Journal of Sustainable Development of Energy, Water and Environment Systems

http://www.sdewes.org/jsdewes

Year 2024, Volume 12, Issue 1, 1110477

Original Research Article

A Machine Learning Approach to Estimating Land Use Change and Scenario Influence in Soil Infiltration at the Sub-Watershed Level

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Cite as: Putra, A. N., Paimin, S. K., Alfaani, S. F., Nita, I., Arifin, S., Munir, M., A Machine Learning Approach to Estimating Land Use Change and Scenario Influence in Soil Infiltration at The Sub-Watershed Level, J.sustain. dev. energy water environ. syst., 12(1), 1110477, 2024, DOI: https://doi.org/10.13044/j.sdewes.d11.0477

ABSTRACT

This research uses random forest machine learning to develop infiltration-friendly land-use scenarios, addressing the global 32% change in land use over the past six decades. The study used Sentinel-2A satellite imagery data for 2017, 2019, 2021, and 2022 as a land use baseline, predicting business as usual using cellular automata and comparing it with regional spatial planning and land capability scenarios. One hundred points of infiltration data were distributed using a random forest. Results showed that deforestation and its change into orchards, rice fields, and settlements over five years affected the infiltration. Business as usual reduces the high infiltration class to approximately 1,545 ha, while regional spatial planning and land capability cover 1,390 ha and 1,316 ha, respectively. The most infiltration-friendly land-use scenario is applicable at the sub-watershed level, with an accuracy of about 97%. The limitations of this research include not comparing extreme dry seasons and using 2022 infiltration values for all other years.

KEYWORDS

Machine learning, Remote sensing, Geostatistics, Hydrology, Disaster.

INTRODUCTION

In the hydrologic cycle, infiltration illustrates how quickly water enters the soil through the pores [1]. Infiltration significantly affects the water balance because it affects surface runoff [2] and subsequent water movement [3]. Land use is an essential factor in influencing the infiltration rate [4], especially in the rainfall kinetic intercept [5], increasing the soil surface roughness [6], improving soil structure stability, and increasing porosity due to the organic matter produced [7].

Ironically, from 1960–2019, there has been a 32% global change in land use (LU), four times greater than the estimated predictions [8]. It also affected the average annual runoff increase by 5% [9]. Human activities and demand are the direct drivers of land-use change [10]. The indirect driver of climate change affects land conditions and influences suitable land use [11]. This change has reduced water catchment capability to infiltrate water [12] and increased the occurrence of hydrometeorological disasters such as droughts [13], floods [4] and landslides [14].

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Land use is closely related to the land arrangement process, following land use considerations, social needs, and economic and political aspects [15]. Land planning certainly has considered various aspects; however, its implementation often goes beyond the regulations set by the government [16]. For instance, even though it has been regulated in the Indonesian Republic's policy (no. 26 year 2007) and concerning spatial planning regulation, Indonesia continues to experience deforestation of about 29.1 million ha in only five years on agricultural land [17]. It reduces the water absorption areas and decreases infiltration rates [18]. Using the latest technology to monitor land use changes and their impact on infiltration needs to be developed as an early warning system before it worsens.

There have been many developments and uses of remote sensing to monitor land use changes [19] and its impact on the water cycle [20] from researchers worldwide. A recent study has used Sentinel 2A (S2A) and obtained a relatively good accuracy to monitor land use change [21]. However, previous studies still have weaknesses when exposing land use as a factor influencing infiltration [22]. This problem occurs because the data used is only a single year's worth of data, and geostatistical extrapolation is not reasonable. There is a need for baseline data on land use change whose results can holistically view the dynamics of infiltration rates from time to time. Meanwhile, due to the low level of accuracy, machine learning-based geostatistical analysis has the potential to be applied [23]. Machine learning can overcome the limitations of processing single-year data and replace it with multi-year data to identify changing trends well and in detail.

By analysing baseline data [24], future land use mosaics (business as usual) can be predicted using an artificial neural network cellular automata Markov chain (ANN CA Markov) [25]. Business as Usual (BAU) land use scenario is then compared with other land use scenarios, such as regional spatial planning (RSP) and land use according to carrying capacity [26]. These three scenarios are used as material for predicting infiltration in an area through machine analysis [27].

The machine learning analysis method that is known to be effective and has the potential to be developed in this research is the random forest [28]. Random forest is a supervised machine-learning algorithm that makes predictions that combine decision trees [29]. Predictions can be made through classification or regression. Random forests have been widely used in hydrological research and have a high accuracy in their results [30]. This study aims to apply a random forest to get the best infiltration-friendly land use scenario, an effective and efficient method. This research will provide an overview of how land use affects infiltration at the sub-watershed level as a case study.

Study Area

The research was conducted in the critical Sumber Brantas and Kali Konto sub-watersheds [31] with a total area of 40,943.50 ha (**Figure 1**) from July to December 2022. The geographical location of the research location is at 7°44'47.8896"–7°56'52.026" South Latitude and 112°19'22.0008"–112°35'22.8048" East Longitude. The selection of the research location was based on the status of the watershed, which is classified as critical, where the two upstream watersheds experience high levels of land conversion and have a historical potential for landslides [32] and high floods [33] as the end product of unhealthy sub-watershed.

The Sumber Brantas and Kali Konto sub-watersheds are volcanic regions surrounded by active and inactive volcanoes. Mount Anjasmoro is the oldest mountain in the north, while Mount Kawi-Butak is on the southeast side. Mount Kelud is an active volcano southwest of the research location.

