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Enhancing Watershed Management through Seasonal Water Yield Modelling using InVEST (Case Study: Rawa Pening Catchment Area)

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Abstract. Located in the upstream of the Tuntang Watershed in Indonesia, Rawa Pening catchment is a significant watershed, recognized as one of the nation's priority watersheds. Evaluating the catchment's sustainability relies on its water yield, a crucial determinant in guaranteeing a steady water supply, thereby enhancing water security. This study aims to achieve the following objectives: 1.) To utilize the InVEST model for the estimation of temporal water yield potential within the Rawa Pening Catchment Area from 2018 to 2022, 2.)To assess the accuracy of the InVEST model in temporally estimating water yields within the Rawa Catchment Area, and 3.) To investigate the spatial distribution and characteristics of water yield in the Rawa Pening Catchment Area between 2018 and 2022.The results of the study demonstrate significant trends: The peak rate of flow was recorded in November 2022, reaching 645.87 mm/month, and the minimum rate was seen in July 2018, measuring only 0.82 mm/month. The model calibration shows a substantial correlation value of 0.95, a PMARE Index of 12.84%, and a determination coefficient of 0.9011. Despite minor variations, the InVEST model's accuracy remains substantial due to the high interconnectivity of variables. Various elements, including rainfall patterns, land use practices, soil hydrological characteristics, and threshold flow accumulation, influence the spatial dynamics of quick flow.
Keywords: rawa pening catchment area, water yield, InVEST model

1. Introduction

The Rawa Pening catchment area is located upstream of the Tuntang Watershed. The Tuntang Watershed is distinguished among the 108 priority watersheds since it is identified as an essential domain of concern in Indonesia. This recognition is based on the urgent problems highlighted in the Decree of the Minister of Forestry of the Republic of Indonesia No. SK 328/Menhut-II/2009 [20]. Furthermore, according to the Regional Government of Central Java, the Tuntang Watershed has been identified as one of the revitalized watersheds in Central Java. Revitalized watersheds refer to those that have undergone restoration to achieve functional levels in terms of ecological balance, water quality, quantity, continuity, socio-economic aspects, water infrastructure investments, and regional spatial utilization, as defined by the Government of the Republic of Indonesia [10].

The study conducted by Ramirez [25] reveals a significant change in land use patterns within the Rawa Pening catchment area, which indicates increasing from 8.48% to 18.64% of the total area allocated for residential purposes between 1996 and 2010. The research of Kamble et al. [14] supports this trend by highlighting an increase in settlement land. These land-use changes substantially affect hydrological responses, notably reducing the area's capacity to absorb water and causing increased discharge rates [21, 24]. These changes in hydrological behavior reverberate as obstacles throughout the catchment. Natural disasters that disrupt the hydrological function of a catchment or watershed indicate a reduction in its functional integrity [35]. The consequences manifest as seasonal inundation and droughts, each presenting unique difficulties. According to the Permatasari et al. [23] flooding is an urgent issue in the Lake Rawa Pening catchment area and its surrounding riparian zone. This dilemma is directly related to the water discharge dynamics of the catchment.

The investigation of water yield is of the utmost importance, serving as a crucial indicator of the overall health of a watershed. The key to establishing water security is ensuring a reliable supply and uninterrupted water movement within a watershed [5]. Directorate General of Land Rehabilitation and Social Forestry procuring water yield data is essential for coordinating resource conservation initiatives, supporting water system valuation, and identifying priority zones [7]. Therefore, investigating the potential water yield, notably within the Rawa Pening catchment area, is a crucial research endeavor. Given that the distinct characteristics of a watershed substantially affect the volume of water generated, a comprehensive watershed-based approach is considered necessary for this study.

A hydrological model is utilized to determine water yield's spatial distribution and temporal trends. This model type can convert water yield parameter values into actual yield values. The InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model stands out among the models designed for this purpose. Due to its global applicability and commendable results, the InVEST model has been widely adopted. It has been utilized in numerous studies, including global evaluations of ecosystem services. It has, for example, facilitated efforts to increase water yields, reduced sedimentation, and laid the groundwork for prioritized location-based project activities (hydroelectric power plant) in India [36]. Similarly, a global study in China [9] demonstrated the model's utility in estimating water yield changes due to land use dynamics. Consequently, the InVEST model helps dissect both the spatial and temporal aspects of water yield within the Rawa Pening catchment area while maintaining its accuracy under scrutiny.

2. Research Methods

2.1. Study Area

Rawa Pening Catchment Area is located within Central Java Province and encompasses both the Semarang Regency and Salatiga City. Astronomically positioned at coordinates 70°10'49" S - 70°26'41" S and 110°17'52" E - 110°30'45" E, the Rawa Pening Catchment Area comprises nine distinct sub-catchments: Galeh, Torong, Panjang, Legi, Parat, Sraten, Rengas, Kedungringin, and Ringin—each of these sub-catchments feeds into Lake Rawa Pening.

The landscape of the Rawa Pening Catchment Area is predominantly characterized by mixed cropland, spanning an expanse of 99.63 km², which predominantly occupies the upstream regions in the north, west, and south. Concurrently, the area also features extensive irrigated rice fields, covering approximately 66 km² and numerous settlements encompassing a total area of 49.69 km². Annual precipitation exhibits fluctuations contingent upon topographical variations, ranging from 4,344.6 mm over the past decade in the northern sector of the catchment to 4,546.1 mm in the southern expanse. In the western part of the Lake Rawa Pening catchment area, a notable prevalence of clay content is observed, an attribute linked to the tertiary mountain association predominant in the upstream western region, thus signifying advanced land development. In contrast, the northern and southern upstream parts exhibit a relatively elevated presence of silt and sand due to the significant influence of quaternary volcanic materials.

