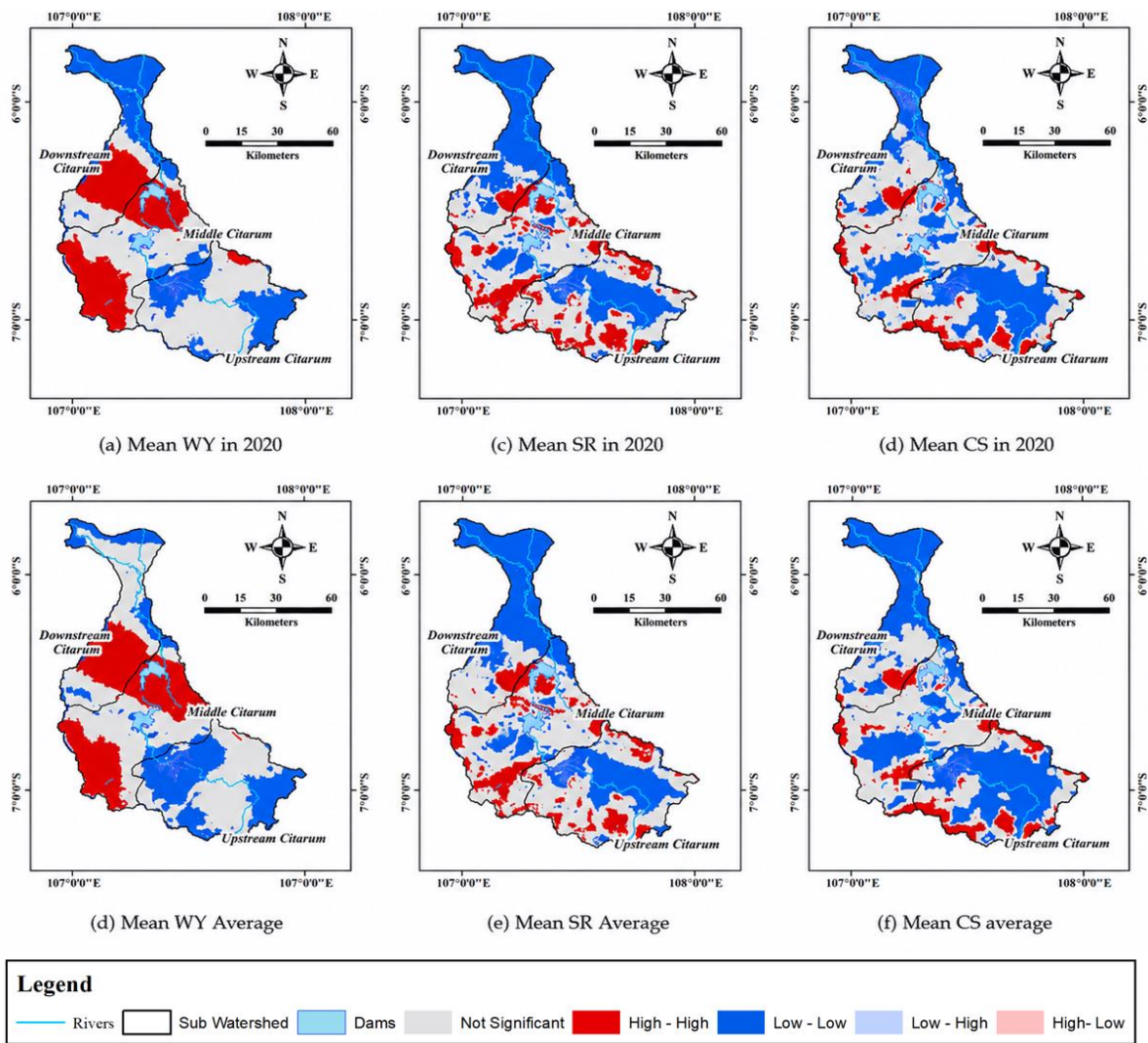


Figure 5. Local Indicators of Spatial Association (LISA) cluster of ecosystem services (ES) in Citarum Watershed

Nevertheless, the precautionary conservation framework developed in this study was designed to provide spatial flexibility and ecological resilience under potential future environmental changes. Future research should integrate climate-change scenarios into ecosystem service modeling and conservation optimization to evaluate the long-term robustness of conservation priorities under changing climatic conditions.

Global Moran’s I values for all three ESs were positive and statistically significant ($p < 0.001$), indicating strong spatial clustering patterns. The Local Moran’s I maps (Figure 5) further show that more than 60% of high-value ESs were concentrated within high–high (HH) clusters, particularly in the upstream and midstream regions, indicating dominant spatial synergies among ESs. In contrast, only a limited number of high–low (HL) clusters were identified, indicating

relatively localized trade-offs. The local Moran's I analysis was used to describe the spatial distribution of areas with high and low ES values across the Citarum Watershed. The spatial autocorrelation patterns are presented in Figure 5 and Table 5.

As shown in Figure 5, the spatial distribution patterns of the three ESs (WY, SR, and CS) in 2020 are generally consistent with the average patterns observed between 2010 and 2020. Overall, the three ES were predominantly characterized by synergistic spatial patterns represented by High–High (HH) and Low–Low (LL) clusters, whereas trade-off patterns represented by High–Low (HL) and Low–High (LH) interactions accounted for only a relatively small proportion of the observed spatial relationships. These results indicate that ecosystem service interactions within the Citarum Watershed are generally synergistic rather than strongly conflicting at the watershed scale. The spatial patterns of SR and CS were relatively similar, suggesting comparable ecological responses associated with vegetation cover and landscape structure.

Localized trade-offs were primarily identified between WY

and vegetation-related ES. Areas with higher vegetation density tended to exhibit improved CS and SR but occasionally showed reduced WY due to increased evapotranspiration. In addition, Low–Low clusters should not be interpreted exclusively as indicators of ecological degradation. In several cases, these clusters may reflect naturally low ecosystem service supply associated with specific biophysical conditions, land-cover characteristics, or landscape functions. Therefore, interpretation of Local Moran's I clusters should consider both ecological condition and natural environmental variability.

Areas with high spatial autocorrelation are mainly distributed in the middle and downstream parts of the watershed and are generally associated with vegetated land cover. In contrast, areas with low autocorrelation are commonly characterized by non-vegetated land cover, such as bare land and shrubland, and are mainly located in downstream areas and several parts of the upstream region.

Table 5. Distribution of Local Indicators of Spatial Association (LISA) clusters of ESs in the Citarum Watershed

LISA	WY		SR		CS	
	Average	2020	Average	2020	Average	2020
Not significant	47.79	46.73	48.35	46.66	43.9	41.78
High-High	24.67	24.34	13.78	14.84	10.48	10.82
Low-Low	27.36	28.81	37.51	38.07	45.33	47.15
Low-High	0.04	0.04	0.32	0.41	0.28	0.24
High-Low	0.15	0.08	0.02	0.02	0	0.01

