



## **Innovative Data Integration for Resilient Irrigation Planning and Food Security: A Remote Sensing and AI-Based Approach**

Salwa Rizqina Putri

Politeknik Statistika STIS, Jakarta, Indonesia – salwa@stis.ac.id

Natasya Afira

BPS-Statistics Indonesia, Jakarta, Indonesia – natasya.afira@bps.go.id

Yoga Cahya Putra

BPS-Statistics Indonesia, Jakarta, Indonesia – putra.yoga@bps.go.id

Fauzan Faldy Anggita

BPS-Statistics Indonesia, Jakarta, Indonesia – fauzanfaldy@bps.go.id

Jafar Husaini Aziz

BPS-Statistics Indonesia, Jakarta, Indonesia – jafar.aziz@bps.go.id

Arie Wahyu Wijayanto

Politeknik Statistika STIS, Jakarta, Indonesia – ariewahyu@stis.ac.id

### **Abstract**

Ensuring resilient agri-food systems requires integrated environmental monitoring, digital innovation, and policy-relevant statistics. In East Java—Indonesia’s largest rice-producing province with over 9.27 million tons of rice production in 2024—drought remains a major challenge, particularly for the 488,000 hectares of rainfed rice fields. During the 2024 dry season, more than 31,000 hectares were affected by drought, including nearly 8,000 hectares with complete crop failure. This study develops an integrated framework combining remote sensing, geospatial analytics, Input–Output (I/O) modeling, and Generative AI through the development of AgriPolicy AI for evidence-based irrigation planning. A Water Deficit Risk Score was constructed using six satellite-derived indicators: precipitation, land surface temperature, soil moisture, evapotranspiration, NDVI, and Solar-Induced Fluorescence (SIF). Using entropy gain weighting at 500-meter resolution, the analysis captures spatial and seasonal drought patterns across Malang, Lumajang, and Jember. Results show that drought risk intensifies during the dry planting season, especially in upland and rain-shadow areas. By integrating drought risk, water availability, and irrigation proximity, the study calculates a Irrigation Rehabilitation Priority Index to identify intervention areas. Economic simulations further indicate that irrigation rehabilitation can increase agricultural output, household income, and rural employment. The framework demonstrates how remote sensing, official statistics, and AI can support resilient irrigation planning and agricultural policymaking in climate-vulnerable regions.

**Keywords:** agricultural statistics, food security, resilience, irrigation, remote sensing, digital agriculture, Generative AI, geospatial integration, policy support

### **1. Introduction**

Agriculture plays a critical role in ensuring food security, rural livelihoods, and economic stability, particularly in developing countries where a significant proportion of the population depends on the agricultural sector (Pawlak and Kołodziejczak, 2020). However, climate

The authors declare that this manuscript and all accompanying materials are original and free from copyright violations.

change, drought, and increasing pressure on water resources continue to threaten agricultural sustainability, including in Indonesia (Aldyan, 2023). Because much of Indonesia's agriculture still relies heavily on rainfall and irrigation availability, climate variability directly affects agricultural productivity and national food security. Within this context, East Java Province represents one of Indonesia's most strategic agricultural regions. In 2024, the agricultural sector contributed approximately 10% of East Java's Gross Regional Domestic Product (GRDP), while rice production reached more than 9.27 million tons, making East Java the country's largest rice-producing province (BPS Statistics Indonesia, 2024).

Despite its strategic importance, East Java remains highly vulnerable to drought and climate variability. According to the 2023 Agricultural Census, more than 4 million agricultural business units in East Java still rely primarily on rainfall as their main irrigation source. During the 2024 dry season, more than 31,000 hectares of rice fields were affected by drought, including nearly 8,000 hectares experiencing complete crop failure (East Java Provincial Agriculture and Office, 2024). East Java's geographical position within a rain-shadow zone and its strong exposure to El Niño events further intensify drought conditions (Ahmad et al., 2022; Mulyanti et al., 2023). These conditions highlight the importance of irrigation development and rehabilitation to maintain agricultural productivity and strengthen food security.

The Indonesian government has prioritized irrigation infrastructure optimization through various national food security programs, including Presidential Instruction No. 2 of 2025 on irrigation rehabilitation and planting area expansion. Nevertheless, irrigation planning and rehabilitation in many regions remain constrained by limited spatial data integration and insufficient evidence-based policy support (Raihan and others, 2024; Ali et al., 2026). Although Geographic Information Systems (GIS), remote sensing, and drought monitoring techniques have increasingly been applied in agriculture, their integration into irrigation policy evaluation systems remains limited in Indonesia.

Recent advances in remote sensing provide important opportunities to improve irrigation planning and agricultural monitoring. Previous studies demonstrated that satellite-derived indicators such as precipitation, Land Surface Temperature (LST), Soil Moisture Index (SMI), evapotranspiration, Normalized Difference Vegetation Index (NDVI), and Solar-Induced Fluorescence (SIF) are effective for drought detection and crop water monitoring (Sun et al., 2023). Remote sensing has also been widely used for irrigation mapping, soil moisture estimation, and crop stress detection through Sentinel, MODIS, and TerraClimate imagery (Maselli et al., 2020). Studies in Indonesia further demonstrated that integrating GIS and remote sensing improves spatial irrigation planning and drought monitoring (Putri et al., 2024).

