ASIA-PACIFIC NETWORK FOR
GLOBAL CHANGE RESEARCH

FINAL REPORT

Project ASIA PACIFIC NETWORK FOR GLOBAL CHANGE RESEARCH (APN) COLLABORATIVE REGIONAL RESEARCH PROGRAMME (CRRP) ADAPTING THE IMPACT OF LAND USE AND CLIMATE CHANGE THROUGH SMART IRRIGATION WATER MANAGEMENT TO SUPPORT FOOD SECURITY (SIWAMA)

CRRP2024-10SY-Setyawan

2025

UNIVERSITAS GADJAH MADA

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1. Summary

The project “Adapting the Impact of Land Use and Climate Change through Smart Irrigation Water Management to Support Food Security (SIWAMA)” aims to enhance the resilience and sustainability of irrigation systems in the face of changing land use patterns and climate variability. Recognizing that food security is strongly dependent on stable and efficient irrigation water management, this project seeks to evaluate, model, and develop adaptive strategies that integrate scientific understanding with practical applications in agricultural water systems.

The project is structured around a comprehensive approach that combines spatial analysis, hydrological modeling, and participatory engagement. It begins with the evaluation of land use and climate change impacts on water availability in irrigation schemes, with a focus on regions where agricultural productivity, especially rice production, depends heavily on irrigation. Through spatial data analysis and modeling, the project identifies how shifts in land cover, deforestation, urban expansion, and climate-induced changes in rainfall and temperature affect the availability, timing, and reliability of irrigation water.

A key outcome of this evaluation is the development of a framework for Smart Irrigation Water Management (SIWAMA). This framework integrates real-time data, digital monitoring, and predictive modelling to support efficient water allocation under uncertain climate and land-use conditions. It incorporates adaptive management principles that consider both short-term operational needs and long-term sustainability goals. The framework also emphasizes the five pillars of irrigation sustainability, such as water availability, infrastructure efficiency, governance, institutional capacity, and farmers’ adaptation behaviour, ensuring that technological innovation is matched with social and institutional readiness.

The project’s implementation includes two major learning and dissemination milestones: the Midterm Workshop and the Final Workshop. The midterm workshop serves as a platform to share interim findings, discuss modeling results, and refine methodologies based on stakeholder feedback. It facilitates dialogue between researchers, local government agencies, water user associations, and farmers to ensure that the research outcomes remain relevant and applicable to field realities. The final workshop presents the project’s consolidated results, including projections of future land use and climate scenarios and their implications for irrigation water management.

Another essential component of SIWAMA is capacity building and knowledge dissemination. The project emphasizes translating research outputs into practical guidelines and policy recommendations that can be adopted and scaled up by irrigation authorities, extension officers, and local farmers. Dissemination activities include the publication of scientific papers, technical briefs, and training materials that demonstrate the integration of smart technologies such as sensors, IoT-based monitoring, and decision support systems—into irrigation management practices.

Ultimately, the SIWAMA project contributes to strengthening climate resilience and food security in irrigated agriculture. By developing a smart, adaptive, and evidence-based framework, the project enables local and regional stakeholders to manage irrigation resources more effectively in the context of rapid environmental change. Its outcomes are expected to provide both scientific advancement and tangible policy tools for sustainable water and land management in agricultural landscapes.

2. Objectives

The main objectives of the proposed project are to adapt the impacts of land use and climate change through smart irrigation water management to support food security via three specific objectives: (1) to evaluate the land use and climate change impacts on five pillars of irrigation water management i.e. (i) water availability, (ii) infrastructure, (iii) management system, (iv) institution, and (v) human capital that supports rice production, (2) to develop a framework for smart irrigation water management that takes into account the combined impact of land use and climate change, (3) to disseminate research findings and build stakeholders' capacities to adopt and upscale smart irrigation water management through (i) scientific publications, (ii) policy briefs, (iii) knowledge-sharing events, and (iv) social-media products.