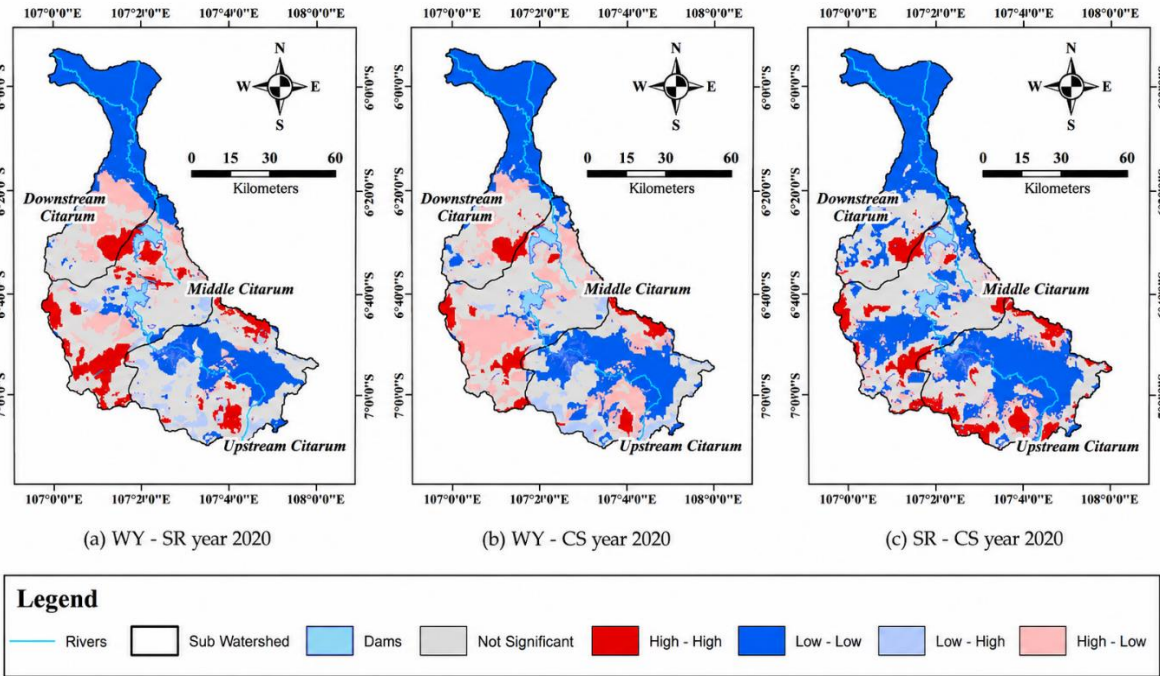


Figure 6. Bivariate Local Indicators of Spatial Association (LISA) cluster of ecosystem services (ES) in Citarum Watershed

Table 6. Distribution of the bivariate Local Indicators of Spatial Association (LISA) cluster of ecosystem services (ES) in the Citarum Watershed

Bivariate	WY-SR	WY-CS	SR-CS	Average
Not significant	46.66	41.78	41.78	46.07
High-High	10.36	6.01	9.86	12.29
Low-Low	27.82	30.39	42.05	30.38
Low-High	4.89	5.05	1.20	5.25
High-Low	10.27	16.77	5.11	6.02
Total	100.00	100.00	100.00	

The bivariate local spatial autocorrelation analysis of WY, SR, and CS in the Citarum Watershed (Figure 6 and Table 6) also shows dominant synergy relationships among ESs. High-high and low-low clusters account for approximately 36–50% of the observed ES interactions. The interaction patterns among ESs are relatively similar, with most combinations showing predominantly synergistic spatial relationships.

3.2 Multi-ES approach to conservation areas

The simulation results of the AES approach under protection targets ranging from 20% to 50% are presented in Table 7. For Priority II, the extent of conservation areas ranges from 10.58% to 28.62%, while for Priority I, it ranges from 9.36% to 25.51%. Increasing ES protection targets consistently resulted in larger designated conservation areas. In the subsequent stage, Marxan optimization was conducted using a 50% protection target, with Priority I areas used as the basis for defining conservation zones.

Table 7. Conservation areas in the Citarum Watershed based on the Aggregated Ecosystem Services (AES) multi-ES approach under different protection targets

Protection Target	Priority II		Priority I	
	Ha	%	Ha	%
20%	73,059.87	10.58	64,635.20	9.36
30%	107,656.28	15.59	96,400.36	13.96
40%	149,296.26	21.62	130,306.22	18.87
50%	197,634.55	28.62	176,158.54	25.51

Previous studies have reported comparable results. Using an ES hotspot approach, Nahib et al. [39] identified 189,523 ha (27.43%) of potential conservation areas in the Citarum Watershed. Similar results were reported by Mu et al. [13] and

Pusparini et al. [27], who showed that multi-ES approaches tend to provide more effective and spatially representative conservation outcomes than single-ES assessments. In Sulawesi, Pusparini et al. [27] demonstrated that multi-ES conservation networks produced more optimal protection scenarios.

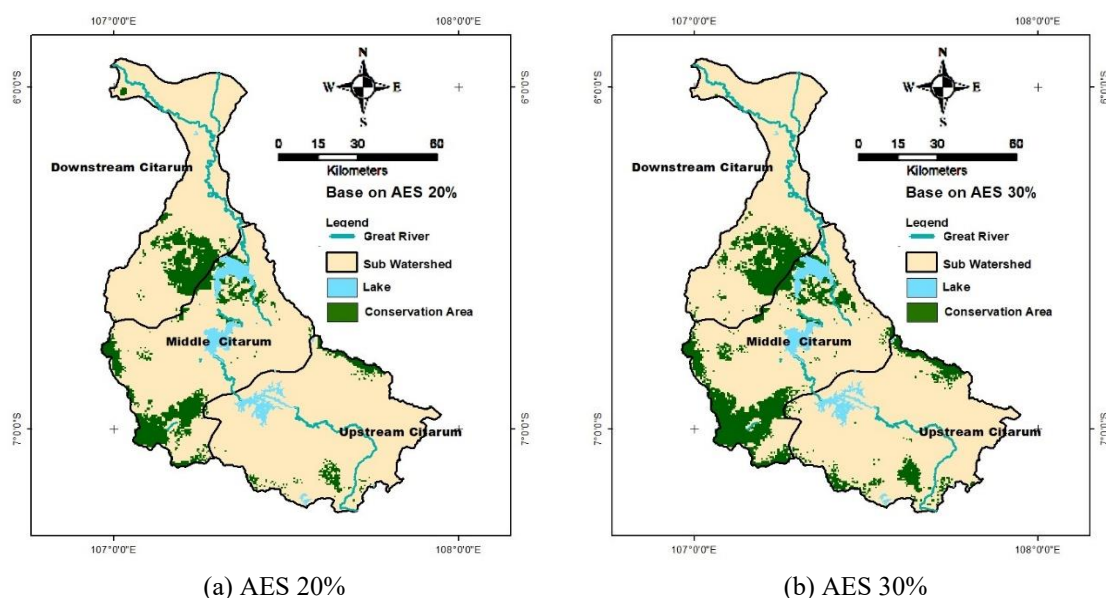
Several previous studies have also highlighted the importance of integrating ES into conservation planning. For example, Kukkala et al. [38] emphasized that AES-based approaches can improve spatial representativeness, ecological connectivity, and resource-use efficiency. Similarly, Kukkala and Moilanen [12] emphasized that incorporating ES and spatial connectivity into SCP enhances the identification of priority conservation areas that support both biodiversity conservation and ecosystem functionality. In heterogeneous landscapes, Cimon-Morin et al. [40] further demonstrated that incorporating ES into conservation prioritization frameworks can enhance ecological effectiveness and socio-environmental relevance. In addition, Mitchell et al. [41] highlighted the importance of landscape connectivity and reduced fragmentation for maintaining ES provision across multiple spatial scales.