In addition to spatial analysis, Input–Output (I/O) modeling has been widely used to evaluate the economic impacts of irrigation investment. Previous studies found that irrigation infrastructure contributes significantly to agricultural output, household income, and employment creation while generating multiplier effects on manufacturing, trade, and service sectors (Geda, 2023). However, studies integrating remote sensing, geospatial analysis, and economic simulation within a unified irrigation planning framework remain relatively limited.

At the same time, developments in Generative Artificial Intelligence (AI) create new opportunities for evidence-based policymaking. Generative AI systems are increasingly capable of transforming complex spatial and statistical information into adaptive policy recommendations and scenario simulations (Vamvakas et al., 2025). Applications such as Microsoft AI for Earth and Copilot for Agriculture demonstrate the potential of AI-integrated policy support systems in water management and agriculture (FAO, 2023). Nevertheless, the

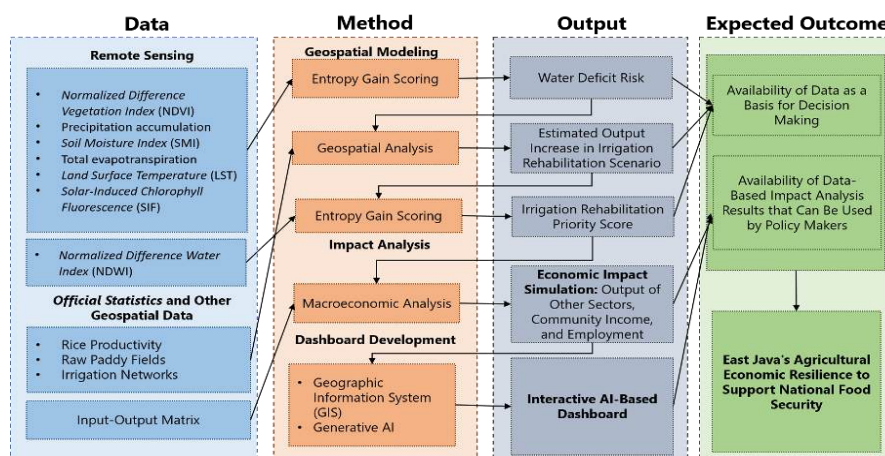
integration of Generative AI into irrigation planning and geospatial economic simulation remains underexplored, particularly in the Indonesian context.

Therefore, this study develops an integrated framework combining remote sensing, geospatial analysis, Input–Output modeling, and Generative AI to support evidence-based irrigation planning and food security in East Java Province. The study aims to calculate agricultural water shortage risk scores, estimate rice production increases under irrigation rehabilitation scenarios, calculate Priority Irrigation Rehabilitation Score, simulate economic impacts using the East Java Input–Output Matrix, and develop a web-based dashboard integrating spatial visualization, economic simulation, and an AI-based policy co-pilot. The study contributes by integrating remote sensing, economic modeling, and AI-driven policymaking into an adaptive framework for resilient irrigation planning and sustainable agri-food development.

## 2. Methods

### 2.1. Research Framework

**Figure 1** illustrates the research framework of this study. The initial stage begins with the collection of primary datasets, including satellite imagery (NDVI, LST, SMI, SIF, evapotranspiration, NDWI, and precipitation), geospatial data such as official rice field maps and irrigation networks, as well as agricultural productivity statistics and Input–Output Matrix data. These datasets are then processed through geospatial modeling using the entropy gain method to calculate agricultural water shortage risk scores, followed by geospatial analysis to estimate potential rice production increases under irrigation rehabilitation scenarios and the development of Irrigation Rehabilitation Priority Index. Subsequently, the study conducts economic impact analysis through a macroeconomic approach using the East Java Input–Output Matrix to simulate the effects of irrigation interventions on cross-sectoral output, household income, and employment. All analytical outputs are presented through an interactive dashboard integrating Geographic Information Systems (GIS) and Generative AI, providing spatial visualization, impact simulation, and a policy co-pilot feature to support data-driven policymaking. Overall, this framework is intended to generate comprehensive and applicable information to support the agricultural economic resilience of East Java as one of the pillars of Indonesia’s national food security.

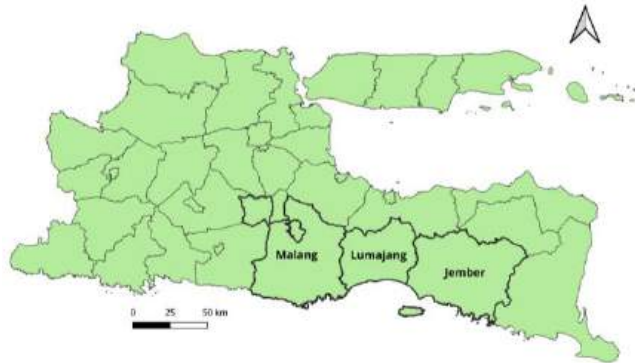


**Figure 1.** Research Framework

### 2.2. Case Study

**Figure 2** presents the case study location map covering three strategic districts in East Java: Malang, Lumajang, and Jember. These districts were selected because they are among the

major rice-producing regions in East Java. From a policy perspective, all three districts are also included as irrigation rehabilitation priorities through the IDR 45.4 billion Special Allocation Fund (DAK) designated for the rehabilitation of irrigation areas covering 5,281 hectares in 2025, including pumping irrigation initiatives and weir revitalization projects in Jember.



**Figure 2.** Research Case Study (Malang, Lumajang, and Jember Districts)

### 2.3. Data and Data Sources

This study utilizes two primary categories of data: remote sensing satellite imagery and official statistics combined with supporting geospatial datasets.