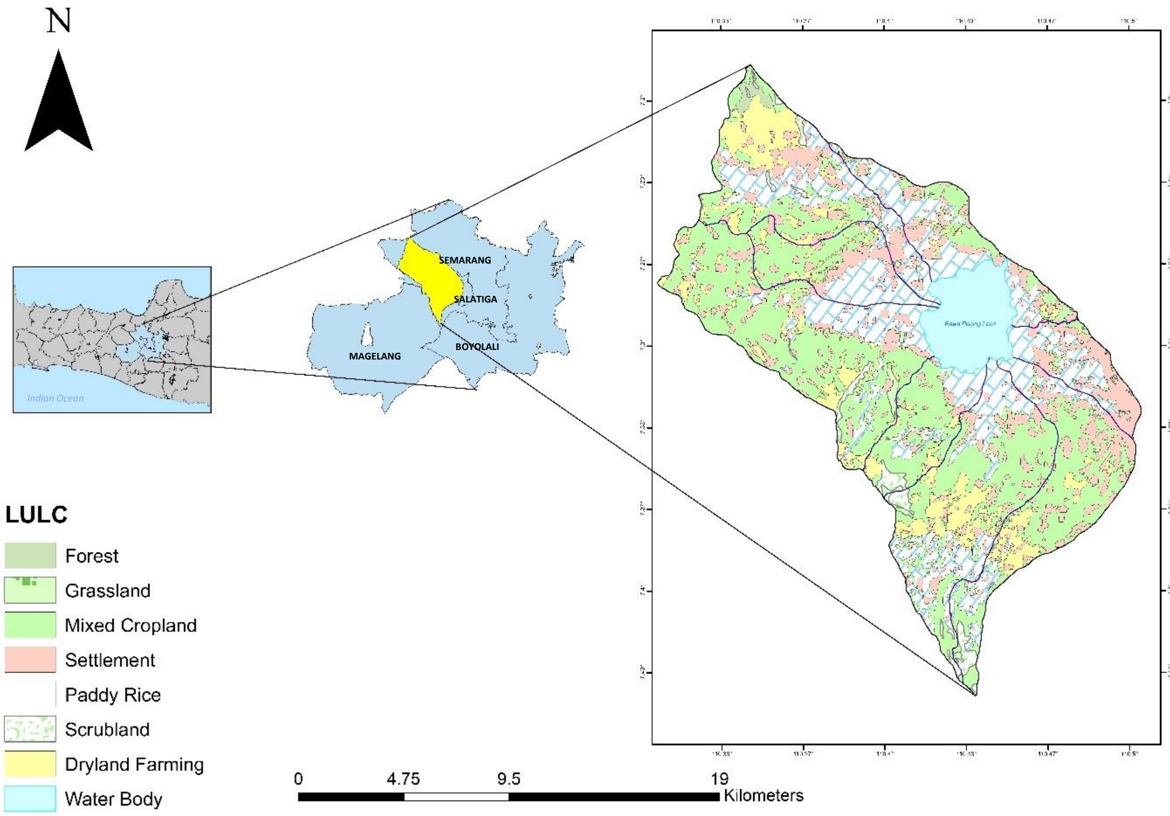

Figure 1. Land use in the Rawa Pening catchment area

The hydrological characteristics of the Rawa Pening catchment region are predominantly influenced by the soil hydrological classification, as D class. In this course, and the dominant features include significant capacity for runoff and extended rates of water infiltration. Class D soil hydrological group is commonly composed of clay, which frequently has a significant capability for swelling. Furthermore, this class exhibits characteristics such as a significantly elevated permanent groundwater table, a relatively shallow layer of clay, and a protective layer of impermeable materials.

The curve number in the Rawa Pening catchment area is influenced by both the soil hydrological class and the complexities of land use. The curve number in this particular region is primarily distinguished by a numerical value of 84, corresponding to the land use of mixed agriculture and the hydrological classification of class D soil. The percentage of land use in the Rawa Pening catchment can be seen in Figure 2.

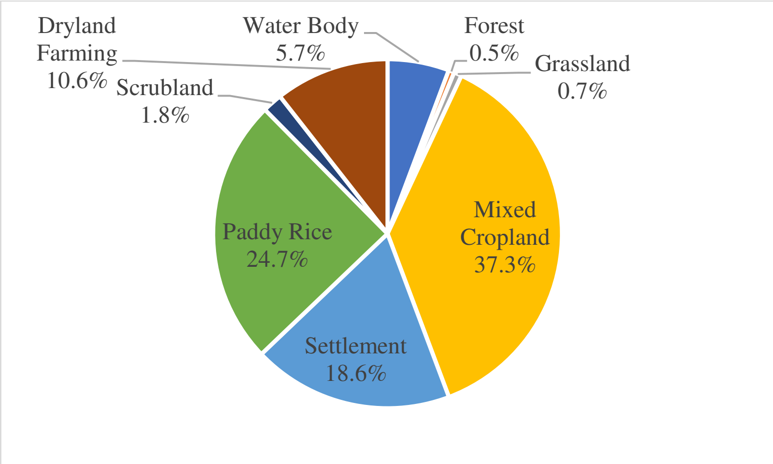

Figure 2. Percentage of the land use in the Rawa Pening catchment area

2.2. Data Collection

The data used in this study are shown in Table 1

Table 1. Research Data

Data Type	Data Name	Data source
Primary Data	Data from laboratory test results for soil samples in the Rawa Pening catchment in 2022	Field survey data
Secondary Data	Topographic Map of Indonesia	Geospatial Information Agency
	DEM data for Semarang Regency and Salatiga City with a spatial resolution of 30 meters.	*Google Earth Engine*
	Rawa Pening Catchment Land Use Map	Central Java Province Geoportal
	Semarang Climatology Station temperature data	Meteorology, Climatology and Geophysics Agency of Semarang
	Measured discharge data at the Sraten gauged in 2021	Pemali Juana River Region Centre
	Rainfall data for the Rawa Pening catchment for the period 2013-2022 (satellite rainfall data uses a spatial resolution of 4 x 4 km)	Water Resources Management Centre Bodri Kuto and *Center for Hydrometeorology and Remote Sensing* (CHRS)

The SWYM InVEST model requires using accumulated monthly rainfall data rather than daily accumulations. Nevertheless, a crucial factor for the model involves the presence of monthly precipitation occurrences within the simulated hydrological basin. The accuracy of this calculation relies on estimating the mean daily precipitation value over all pixels. Rainfall events are events where the average rainfall per pixel exceeds 0.1 mm. These events are detected, and total monthly averages are calculated to provide the SWYM dataset.

Transitioning from daily to monthly records involves merging the daily rainfall measurements for each pixel within the raster. This consolidation results in a new raster representing the total monthly rainfall. The rainfall data is represented in a raster format, with a spatial resolution of 30 meters, and is stored in the specified "rain" directory. The files in this directory are each assigned a numerical label corresponding to the month in which they are associated. Before running the model, it is essential to perform resampling on the Digital Elevation Model (DEM) to get a pixel size of 30 x 30 meters.

2.3. Data Analysis

a. Reference Evapotranspiration

Evapotranspiration was calculated using the Thornthwaite-Mather method. The temperature difference between the climatology station and the point elevation in the Rawa Pening catchment area is calculated using the following formula.

$$\Delta t = 0.006\ x\ (Z_1 - Z_2)\ (1)$$

Where Δt is the difference in temperature of the two stations, Z_1 is the altitude of the reference station, and Z_2 is the calculated altitude of the station.