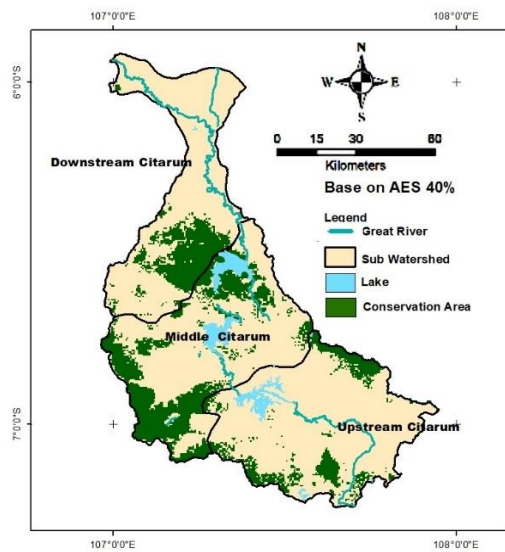
3.3 Priority conservation areas based on Scenario A

The Marxan analysis for Scenario A, which incorporated existing conservation areas and applied ES protection targets ranging from 20% to 50%, is presented in Table 8 and Figure 7. The resulting conservation areas ranged from 72,563.31 ha (10.51%) to 201,708.43 ha (29.21%) of the total Citarum Watershed area. The highest protection target produced a conservation extent approaching 30% of the watershed area, reaching 29.21%. In general, higher ES protection targets resulted in larger designated conservation areas.

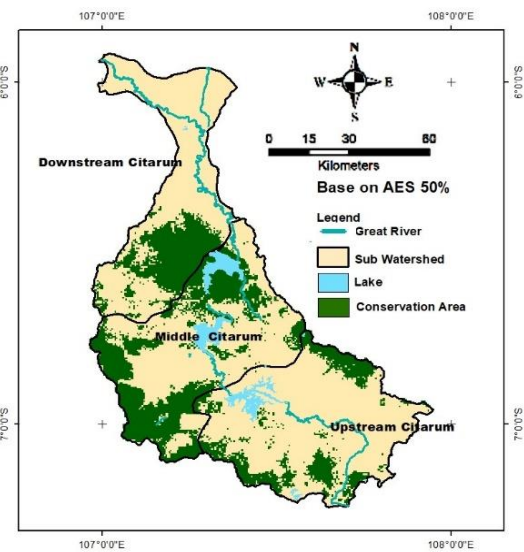
Table 8. Extent of priority conservation areas under Scenario A in the Citarum Watershed

Conservation Status	20%	30%	40%	50%
Other Land Uses	46,675.73	68,342.24	95,278.99	132,292.62
Existing Conservation Areas	16,347.48	27,131.94	40,039.14	52,555.94
Cultivation/ Production Areas	9,540.10	11,858.03	13,931.96	16,859.87
Total Conservation Area	72,563.31	107,332.21	149,250.09	201,708.43
Total Conservation Area (%)	10.51	15.54	21.61	29.21



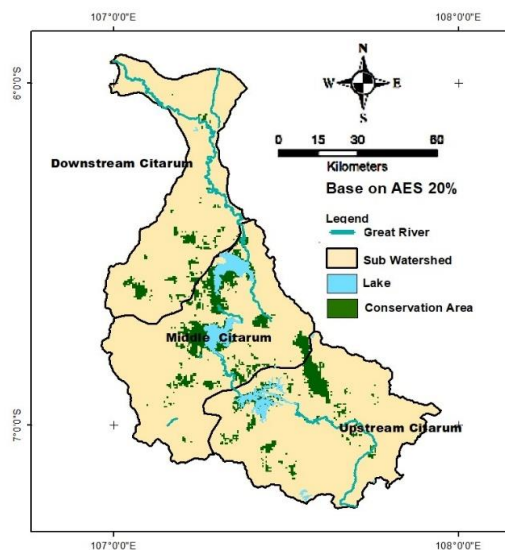


(c) AES 40%

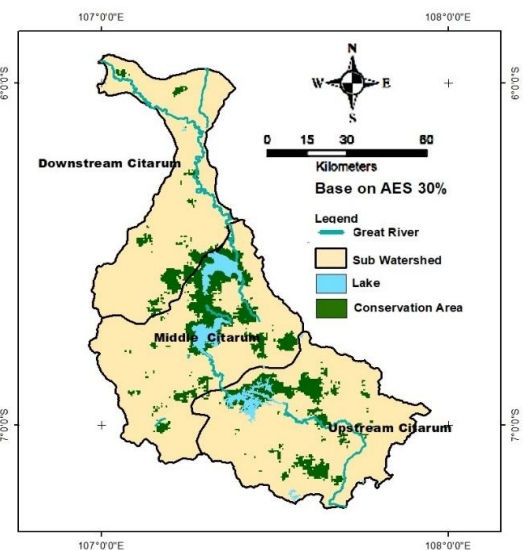


(d) AES 50%

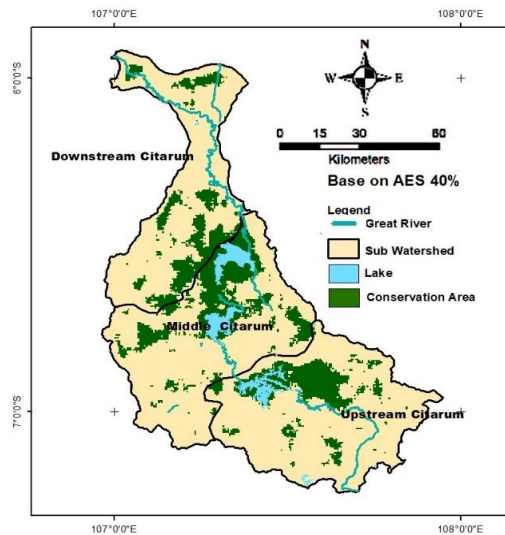
Figure 7. Conservation areas under Scenario A in the Citarum Watershed
Note: AES = Aggregated Ecosystem Services.



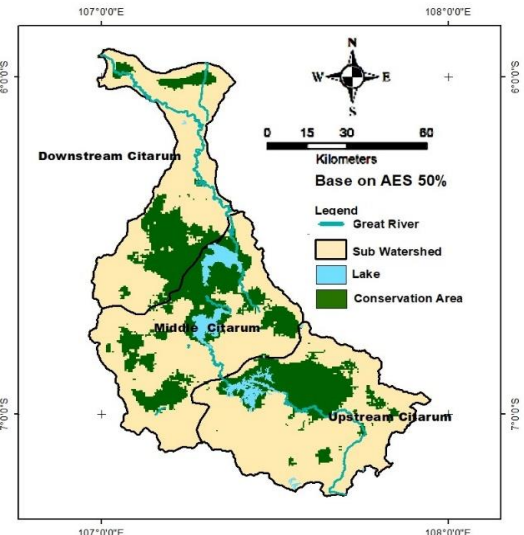
(a) AES 20%



(b) AES 30%



(c) AES 40%



(d) AES 50%

Figure 8. Priority conservation areas under Scenario B in the Citarum Watershed
Note: AES = Aggregated Ecosystem Services.

Table 9. Extent of priority conservation areas under Scenario B in the Citarum Watershed

Conservation Status	20%	30%	40%	50%
Other Land Uses	62,291.23	83,054.98	125,290.04	170,941.00
Existing Conservation Areas	4,172.27	7,417.37	13,785.56	13,883.16
Cultivation/ Production Areas	2,293.53	5,855.82	9,418.10	10,638.06
Total Conservation Area	68,757.03	96,328.16	148,493.71	195,462.23
Total Conservation Area (%)	9.96	13.95	21.50	28.31

The 50% protection target was designed to achieve a minimum conservation coverage approaching 30% of the total watershed area, in line with national conservation policy targets. The selected conservation areas represent Priority I conservation zones, defined by planning units with a selection frequency greater than 75%. Although the 50% target may appear relatively high, it was intended to provide a precautionary and flexible conservation reserve to anticipate future pressures from climate change and LULC change. Before practical implementation, the proposed conservation areas should be further evaluated by overlaying them with population density and settlement distribution maps. Conservation areas that overlap with densely populated regions may need to be reconsidered to reduce potential land-use conflicts. In this context, the 50% protection target also serves as an anticipatory strategy to accommodate future environmental change and land-use dynamics.