#### 2.3.1. Data Remote Sensing

**Table 1** summarizes the satellite datasets used in this study to construct agricultural water requirement indicators.

**Table 1.** Remote Sensing Data Used in This Study

Proxy Indicator	Data	Satellite Source	Update Period	Spatial Resolution
Vegetation Condition	<i>Normalized Difference Vegetation Index (NDVI)</i>	Sentinel-2 ( <a href="#">Link</a> )	5 days	5 days
Precipitation	<i>Precipitation accumulation</i>	Terra-Climate ( <a href="#">Link</a> )	1 month	4638.3 meters
Soil Moisture	<i>Soil Moisture Index (SMI)</i>	Sentinel-2 ( <a href="#">Link</a> )	5 days	10 meters
Crop Evapotranspiration	<i>Total evapotranspiration</i>	Terra-MODIS ( <a href="#">Link</a> )	8 days	500 meters
Land Surface Temperature	<i>Land Surface Temperature (LST)</i>	Terra-MODIS ( <a href="#">Link</a> )	8 days	500 meters
Chlorophyll Fluorescence	<i>Solar-Induced Chlorophyll Fluorescence</i>	GOSIF GPP ( <a href="#">Link</a> )	8 days	5566 meters
Water Availability	<i>Normalized Difference Water Index (NDWI)</i>	Sentinel-2 ( <a href="#">Link</a> )	5 days	10 meters

#### 2.3.2. Official Statistics and Supporting Geospatial Data

**Table 2** summarizes the official statistical and supporting geospatial datasets used in this study.

**Table 2.** Official Statistics and Supporting Geospatial Data Used in This Study

Data	Description	Data Source
Agricultural Productivity	Rice production (quintals) per hectare of land	East Java BPS Statistics Indonesia, 2024
Input–Output Matrix	Quantitative table describing intersectoral economic relationships used to analyze the impacts of sectoral changes on output, income, and employment	East Java BPS Statistics Indonesia, 2020
Administrative SHP	Official administrative boundary shapefiles used in planning and government administration	BPS Statistics Indonesia
Official Rice Field SHP	Official rice field area shapefiles based on maps and administrative data	Indonesia Geospatial Information Agency (BIG)
Irrigation Network SHP	Primary and secondary irrigation network shapefiles	Indonesia Geospatial Information Agency (BIG)

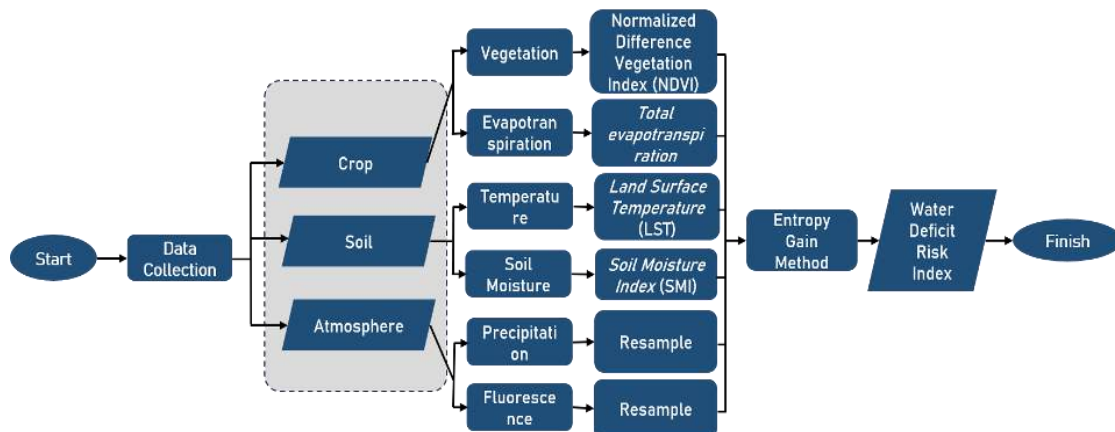
## 2.4. Analytical Methods

This study consists of five integrated analytical stages. The first stage calculates agricultural water shortage risk scores using six remote sensing-based variables at a 500-meter spatial grid unit. The second stage models estimated rice production increases under irrigation rehabilitation scenarios assuming optimal water fulfillment in affected areas. The third stage calculates Priority Irrigation Rehabilitation Score by integrating potential production increases, groundwater availability within a 5 km radius, and distance to existing irrigation networks. The fourth stage analyzes the economic impacts of irrigation interventions using the East Java Input–Output Matrix to measure impacts on output, household income, and employment absorption. Finally, the fifth stage develops a web-based dashboard that visualizes analytical results and provides a Generative AI-based policy co-pilot feature to support interactive and evidence-based policymaking.

### 2.4.1. Agricultural Water Shortage Risk Score Calculation

The agricultural water shortage risk score in this study is calculated using a multivariate indicator framework adapted from (Liu et al., 2020), which recommends six remote sensing-based variables for detecting agricultural drought spatially and temporally. These variables include: (a) Normalized Difference Vegetation Index (NDVI) to measure vegetation health, (b) Total Evapotranspiration as a proxy for water loss through soil and plants, (c) Land Surface Temperature (LST) to monitor surface heat accumulation, (d) Soil Moisture Index (SMI) as an indicator of soil moisture conditions, (e) monthly precipitation, and (f) Solar-Induced Chlorophyll Fluorescence (SIF) to capture crop photosynthetic efficiency. All variables are normalized to a 0–1 scale and analyzed within 500-meter spatial grids for each planting subround. This study applies the entropy gain method during variable integration because it provides objective weighting based on the information diversity of each indicator without requiring subjective prior assumptions. The method is considered superior for integrating heterogeneous variables and has been widely applied in composite index development within environmental and agricultural studies (Wu et al., 2022). The analytical process generates a final agricultural water shortage risk score, where values closer to 1 indicate higher water shortage risk levels. **Figure 3** presents the workflow diagram of the calculation process. The

final score serves as the basis for affected area mapping and irrigation intervention prioritization.