3. Outputs, Outcomes, and Impacts

Outputs	Outcomes	Impacts
Projected future land use	The result led to better land and water resource planning, improved agricultural productivity on converted or marginal lands, and more sustainable land management practices in response to climate and land use changes.	● Enhanced climate resilience and food security in tropical developing countries across Southeast Asia through the sustainable adaptation of land use systems. ● In the long term, smart irrigation-driven land use adaptation contributes to balanced ecosystem services, reduced environmental degradation, and improved livelihoods for farming communities
Projected future climate	The result led to	Strengthened climate change

Outputs	Outcomes	Impacts
	evidence-based decision-making, more efficient water allocation in agriculture, and increased resilience of farming systems to droughts and erratic rainfall patterns	adaptation and enhanced food security
Impacts of future land use and climate on food security	The analysis revealed that climate variability significantly affects river discharge and irrigation water availability in the study area. Increased evapotranspiration under warmer conditions elevates crop water requirements, creating potential stress during high-demand periods. While rice productivity remains generally stable, it becomes more vulnerable when irrigation reliability declines, emphasizing the need to enhance water management efficiency and adaptive irrigation scheduling to safeguard agricultural performance under changing climate conditions.	● Improved understanding of the linkages between climate variability, water availability, and crop productivity to inform adaptive irrigation and agricultural management. ● Strengthened resilience of farming systems through optimized water allocation, climate-responsive cropping patterns, and more reliable irrigation services. ● In the long term, maintaining productivity and reducing vulnerability of irrigated agriculture contribute to regional food security and livelihood stability in tropical developing regions.
Midterm workshop	The workshop produces technical maps, summary reports, and feedback on projected changes in land cover, temperature, and rainfall patterns, providing an evidence base for adaptive irrigation and land	The workshop outcomes facilitate shared awareness and initial policy alignment toward adaptive land and water management strategies in the study site (the Kedung Putri irrigation system)

Outputs	Outcomes	Impacts
	management planning	
Final workshop	The workshop also produces the SIWAMA (Smart Irrigation Water Management) framework, designed to integrate land use, climate, and irrigation system data for adaptive management under future scenarios	Strengthened scientific and institutional capacity to assess and manage the combined effects of land use and climate change on irrigation systems. Stakeholders—including researchers, local authorities, and water managers—gain actionable insights and tools to plan adaptive strategies using the SIWAMA framework.
Scientific Publication	The paper includes model validation, scenario simulations, and policy-relevant recommendations for improving irrigation management under changing land use	Strengthened capacity of tropical developing countries, particularly in Southeast Asia, to design climate-resilient and adaptive irrigation systems. Over time, the integration of LULC modeling and the SIWAMA framework contributes to sustainable agricultural intensification, efficient water use, and enhanced food security at regional and national levels

4. Key facts/figures

- Three (3) regional workshops were organized in Indonesia, representing a sequence of collaborative research activities involving both national and international partners. The Kick-Off Meeting (December 2024) and Midterm Workshop (May 2025) included active participation from collaborators in Thailand, Vietnam, and Australia through online and onsite sessions, while the Final Workshop (September 2025) combined onsite and virtual participation, with one international collaborator attending in person. These workshops served as important milestones for planning, sharing research progress, and consolidating outcomes within the framework of the APN-supported collaborative regional research programme.
- Four (4) institutional partners from Indonesia, Thailand, and Vietnam (UGM, AIT, TLU, and TUAF) collaborated closely with government representatives from the Ministry of Public Works and the Ministry of Agriculture of Indonesia. These partnerships

established a solid foundation for continued regional collaboration in advancing smart irrigation and sustainable agricultural development.