Calculation of the reference evapotranspiration value can be done with the following equation:

$$ET_0 = 16\ x\ \left[\frac{(10xt)^a}{I}\right] x\ \left[\frac{N}{12}\right] x\ \left[\frac{1}{30}\right]\ (2)$$

ET_0 is reference evapotranspiration (mm/month), t is the monthly average temperature (^{0}C), N is the monthly average solar radiation, *a* is the coefficient based on the latitude of an area, and I is the annual heat index. The coefficient and annual heat index can be calculated using the following equation.

$$a = (675\ x\ 10^{-9}) x\ I^3 - (771\ x\ 10^{-7})\ x\ I^2 + (179\ x\ 10^{-4})\ x\ I + 0{,}492\ (3)$$

$$I = \sum_{m=1}^{12} \left(\frac{t}{5}\right)^{1{,}51}\ (4)$$

b. Running the InVEST SWYM Model

The InVEST Seasonal Water Yield model was developed to provide a spatial evaluation of the water yield production within a catchment. In addition, the model provides monthly estimates of surface discharge, referred to as "quick flow" in this context. Its conceptual framework matches the network water balance model developed by Thompson et al. [33], incorporating two central characteristics: sensitivity to vegetation and land use and an explicit representation of the river network. The model operates on a simple input dataset that includes digital elevation models (DEM), climate records, and soil data – all of which are readily available – and is based on the fundamental principle of water partitioning (allocating precipitation to runoff or evapotranspiration) and the configuration of river networks. This investigation concentrates solely on two phases of the model. Initially, the calculation of monthly quick flow (QF) at each pixel is derived using an adaptation of the NRCS curve number approach [22], which bases monthly quick flow on monthly precipitation and the frequency of rainfall occurrences during a given timeframe. Simultaneously, the second stage involves calculating water loss via evapotranspiration, which is influenced by local recharge and vegetation dynamics. The parameters regulate subsurface water availability for evapotranspiration at specific pixels. While the model also estimates an annual baseflow, this study focuses exclusively on the quick flow component.

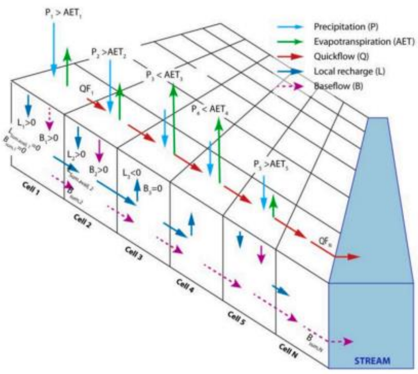

Figure 3. Routing scheme used in InVEST SWYM model

The steps of calculating seasonal water yields in the InVEST model are shown through the following equations.

$$QF_{i,m} = n_m \left((a_{i,m} - S_i)\, exp\left(-\frac{0.2S_i}{a_{i,m}}\right) + \frac{Si^2}{a_{i,m}} exp\left(\frac{0.8S_i}{a_{i,m}}\right) E_1\left(\frac{S_i}{a_{i,m}}\right)\right) \left(25.4 \left[\frac{mm}{in}\right]\right) \quad (4)$$

$$QF_i = \Sigma_{m=1}^{12} QF_{i,m} \quad (5)$$

$$AET_{i,m} = min(PET_{i,m}; P_{i,m} - QF_{i,m} + \alpha_m \beta L_{sum.avail,i}) \quad (6)$$

$$L_i = P_i - QF_i - AET_i \quad (7)$$

$$B_i = B_{sum,i}\, x\, \frac{L_{avail,i}}{L_{sum,i}} \quad (8)$$

$$L_{sum,i} = L_i + \Sigma_j^i L_{sum,j}\, x\, P_{ji} \quad (9)$$

Where:

S_i	:	maximum potential retention of water by soil at pixel i
CN_i	:	curve number at pixel i
$a_{i,m}$	:	average rain depth on rainy days at pixel i and month m
E_1	:	integral function
$L_{sum.avail,i}$	:	the amount of subsurface water on the upper slope at pixel i
β	:	spatial accessibility, value 0-1
L_i	:	local recharge index
P_i	:	annual precipitation on pixel i
$AET_{i,m}$	:	annual actual evapotranspiration on pixel i
B_i	:	baseflow on pixel i
$L_{sum,i}$	:	cumulative recharge

The InVEST Seasonal Water Yield model (SWYM) offers a range of parameters that can be fine-tuned to enhance model performance, including α, β, γ, and the threshold flow accumulation. The threshold flow accumulation, which is influenced by the Digital Elevation Model (DEM) [4], needs to be set appropriately to reflect the actual stream configuration within the watershed [27]. The correct threshold value ensures alignment between the modeled stream layer and the real-world stream conditions. Higher threshold values result in fewer stream tributaries, underscoring the need to harmonize the stream network generated by the InVEST model with the observed field stream network. Research by Ariza-Villaverde et al. [3] suggests that a DEM with a spatial resolution of 25-30 meters is well-suited for threshold flow accumulation values ranging from 10 to 900. Nevertheless, the selection of these values must be informed by the geomorphological characteristics of the area. The parameter values are tailored to the InVEST model's specifics, as presented in Table 2.

Table 2. Model InVEST's Parameters Value

Parameter	Value
alpha_i	12/12
beta_i	1
gamma_i	1
Threshold flow accumulation	125

The optimization results depend on the default parameter values (α, β, γ) of the InVEST model. The justification for this decision is based on the assumption that these parameters demonstrate a limited level of sensitivity to the quick flow results, as supported by previous scientific research [4, 8, 11, 26]. Given the specified parameter values, it is justifiable to propose that the quick flow originating from the upstream area substantially influences the dynamics of the downstream quick flow.

c. Model Performance

The components tested for validation are flow discharge that has gone through a process of separation of base flow and the quick flow from the results of the InVEST model which has converted to the m^3/s units. The results of the InVEST model were validated using the correlation coefficient (r), the PMARE index and the coefficient of determination (r^2) with measured data as model input. The correlation significance test of the two data was carried out by looking at the r-value at the 5% significance level. The correlation coefficient can be known by the following equation.

$$r = \frac{\sum_{i=1}^{N}(Q_{obs}-Q)^2 - \sum_{i=1}^{N}(Q_{obs}-Q_{cal})^2}{\sum_{i=1}^{N}(Q_{obs}-Q)^2} \text{..........................} (10)$$

where r is correlation coefficient, Q_{obs} is the direct runoff (observed), Q_{cal} is the quick flow from InVEST model results (predicted), Q is average of direct runoff (observed) and N is number of data. The level of the correlation coefficient can be known by Table 3.

Table 3. The Level of Correlation Coefficient

Correlation Intervals	Level
0.00 - 0.199	Very low

0.20 - 0.399	Low
0.40 - 0.599	Intermediate
0.60 - 0.799	Strong
0.80 - 1.00	Very strong

Source: Sugiyono (2013)

The correlation significance test of the two data was carried out by looking at the r-value at the 5% significance level. The value in the table is the limit of a correlation that can be said to be significantly correlated. If the value of $r_{count} > r_{table}$ for a certain value of N (amount of data), then the two data are significantly correlated, and vice versa.