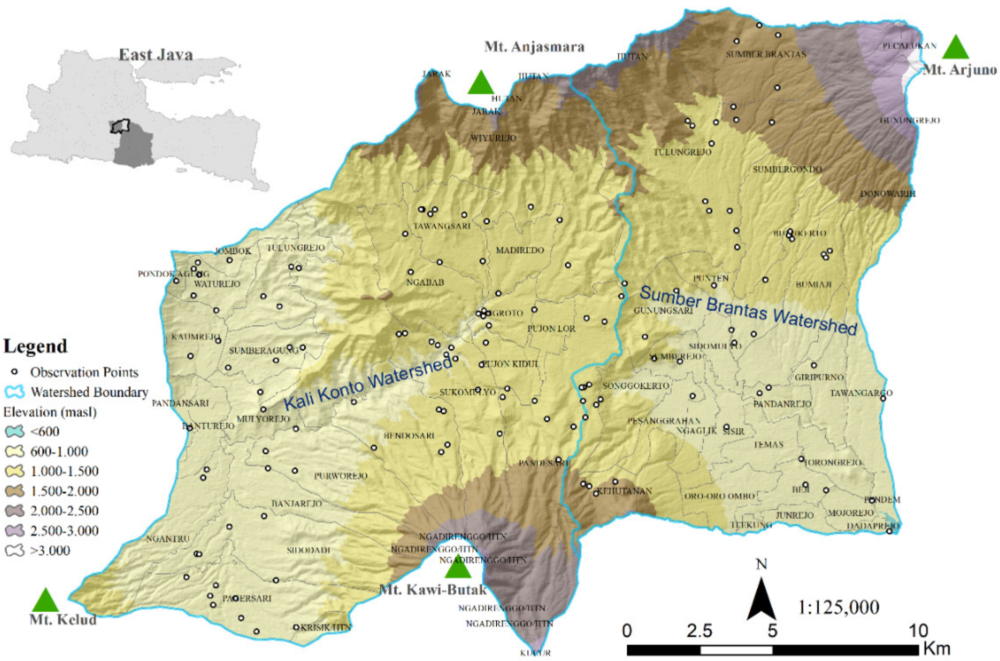

Figure 1. Sub-catchment boundaries and infiltration measurement locations in the field

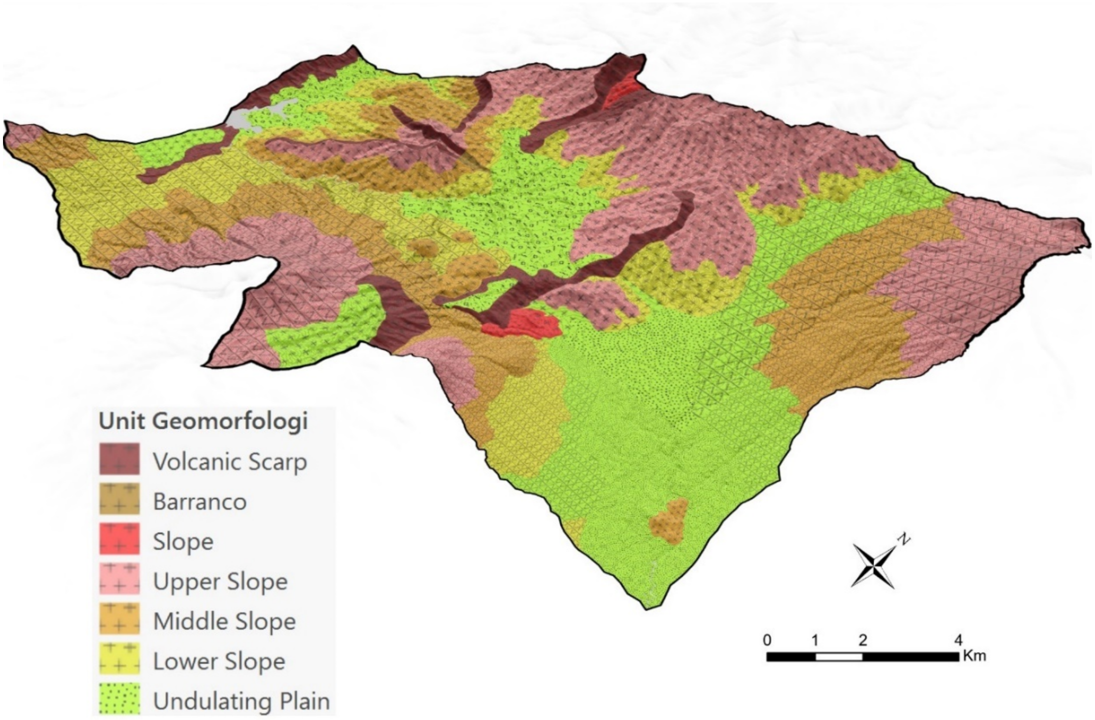

Figure 2. Geomorphology of the research location

The Sumber Brantas sub-watershed has a longer circumference of 122.03 km than the Kali Konto sub-watershed of 75.79 km. It also has a higher flow density of 2.93 km km^{-2} than the Kali Konto sub-watershed. Both sub-watersheds are part of the elongated sub-watershed, with a circularity ratio of 0.38 or greater.

Rainfall at the study site averages 2,276 mm year^{-1} and is included in the "C" climate type based on the Schmidt-Ferguson classification system. The development of soil types in the Kali Konto sub-watershed was influenced by the volcanic activity of Mount Anjasmoro Tua in the north and Mount Kawi-Butak in the south [34]. The types of soil that develop at the study site are udepts, udands, psamments and orthents [35]. The geomorphology in the site location is divided into seven groups to figure out and fulfil the research location. A volcanic scarp, barranco, slope and upper slope have been identified in the upper part of the sub-watersheds. Subsequently, a middle slope formed in the middle part, while in the lower part, a lower slope and undulating plain (inter volcanic plain), **Figure 2**.

METHOD

This research uses several combinations of methods stated in the form of a framework. To expedite the data analysis process, the tools used in the research activities included laptops, ArcMap 10.8 software, QGIS 2.18 software, Garmin 78s GPS, a single-ring infiltrometer (10–50 cm in diameter and 10–20 cm in height), a casserole, wooden blocks, a hammer, a stopwatch, a jerry can, a ruler, duct tape, stationery, a camera, R Studio software, and Microsoft Office software. Materials that support research activities included Sentinel-2A imagery, geological maps at a scale of 1:100,000, digital elevation model DEMNAS, maps of the Indonesian Topic Earth at a scale of 1:25,000, maps of RSP at a scale of 1:25,000, maps of land systems at a scale of 1:50,000, rainfall data for 1992–2021, and maps of the Sumber Brantas and Kali Konto sub-watersheds.

Land-use change analysis

Land-use change analysis was carried out by classifying Sentinel-2A satellite imagery with four years of recording, namely 2017, 2019, 2021, and 2022. Sentinel-2A satellite imagery, which has a spatial resolution of 10 m, can be downloaded via the Copernicus website (https://scihub.copernicus.eu/).

Image pre-processing and classification. The image pre-processing stage is the improvement stage of satellite imagery before it is used. This stage consists of geometric correction, radiometric correction, atmospheric correction, and haze removal. The Sentinel-2A satellite image pre-processing stage used QGIS and PCI Geomatica software [36].