Figure 7 further shows that newly designated conservation areas are generally distributed around existing protected areas, indicating a spatial pattern that supports ecological connectivity and landscape continuity. Incorporating existing protected areas into the planning process resulted in a more coherent spatial configuration that is well aligned with the current conservation network, thereby strengthening the continuity and integration of the overall conservation system.

3.4 Priority conservation areas under Scenario B

Under Scenario B, which excluded existing protected areas from the planning process, the multi-ES simulations produced conservation areas ranging from 9.96% to 28.31% of the total Citarum Watershed area (Table 9 and Figure 8), with the maximum extent reaching 195,462.23 ha (28.31%). Similar to Scenario A, increasing ecosystem service protection targets consistently resulted in a substantial expansion of conservation areas.

The AES-based Scenario B exhibited a more compact spatial distribution compared with the individual ES approaches. The resulting conservation areas were mainly concentrated in the central to southern parts of the watershed. This pattern indicates that integrating multiple ES functions can produce more effective and spatially efficient conservation priorities. With broader, more strategic, and less fragmented spatial coverage, the AES approach is considered a suitable basis for conservation planning in the Citarum Watershed.

These findings also highlight opportunities to expand conservation strategies beyond the existing protected area network. Higher protection targets require substantial additions of new conservation zones, indicating limited spatial efficiency within the current protected area system. Therefore, the establishment of additional conservation areas is recommended, consistent with previous findings [27]. This approach also aligns with the global “30 by 30” initiative, which aims to protect at least 30% of the world’s terrestrial and marine areas by 2030 under the United Nations

Convention on Biological Diversity [11].

Although synergistic relationships dominated the watershed, localized trade-offs were identified primarily between WY and vegetation-related ES. Areas with denser vegetation generally exhibited higher CS and SR but occasionally showed reduced WY due to increased evapotranspiration. These findings indicate that ecosystem service interactions in the Citarum Watershed are largely synergistic, while trade-offs remain spatially limited and context-dependent. Consequently, conservation planning should focus on balancing ecosystem functions across spatial contexts rather than assuming uniform trade-off relationships throughout the watershed.

However, integrating multiple ESs produces a more compact conservation configuration characterized by larger and more connected conservation blocks extending from the central to the eastern watershed regions. This pattern represents a more optimal conservation configuration because it maintains landscape connectivity while maximizing multi-ES protection. Overall, the AES approach emerges as the most strategic conservation framework for supporting long-term watershed sustainability.

These findings are consistent with studies conducted in Sulawesi [27], which showed that conservation approaches excluding existing protected areas tend to produce smaller total conservation areas but require substantially larger additions of new conservation areas to achieve biodiversity protection targets.

3.5 Spatial similarity analysis of conservation areas

The comparison of conservation areas under Scenarios A and B is presented in Table 10 and Figure 9. As shown in Table 9, the overlay analysis indicates that areas with consistent conservation status account for 463,438 ha (67.11%) of the total watershed area. This consists of 85,031 ha (12.31%) classified as conserved areas and 378,407 ha (54.80%) classified as non-conserved areas.

The JSD between the normalized planning-unit selection-frequency distributions of Scenario A and Scenario B was 0.78, indicating substantial divergence in spatial conservation priorities. Although both scenarios achieved comparable conservation targets, the probability of selecting individual planning units differed markedly because Scenario A constrained existing protected areas whereas Scenario B optimized freely across the landscape.

Similar findings have been reported in studies conducted in Sichuan Province, China, where conservation planning approaches that exclude existing protected areas were considered more suitable for developing entirely new conservation systems without constraints from previously designated zones. Such approaches generally produce smaller total conservation areas but require broader allocation of complementary conservation zones to achieve biodiversity protection targets [42].

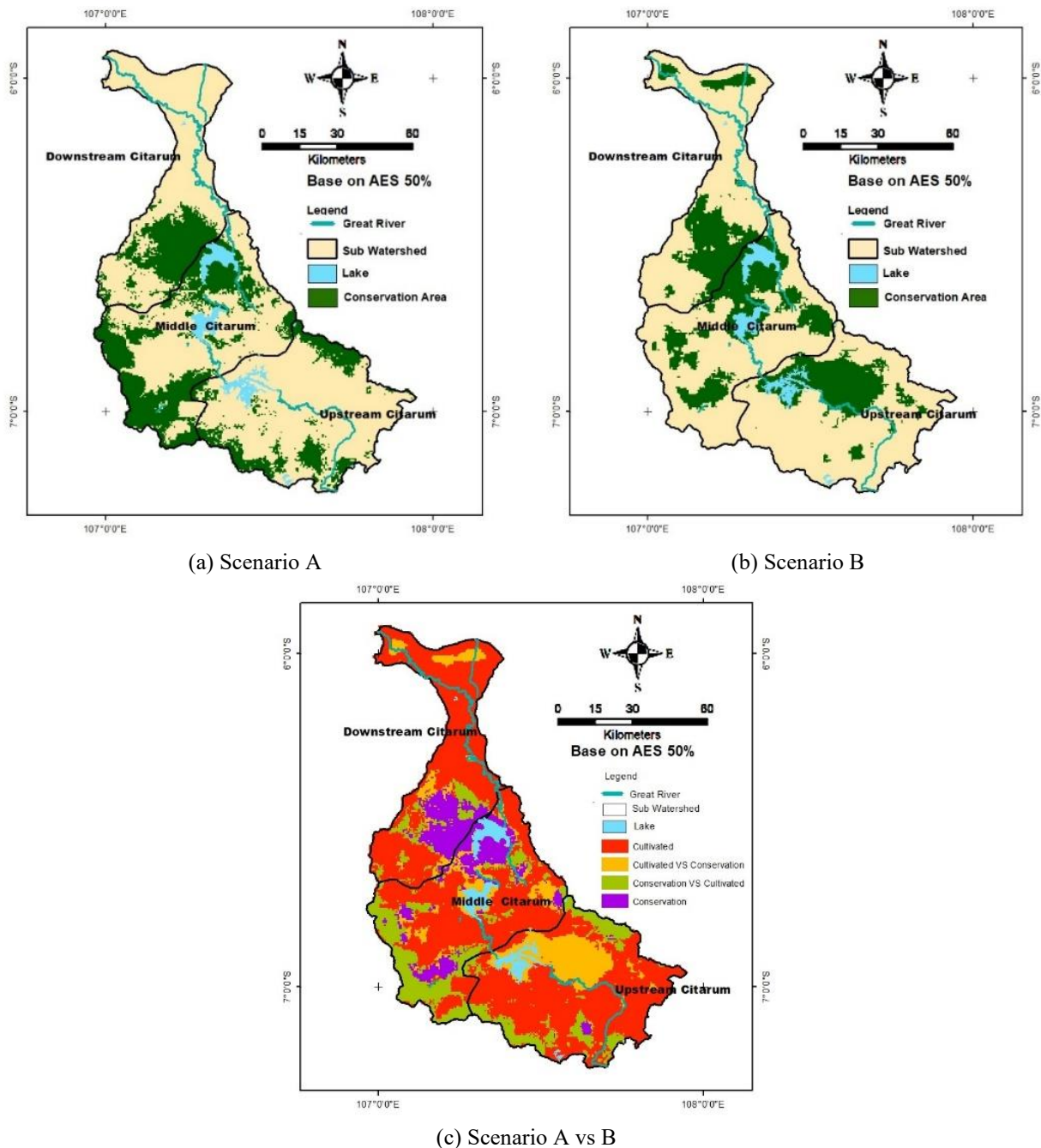


Figure 9. Conservation areas in the Citarum Watershed: (a) Scenario A, (b) Scenario B, and (c) Scenario A vs. Scenario B

Table 10. Area of conservation priority zones under Scenario A and Scenario B

Scenario A	Scenario B				Total	
	Conservation Area		Non-Conservation			
	Ha	%	Ha	%	Ha	%
Conservation Area	85,031.32	12.31	116,677.12	16.90	201,708.43	29.21
Non-Conservation Area	110,430.91	15.99	378,407.65	54.80	488,838.57	70.79
Total	195,462.23	28.31	495,084.77	71.69	690,547.00	100.00

Although the JSD provides a quantitative measure of spatial divergence, its ecological interpretation remains relatively underexplored. The high JSD value obtained in this study (0.89) indicates considerable spatial inconsistency between the two planning scenarios. Future studies should further examine how spatial divergence relates to ecological outcomes, conservation efficiency, and spatial resilience [29].