Level testing error prediction results are performed by calculating the PMARE index (percent mean absolute relative error) based on prediction and observation data. PMARE is good in evaluating models because it is logical, consistent, interpretive, and can accurately and precisely measure model errors [2]. PMARE index can be calculated based on the following equation.

$$PMARE\ (\%) = \frac{100}{n} \sum_{1}^{n} \frac{|(o-p)|}{o} \quad (11)$$

where n is amount of data, o is observed value, p is predicted value and |(o-p)| is absolute value of the difference between o and p.

The PMARE index classification used to determine the quality of the prediction model is presented in Table x.

Table 4. PMARE Index Classification

PMARE Value (%)	Classification
0 - 5	Perfect
5 - 10	Very good
10 - 15	Good
15 - 20	Fair
20 - 25	Moderate
>25	Unsatisfactory

Source: Ali & Abustan (2014)

3. Result and Discussion

3.1. InVEST Performace

The validation approach incorporates the parameter values of the InVEST model, which are obtained using the calibration and validation stages. Testing the performance of the InVEST model uses direct runoff based on measurement data of the Sraten gauging station flow derived from data from the Pemali Juana River Region Centre as measured data and the quick flow generated by the InVEST model as the calculated data. The data used is monthly data in 2021. The results of this validation are shown in Figure 4.6. According to the validation results, the R-squared value (R^2) appears as 0.9011. This graphic demonstrates a noticeable relationship between the observed direct runoff and the expected quick flow flow generated by the model. A linear relationship between the observed direct runoff and the simulated quick flow can be established, accounting for approximately 90% of the direct runoff or quick flow. The remaining 10% can be ascribed to external causes that lie beyond the scope of this studies.

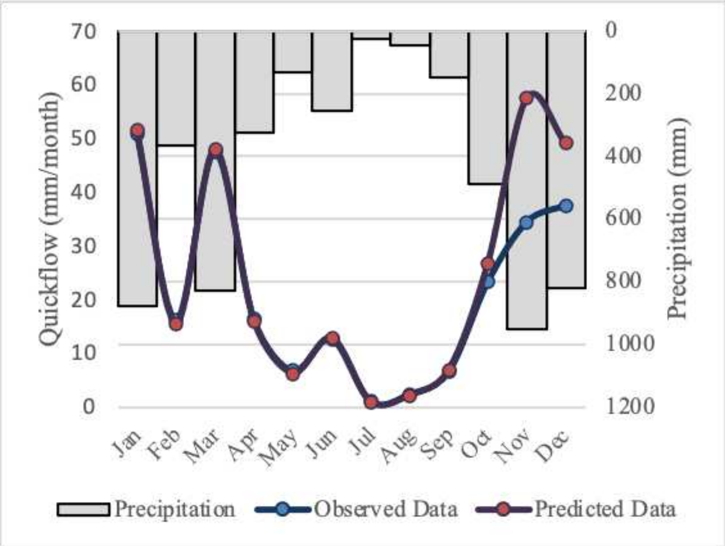

Figure 4. Graph of Quick Flow from InVEST Model Results and Measured Direct Runoff
Source: Research Data (2023)

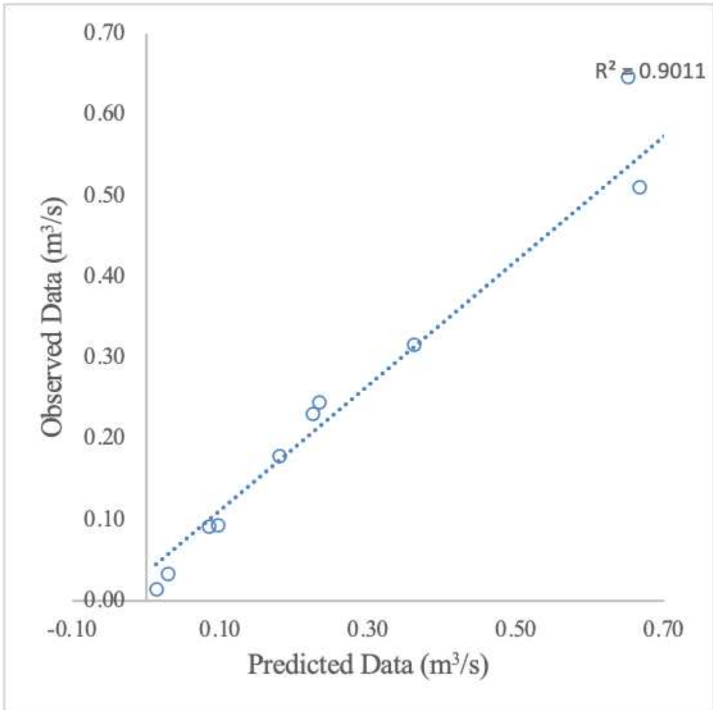

Figure 5. Graph of Predicted Data and Observed Data Correlation
Source: Research Data (2023)

The statistical assessment reveals a correlation coefficient (r) of 0.95, accompanied by a PMARE index of 12.84. The validation outcomes affirm the substantial strength of the correlation between the modeled (predicted) direct runoff and the measured (observed) direct runoff, denoted by the r value of 0.95. A 5% significance test indicates an r_{count} value of 0.95, where the r_{table} for N (with a value of 12) corresponds to 0.576. This outcome implies a significant and meaningful correlation between the two datasets. Additionally, the PMARE index categorizes the prediction outcomes as falling within the "good" classification [17].

3.2. Actual Evapotranspiration

The spatiotemporal pattern of actual evapotranspiration remains consistent from 2018 to 2022. The actual evapotranspiration magnitude is influenced by the specific plant species within a given land use and the prevailing temperature conditions. Notably, paddy rice fields exhibit elevated actual evapotranspiration levels. This phenomenon can be attributed to their higher crop coefficient values than other land uses. Research by Kamble et al. [14] and Singh et al. [28] suggests that paddy fields or irrigated lands exhibit more pronounced evapotranspiration than areas reliant solely on rainwater. Water availability within plants is a pivotal determinant of evapotranspiration, indicating that increased water content within the land leads to heightened evapotranspiration rates [31]. Water bodies, too, exhibit substantial actual evapotranspiration. Liu et al. [18] found that water bodies manifest the highest evapotranspiration rates relative to other land uses. Water hyacinth within Lake Rawa Pening adds further complexity to the evapotranspiration dynamics, enhancing its overall value.