The image classification method used is the supervised classification method or the guided classification method. Sentinel-2A satellite image classification was carried out using ArcGIS software [37]. The image classification results are land use classes, categorised into agroforestry, natural forest, artificial forest, production forest, built-up areas, orchards, vacant land, grasslands, paddy fields, shrubs, dry fields, and bodies of water.

The naming of land use (LU) or land cover (LC) classes is based on a hierarchy following the Indonesian National Standard on land cover classification at a scale of 1:250,000 [26].

Accuracy assessment. The results of the land use classification are then carried out in an accuracy test by comparing the 100 points resulting from the classification of land use in 2022 with the land use results from ground checks in the field. The accuracy test aims to quantitatively determine how pixels are grouped into the correct feature class in the observed area [38]. The coordinates of the validation point are recorded using the Garmin 78s GPS. The accuracy test used is the Kappa analysis method by creating a confusion matrix [39].

Land use scenario

The results of the analysis of land use classification for 2017, 2019, 2021, and 2022 are used to compile baseline trends of land use change [36]. This changing trend is then used to determine the BAU scenario using cellular automata. As a comparison, the RSP and LC land use analyses were carried out (**Figure 3**).

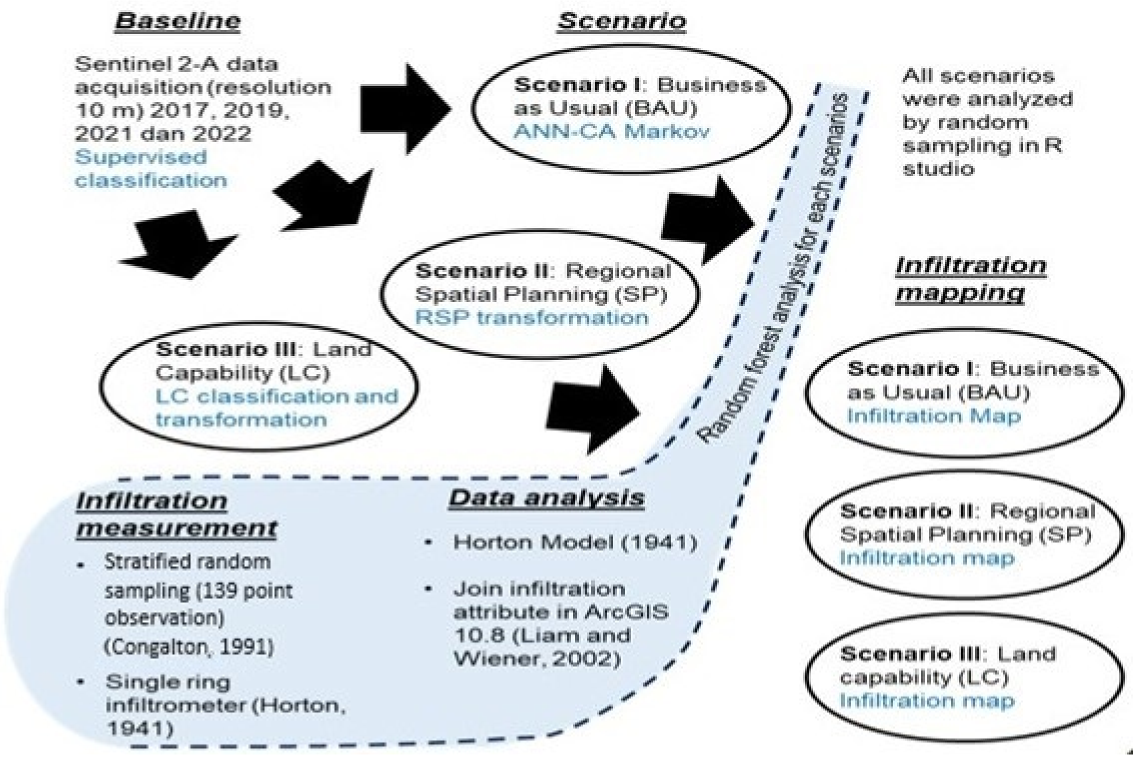

Figure 3. Research framework and scenarios

Business as Usual scenario. The BAU land use scenario represents land use and cover developments without intervention. Data on road area (https://tanahair.indonesia.go.id/) and land use for extraction built-up areas in 2022 are driving factors for BAU land use predictions. The land use prediction process was carried out using the ANN CA Markov method in QGIS 2.18 software using the MOLUSCE plugin. The 2019 and 2021 LU classification results and the driving factors for roads and built-up areas are used as material for analysis. Land use prediction simulations are carried out for 2022, and validation is carried out before making predictions for 2025. The 2022 land use prediction map is then validated with a 2022 map of land use classification result and tested for accuracy (ground check) at the validation stage. If the model has a Kappa value of more than 70%, it can predict land-use change in 2025 **[40]**.

Regional Spatial Planning scenario. The Regional Spatial Planning (RSP) scenario includes policies, strategies, plans and directions for spatial patterns for 20 years prepared by the government (Ministry of Agrarian Affairs and Spatial Planning/Head of the National Land Agency, 2018). The RSP map was obtained from the Directorate General of Spatial Planning (https://gistaru.atrbpn.go.id/), including the RSP Map for Batu City 2010–2030, the Spatial Planning Map for Malang Regency 2010, the RSP Map for Mojokerto Regency 2012–2032, the RSP Map for Blitar Regency 2011–2031, and the Spatial Pattern Plan Map for Pasuruan Regency 2029. The RSP map is then rectified and digitised according to the spatial pattern on each RSP map. The naming of land uses on the RSP map is adjusted to the classification results according to **Figure 4**.