**Figure 3.** Agricultural Water Shortage Risk Score Calculation Workflow

#### 2.4.2. Rice Production Increase Estimation under Irrigation Rehabilitation Scenarios

The rice production increase estimation model in this study is designed to calculate additional potential harvest output if crop water requirements can be optimally fulfilled through irrigation rehabilitation or irrigation infrastructure development. The analysis is conducted at the 500-meter spatial grid level based on a combination of agricultural water shortage risk scores, productivity data per hectare from BPS, and official rice field area data from BIG. The model uses Equation (1) below:

$$\text{Potential Rice Production Increase} = (3 - \Sigma P) \times \text{Productivity} \times \text{Rice Field Area} \quad (1)$$

Where  $\Sigma P$  represents the reduction in harvest frequency (maximum of 3 harvests corresponding to each planting subround) caused by insufficient irrigation. Under the irrigation rehabilitation scenario, rice fields with high water shortage risk are assumed to experience complete crop failure ( $P = 0$ ), rice fields with moderate water shortage risk are assumed to lose 50% of harvests ( $P = 0.5$ ), and rice fields with low water shortage risk are assumed to lose 25% of harvests ( $P = 0.25$ ). Productivity data are calculated per hectare based on BPS statistics, while rice field area data are derived from official rice field maps (LBS).

#### 2.4.3. Irrigation Rehabilitation Priority Index Calculation

The Irrigation Rehabilitation Priority Index is calculated by considering three complementary variables. First, the estimated potential increase in rice production under irrigation rehabilitation scenarios, where higher values indicate greater urgency for intervention. Second, water availability within a 5 km radius of each spatial grid, calculated using a combination of the Normalized Difference Water Index (NDWI) and Soil Moisture Index (SMI); higher values indicate greater feasibility for irrigation development based on local water resources such as groundwater or small rivers. Third, spatial proximity to existing irrigation networks, which is assumed to influence rehabilitation cost and technical efficiency; areas located closer to existing networks receive higher scores. These variables are normalized and integrated using the entropy gain method, which assigns objective weights based on the diversity of information within each variable without subjective intervention. The final output is a quantitative irrigation rehabilitation priority map responsive to actual field conditions.

#### **2.4.4. Economic Impact Analysis Based on Input–Output Matrix for Irrigation Rehabilitation**

To measure the economic impacts of irrigation interventions, this study applies an East Java Input–Output (I/O) Matrix approach. The matrix describes intersectoral relationships within the regional economy and is used to simulate the impacts of changes in agricultural output—particularly rice production—on other sectors such as food and beverage manufacturing, trade, and agricultural services. Impact estimation is conducted through the calculation of output multipliers, income multipliers, and employment multipliers, reflecting the potential increase in income, employment creation, and output growth resulting from post-irrigation productivity improvements (Ariutama et al., 2022).

#### **2.4.5. Development of a Web-Based Dashboard Implementing Generative AI**

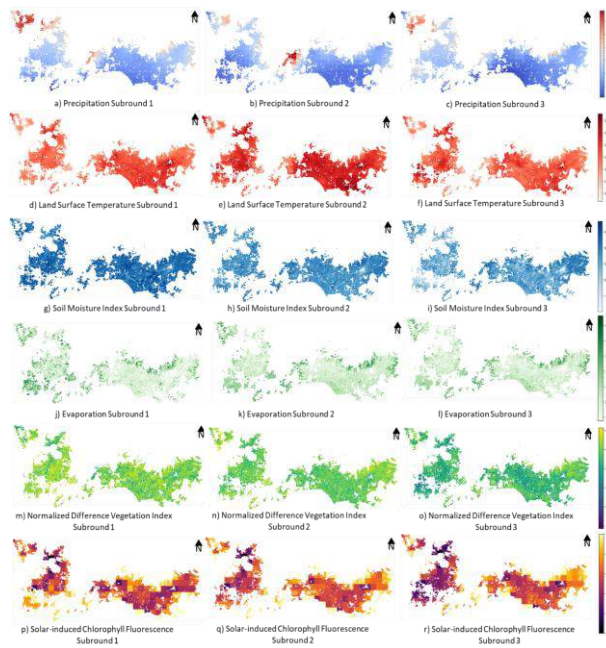
All spatial and economic analysis results are presented through an interactive web-based dashboard. The dashboard consists of three main components: visualization of risk and intervention priority maps, economic impact simulation based on the Input–Output Table, and a policy co-pilot implementing Generative Artificial Intelligence (AI). The co-pilot feature is designed to automatically generate policy narratives according to user needs. Using a retrieval-augmented generation (RAG) approach, the system can provide adaptive, concise, and context-sensitive policy recommendations useful for regional policymakers and technical planners (Binns et al., 2023).