- More than 50 young researchers, students, and junior lecturers in Indonesia, Thailand, and Vietnam played active roles in organizing and documenting the events, gaining valuable capacity-building experiences through engagement with professionals and international experts in water and agricultural management.
- Two (2) scientific papers were produced as part of the project's dissemination outputs. The first paper discusses future land use dynamics and their implications for irrigation and agricultural sustainability, while the second focuses on projected climate patterns and their influence on irrigation water management and food security in Indonesia. Both manuscripts contribute to advancing regional knowledge on the interaction between land use, climate change, and irrigation systems, aiming to strengthen adaptive management and policy support for sustainable food production across Southeast Asia. One paper has been submitted to an international peer-reviewed journal, and another is currently being prepared for submission to the APN Science Bulletin.
- Additional training on Machine Learning and GIS for Future Land Use Projection was conducted at Universitas Gadjah Mada, enhancing the technical competencies of young researchers in spatial analysis, remote sensing, and predictive modeling for sustainable land and water resource management.
- A field visit and demonstration activity at Sapon Weir and the Samas coastal agricultural area were conducted together with international and national partners. The visit showcased smart irrigation technologies, including automated gates, water-level monitoring, and efficient drip and sprinkler systems, demonstrating practical solutions for water-saving and productivity enhancement in diverse agroecological zones.
- Our research finding is divided into three work packages: there are LULC projections, climate projections, and the Impact of Land Use and Climate Change on Irrigation systems. We conclude that:
    - The Bogowonto Watershed (59,752 ha) and Kedung Putri Irrigation Area (1,181 ha) experienced notable land use changes between 2015–2023. Rice fields, mainly in the southern part, declined by 557 ha, replaced largely by built-up areas. MOLUSCE projects an additional 5,271 ha loss by 2103, driven by proximity to roads, rivers, and settlements. In Kedung Putri, rice fields are projected to shrink by 236 ha in the year 2103.
    - CMIP6 GCMs-based projections indicate a temperature increase and reduced rainfall during the dry season (JJA–SON), leading to higher evapotranspiration and drought risk. Extreme indices (TN90p, TX90p) show rising frequencies of hot days and warm nights, potentially stressing crops. These results emphasize the need for climate adaptation and resilient planning in agriculture and water management.
    - SWAT simulations show climate variability significantly affects water discharge at Kedung Putri. Increased evapotranspiration raises crop water demand, while rice

productivity remains stable but vulnerable during high-demand periods, highlighting the importance of maintaining irrigation reliability under future climate conditions.

5. Publications

- Journal Submission
    - Manuscript Title: Predicting Future Land Use and Land Cover Dynamics in a Tropical Watershed for Irrigation Planning and Agricultural Sustainability Using a Hybrid Modeling Approach
    - Authors: Ansita Gupitakingkin Pradipta, Chandra Setyawan, Isnaini Dairina, Ismi Nuari Puspitaningrum, Yuli Widyaningsih, Dede Sulaeman, Ngadisih, Muhamad Khoiru Zaki, Muhammad Rasyid Ridla Ranomahera, Murtiningrum, Sigit Supadmo Arif, Sushil Kumar Himanshu, Hanggar Ganara Mawandha, Andri Prima Nugroho, Ha Thi Hoa, Propezite Nurhutama Mustain, Trang Dang An, Phantipa Plangkang, Teguh Triyana
    - Journal: Land Use Policy
    - Status: submitted (October 14, 2025)
- APN Science Bulletin
    - Manuscript Title: Projecting Future Climate and Its Implications for Irrigation Water Management and Food Security in Indonesia
    - Authors: Ansita Gupitakingkin Pradipta, Muhamad Khoiru Zaki, Chandra Setyawan
    - Status: draft

6. Media reports, videos, and other digital content

- Kick-off Meeting

The kick-off meeting of the CRRP-APN project was held online on Monday, December 16, 2024, to initiate the 2023–2024 research activities. The event was attended by the research team led by Dr. Chandra Setyawan, involving researchers from Universitas Gadjah Mada (UGM), the Asian Institute of Technology (Thailand), Thuy Loi University and Thai Nguyen University of Agricultural and Forestry (Vietnam), and Flinders University (Australia), as well as representatives from the Indonesian Ministry of Public Works and the Ministry of Agriculture.