4. DISCUSSION

4.1 Spatial autocorrelation and interactions among ecosystem services

The results indicate that ecosystem service dynamics in the Citarum Watershed were strongly influenced by land-use change between 2010 and 2020. WY and CS declined by 15.08% and 7.16%, respectively, whereas SR increased by

12.46%. These contrasting trends suggest that land-use transformation altered the balance among hydrological regulation, soil conservation, and carbon sequestration functions across the watershed. Similar patterns have been reported in tropical watersheds where urban expansion and agricultural intensification reduce ecosystem service capacity and ecological resilience [19, 43].

The contrasting ecosystem service dynamics observed between 2010 and 2020 reflect differences in the ecological processes governing hydrological regulation, soil conservation, and carbon sequestration. WY declined primarily because increased vegetation cover and restoration activities enhanced evapotranspiration and infiltration, reducing surface runoff, while decreasing rainfall further limited water availability [44]. CS also decreased as a consequence of forest conversion and continued land-use intensification, which reduced aboveground biomass and soil carbon pools [4, 5]. In contrast, SR increased because improvements in vegetation cover, conservation practices, and reduced sediment connectivity enhanced the landscape's capacity to trap eroded soil before it reached the stream network. Since SR is influenced by land management, slope characteristics, and hydrological connectivity rather than biomass alone, it can improve even when CS declines. Similar contrasting responses among ES have been reported in tropical watersheds where restoration measures effectively reduce soil erosion despite ongoing losses of mature forest cover [2, 20].

In contrast, SR increased because it is controlled not only by biomass, but also by vegetation cover, land management practices, topography, and sediment connectivity. Localized improvements in vegetation cover and soil conservation measures, particularly in upstream areas, may have enhanced the landscape's capacity to retain eroded soil before it reached the river network. Consequently, SR can increase even when total CS declines, as these ES respond to different controlling factors.

Spatial autocorrelation analysis showed that WY, SR, and CS were dominated by high-high and low-low clusters, indicating strong spatial synergies among ES. High-value ecosystem service clusters were concentrated primarily in upstream and midstream areas, suggesting that these regions function as ecosystem service hotspots capable of simultaneously supporting hydrological regulation, soil conservation, and CS. Such co-occurrence reflects the influence of common biophysical drivers, including vegetation cover, topography, and landscape condition, including vegetation cover and topographic characteristics. Similar spatial synergy patterns have been reported in other watershed systems, supporting the concept of ecosystem service bundles [45].

Although synergistic relationships dominated, localized trade-offs were also identified, particularly between WY and vegetation-related ES. Areas with higher vegetation density generally exhibited improved CS and SR but may experience reduced WY due to increased evapotranspiration [46]. These results highlight the importance of spatially differentiated management strategies because conservation actions that maximize one ecosystem service may not always maximize others.

From a management perspective, the concentration of multiple ES in upstream and midstream areas suggests that conservation and restoration efforts should prioritize these regions. Protecting ecosystem service hotspots can simultaneously support several ecological functions, thereby

improving conservation efficiency and long-term watershed sustainability [47, 48].

4.2 Scenario-based spatial optimization of conservation areas

The apparent difference between the 50% ecosystem service target and the resulting conservation coverage (29.21 % of the watershed) reflects the optimization principle implemented in Marxan. ES are spatially heterogeneous and highly concentrated in ecologically valuable planning units, particularly in the upstream forested landscape. Consequently, many selected planning units simultaneously satisfy multiple ecosystem service targets (feature complementarity), allowing Marxan to achieve high ecosystem service representation while minimizing total conservation area and implementation costs. This result demonstrates that ecosystem service representation targets should not be interpreted as equivalent to land-area conservation targets.

The 20–50% feature targets were evaluated as sensitivity scenarios to assess the response of conservation solutions to increasing ecosystem service representation requirements. The final analysis adopted the 50% ecosystem service representation target because it generated a stable and spatially connected conservation network while producing approximately 29.21 % watershed coverage, closely matching the international 30 × 30 conservation objective. This wording resolves the apparent contradiction and aligns the methodology with standard Marxan practice.

These findings suggest that existing protected areas provide an important spatial foundation for conservation planning. By serving as anchors within the optimization process, they enhance connectivity and reduce the amount of additional land required to meet conservation objectives. Similar observations have been reported in SCP studies emphasizing the role of protected areas in reducing fragmentation and improving conservation efficiency [29].

However, the results also indicate that the current protected-area network alone is insufficient to achieve higher ecosystem service conservation targets. Additional conservation zones are required, particularly in areas with high ecosystem service values outside the existing network. This finding supports the need for integrated conservation strategies that combine protected-area strengthening with targeted expansion into priority non-protected areas [49, 50]. The ability of Scenario A to approach the global "30 by 30" conservation target demonstrates the practical value of ecosystem service-based SCP for supporting biodiversity and sustainability objectives at the watershed scale [11, 51].

4.3 Spatial divergence and multi-ecosystem service optimization

The high JSD = 0.78 demonstrates substantial differences between the normalized planning-unit selection-frequency distributions generated under Scenarios A and B. This result indicates that incorporating existing protected areas strongly influences the spatial allocation of conservation priorities. Importantly, the JSD compares the probability distributions of planning-unit selection frequencies across all Marxan runs rather than simple overlap of the final conservation maps. Consequently, the high divergence reflects different optimization pathways and conservation priorities instead of disagreement in overall conservation targets.

Rather than indicating planning inconsistency, the observed divergence reflects the existence of multiple spatially viable conservation solutions within the watershed. Scenario A produced a more connected conservation network because existing protected areas functioned as ecological anchors that improved landscape continuity. In contrast, Scenario B identified alternative conservation opportunities outside the existing protected-area system, thereby increasing spatial flexibility but producing a more fragmented configuration [52].

The high spatial divergence also highlights the importance of spatial complementarity in SCP. Conservation efficiency is achieved not solely by selecting areas with the highest ecosystem service values, but by identifying combinations of planning units that collectively maximize ecosystem service representation while maintaining connectivity and reducing redundancy [53]. Consequently, JSD can be interpreted as an indicator of scenario sensitivity and alternative conservation pathways rather than simply a measure of spatial inconsistency [13, 54].

4.4 Implications for this study and policy

This study demonstrates how multiple ES can be integrated into a SCP framework to support watershed-scale conservation decision-making. Unlike conventional approaches that focus primarily on biodiversity representation, the proposed framework incorporates WY, SR, and CS simultaneously, providing a broader representation of ecosystem functions and socio-ecological processes. The results further show that incorporating existing protected areas improves spatial coherence and connectivity while reducing the need for extensive land conversion [55].

Despite its practical value, the framework remains predominantly biophysical and does not explicitly incorporate social, economic, governance, or climate-change dimensions. Future studies should integrate stakeholder preferences, economic valuation, and alternative land-use and climate scenarios to improve the applicability and long-term robustness of conservation planning outcomes [47].

The findings have direct implications for land-use governance and watershed management in the Citarum region. Integrating ecosystem service priorities into regional spatial planning instruments, such as RTRW and RDTR, could strengthen ecological connectivity and reduce future land-use conflicts. The identified priority conservation areas, particularly in upstream and midstream regions, provide important guidance for protecting hydrological regulation, soil conservation, and CS functions.