### **3. Results and Discussion**

#### **3.1. Results of Agricultural Water Deficit Risk Score Calculation Based on Remote Sensing Variables**

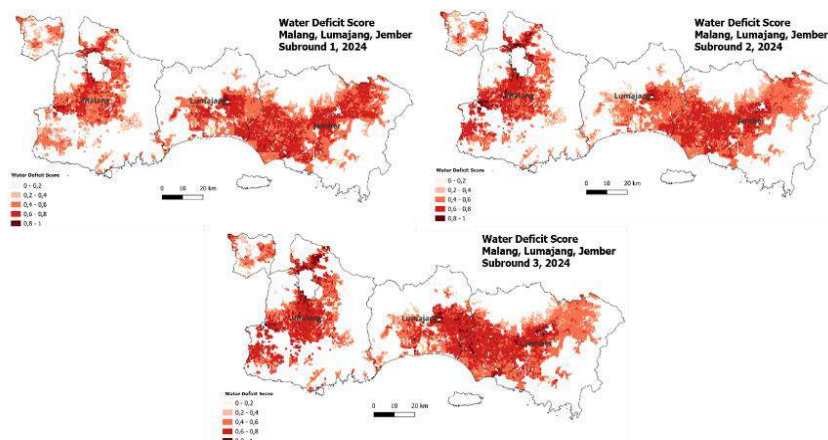
To ensure the sustainability of food production amid climate variability, irrigation system development and rehabilitation require decision-making processes supported by spatial data and agricultural water deficit risk assessments. Spatial and temporal analyses reveal dynamics consistent with the seasonal climate patterns of East Java, where fluctuations in these variables provide a comprehensive overview of crop water supply and water stress conditions in rice fields (**Figure 4**).

**Figure 4** shows that during Subround 2, there was a significant decline in precipitation values, reflecting the onset of the dry season in East Java. This decline was accompanied by an increase in Land Surface Temperature (LST), indicating increasing heat stress within agricultural ecosystems. This phenomenon is consistent with the monsoonal climate characteristics of tropical regions such as East Java, where rainfall trends decline significantly after late April while temperatures tend to increase (Handoko et al., 2020). Soil Moisture Index (SMI) and evapotranspiration values were highest during Subround 1, which corresponds to the peak rainy season in the study area. These conditions reflect abundant soil water supply and high water loss through evaporation, consistent with findings by (Prasetyo and Ardiansyah, 2021), who stated that during peak rainfall periods, rice fields experience excess water conditions that increase evaporation and soil moisture retention. NDVI and Solar-Induced Chlorophyll Fluorescence (SIF) values reached their lowest levels during Subround 3, coinciding with the peak dry season. Low NDVI values indicate reduced vegetation density and health caused by water deficits, while low SIF values reflect declining photosynthetic activity in rice plants due to drought stress. This finding is supported by the study of Chen et al., which explained that drought stress reduces chlorophyll fluorescence as a physiological response of plants to water scarcity.



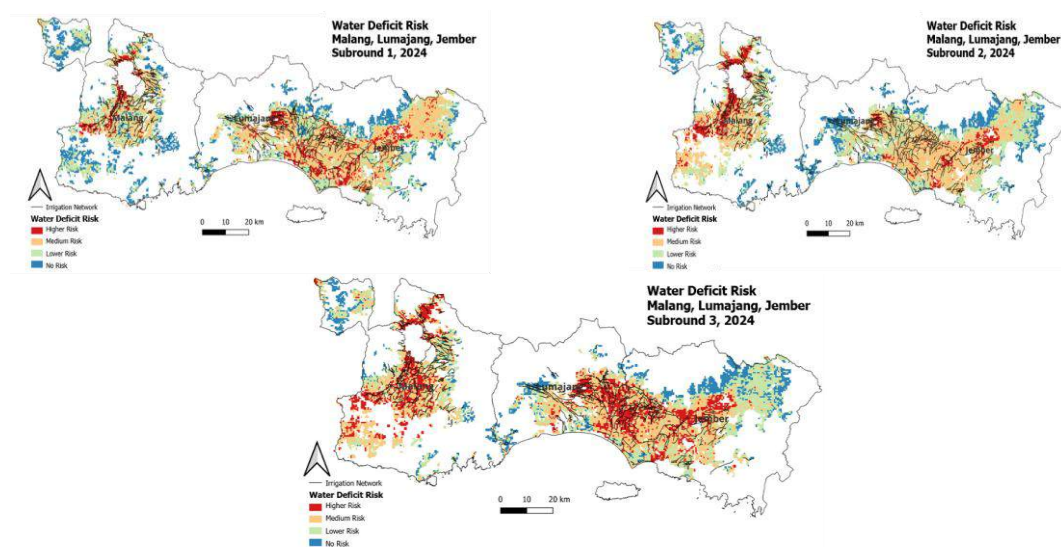
**Figure 4.** Variables Composing the Agricultural Water Deficit Risk Index

Atmospheric variables (precipitation and land surface temperature), hydrological variables (soil moisture and evapotranspiration), and crop biophysical variables (NDVI and chlorophyll fluorescence) were integrated to generate agricultural water deficit scores for 500-meter rice field grids across Malang, Lumajang, and Jember Regencies. The scores were calculated using the entropy gain method. **Figure 5** shows that agricultural water deficit risk generally increased from Subround 1 to Subround 3, following declining precipitation and worsening vegetation conditions during the dry season. **Figure 5** also shows that areas experiencing the highest increases in agricultural water deficit risk are spatially concentrated in the northern and western parts of Malang Regency, as well as the southern regions of Lumajang and Jember Regencies. This pattern indicates localized vulnerability to water shortages influenced by topographic conditions, limitations of existing irrigation infrastructure, and the spatial distribution of groundwater resources. These findings support the importance of spatial approaches in irrigation intervention prioritization, where areas experiencing high increases in water deficit risk can become primary targets for irrigation infrastructure development or rehabilitation in a more efficient and high-impact manner.