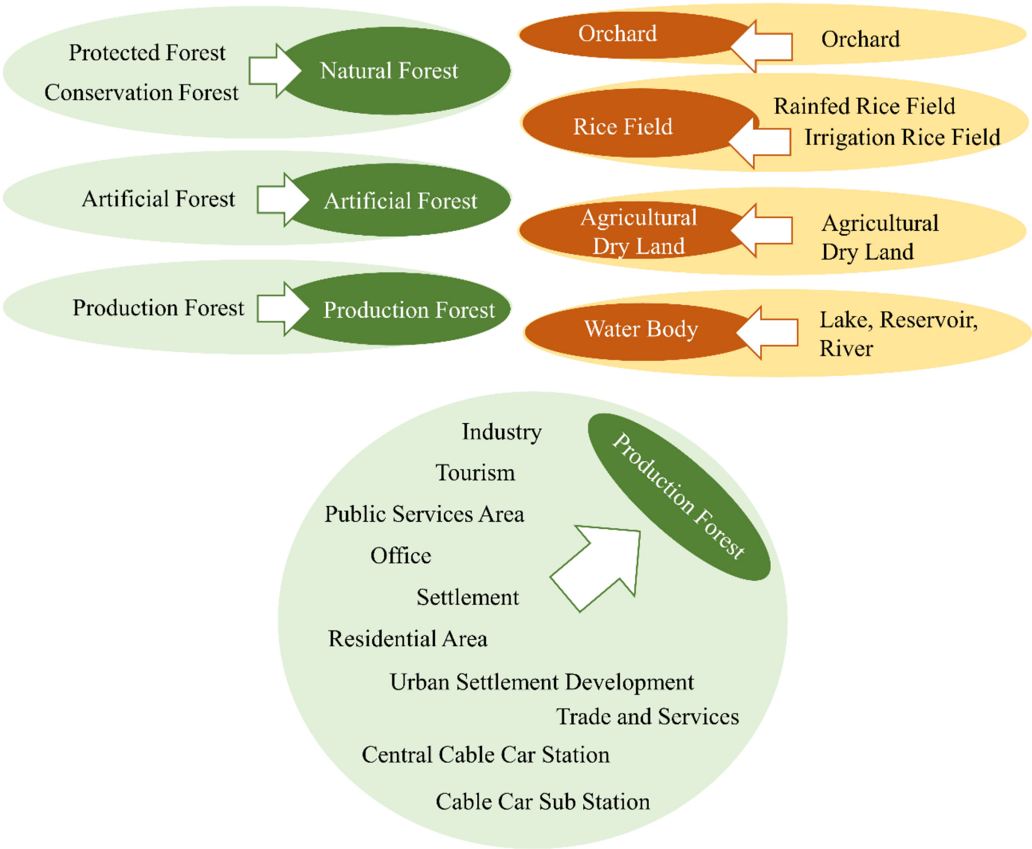

Figure 4. Regional Spatial Planning transformation to Land Use classification

Land capability class scenario. The LC scenario refers to grouping potential land to support sustainable agriculture based on the land characteristics [41]. Land Capability Class (LC) maps were prepared using a 1:50,000 scale Land System Map as a secondary data source from soil texture maps, drainage maps, permeability maps, and effective depth maps [42] and DEMNAS BIG data (https://tanahair.indonesia.go.id/demnas/) for slope maps. The limiting factor maps were combined and then analysed using the Klingebiel and Montgomery method [43]. The designation of land use for each class is I (Settlement, Paddy Field, Water Body), II (Agricultural dry land), III (Agricultural dry land), IV (Agricultural dry land and Orchards), V (Orchards), VI (Production Forest), VII (Natural Forest, Shrub, Grassland) and VIII (Natural Forest, Shrub, Grassland).

Infiltration measurement and calculation

Infiltration rate values were obtained through field measurements at 36 points, distributed using a stratified random sampling method representing 11 types of land use (**Figure 1**). Infiltration measurements were carried out using the single-ring infiltrometer method, which can describe infiltration in the soil [44].

The average infiltration rate [45] was calculated using the Horton equation [28].

$$ft = \Delta h / \Delta t \tag{1}$$

Where ft is the infiltration rate [cm h^{-1}], Δh is the lowering of the water level [cm], and Δt is the measurement time [h]. The validation test was carried out using a paired t-test at Rstudio.

Random forest analysis and model validation

Infiltration mapping in the Sumber Brantas and Kali Konto sub-watershed areas was done using random forest analysis in the R Studio software [28]. The data needed in the random forest analysis are infiltration measurements and land use data at observation points in the field. As much as 80% of infiltration data from measurements in the field is used for model development, and 20% of infiltration data from the field is used for validation. Infiltration mapping was carried out based on land use scenarios to obtain infiltration maps for 2017, 2019, 2021, 2022, and 2025 (BAU), infiltration maps based on LCs, and infiltration maps based on RSP. Spatial data for the random forest model was created using R software packages, including rsample, random forest, ranger, caret, and snow. Spatial data manipulation was done using R packages raster, rgeos, sf, sp, rgdal, classInt, ggmap, tmap, leaflet, and ggpubr [28].

The validation test compared the infiltration model with the infiltration value measured in the field. The validation test method is the Nash-Sutcliffe Model Efficiency Coefficient (NSE) [46]. The NSE method efficiently evaluates rainfall-runoff models for estimating infiltration [28]. The NSE score criteria are divided into good (above 0.75), acceptable (0−0.75), and bad (below 0).

RESULTS AND DISCUSSION

The Results and Discussion section represents the pivotal phase of this study, where we delve into the outcomes of land use changes across different scenarios, infiltration data analysis, infiltration modelling, the interconnectedness of land use with infiltration, and the inherent limitations of this research.

Land Use Land Cover changes and accuracy assessment

Forest areas of 2017 were identified as the main land use, covering 31% of the Sumber Brantas and Kali Konto sub-watersheds. The dominant land use type is natural forest (12,855 ha). Dry land agriculture was identified as the second largest land use (8,683 ha), followed by production forest (8,637 ha), orchards (3,646 ha), and built-up areas (3,533 ha). Using the supervised method used in 2017, the Land Use Land Cover (LULC) classification in 2022 will produce 18 LULC species in the Sumber Brantas and Kali Konto sub-watersheds. Dryland farming is the dominant land use (9,439 ha). In comparison, natural forest was identified as the second largest land use (9,366 ha), followed by orchards (8,688 ha) and built-up areas (4,981 ha).

A multi-temporal comparison of land use (2017–2022) shows some land-use configuration changes. Natural and production forests decreased by 3,489 ha and 4,661 ha, respectively. On the other hand, the built-up area has increased by 1,555 ha. On agricultural land, agroforestry has decreased by 110 ha. Meanwhile, paddy fields experienced an increase of 488 ha. Details of changes in the 18 types of LULC from 2017 to 2022 are presented in Figure 5 and Figure 6.

The Kappa accuracy test results for the 2022 LULC classification show a value of 0.79, which is included in the excellent category [47] so that the 2017 to 2022 classification can be used as a baseline, followed by three land use scenarios consisting of Business as Usual (BAU) in 2025, Regional Spatial Planning (RSP), and Land Capability Class (LC).