The ecosystem service trade-off and synergy maps generated in this study can support conservation and restoration planning. Areas characterized by strong ecosystem service synergies represent priority conservation zones, whereas areas with consistently low ecosystem service performance may be prioritized for rehabilitation and restoration interventions [45]. In addition, mechanisms such as Payments for Ecosystem Services (PES) may help encourage conservation practices on private and community-managed lands while promoting stakeholder participation and long-term sustainability.

Although developed for the Citarum Watershed, the proposed framework has potential applicability in other tropical watersheds experiencing rapid land-use change and ecosystem degradation. Future applications should emphasize

local parameter calibration, higher-resolution datasets, and site-specific validation to improve predictive accuracy and support broader implementation.

5. CONCLUSION

This study demonstrates the effectiveness of integrating multiple ES within a spatially explicit SCP framework for watershed-scale management in the Citarum Watershed. By combining ecosystem service modeling, spatial autocorrelation analysis, and Marxan-based optimization, the study identified priority conservation areas that support WY, SR, and CS simultaneously. Between 2010 and 2020, WY and CS declined, whereas SR increased, reflecting ongoing environmental pressures and the growing need for integrated watershed management.

The ES generally exhibited synergistic relationships, particularly in upstream and midstream areas, indicating that conservation actions in these regions can generate multiple ecological benefits simultaneously. Nevertheless, localized trade-offs highlight the importance of spatial prioritization to reduce conflicts among conservation objectives. The comparison of conservation scenarios revealed that incorporating existing protected areas generated more spatially efficient and less fragmented conservation networks, while excluding them produced substantially different spatial configurations.

These findings emphasize the strategic role of existing conservation areas in supporting landscape connectivity and ecosystem function preservation. The study also extends conventional SCP approaches by integrating multiple overlapping ES into a unified optimization framework, providing a more comprehensive basis for conservation planning in tropical watersheds. The resulting conservation and trade-off maps offer practical guidance for watershed rehabilitation, ecological restoration, and regional spatial planning.

Overall, the proposed framework supports adaptive watershed management, cross-sectoral policy coordination, and sustainable land-use planning aligned with long-term ecological and socio-economic objectives.

Several limitations should be considered when interpreting the ecosystem service estimates in this study. The primary limitation is the limited availability of field-based observational data, particularly for SR and CS, resulting in reliance on benchmarking against previously published model outputs from the same watershed. Although high R^2 and low RMSE values indicated strong agreement, these metrics mainly reflect consistency between comparable modeling approaches rather than true empirical validation. Additional uncertainties related to land use classification, parameterization, spatial resolution, and model assumptions may also affect accuracy. Future studies should incorporate field observations and alternative models (e.g., Soil and Water Assessment Tool (SWAT) and Revised Universal Soil Loss Equation (RUSLE)) to improve validation robustness.

ACKNOWLEDGMENT

This research was supported by an Internal Research Grant from Universitas Esa Unggul (UEU). The study was conducted under the cooperation agreement between UEU and

the National Research and Innovation Agency (BRIN), under Agreement No. 207/I/KS/12/2023 and No. 97/MOU/R/UEU/XII/2023, dated 01 December 2023. The authors acknowledge the support of the Research Center for Limnology and Water Resources BRIN, the Institute for Research and Community Service, and the Faculty of Engineering UEU, in facilitating this collaborative research.

REFERENCES

- [1] Kaufman, D.E., Shenk, G.W., Bhatt, G., et al. (2021). Supporting cost-effective watershed management strategies for Chesapeake Bay using a modeling and optimization framework. *Environmental Modelling & Software*, 144: 105141. <https://doi.org/10.1016/j.envsoft.2021.105141>
- [2] Li, J.H., Zhou, K.C., Xie, B.G., Xiao, J.Y. (2021). Impact of landscape pattern change on water-related ecosystem services: Comprehensive analysis based on heterogeneity perspective. *Ecological Indicators*, 133: 108372. <https://doi.org/10.1016/j.ecolind.2021.108372>
- [3] Liu, B.W., Wang, M.H., Chen, T.L., et al. (2020). Establishment and implementation of green infrastructure practice for healthy watershed management: Challenges and perspectives. *Water-Energy Nexus*, 3: 186-197. <https://doi.org/10.1016/j.wen.2020.05.003>
- [4] Costanza, R., de Groot, R., Braat, L., et al. (2017). Twenty years of ecosystem services: How far have we come and how far do we still need to go? *Ecosystem Services*, 28: 1-16. <https://doi.org/10.1016/j.ecoser.2017.09.008>
- [5] Strassburg, B.B.N., Iribarrem, A., Beyer, H.L., et al. (2020). Global priority areas for ecosystem restoration. *Nature*, 586: 724-729. <https://doi.org/10.1038/s41586-020-2784-9>
- [6] Tan, Q., Huang, G., Cai, Y.P., Yang, Z.F. (2016). A non-probabilistic programming approach enabling risk-aversion analysis for supporting sustainable watershed development. *Journal of Cleaner Production*, 112: 4771-4788. <http://doi.org/10.1016/j.jclepro.2015.06.117>
- [7] Ambarwulan, W., Nahib, I., Widiatmaka, W., et al. (2021). Using geographic information systems and the analytical hierarchy process for delineating erosion-induced land degradation in the middle Citarum Sub-Watershed, Indonesia. *Frontiers in Environmental Science*, 9: 710570. <https://doi.org/10.3389/fenvs.2021.710570>
- [8] KLHK. (2018). KLHK siapkan masterplan selesaikan rehabilitasi lahan kritis pada 2030. <https://dislhk.badungkab.go.id/artikel/18234-klhk-siapkan-masterplan-selesaikan-rehabilitasi-lahan-kritis-pada-2030>, accessed on Jan. 12, 2024.
- [9] Gao, J.B., Zuo, L.Y. (2021). Revealing ecosystem services relationships and their driving factors for five basins of Beijing. *Journal of Geographical Sciences*, 31: 111-129. <https://doi.org/10.1007/s11442-021-1835-y>
- [10] Indonesia, Pemerintah Pusat. (2007). Undang-undang (UU) Nomor 26 Tahun 2007 tentang Penataan Ruang. <https://peraturan.bpk.go.id/Details/39908/uu-no-26-tahun-2007>.
- [11] Convention on Biological Diversity. (2022). Kunming-Montreal Global Biodiversity Framework. <https://www.unep.org/resources/kunming-montreal-global-biodiversity-framework>.
- [12] Kukkala, A.S., Moilanen, A. (2017). Ecosystem services and connectivity in spatial conservation prioritization. *Landscape Ecology*, 32: 5-14. <https://doi.org/10.1007/s10980-016-0446-y>
- [13] Mu, Y.L., Wang, J., Zhao, C.S., Li, X.W., Liu, Y.B., Lv, J.T. (2024). Conservation planning of multiple ecosystem services in the Yangtze River basin by quantifying trade-offs and synergies. *Sustainability*, 16(6): 2511. <https://doi.org/10.3390/su16062511>
- [14] Sholeh, M., Pranoto, P., Budiastuti, S., Sutarno, S. (2018). Analysis of Citarum River pollution indicator using chemical, physical, and bacteriological methods. *AIP Conference Proceedings*, 2049: 020068. <https://doi.org/10.1063/1.5082473>
- [15] Khairunnisa, F., Tambunan, M.P., Marko, K. (2020). Estimation of soil erosion by USLE model using GIS technique (A case study of upper Citarum Watershed). *IOP Conference Series: Earth and Environmental Science*, 561: 012038. <https://doi.org/10.1088/1755-1315/561/1/012038>
- [16] Qiao, P.W., Yang, S.C., Lei, M., Chen, T.B., Dong, N. (2019). Quantitative analysis of the factors influencing spatial distribution of soil heavy metals based on geographical detector. *Science of The Total Environment*, 664: 392-413. <https://doi.org/10.1016/j.scitotenv.2019.01.310>
- [17] Sharp, R., Douglass, J., Wolny, S., et al. (2020). InVEST 3.9.0 user's guide. The Natural Capital Project, Stanford University, University of Minnesota, The Natural Capital Project. <https://storage.googleapis.com/releases.naturalcapitalproject.org/invest/3.9.0/userguide/index.html>.
- [18] Watts, M.E., Ball, I.R., Stewart, R.S., et al. (2009). Marxan with Zones: Software for optimal conservation based land- and sea-use zoning. *Environmental Modelling & Software*, 24(12): 1513-1521. <https://doi.org/10.1016/j.envsoft.2009.06.005>
- [19] Nahib, I., Widiatmaka, W., Tarigan, S.D., Ambarwulan, W., Ramadhani, F. (2024). Exploring ecosystem service trade-offs and synergies for sustainable urban watershed management in Indonesia – A case study of the Citarum River basin, West Java, Indonesia. *Ecological Engineering & Environmental Technology*, 12: 315-332. <https://doi.org/10.12912/27197050/195008>
- [20] Sun, X., Lu, Z.M., Li, F., Crittenden, J.C. (2018). Analyzing spatio-temporal changes and trade-offs to support the supply of multiple ecosystem services in Beijing, China. *Ecological Indicators*, 94: 117-129. <https://doi.org/10.1016/j.ecolind.2018.06.049>
- [21] Artikanur, S.D., Widiatmaka, W., Ambarwulan, W., Nahib, I., Asriningrum, W., Parwati, E. (2026). Multi-scenario modeling of carbon storage services for evaluating land use/land cover protection strategies in the Cimanuk Watershed, Indonesia. *Earth*, 7(3): 74. <https://doi.org/10.3390/earth7030074>
- [22] Fabbriizzi, E., Giakoumi, S., De Leo, F., et al. (2023). The challenge of setting restoration targets for macroalgal forests under climate changes. *Journal of Environmental Management*, 326: 116834. <https://doi.org/10.1016/j.jenvman.2022.116834>
- [23] Liu, K., Wang, X.Y., Zhang, Z.B. (2022). Assessing urban atmospheric environmental efficiency and factors