**Figure 5.** Agricultural Water Deficit Score

The agricultural water deficit risk in rice fields across Malang, Lumajang, and Jember Regencies was classified into four categories: no risk (0.0–0.5), low risk (0.5–0.75), moderate risk (0.75–0.9), and high risk (0.9–1.0), and overlaid with existing irrigation networks (Figure 6). The results show that water deficit risk increased significantly during Subround 2 and peaked in Subround 3 during the dry season. Despite the presence of technical irrigation systems, several areas in Lumajang, Malang, and Jember remained categorized as high-risk zones, indicating that irrigation infrastructure does not always ensure effective water distribution due to canal damage, water losses, or limited system capacity. These findings are consistent with rehabilitation initiatives highlighted by the Indonesian Ministry of Agriculture, the Ministry of Public Works and Housing, and the East Java Provincial Government in Lumajang, Malang, and Jember.

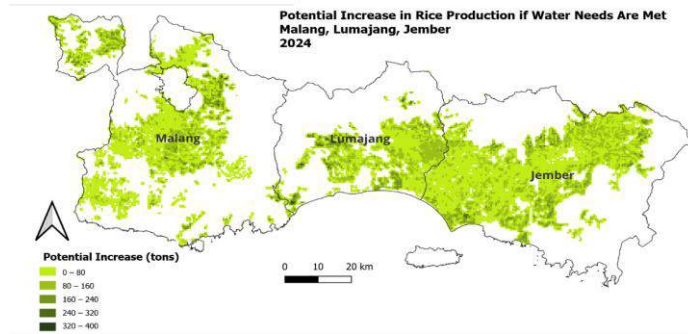


**Figure 6.** Agricultural Water Deficit Risk Score for Subrounds 1, 2, and 3

### 3.2. Estimated Rice Production Increase under the Irrigation Rehabilitation Scenario

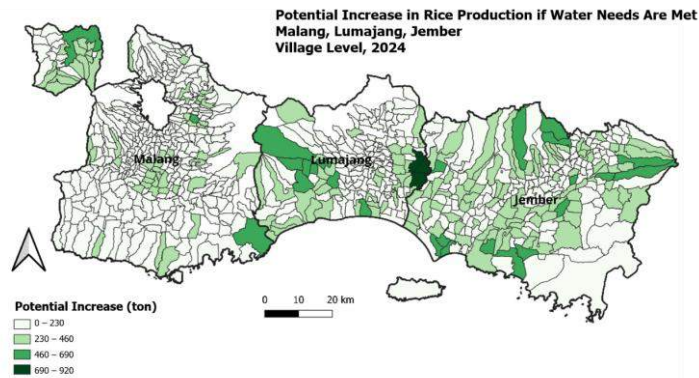
The irrigation rehabilitation scenario was developed to estimate potential increases in rice production under optimal irrigation conditions, where crop water requirements are fully met. The model also supports two subsequent analyses: economic impact simulation on downstream sectors and the prioritization of irrigation intervention areas. Regions with higher estimated production gains receive greater priority in irrigation development and rehabilitation planning. In this scenario, areas with high water deficit risk are assumed to experience complete crop failure (100% production loss), while moderate- and low-risk areas are assumed to lose 50% and 25% of potential production, respectively, relative to ideal conditions. This assumption follows previous studies showing that water deficits affect crop productivity non-linearly depending on drought severity and crop growth stages.

The analysis was conducted spatially for each planting subround using 500-meter grid units by integrating water deficit risk scores, regency-level rice productivity, and paddy field area. Figure 7 shows that the highest production increase potential is concentrated in the northern and western parts of Malang Regency, the southern part of Lumajang Regency, and the northern and southern parts of Jember Regency. These areas previously experienced severe water stress and therefore have high potential for yield recovery following irrigation improvement.



**Figure 7.** Potential Increase in Rice Production (tons) at the 500m Grid Level if Water Requirements are Met in Three Subrounds

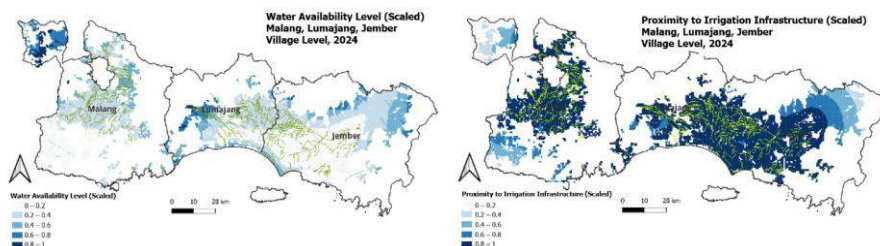
**Figure 8** presents the estimated village-level increase in rice production (tons) under fully satisfied water requirements across three planting subrounds, representing the potential production gains achievable through optimal irrigation rehabilitation. The results highlight the northern and western parts of Malang Regency, southern Lumajang Regency, and several villages in northern Jember Regency as the main areas with the highest rice production growth potential.