Based on the results of the LULC classification (2017–2022), it can be seen that mosaics typical of mountainous areas are found in the Sumber Brantas and Kali Konto sub-watersheds. The upper slope is included in the Tahura or Perhutani area, which is dominated by land use in the form of natural forest and production forest and shrubs. The middle slope is dominated by land use in the form of plantations, several villas, and tourist buildings. Meanwhile, the lower slopes are dominated by seasonal crops (agricultural dry land fields and paddy fields) and built-up areas.

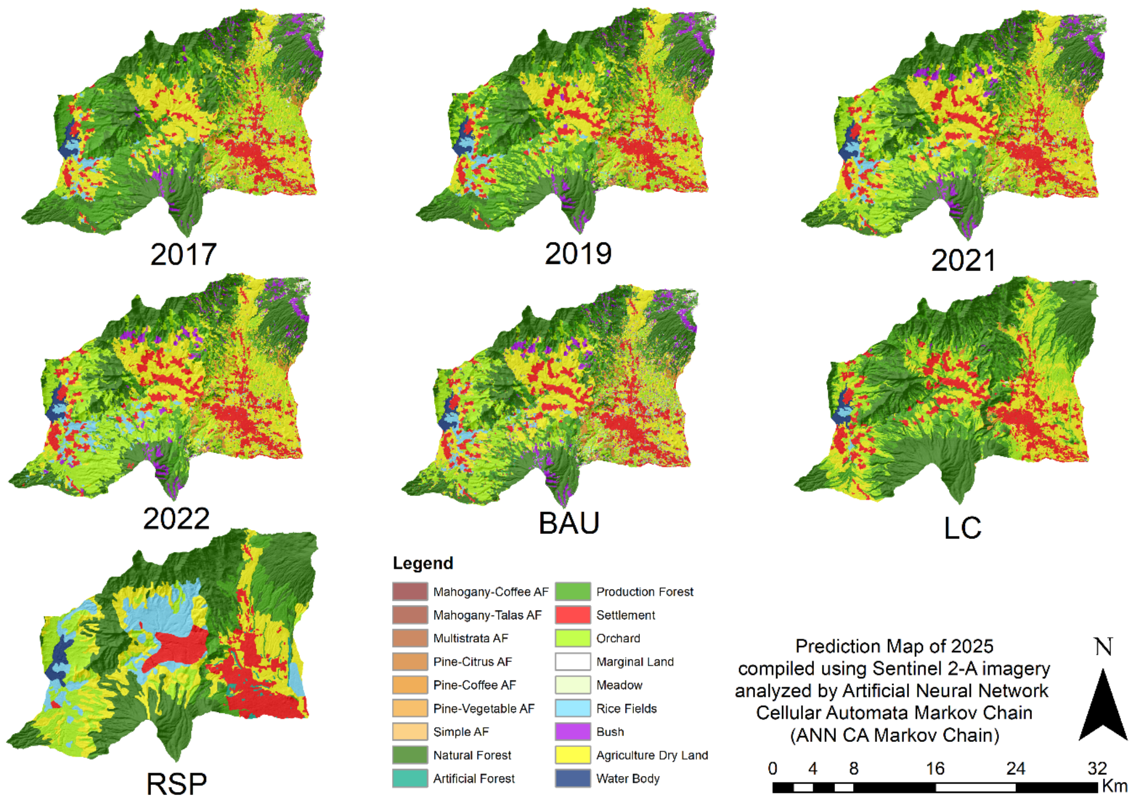

Figure 5. Land use change patterns 2017–2022 and land use scenarios

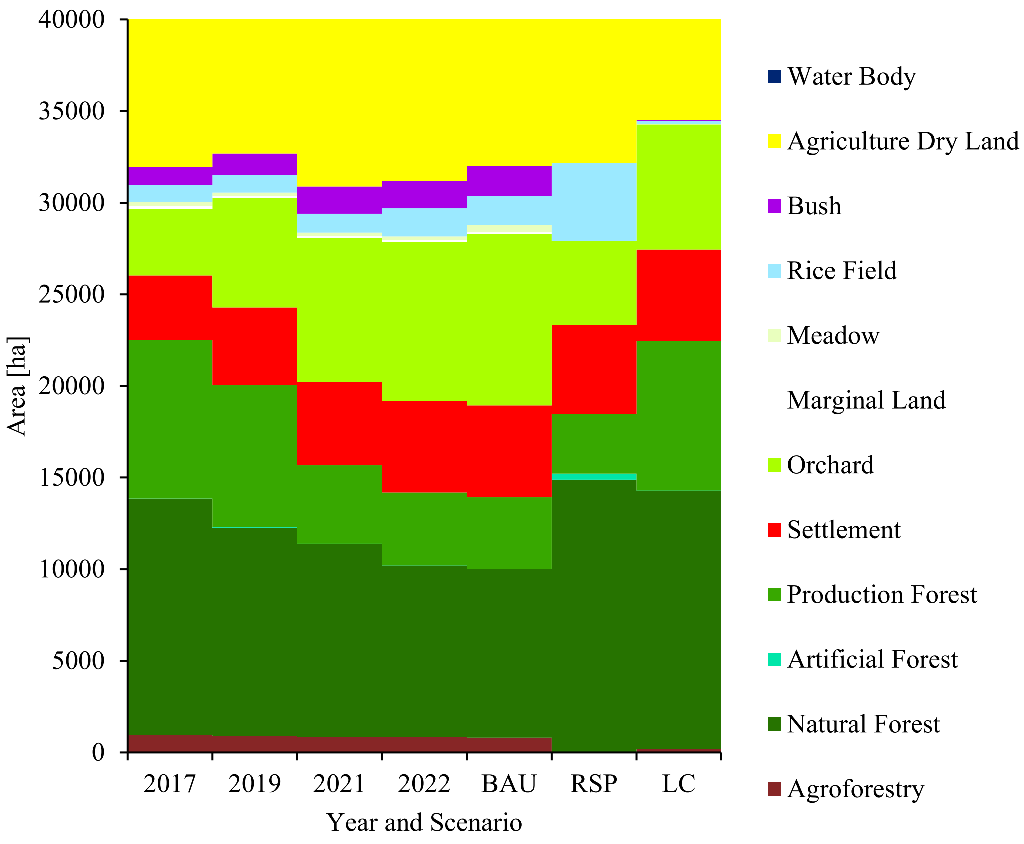

Figure 6. Graph of 2017–2022 land use areas and scenarios

Land use scenarios

The analysis results of land use in 2019 and 2021 are used to predict land use in 2025 using the ANN Cellular Automata-Markov Chain, showing a Kappa accuracy rate of 82% and is included in the excellent category [48]. Orchard land use will dominate 22.82% of the sub-watershed area in 2025, with a changing pattern of decreasing natural forest area and production forest (2%) followed by agroforestry (4%) and increasing built-up area (1%) from 2022. The pattern predictions of changes in land use like this will also occur in Selangor, Malaysia, in 2031, 2041, and 2051, which state that there has been a decrease in the area of forest area of 1,357.74 ha and an increase in the built-up area of 2,585.08 ha since 1991 [19].