- influencing it in China. *Environmental Science and Pollution Research*, 29: 594-608. <https://doi.org/10.1007/s11356-021-15692-7>
- [24] Shi, F.F., Zhou, B.R., Zhou, H.K., et al. (2022). Spatial autocorrelation analysis of land use and ecosystem service value in the Huangshui River basin at the grid scale. *Plants*, 11(17): 2294. <https://doi.org/10.3390/plants11172294>
- [25] Anselin, L., Rey, S.J. (2014). *Modern Spatial Econometrics in Practice: A Guide to GeoDa, GeoDaSpace and PySAL*. GeoDa Press LLC. <https://www.amazon.com/Modern-Spatial-Econometrics-Practice-GeoDaSpace/dp/0986342106>.
- [26] Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, 27(2): 93-115. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
- [27] Pusparini, W., Cahyana, A., Grantham, H.S., Maxwell, S., Soto-Navarro, C., Macdonald, D.W. (2023). A bolder conservation future for Indonesia by prioritising biodiversity, carbon and unique ecosystems in Sulawesi. *Scientific Reports*, 13: 842. <https://doi.org/10.1038/s41598-022-21536-2>
- [28] Watts, M.E., Stewart, R.R., Martin, T.G., Klein, C.J., Carwardine, J., Possingham, H.P. (2017). Systematic conservation planning with Marxan. In *Learning Landscape Ecology*, Springer, New York, NY, pp. 211-227. https://doi.org/10.1007/978-1-4939-6374-4_13
- [29] Ball, I.R., Possingham, H.P., Watts, M.E. (2009). Marxan and relatives: Software for spatial conservation prioritization. In *Spatial Conservation Prioritisation: Quantitative Methods and Computational Tools*, Oxford Academic, pp. 185-195. <https://doi.org/10.1093/oso/9780199547760.003.0014>
- [30] Ball, I., Possingham, H. (2000). Marine reserve design using spatially explicit annealing. https://courses.washington.edu/cfr590/software/Marxan1810/marxan_manual_1_8_2.pdf.
- [31] Moilanen, A., Leathwick, J.R., Quinn, J.M. (2011). Spatial prioritization of conservation management. *Conservation Letters*, 4: 383-393. <https://doi.org/10.1111/j.1755-263X.2011.00190.x>
- [32] Ardron, J.A., Possingham, H.P., Klein, C.J. (2010). *Marxan Good Practices Handbook*. Version 2. Pacific Marine Analysis and Research Association, Vancouver, BC, Canada. https://learn.landscapepartnership.org/pluginfile.php/597/mod_resource/content/2/Marxan%20Good%20Practices%20Handbook%20v2%202013.pdf.
- [33] Game, E.T., Grantham, H.S. (2008). Marxan user manual. For Marxan version 1.8.10. <https://courses.washington.edu/cfr590/projectreadings/marxan-manual-1.8.10.pdf>.
- [34] Serra-Sogas, N., Kockel, A., Game, E.T., Possingham, H., McGowan, J. (2020). Marxan user manual: For Marxan version 2.43 and above. The Nature Conservancy (TNC), Arlington, Virginia, United States and Pacific Marine Analysis and Research Association (PacMARA), Victoria. British Columbia, Canada.
- [35] Darmawan, M., Simamora, D.C., Nahib, I., et al. (2025). Spatial planning model for optimizing conservation priorities for local community utilization on Arefi Island in the Raja Ampat Marine Protected Area (MPA) Southwest Papua, Indonesia. *PeerJ*, 13: e19292. <https://doi.org/10.7717/peerj.19292>
- [36] Islami, F.A., Tarigan, S.D., Wahjunie, E.D., Dasanto, B.D. (2022). Accuracy assessment of land use change analysis using Google Earth in Sadar Watershed Mojokerto Regency. *IOP Conference Series: Earth and Environmental Science*, 950: 012091. <https://doi.org/10.1088/1755-1315/950/1/012091>
- [37] Nielsen, F. (2019). On the Jensen–Shannon symmetrization of distances relying on abstract means. *Entropy*, 21(5): 485. <https://doi.org/10.3390/e21050485>
- [38] Kukkala, A.S., Moilanen, A. (2013). Core concepts of spatial prioritisation in systematic conservation planning. *Biological Reviews*, 88(2): 443-464. <https://doi.org/10.1111/brv.12008>
- [39] Nahib, I., Widiatmaka, W., Tarigan, S.D., Ambarwulan, W., Ramadhani, F. (2025). Determining conservation priorities in the urban Citarum Watershed, West Java: An ecosystem services approach. *International Journal of Sustainable Development & Planning*, 20(1): 195-208. <https://doi.org/10.18280/ijstdp.200119>
- [40] Cimon-Morin, J., Darveau, M., Poulin, M. (2013). Fostering synergies between ecosystem services and biodiversity in conservation planning: A review. *Biological Conservation*, 166: 144-154. <https://doi.org/10.1016/j.biocon.2013.06.023>
- [41] Mitchell, M.G.E., Bennett, E.M., Gonzalez, A. (2015). Strong and nonlinear effects of fragmentation on ecosystem service provision at multiple scales. *Environmental Research Letters*, 10: 094014. <https://doi.org/10.1088/1748-9326/10/9/094014>
- [42] Yang, X.N., Sun, W.Y., Li, P.F., Mu, X.M., Gao, P., Zhao, G.J. (2019). Integrating agricultural land, water yield and soil conservation trade-offs into spatial land use planning. *Ecological Indicators*, 104: 219-228. <https://doi.org/10.1016/j.ecolind.2019.04.082>
- [43] Nahib, I., Wahyudin, Y., Widiatmaka, W., et al. (2026). Spatio-temporal dynamics of land use and land cover change and ecosystem service value assessment in Citarum Watershed, Indonesia: A multi-scenario and multi-scale approach. *Resources*, 15(2): 24. <https://doi.org/10.3390/resources15020024>
- [44] Hamel, P., Bryant, B.P. (2017). Uncertainty assessment in ecosystem services analyses: Seven challenges and practical responses. *Ecosystem Services*, 24: 1-15. <https://doi.org/10.1016/j.ecoser.2016.12.008>
- [45] Zhou, J., Zhang, B., Zhang, Y.W., Su, Y.H., Chen, J., Zhang, X.F. (2023). Research on the trade-offs and synergies of ecosystem services and their impact factors in the Taohe River basin. *Sustainability*, 15(12): 9689. <https://doi.org/10.3390/su15129689>
- [46] Pan, T.S., Zuo, L.J., Zhang, Z.X., et al. (2022). Effects of afforestation projects on tradeoffs between ecosystem services: A case study of the Guanting Reservoir basin, China. *Forests*, 13(2): 232. <https://doi.org/10.3390/f13020232>
- [47] Brown, G., Fagerholm, N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem services*, 13: 119-133. <https://doi.org/10.1016/j.ecoser.2014.10.007>
- [48] Maimaiti, B., Chen, S.S., Kasimu, A., Mamat, A., Aierken, N., Chen, Q.L. (2022). Coupling and coordination relationships between urban expansion and ecosystem service value in Kashgar City. *Remote Sensing*, 14(11): 2557.