The meeting aimed to align understanding among all members regarding the project objectives and implementation framework. The opening remark was delivered by the Dean of the Faculty of Agricultural Technology, Prof. Dr. Eny Harmayani, who emphasized the importance of collaborative efforts to address climate change impacts on water resources and food production. Dr. Chandra Setyawan then introduced the research team and presented the three-year research plan, followed by Dr. Ansita Gupitakingkin Pradipta, who explained the research framework and progress from

October to December 2024. The session, moderated by Dr. Ngadisih, concluded with a discussion on refining objectives and determining the next steps.

The kick-off meeting marked the formal start of the CRRP-APN research collaboration under the Asia-Pacific Network for Global Change Research, reinforcing regional partnerships in climate-resilient agriculture and sustainable water management.

Related link:

Website:

https://tpb.tp.ugm.ac.id/id/2024/12/20/pertemuan-peluncuran-riset-kolaborasi-tentang-adaptasi-dampak-perubahan-iklim-dan-tata-guna-lahan-melalui-pengelolaan-irigasi-cerdas-untuk-mendukung-ketahanan-pangan.xhtml

- Midterm Workshop

  The Department of Agricultural and Biosystems Engineering held a midterm workshop on CRRP-APN on Friday, May 16, 2025, from 1:00 PM to 5:00 PM WIB in the Agricultural & Biosystems Engineering Department meeting room, Faculty of Agricultural Technology, Universitas Gadjah Mada, and via Zoom. The main focus of the midterm workshop was a case study of the Kedung Putri irrigation scheme (Indonesia) and the development of smart irrigation in Thailand and Vietnam. Researchers presented field data and preliminary findings, including the importance of sensors and automated systems in efficient water distribution.

  The midterm workshop is expected to encourage technical innovation, new monitoring systems, and predictive models in smart irrigation. This research supports SDG 2 (Zero Hunger), SDG 6 (Clean Water), SDG 13 (Climate Action), and SDG 17 (Global Partnerships) through cross-sector collaboration and innovative technologies.

  Related links:

  Instagram:
  https://www.instagram.com/reel/DJ89ZG1TTx_/?igsh=MWJpNWI0bW1mbXN4YQ==

  Website:
  https://tpb.tp.ugm.ac.id/id/2025/05/19/midterm-workshop-collaborative-regional-research-programme-crrp-apn-ftp-ugm-bahas-pengelolaan-air-irigasi-cerdas-untuk-ketahanan-pangan.xhtml

- Final Workshop

  Following a research journey that began in 2024, the CRRP–APN team held a Final Workshop, culminating in international collaboration in smart irrigation water management research to support food security amidst climate change. The first session presented research results from the CRRP–APN DTPB FTP UGM team, led by Dr. Chandra Setyawan, focusing on the application of Smart Irrigation Water Management for sustainable food systems. The second session (Guest Lecture) featured international and national experts, including Dr. Sushil Kumar Himanshu (Asian Institute of

Technology, Thailand) on "Advancing Water Use Efficiency and Agricultural Sustainability through Smart Irrigation Technologies," Dr. Ha Thi Hoa (Thai Nguyen University of Agriculture and Forestry, Vietnam) on "Promoting Indigenous Knowledge and Technology in Sustainable Water Management in Mountainous Areas of Vietnam," and Dr. Dede Sulaeman (Ministry of Agriculture, Republic of Indonesia) on "Experience of Land and Water Development for Agricultural Sustainability in Indonesia." Mr. Propezite Nurhutama Mustain, S.T., M.T. (Ministry of Public Works and Public Housing of the Republic of Indonesia) "Development of Rainfall and Water Level Prediction to Support Hydrological Analysis and Operations." This activity supports SDGs 2, 6, 13, and 17 through cross-border research and collaboration for resilient, adaptive, and sustainable agriculture and food systems.