There are vast differences in the use of existing land (2022), the 2025 scenario, and RSP because of population growth, which encourages the development of built areas and infrastructure (roads), as well as agricultural land, to meet the economic needs of the community [49]. Meanwhile, land incompatibility based on LCs and existing land occurs due to human intervention in cultivating land [50], land clearing, or land not following its designation due to population density factors [51].

Infiltration data

Variations in infiltration rates in the Sumber Brantas sub-watershed and Kali Konto sub-watershed are strongly influenced by the land use type, Figure 7. The natural forest in the two sub-watersheds has the highest infiltration value compared to other land uses. Artificial forests, production forests, agroforestry and orchards are in the same class as natural forests. However, there is a tendency where the quality of cover decreases and the rate of infiltration decreases. One of the many factors that affect a watershed's rate of infiltration is management and land cover, which are typically linked to the characteristics of the soil. Rainfall volume, infiltration rate, and surface runoff correlate with soil infiltration [52]. Suppose the phenomenon increases the level of soil density. In that case, it is likely to slow down soil infiltration because the level of management with a certain intensity has to change the soil moisture level, affecting how much water can be absorbed into the soil [53].

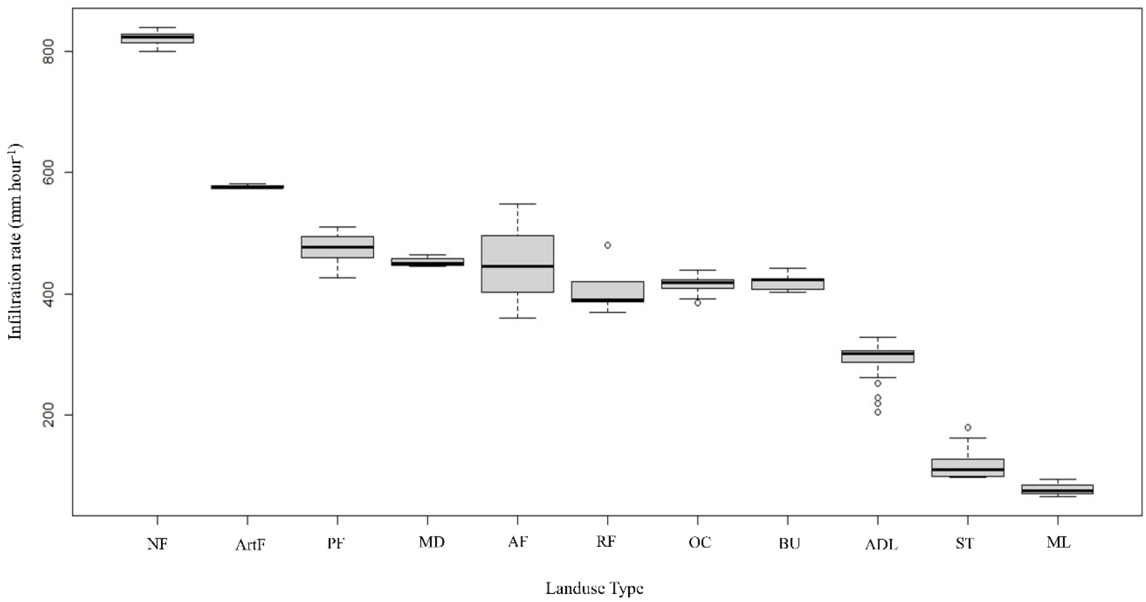

Figure 7. Infiltration rate for each land use (NF: Natural Forest; ArtF: Artificial Forest; PF: Production Forest; MD: Meadow; AF: Agroforestry; RF: Rice Field; OC: Orchard; BU: Bush; ADL: Agricultural Dry Land; ST: Settlement; ML: Marginal Land)

Classification very quickly entered into agroforestry land use, natural forest, artificial forest, production forest, orchards, grasslands, paddy fields, and shrubs. Fast infiltration rates are found in land use in built-up and agricultural dry land areas, while infiltration rates are relatively fast in vacant land use. The faster the infiltration rate, the better the absorption capacity of the land [54]. Land use is quickly dominated by forest land and dense vegetation. Trees can increase soil pores and soil organic matter due to a large amount of litter and tree roots, thus influencing the rate of soil infiltration [28].

The Sumber Brantas and Kali Konto sub-watersheds are volcanic regions surrounded by active and inactive volcanoes. Volcanic eruption activity with various materials significantly impacts soil formation in these two sub-watersheds, resulting in a variety of parent materials and resulting variances in soil texture characteristics. Soil texture also influences the results of observations of soil infiltration rates. The soil texture at the study site is dominated by clay loam, loam, and sandy loam textures. Soil texture is related to the number of soil pores. The coarser the soil texture, the more macro pores it has, so the water can enter the soil faster [55]. The fine soil fraction can inhibit water movement because when the soil is moist, it expands and closes the pore spaces [56]. Compared to soil with a lot of clay, soil with lots of macropores makes it faster for water to infiltrate the soil [57].

Random forest infiltration model results

The results of the infiltration analysis were categorised into three classes: very slow, somewhat fast, and very fast. The infiltration rate class in 2017 was dominated by the very fast class, covering 36,958.40 ha (90.27%); the rather fast class, covering 3,679.18 ha (8.99%); and the very slow class (body of water), covering 305.88 ha (0.75%). In 2019, the infiltration distribution was dominated by the very fast class covering 36,284.56 ha (88.62%), the rather fast class covering 4,351.51 ha (10.63%), and the very slow class (body of water) covering 307.39 ha (0.75%). In 2021, the distribution of infiltration was dominated by the very fast class with an area of 35,547.69 ha (86.82%), the rather fast class with an area of 5,091.12 ha (12.43%), and the very slow class of 304.65 ha (0.74%). Meanwhile, in 2022, the infiltration rate class will be dominated by the very fast class covering 35,547.69 ha (86.82%), the rather fast class covering 5,091.12 ha (12.43%), and the very slow class covering 304.65 ha (0.74%).