- <https://doi.org/10.3390/rs14112557>
- [49] Shiono, T., Kubota, Y., Kusumoto, B. (2021). Area-based conservation planning in Japan: Protected area network effectiveness to the post-2020 global biodiversity framework. *bioRxiv*. <https://doi.org/10.1101/2021.07.07.451416>
- [50] Sun, Q.Y., Yu, J.Q., Zeng, Y.R., Gai, Y.F., Wang, J., Zhang, Y.J. (2024). Mapping biodiversity conservation priorities for protected areas for spatial optimization: A case study in the Songnen Plain, China. *Ecology and Evolution*, 14(11): e70516. <https://doi.org/10.1002/ece3.70516>
- [51] Strategi dan Rencana Aksi Keanekaragaman Hayati Indonesia (Indonesian Biodiversity Strategy and Action Plan/IBSAP 2025-2045) IDN. <https://lcdi-indonesia.id/books/strategi-dan-rencana-aksi-keanekaragaman-hayati-indonesia-indonesian-biodiversity-strategy-and-action-plan-ibsap-2025-2045-idn/>.
- [52] Han, P.D., Yang, G., Wang, Z.J., et al. (2024). Driving factors and trade-offs/synergies analysis of the spatiotemporal changes of multiple ecosystem services in the Han River basin, China. *Remote Sensing*, 16(12): 2115. <https://doi.org/10.3390/rs16122115>
- [53] Schröter, M., Remme, R.P. (2016). Spatial prioritisation for conserving ecosystem services: Comparing hotspots with heuristic optimisation. *Landscape Ecology*, 31: 431-450. <https://doi.org/10.1007/s10980-015-0258-5>
- [54] Cai, W.B. (2022). Identifying ecosystem services bundles for ecosystem services trade-off/synergy governance in an urbanizing region. *Land*, 11(9): 1593. <https://doi.org/10.3390/land11091593>
- [55] Schuster, R., Buxton, R., Hanson, J.O., et al. (2023). Protected area planning to conserve biodiversity in an uncertain future. *Conservation Biology*, 37(3): e14048. <https://doi.org/10.1111/cobi.14048>

APPENDIX

Appendix 1A. Input datasets for the InVEST Annual Water Yield (AWY) module

Input	Source	Resolution	Format	Processing
Land use/Land cover (2010, 2020)	USGS Landsat 5 TM / Landsat 8 OLI-TIRS	30 m	Raster	Random Forest classification in Google Earth Engine
Annual precipitation	BMKG; Citarum–Ciliwung River Basin Center	Interpolated to 30 m	Raster	Spline interpolation
Reference evapotranspiration	WorldClim	~1 km (resampled to 30 m)	Raster	Resampling
Digital Elevation Model (DEM)	USGS SRTM	30 m	Raster	Hydrological preprocessing
Soil properties*	Citarum–Ciliwung River Basin Center	Polygon → 30 m	Raster	Rasterization and resampling

*Soil properties include plant available water content (PAWC), rooting depth, and soil depth required by the InVEST Annual Water Yield model.

Note: SRTM = Shuttle Radar Topography Mission, Indonesian Agency for Meteorology, BMKG = Climatology and Geophysics.

Appendix 1B. Input datasets for the InVEST Sediment Delivery Ratio (SDR) module

Input	Source	Resolution	Format	Processing
Land use/Land cover (2010, 2020)	USGS Landsat 5 TM / Landsat 8 OLI-TIRS	30 m	Raster	Random Forest classification
DEM	USGS SRTM	30 m	Raster	Flow direction and slope derivation
Rainfall erosivity (R)	BMKG	Interpolated to 30 m	Raster	Spatial interpolation
Soil properties**	Citarum–Ciliwung River Basin Center	Polygon → 30 m	Raster	Rasterization and resampling
Biophysical table	InVEST User Guide	—	CSV	Assignment of C and P factors

** Soil properties were used to derive soil erodibility (K factor). Topographic factors (LS) were generated from the DEM following the InVEST SDR workflow.

Note: SRTM = Shuttle Radar Topography Mission, BMKG = Climatology and Geophysics.

Appendix 1C. Input datasets for the InVEST Carbon Storage (Carbon) module

Input	Source	Resolution	Format	Processing
Land use/Land cover (2010, 2020)	USGS Landsat 5 TM / Landsat 8 OLI-TIRS	30 m	Raster	Random Forest classification
Carbon pool table	Indonesian land-cover carbon pool database (after Bassi et al.)	Land-cover based	CSV	Assignment of aboveground, belowground, soil, and dead organic matter carbon values

Appendix 2. Summary of benchmarking results for InVEST ecosystem service models

Ecosystem Service	RMSE	Units	R ²	p-Value	Interpretation
Water Yield (WY)	2.25	×10 ⁶ m ³ yr ⁻¹	0.98	<0.001	Excellent agreement
Sediment Retention (SR)	18.67	×10 ⁶ tons yr ⁻¹	0.97	<0.001	Strong agreement
Carbon Storage (CS)	4.63	×10 ⁶ tons	0.98	<0.001	Excellent agreement

Note: Carbon storage was estimated by assigning carbon density values to each land-use class. Total carbon stock represents the sum of aboveground biomass, belowground biomass, soil organic carbon, and dead organic matter following the InVEST Carbon Storage model. RMSE = Root Mean Square Error.

Appendix 3. Summarize key regression stats in a concise table

Ecosystem Service	Regression Equation	R²	RMSE	p-Value
Water Yield (WY)	$y = -0.2236 + 1.059x$	$2.25 \times 10^6 \text{ m}^3 \text{ yr}^{-1}$	0.98	<0.001
Sediment Retention (SR)	$y = -0.28674 + 2.4308x$	$18.67 \times 10^6 \text{ tons yr}^{-1}$	0.97	<0.001
Carbon Storage (CS)	$y = 1.8227 + 0.936x$	$4.64 \times 10^6 \text{ tons yr}^{-1}$	0.98	<0.001

Note: RMSE = Root Mean Square Error.