**Figure 8.** Estimated Village-Level Rice Production Increase (Tons) under Fulfilled Water Requirements across Three Subrounds

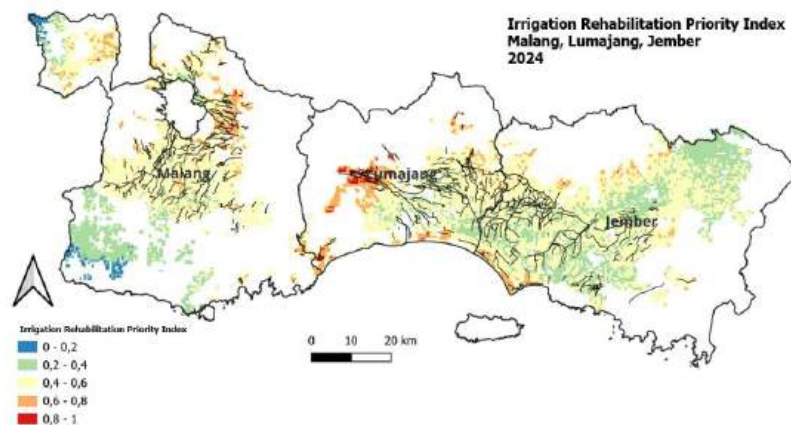
### 3.3. Irrigation Rehabilitation Priority Index Development

The Irrigation Rehabilitation Priority Index was calculated by integrating three main components: (1) the estimated rice production increase under the irrigation rehabilitation scenario at the 500-meter grid level (Figure 7), (2) groundwater availability within a 5 km radius of agricultural land (Figure 9, left), and (3) spatial proximity to existing irrigation networks (Figure 9, right). Together, these factors provide a comprehensive spatial indicator of the urgency and technical feasibility of irrigation development or rehabilitation.



**Figure 9.** Water Availability within a 5 km Radius and Proximity to Irrigation Networks

**Figure 10** presents the priority index calculated using the entropy gain method. The results show that although the northwestern part of Malang Regency is not connected to major irrigation networks, the area receives a high priority score due to its substantial rice production increase potential and the presence of relatively abundant shallow groundwater resources. Meanwhile, the central and southern parts of Lumajang Regency also show high priority scores because they are supported by existing irrigation infrastructure as well as sufficient surface and groundwater availability within a 5 km radius. In contrast, the northern part of Jember Regency, particularly the Sumberjambe and Sukowono areas, shows relatively low water availability within a 5 km radius despite having high production increase potential. As a result, irrigation development in these areas would require more complex technical planning, including alternative irrigation technologies such as solar-powered water distribution systems or retention reservoirs.



**Figure 10.** Irrigation Rehabilitation Priority Index in Malang, Lumajang, Jember, 2024

### 3.4. Economic Impact Simulation Using a Village-Level Input–Output Matrix under the Irrigation Rehabilitation Scenario

This section focuses on the simulated economic impacts of irrigation rehabilitation in Kemiri Village, located in the Panti area of Jember Regency. Based on the previous modeling results, the estimated increase in agricultural output under the optimal rehabilitation scenario reaches approximately IDR 20 billion, highlighting the substantial potential of water infrastructure interventions in the area. In addition, Kemiri Village recorded a high Irrigation Rehabilitation Priority Index, indicating favorable biophysical and spatial conditions for intervention. This is supported by the availability of water resources within a 5 km radius and proximity to existing irrigation networks, which enhance the technical feasibility and efficiency of program implementation.

#### 3.4.1. Economic Impacts of Irrigation Rehabilitation on Other Sectors

The Input–Output matrix simulation indicates that irrigation rehabilitation in Kemiri Village is projected to increase output in non-agricultural sectors by approximately IDR 31.7 billion. The largest impact is observed in the Chemical, Pharmaceutical, and Traditional Medicine Industry, followed by the Wholesale and Retail Trade sector (excluding motor vehicles). These findings confirm that agricultural interventions generate multiplier effects on processing and distribution sectors, consistent with previous studies by (Ariutama et al., 2022).

#### 3.4.2. Economic Impacts of Irrigation Rehabilitation on Household Income

From an income perspective, irrigation rehabilitation in Kemiri Village is estimated to increase total household income by approximately IDR 94.6 billion. The Food Crops

Agriculture sector contributes the largest share, followed by the Chemical and Pharmaceutical Industry and the Wholesale and Retail Trade sector. These findings indicate that the economic benefits of irrigation rehabilitation extend beyond agricultural production and also increase household income across related downstream sectors, reinforcing the role of irrigation as a strategic socio-economic investment (Firmansyah and Cabalu, 2011).

### **3.4.3. Economic Impacts of Irrigation Rehabilitation on Employment Growth**

The simulation also estimates significant labor impacts, with irrigation rehabilitation in Kemiri Village projected to generate approximately 582 additional jobs. The Food Crops Agriculture sector accounts for the largest employment increase, followed by the Livestock Farming sector and the Wholesale and Retail Trade sector. These results highlight the substantial contribution of irrigation rehabilitation to job creation.

### **3.5. Development of the Web-Based Dashboard**

As part of the research output, a web-based platform called AgriPolicy AI was developed to integrate spatial and economic analyses into an interactive decision-support system for irrigation planning and agricultural development. The platform consists of three main modules: (1) a Geovisualization Panel displaying agricultural water deficit risk, production increase potential, and irrigation rehabilitation priority maps; (2) an Economic Impact Simulation module that estimates the effects of irrigation interventions on sectoral output, household income, and employment using the East Java Input–Output Matrix; and (3) a Generative AI-based Policy Co-Pilot that produces contextualized policy recommendations in natural language. Together, these modules support more accessible, adaptive, and evidence-based policymaking for irrigation rehabilitation and agricultural resilience planning.