Based on the results of the BAU 2025 scenario, the speedy class dominates the distribution of infiltration with an area of 35,413.23 ha (86.49%), the relatively fast class of 5,239.38 ha (12.8%), and the prolonged class (water body) with an area of 290.85 ha (0.71%). Meanwhile, in the RSP scenario, the high-speed category is dominated by 35,567.76 ha (86.87%), the relatively fast class is 4,864.98 ha (11.88%), and the prolonged class (body of water) is 510.78 ha (1.25%). Meanwhile, based on the LC scenario, the broadest distribution of infiltration is in the high-speed class, with an area of 40,604.33 ha (99.17%), and the prolonged class (body of water), with an area of 339.13 ha (0.83%) (**Figure 8** and **Figure 9**).

Random forest algorithms can be used for classification (discrete data) or regression (continuous data) [58]. This technique was chosen because of its ability to model non-linear relationships, handle multicollinearity, reduce model overfitting, and consider qualitative and quantitative variables [59]. The random forest consists of a bagging method with random feature selection to produce a decision tree, and each decision tree will predict the response or class. The final prediction result is calculated based on the average response of each tree. Compared to the single tree method, the bagging method in the random forest can reduce the variance in the estimation of the predictive function [60].

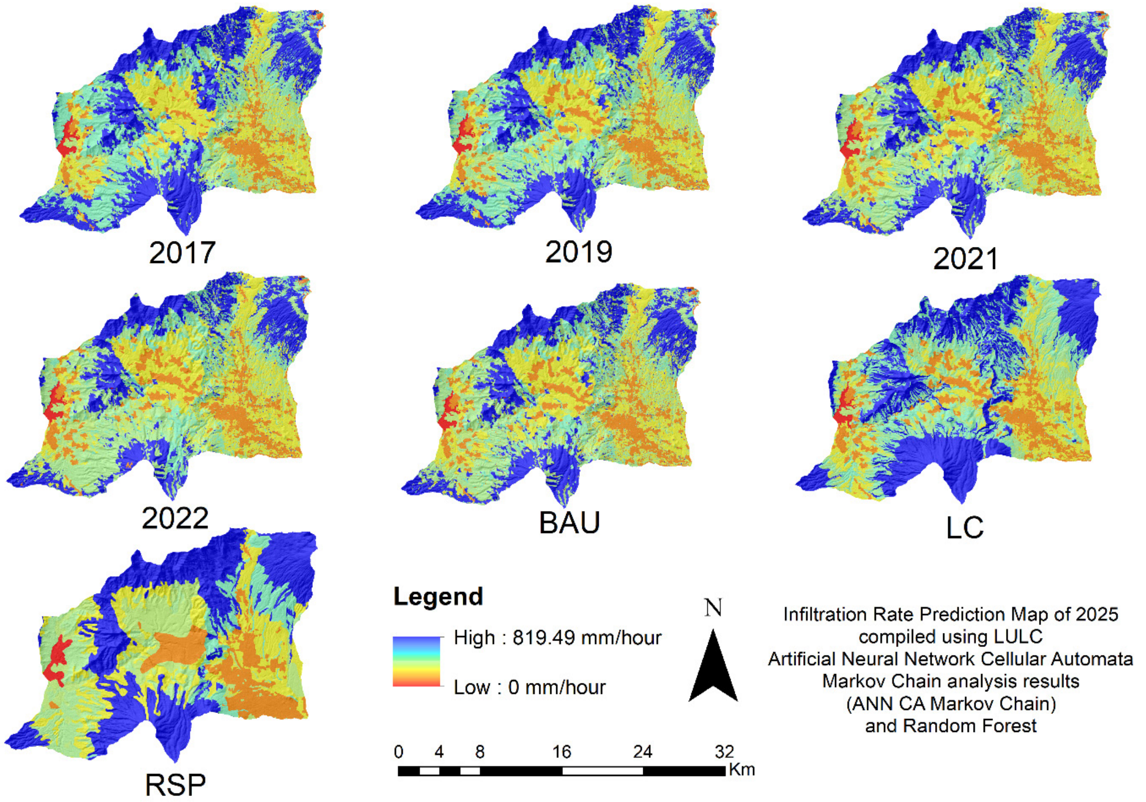

Figure 8. Map of infiltration distribution in the Sumber Brantas and Kali Konto sub-watersheds

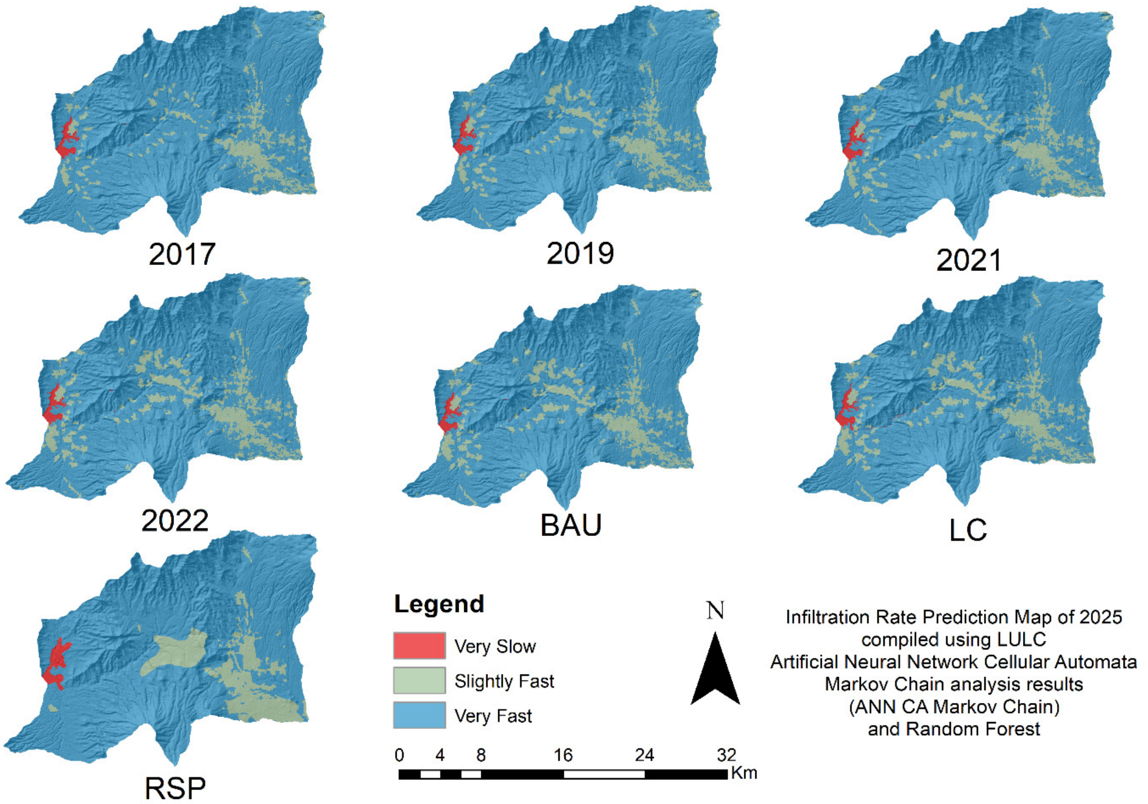

Figure 9. Map of infiltration rate classes in the Sumber Brantas and Kali Konto sub-watersheds