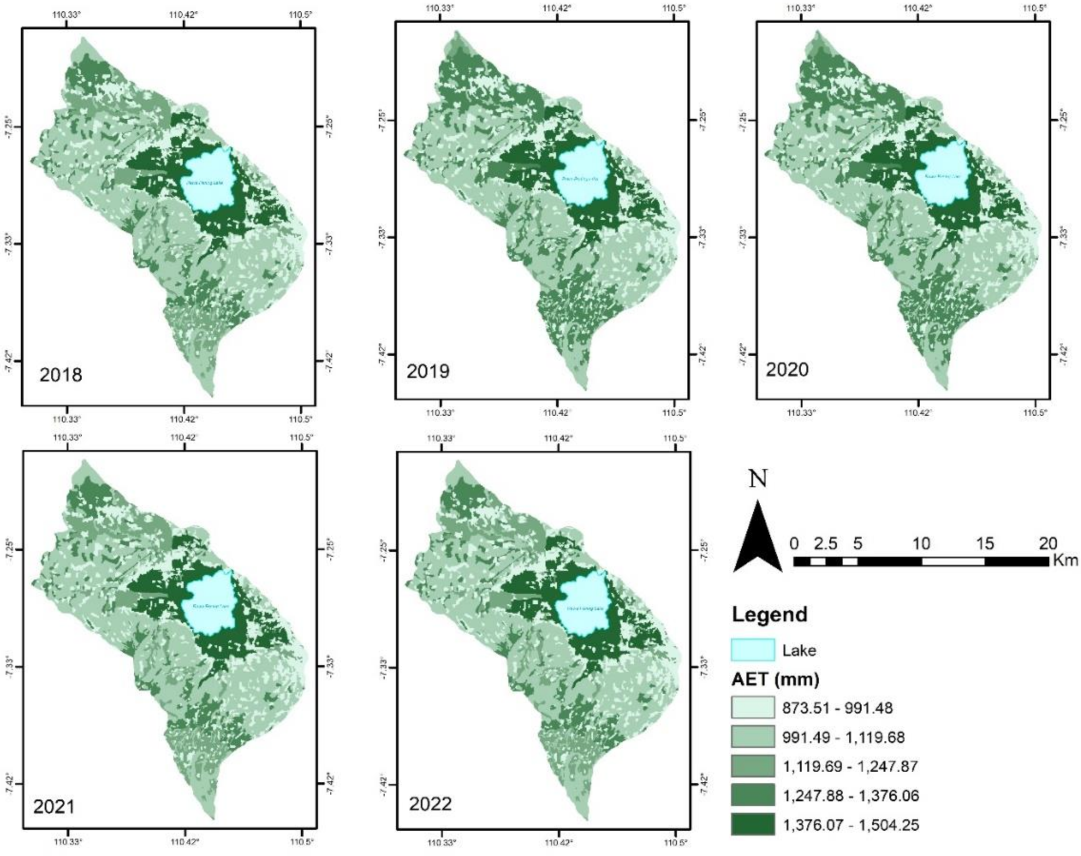

Figure 6. Annual Actual Evapotranspiration in the Rawa Pening Catchment Area
Source: Research Data (2023)

3.3. Quick Flow

The peak of quick flow becomes noticeable at the beginning of each annual cycle, gradually decreasing before experiencing an upward trend towards the end of the year. The peak of quick flow was detected in November 2022, whereas the lowest point was observed in July 2018. Over several months, there were variations in the intensity of quick flow, with values ranging from 0.08 to 645.87

mm per month. Figure 4 presents an illustration highlighting the dynamic progression of fast-moving water within the boundaries of the Rawa Pening catchment region.

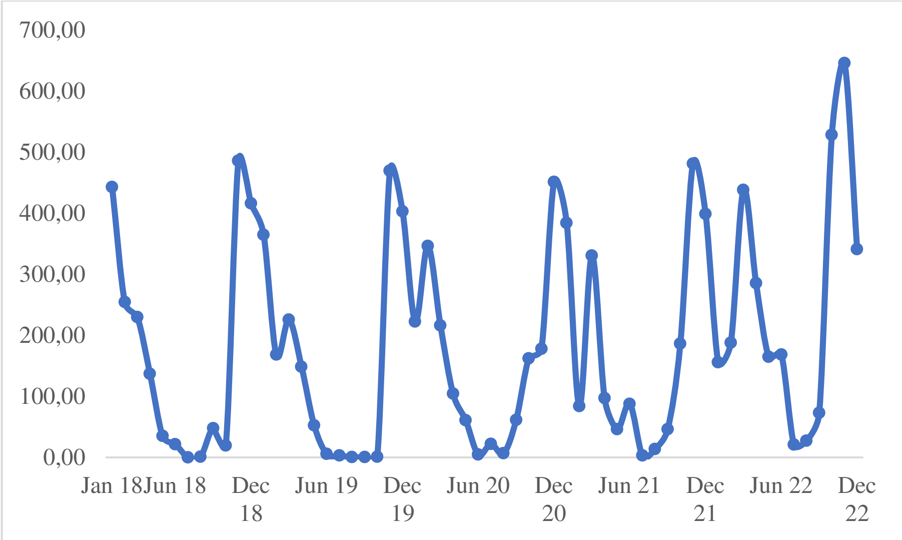

Figure 7. Graph of the quick flow of the Rawa Pening Catchment Area in 2018-2022
Source: Research Data (2023)

The quick flow within the Rawa Pening catchment area, as inferred from the outcomes of the InVEST model, exhibits a recurrent monthly oscillation. This fluctuation results from the parameters influencing the InVEST model's quick flow calculations, most notably rainfall, which similarly varies over time. Whenever rainfall intensity is modest, quick flow values tend to be commensurately modest, and conversely, higher rainfall leads to increased quick flow. The undulations in rainfall, particularly on a monthly and seasonal scale, find their roots in the monsoon system and the shifting position of the intertropical convergence zone (ITCZ) from November to March and May to September [1]. Moreover, these rainfall fluctuations bear the imprint of global climate phenomena such as the El Nino Southern Oscillation (ENSO) and the Indian Ocean Dipole Mode (IOD). The most recent El Nino event transpired in 2019, a pronouncement by the National Oceanic and Atmospheric Administration (NOAA). Furthermore, reports from the National Aeronautics and Space Administration (NASA) and NOAA indicate that the La Nina event 2022 stands as the warmest recorded instance in history [25, 29]. Research by Hidayat et al. (2018) underscores that La Nina occurrences correlate with heightened rainfall in Indonesia. The presence of El Nino and La Nina significantly impacts rainfall levels and shapes the boundaries between rainy and dry seasons within a given year. The curve number also influences quick flow due to the underlying principles governing quick flow calculations. Notably, research by Hamel, et al. [11] highlights the marked sensitivity of quick flow to curve numbers. Additionally, the quick flow remains responsive to the threshold flow accumulation, as it represents actual river conditions in the field. The water flow during July and August holds particular significance, warranting attention in the context of watershed management. Given the critical value of the water supply during these months, preliminary measures must be in place to address the increase of water utilization demands.