Related links:

Instagram:

https://www.instagram.com/reel/DPY81LUEwYr/?utm_source=ig_web_copy_link&igsh=MzRlODBiNWFlZA==

Website:

(https://tpb.tp.ugm.ac.id/id/2025/09/27/final-workshop-crrp-apn-dtpb-ftp-ugm-smart-irrigation-untuk-ketahanan-pangan-berkelanjutan.xhtml)

- Training Application of Machine Learning and GIS for Future Land Use Projection

  The Department of Agricultural and Biosystems Engineering (DTPB), Faculty of Agricultural Technology, Universitas Gadjah Mada, through the Collaborative Regional Research Program – Asia Pacific Network for Global Change Research (CRRP–APN), held a training session titled "Application of Machine Learning and GIS for Future Land Use Projections." Held in Room 384 of the Faculty of Agricultural Technology (FTP) UGM, the training was attended by DTPB students and the general public interested in deepening the application of spatial technology in research and regional planning. The training was opened by Dr. Ngadisih, who emphasized the importance of mastering spatial technology in addressing the challenges of climate change and sustainable land management in the future. The event then continued with a keynote session moderated by Isnaini Dairina, M.Sc., along with other teaching staff.

  During the training, participants received technical training on the use of software such as Google Earth Engine, ArcGIS Pro, and QGIS MOLUSCE. Using these applications, participants learned how to process remote sensing data to project future land use changes. This approach is expected to provide a more comprehensive understanding for spatial planning, environmental risk mitigation, and support sustainable development efforts. Through this activity, the UGM Faculty of Agricultural Technology (FTP) DTPB is committed to continuously encouraging research collaboration and increasing human resource capacity to adapt and innovate in the face of the dynamics of global change.

Related links:

Instagram:

https://www.instagram.com/reel/DPbeYpdkue/?utm_source=ig_web_copy_link&igsh=MzRlODBiNWFlZA==

Website:

(https://tpb.tp.ugm.ac.id/id/2025/09/27/dtpb-ftp-ugm-gelar-pelatihan-machine-learning-dan-gis-untuk-prediksi-penggunaan-lahan.xhtml)

- Field Visit

Thursday, September 25, 2025 – Following the Final Workshop of the Collaborative Regional Research Programme – Asia Pacific Network for Global Change Research (CRRP–APN), DTPB lecturers from the CRRP–APN UGM Program Team visited the implementation sites for modern and micro irrigation systems in Kulon Progo and Bantul Regencies, Yogyakarta Special Region. The visit was also attended by Dr. Sushil Kumar Himanshu, a visiting lecturer from the Asian Institute of Technology (AIT), Thailand.

The visit began at the Sapon Dam to review the implementation of irrigation modernization in the Sapon Irrigation Area. This system is equipped with electric motorized intake gates and an Automatic Water Level Monitoring System (AWLMS) developed by the UGM SIPASI (Irrigation Management System) team. The AWLMS is connected to a decision support system, enabling efficient water level monitoring while providing predictive analysis through comparisons of actual and historical data. This technology provides valuable insights for policymakers in determining more appropriate and sustainable water allocation in irrigation areas. In addition, the team also visited a trial location for the implementation of a system on a sluice gate that can adjust the volume of water distribution according to agricultural needs.

The activity then continued with a visit to a sandy farmland at Samas Beach, Bantul, managed by partner farmers of the Agricultural Technology Development Program (DTPB) of Universitas Gadjah Mada (UGM). In this area, various micro-irrigation systems are implemented, such as mist irrigation, drip irrigation, and sprinkler irrigation. These systems are used because they optimize water distribution directly to the root zone, reduce water loss due to evaporation, and maintain stable soil moisture around the plants. Thus, these systems not only support optimal plant growth on marginal land such as sandy areas but also encourage sustainable agricultural practices through more efficient water use.