Accuracy assessment

The validation test of the infiltration prediction model was carried out by comparing the results of infiltration predictions with the results of infiltration calculations in the field. The level of accuracy was calculated using the RMSE, NSE, and paired t-test methods. RMSE test results show a value of 51.73. While the results of the NSE test showed a value of 0.92, the model was considered good at predicting the distribution of infiltration [61]. Meanwhile, the paired t-test results show the value of t-count and t-table (0.02 and 1.81). It shows that the infiltration prediction results are not significantly different from the results of calculations in the field.

Land use baseline and infiltration

Baseline changes in land use in 2017–2022 will impact the distribution of soil infiltration. The area decreased in natural forest land and production forest, while the built-up area increased. This condition aligns with the decrease in the speedy infiltration rate class area while the relatively fast class continues to increase. The built-up area is synonymous with dense land and little vegetation, causing low soil porosity. The lower the porosity of the soil, the lower the opportunity for water to enter the soil [62]. In addition, the lack of vegetation and input of organic matter in built-up areas causes a lack of soil aggregation and protection of soil structure. As a result, the soil structure becomes unstable and easily damaged, inhibiting infiltration and permeability rates [63].

Infiltration response to different land use scenarios

Land-use scenarios also influence the distribution of soil infiltration. The type of stand in each scenario determines the depth and distribution of plant roots, which affect the soil infiltration rate [64]. In the BAU scenario, plantation land and built-up areas experience an increase in area from previously forest land. This condition aligns with the class increase in the relatively fast infiltration rate, and the class decrease is speedy. Coffee plantations have macropores and higher infiltration rates than cane fields in volcanic soils in Costa Rica [65]. The land is increasingly covered with vegetation impact capacity and higher infiltration rates due to increased porosity and soil organic matter content [66]. Land in built-up areas experiences soil compaction due to the construction of buildings and human activities, so soil porosity is low.

The increase in forest area occurred in the RSP and LC scenarios, so the class area increased very quickly. In the LC scenario, the land use types only consist of natural forests, production forests, orchards, and dry fields with a speedy infiltration class. As a result, the infiltration rate class in the LC scenario is dominated by the speedy class. Land use with woody plant stands has a broader distribution of roots and more macropores, positively impacting soil infiltration [67]. Forests have a more complex canopy arrangement than other, more open land uses. The existence of the canopy can intercept falling water droplets and produce much litter on the ground surface. This impact protects the soil from splashing water and holding water from reaching the surface to maintain the infiltration rate and capacity [68]. The litter produced by the canopy is a food source for soil fauna. The activities of soil fauna make the soil structure more brittle, so water can more easily enter the soil [69].

The best infiltration-friendly land use scenario

The results of the implemented scenarios show differences in the distribution of infiltration rate predictions in each scenario. Scenarios with the highest infiltration rate distribution were obtained sequentially in the LC, BAU, and RSP scenarios. The three scenarios have areas with a very high infiltration rate class that are quite broad, but the highest area is in the LC scenario. Applying the LC scenario increased the area with a speedy infiltration class by 20 ha (0.06%) compared to the BAU scenario and 94 ha (0.26%) compared to the RSP scenario. The LC scenario focuses on the physical ability of the land to be utilised continuously by minimising land degradation [70]. Based on each scenario's area, the LC scenario's application can be used as a reference for developing regional spatial planning to maintain the infiltration rate in the Sumber Brantas and Kali Konto sub-watersheds.

Limitation

The limitation of this article is that the research carried out was not compared to extreme dry seasons, so it is not known what the trends in the rate and extent of each level of infiltration are under these conditions. Apart from that, the infiltration value has only taken some years because it uses a baseline in 2022 to see the effect of land use. We suggest further research that will refer to this work to conduct it under several conditions (dry and wet seasons).

CONCLUSIONS

Several LULC scenarios in this study aim to determine the effect on the level of soil infiltration. The main driving factors for changes in LULC in the Sumber Brantas and Kali Konto sub-watersheds are a decrease in the area of natural forest and production forest and an increase in built-up area, which contributes to a decrease in the level of soil infiltration and has an impact on increasing surface runoff. The results of the BAU, RSP, and LC scenarios in this study provide information on the level of soil infiltration in the future. The BAU scenario reduced soil infiltration by 0.3%, while the RSP and LC scenarios increased soil infiltration by 0.05% and 14.22%, respectively. The LC scenario is the best land use scenario that can increase the area of soil infiltration in the Sumber Brantas and Kali Konto sub-watersheds. Infiltration distribution modelling has a high level of accuracy to provide accurate information about infiltration values in the field. Therefore, it can be used to determine the impact of various LULC scenarios on soil infiltration rates and as a basis for determining the best land use.

ACKNOWLEDGMENTS

The authors acknowledge the work and support of the internal funding (PNBP) of the Faculty of Agriculture, University of Brawijaya, with contract number 4108.22/UN10.F04/PN/2022.

NOMENCLATURE

ft	infiltration rate	[cm h^{-1}]
Δh	lowering of the water level	[cm]
Δt	measurement time	[h]

Abbreviations

ANN-CA	Artificial Neural Network-Cellular Automata
BAU	Business as Usual
GPS	Global Positioning System
LC	Land Capability Class
LULC	Land Use Land Cover
NSE	Nash-Sutcliffe Model Efficiency Coefficient
RMSE	Root Mean Square Error
RSP	Regional Spatial Planning
S2A	Sentinel 2A

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Paper submitted: 25.07.2023
Paper revised: 16.10.2023
Paper accepted: 18.10.2023