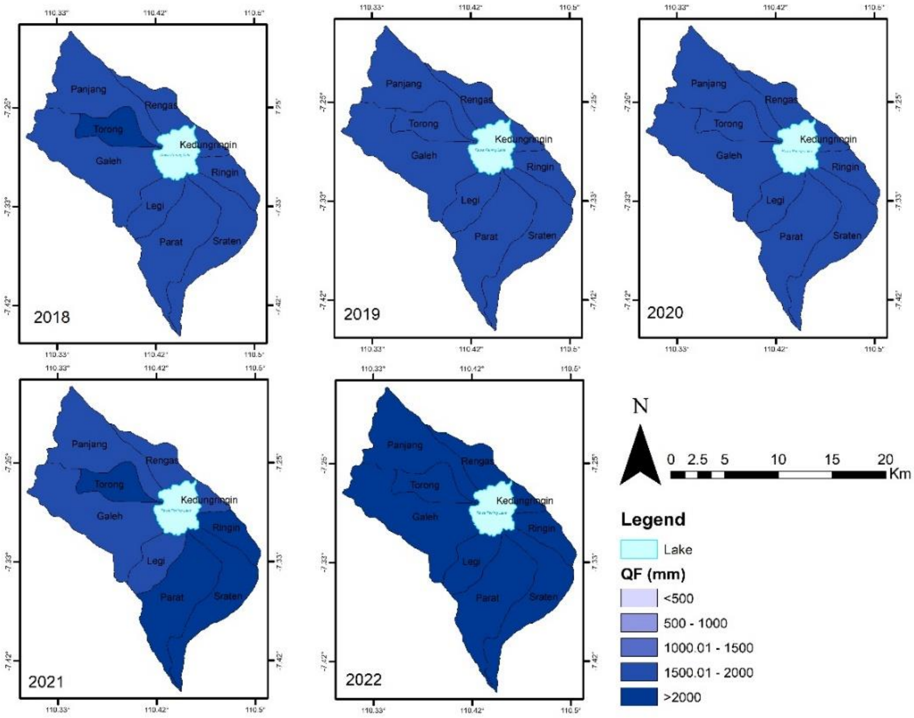

Figure 8. Spatial Distribution of Rawa Pening Catchment Area's Average Quick Flow During the Rainy Season Based on sub-Catchment
Source: Research Data (2023)

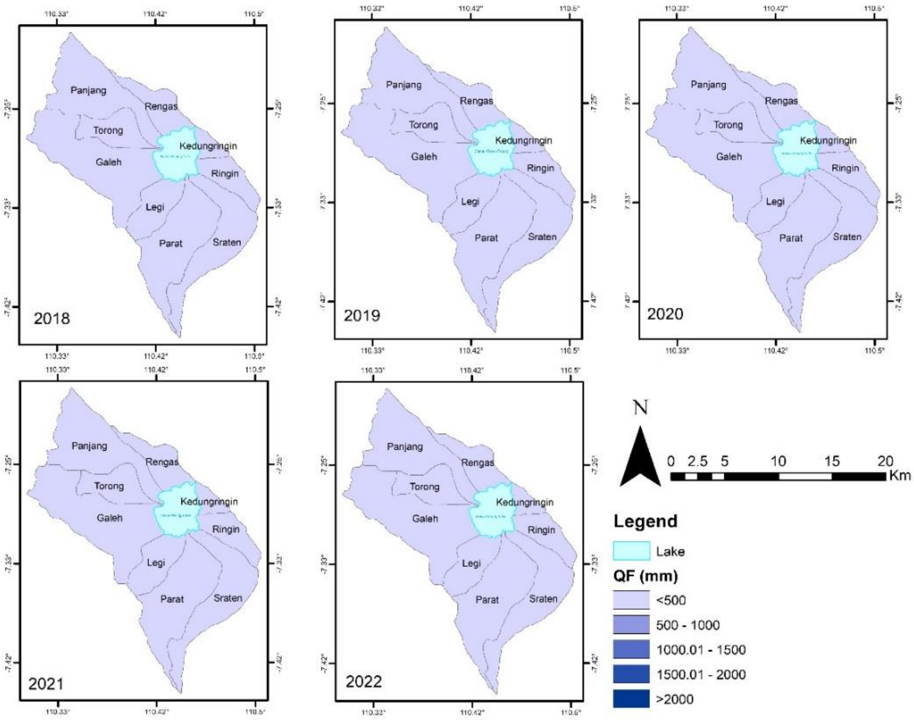

Figure 9. Spatial Distribution of Rawa Pening Catchment Area's Average Quick Flow During the Dry Season Based on sub-Catchment
Source: Research Data (2023)

Among the sub-catchments, the Legi sub-catchment emerges as the primary contributor to quick flow, surpassing others in this regard. This prominence can be attributed to both soil characteristics and land use patterns. The soil belongs to class D within the Legi sub-catchment, characterized by notable clay content and its association with tertiary mountain terrain. Such soil exhibits a lower infiltration rate, thereby amplifying quick flow values. In contrast, the Panjang and Ringin sub-catchments exhibit comparatively lower quick flow values. The Panjang sub-catchment, utilized for plantations including forests, paddy fields, dry fields, and mixed cropland, presents a soil makeup falling within classes C and D. These soil conditions entail an elevated potential for runoff and a reduced infiltration rate. The Ringin sub-catchment, dominated by paddy rice fields known for high evapotranspiration, contributes to the landscape's characteristics. The intricate interplay of factors influencing quick flow within each sub-catchment encompasses soil type, land use patterns, and the stream network's characteristics, symbolized by the threshold flow accumulation. Sub-catchments boasting a profusion of stream tributaries tend to yield significant quick flows. As per Kiss [15], the slope significantly influences each formation's threshold flow accumulation algorithm. Lin and Oguchi [16] corroborate this observation, affirming that slope and drainage density share a positive correlation, directly impacting river length and the presence of tributaries. Analyzing the hydrological response unit underscores that elevated direct runoff values are prominent in streams and water bodies at lower elevations. Novikov's research supports this by indicating that higher-elevation areas typically exhibit lower direct runoff values due to the swift movement of runoff towards lower terrain. The InVEST model concept defines direct runoff as the flow that reaches the river network within a specific time, in this case, monthly [27].