## **4. Conclusions**

This study demonstrates that integrating remote sensing, geospatial analysis, Input–Output modeling, and Generative AI can support adaptive and evidence-based irrigation planning. Using six satellite-derived indicators (Precipitation, LST, SMI, Evapotranspiration, NDVI, and SIF), the study identified increasing agricultural water deficit risks across Malang, Lumajang, and Jember during the dry season. The results show that several agricultural areas remain vulnerable to water shortages despite existing irrigation infrastructure, highlighting the need for targeted rehabilitation. By integrating drought risk, production potential, water availability, and irrigation accessibility, the study developed a quantitative irrigation rehabilitation priority framework. Economic simulations further indicate that irrigation rehabilitation can increase agricultural output, household income, and employment while generating multiplier effects on related sectors. Overall, the proposed framework provides an integrated and transferable approach for resilient irrigation planning and evidence-based agricultural policy development.

## **References**

- Ahmad MM, Yaseen M, Saqib SE. Climate change impacts of drought on the livelihood of dryland smallholders: Implications of adaptation challenges. *International Journal of Disaster Risk Reduction* 2022;80:103210.
- Aldyan RA. The impact of climate change on water resources and food security in Indonesia. *Journal of Law, Environmental and Justice* 2023;1:50–63.

- Ali A, Ahmad M, Nawaz M, Sattar F. Spatial data infrastructure as the means to assemble geographic information necessary for effective agricultural policies in Pakistan. *Information Development* 2026;42:805–27.
- Ariutama IGA, Saputra AH, Muis MA, Nugroho A. The impact of fiscal stimulus on agriculture sector in Bali: interregional input-output analysis. *Jurnal Manajemen Keuangan Publik* 2022;6:152–67. <https://doi.org/10.31092/jmkgp.v6i2.1956>.
- Binns R, Veale M, Edwards L. Generative AI and the policy-making process: risks and opportunities. *AI Soc* 2023. <https://doi.org/10.1007/s00146-023-01606-9>.
- BPS Statistics Indonesia. Complete Enumeration Results of the 2023 Census of Agriculture: Food Crops Individual Agricultural Holdings – Stage II, East Java Province. 2nd Edition. Jakarta: Statistics Indonesia (BPS); 2024.
- East Java Provincial Agriculture, Office FS. Report on agricultural land damage due to drought 2023. Surabaya: 2024.
- FAO. Artificial intelligence and big data in agriculture: technical background document. Rome: 2023.
- Firmansyah, Cabalu H. The impact of irrigation infrastructure development on agriculture and household incomes in Indonesia. *ASAE International Conference Proceedings*, 2011. <https://doi.org/10.22004/ag.econ.290615>.
- Geda A. Advancing Rural Welfare-The Role of Irrigation Technology in Ethiopia's Agricultural Sector. *Journal of Business and Economic Options* 2023;6:32–8.
- Handoko Y, Rahman A, Sari DN. Analisis pola curah hujan dan suhu udara di wilayah Jawa Timur. *Jurnal Meteorologi Dan Geofisika* 2020;21:93–102.
- Liu Q, Zhang S, Zhang H, Bai Y, Zhang J. Monitoring drought using composite drought indices based on remote sensing. *Science of the Total Environment* 2020;711:134585.
- Maselli F, Angeli L, Battista P, Fibbi L, Gardin L, Magno R, et al. Evaluation of Terra/Aqua MODIS and Sentinel-2 MSI NDVI data for predicting actual evapotranspiration in Mediterranean regions. *Int J Remote Sens* 2020;41:5186–205.
- Mulyanti T, Setyowati DL, Hadi P. Distribusi curah hujan dan dampaknya terhadap kekeringan di Jawa Timur. *Jurnal Klimatologi Dan Ketahanan Iklim* 2023;15:47–56.
- Pawlak K, Kołodziejczak M. The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production. *Sustainability* 2020;12:5488.
- Prasetyo LB, Ardiansyah A. Sistem informasi geografis untuk identifikasi daerah rawan kekeringan di Provinsi Jawa Timur. *Jurnal Geografi* 2021;53:120–9.
- Putri PID, Dharmayasa IGNU, Anggreni NLJ, Suryanti I, Nuraga IK. Application of Remote Sensing and Geographic Information Systems to Transform Sustainable Irrigation Water Management in Bali. 2024 10th International Conference on Smart Computing and Communication (ICSCC), 2024, p. 294–9.

- Raihan A, others. A systematic review of Geographic Information Systems (GIS) in agriculture for evidence-based decision making and sustainability. *Global Sustainability Research* 2024;3:1–24.
- Sun H, Xu Z, Liu H. An evaluation of the response of vegetation greenness, moisture, fluorescence, and temperature-based remote sensing indicators to drought stress. *J Hydrol (Amst)* 2023;625:130125.
- Vamvakas D, Papaioannou I, Tsaknakis C, Sgouros T, Korkas C. Generative AI for Sustainable Smart Environments: A Review of Energy Systems, Buildings, and User-Centric Decision-Making. *Energies (Basel)* 2025;18:6163.
- Wu RMX, Zhang Z, Yan W, Fan J, Gou J, Liu B, et al. A comparative analysis of the principal component analysis and entropy weight methods to establish the indexing measurement. *PLoS One* 2022;17:e0262261.