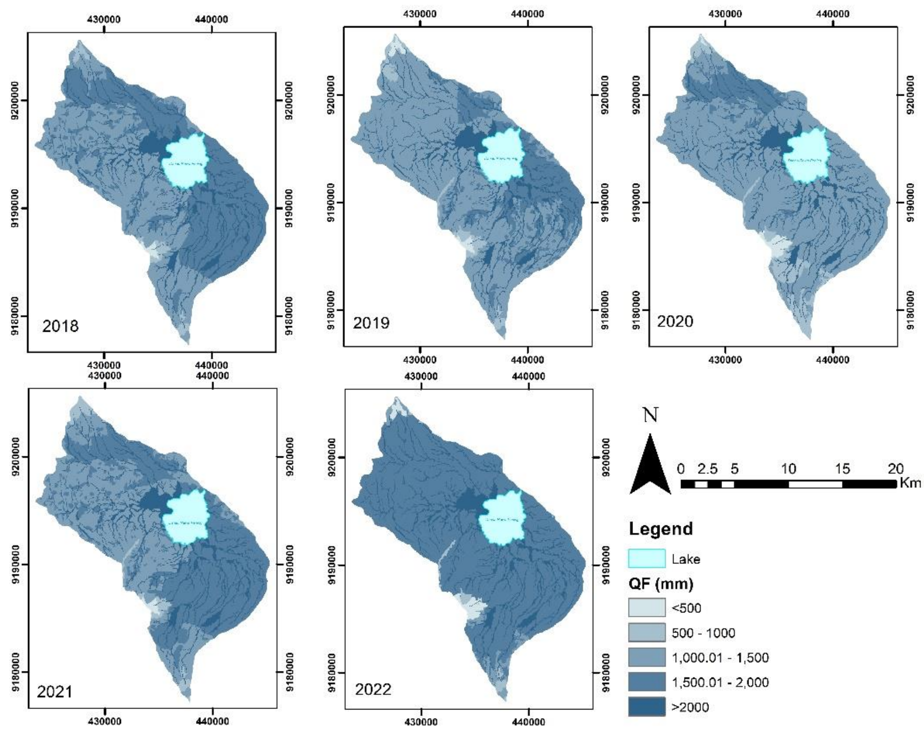

Figure 10. The Map of Rawa Pening Catchment Area's Annual Quick Flow based on Hydrological Response Unit
Source: Research Data (2023)

3.4. Runoff Volume

Based on InVEST modeling results, the volume contribution percentage of each sub-catchment to the total water yield volume in the Rawa Pening catchment is shown in Figure 4.16.

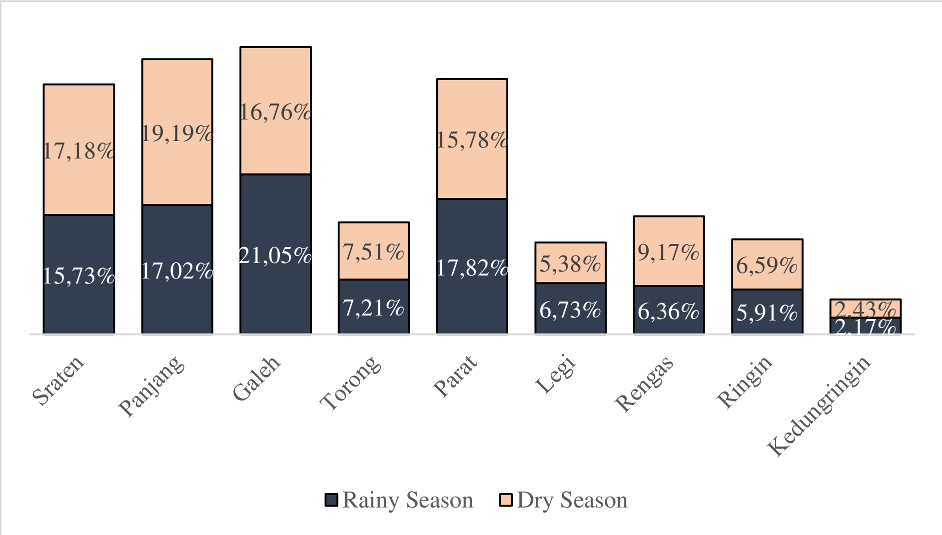

Figure 11. Graph of Contribution of Each Sub-Catchments to Water Management in Lake Rawa Pening Catchment in 2018-2022

The Galeh sub-catchment emerges as the most significant contributor to the Rawa Pening catchment in terms of water volume, spanning rainy, dry, and annual seasons. In contrast, the Kedungringin sub-catchment accounts for the lowest contribution, a disparity primarily influenced by their respective areas. Notably, the Galeh sub-catchment boasts the most significant area, while the Kedungringin sub-catchment ranks lowest within the Rawa Pening catchment. Regions characterized by substantial water yield contributions are expected to play a pivotal role in sustaining Lake Rawa Pening's water supply through water resource conservation initiatives. Lake Rawa Pening is one of Indonesia's 15 national priority lakes, as outlined in Presidential Regulation 60 of 2021, addressing the preservation of such lakes. This classification considers various factors, including the mounting pressures and degradation affecting the catchment area. The Rawa Pening catchment area, situated upstream of the Tuntang watershed, also falls within the ambit of priority watersheds due to its multifaceted challenges, encompassing land conditions, water quality and quantity, social-economic factors, water infrastructure investments, and spatial usage concerns. Evaluating the water system within a catchment area assumes significance as it provides insights into water flow dynamics, including its quantity, quality, and continuity. The framework for monitoring and evaluating watershed management, outlined in Minister of Forestry Regulation Number P.61/Menhut-II/2014 concerning Monitoring and Evaluation of Watershed Management [19], places specific emphasis on water system evaluation, particularly concerning water quantity during rainy and dry seasons. An adequate water system embodies balance, where excess water does not lead to flooding in the rainy season and water scarcity or drought is not encountered in the dry season.

4. Conclusion

The results of the InVEST modeling demonstrate a consistent trend of increased quick flow values at the beginning and end of each year, gradually decreasing during the middle of the year. Over five years, the monthly average water yield regularly exhibits a pattern closely resembling the corresponding rainfall. In November 2022, there was a notable peak in the quick flow, reaching a measurement of 645.87 mm. Conversely, the lowest point was seen in July 2018, with a minimal measurement of 0.08 mm. The procedure of validation, which entails doing statistical calculations on projected quick flow and observed direct runoff, resulted in an r-value of 0.95 and a PMARE index of 12.84%. The precision of the InVEST model can be determined by evaluating the r^2 value. The data obtained from the calibration procedure with the InVEST model demonstrates a r^2 value of 0.9011, indicating considerable accuracy in estimating water yields within the Rawa Pening catchment area, despite minor discrepancies. Spatial variations in quick flow, characterized by high and low points, arise from a range of input factors, such as precipitation, land utilization, soil hydrological classification, and the complexity of the stream network, represented by the threshold flow accumulation and the number of tributaries.

5. Autorship Contribution Statement

Alfina Lismadanti: conceptualisation, methodology, data collection, data analysis, writing - original draft. **Nugroho Christanto**: conceptualisation, methodology, data collection, critical manuscript, editing manuscript. **I Effendy**: editing manuscript.

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7. References

[1] Aldrian E and Dwi S R 2003 Identification of three dominant rainfall regions within indonesia and their relationship to sea surface temperature *International Journal of Climatology* 23 1435–1452.

[2] Ali M H and Abustan I 2014 A new novel index for evaluating model performance *Journal of Natural Resources and Development* 2002 1–9.

[3] Ariza-Villaverde A B, Jiménez-Hornero F J, and Gutiérrez de Ravé E 2015 Influence of DEM resolution on drainage network extraction: A multifractal analysis *Geomorphology* 241 243–254.

[4] Benra F, De Frutos A, Gaglio M, Álvarez-Garretón C, Felipe-Lucia M, and Bonn A 2021 Mapping water ecosystem services: Evaluating InVEST model predictions in data scarce regions *Environmental Modelling and Software* 138.

[5] Bigas 2013 *Water Security and The Global Water Agenda: A UN-Water Analytical Brief.*

[6] Dingman S L 1981 Elevation: A major influence on the hydrology of new hampshire and vermont, USA *Hydrological Sciences Bulletin* 26 399–413.

[7] Directorate General of Land Rehabilitation and Social Forestry 2009 *Regulation of the Director General of Land Rehabilitation and Social Forestry No. P.04/V-SET/2009 Concerning Guidelines for Monitoring and Evaluation of River Basin Areas* 1–89.

[8] Gashaw T, Worqlul A W, Dile Y T, Sahle M, Adem A A, Bantider A, … Bayable G 2022 Evaluating InVEST model for simulating annual and seasonal water yield in data-scarce regions of the abbay (Upper Blue Nile) basin: implications for water resource planners and managers *Sustainable Water Resources Management* 8.

[9] Geng X, Wang X, Yan H, Zhang Q, and Jin G 2015 Land use/land cover change induced impacts on water supply service in the upper reach of Heihe River basin *Sustainability*

(Switzerland) 7 366–383.
[10] Government of the Republic of Indonesia 2012 Government Regulation of the Republic of Indonesia Number 37 of 2012 Concerning Watershed Management (Jakarta: Government of Republic Indonesia) p32.
[11] Hamel P, Valencia J, Schmitt R, Shrestha M, Piman T, Sharp R P, … Guswa A J 2020 Modeling seasonal water yield for landscape management: Applications in Peru and Myanmar *Journal of Environmental Management* 270 110792.
[12] Hidayat R, Juniarti M D, and Ma'Rufah U 2018 Impact of La Niña and La Niña Modoki on Indonesia rainfall variability *IOP Conference Series: Earth and Environmental Science* 149.
[13] Indriyanto I W, Sudarsono B, and Sasmito B 2019 Analysis of the suitability of changes in land use to the regional spatial plan around Lake Rawa Pening, Semarang Regency, in 2013 and 2018 *Jurnal Geodesi Undip* 8 133–142.
[14] Kamble B, Kilic A, and Hubbard K 2013 Estimating crop coefficients using remote sensing-based vegetation index *Remote Sensing* 5 1588–1602.
[15] Kiss R 2004 Determination of drainage network in digital elevation models, utilities and limitations *Journal of Hungarian Geomathematics* 2 16–29.
[16] Lin Z and Oguchi T 2004 Drainage density, slope angle, and relative basin position in Japanese bare lands from high-resolution DEMs *Geomorphology* 63 159–173.
[17] Lismadanti A 2023 Analysis of Water Yield Potential in the Rawa Pening Catchment Area using Integrated Valuation of Ecosystem Services and Tradeoffs *Undergraduate Thesis* Universitas Gadjah Mada, Yogyakarta.
[18] Liu W, Hong Y, Khan S I, Huang M, Vieux B, Caliskan S, and Grout T 2010 Actual evapotranspiration estimation for different land use and land cover in urban regions using landsat 5 data *Journal of Applied Remote Sensing* 4 041873.
[19] Minister of Forestry of the Republic of Indonesia 2014 Regulation of the Minister of Forestry Number P.61/Menhut-II/2014 Concerning Monitoring and Evaluation of Watershed Management (Jakarta: Government of Republic Indonesia).
[20] Mubarok Z, Murtilaksono K, and Wahjunie E D 2015 Study of land use change responses to the hydrological characteristics of the Way Betung watershed - Lampung *Journal of Wallacea Forestry Research* 4 1.
[21] NRCS-USDA 2004 Chapter 10 Estimation of Direct Runoff from Storm Rainfall Part 630 Hydrology National Engineering Handbook (Washington DC: United States Department of Agriculture).
[22] Pemali Juana River Region Centre 2021 Rawa Pening Lake Information Material (Semarang: Pemali Juana River Region Centre).
[23] Permatasari R, Arwin, and Natakusumah D K 2017 The effect of changes in land use on the watershed hydrological regime (Case sudy: DAS Komering) *Journal of Civil Engineering* 24 91–98.
[24] Purboseno S 2013 Evaluation of changes in land use as an effort to maintain the sustainability of reservoir functions *Communication Media of Civil Engineering* 19 167–174.
[25] Ramirez R 2023 2022 was the warmest La Niña Year on Record. Scientists Say this Year will be Warmer. Available at: https://edition.cnn.com/2023/01/12/us/2022-warmest-la-nina-year-climate/index.html (Accessed: 1 June 2023).
[26] Scordo F, Lavender T M, Seitz C, Perillo V L, Rusak J A, Piccolo M C, and Perillo G M E 2018 Modeling Water Yield: Assessing the role of site and region-specific attributes in determining model performance of the InVEST seasonal water yield model *Water*

(Switzerland) 10 1–42.
[27] Sharp R, Nelson E, Ennanay D, Wolny S, Olwero N, Vigerstol K, … Bierbower W 2015 InVEST user guide National Capital Project.
[28] Singh R K, Senay G B, Velpuri N M, Bohms S, Scott R L, and Verdin J P 2013 Actual evapotranspiration (water use) assessment of the Colorado river basin at the landsat resolution using the operational simplified surface energy balance model *Remote Sensing* 6 233–256.
[29] Stallard E 2023 What are El Niño and La Niña, and how do they change the weather? Available at: https://www.bbc.com/news/science-environment-64192508 (Accessed: 1 June 2023).
[30] Sugiyono D 2013 *Quantitative, Qualitative, and Action Research Methods*.
[31] Sujono J 2011 Coefficient of lowland rice plants in water-saving irrigation systems *Agritech* 31 344–351.
[32] Thompson S E, Harman C J, Konings A G, Sivapalan M, Neal A, Troch P A, … Brooks P D 2011 Comparative hydrology across AmeriFlux sites: The variable roles of climate, vegetation, and groundwater *Water Resources Research* 47.
[33] Thompson S E, Harman C J, Troch P A, Brooks P D, and Sivapalan M 2011 Spatial scale dependence of ecohydrologically mediated water balance partitioning: a synthesis framework for catchment ecohydrology *Water Resources Research* 47 1–20.
[34] Wardiman D, Ekaputra E G, and Yonariza 2020 Simulation of critical land conservation on water yield for the Kuranji watershed using the SWAT (Soil and Water Assessment Tool) model *Journal of Andalas Agriculture Technology* 24 76–84.
[35] Wealth Accounting and the Valuation of Ecosystem Services 2015 Managing Catchments for Hydropower Services Technical Report Wealth Accounting and the Valuation of Ecosystem Services.