Related links:

Instagram:

https://www.instagram.com/reel/DPgFITNkLz/?utm_source=ig_web_copy_link&igsh=MzRlODBiNWFlZA==

Website:

https://tpb.tp.ugm.ac.id/id/2025/09/27/crrp-apn-dtpb-ftp-ugm-lakukan-kunjungan-lapangan-bersama-dr-sushil-kumar-himanshu.xhtml

7. Pull quotes

- **Quotes from Head of the Department of Agricultural and Biosystems Engineering (Prof. Lilik Sutiarso)**

  "We truly appreciate the collaboration built through the CRRP Project 2025, which has brought together experts, researchers, and institutions committed to advancing sustainable agricultural practices. This partnership has provided valuable opportunities for knowledge exchange and innovation in irrigation and land management."

  "On behalf of the Department of Agricultural and Biosystems Engineering, Universitas Gadjah Mada, I sincerely hope that this collaboration can be continued and expanded in the next phase. We are ready to strengthen our partnership with all CRRP Project members to achieve greater impacts in improving agricultural productivity and resilience across Southeast Asia."

- **Quotes from the Project Leader (Dr. Chandra Setyawan)**

  "This research seeks adaptation strategies to control the impact of land use and climate on food security through Smart Irrigation Water Management (SIWAMA). The project reflects our strong commitment to developing innovative and technology-based solutions that help communities adapt to environmental changes while ensuring sustainable agricultural practices."

  "Through SIWAMA, we aim to improve irrigation efficiency and strengthen food security, especially in regions vulnerable to climate and land-use changes. The collaboration between UGM and ASEAN partner universities has created a meaningful impact, integrating research, technology, and local wisdom to achieve sustainable water and land management."

  "We hope this initiative will continue and expand in the next phase, allowing more communities to benefit from the outcomes and inspiring similar projects across Southeast Asia."

- **From a member of the research team (Dr. Dede Sulaeman)**

"The CRRP APN program is very interesting as it integrates the concept of smart irrigation water management, which can help developing countries in Southeast Asia adapt to land use and climate changes in order to strengthen food security."

"The research conducted by UGM in collaboration with other universities in ASEAN provides valuable insights into land management, irrigation systems, and the application of technology for agricultural advancement in the region. I hope that such initiatives will continue in the future, expanding the scope of research to other locations, not only in Indonesia but also in other ASEAN partner countries, so that the benefits can be more widespread and impactful."

- **From Local Trainee (Mr. Widi Kuntara)**

  "As a workshop participant and manager of the Kedung Putri irrigation area, I found the research conducted by the CRRP APN UGM team to be highly beneficial as input for more efficient and sustainable irrigation management. The technology-based problem-solving approach represents a breakthrough and can provide a broader perspective on how to improve the quality of irrigation services and impact farmer welfare in both the short and long term."

  "We hope that further research can be conducted, particularly in the Kedung Putri irrigation area, to achieve more detailed and applicable results, thus increasing the impact felt by the community. We fully support activities like this, which have a significant impact and contribution to government programs, particularly in the area of food security."

8. Acknowledgments

The project was sponsored by the Asia Pacific Network (APN) for Global Change Research for this special joint scoping project (Project reference: CRRP2024-10SY). Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada would like to thank for the contributions and supports extended by Dr Sushil Kumar Himanshu and Ms. Phantipa Plangkang (Asian Institute of Technology), Dr. Tran Dang An (Thuyloi University), Dr. Ha Thi Hoa (Thai Nguyen University of Agricultural and Forestry), Muhammad Rasyid Ridho (Flinders University), Dr. Dede Sulaeman (The Ministry of Agriculture), Propezite Nurhutama Mustain (Ministry of Public Works), Prof. Sigit Supadmo Arif, Dr. Murtiningrum, Dr. Ngadisih, Dr. Andri Prima Nugroho, and Dr. Ansita Gupitakingkin Pradipta (Universitas Gadjah Mada).

9. Appendices

- Full report
- Activity report
- Publication manuscript

10. Documentation

- The documentation kick-off meeting CRRP-APN SIWAMA

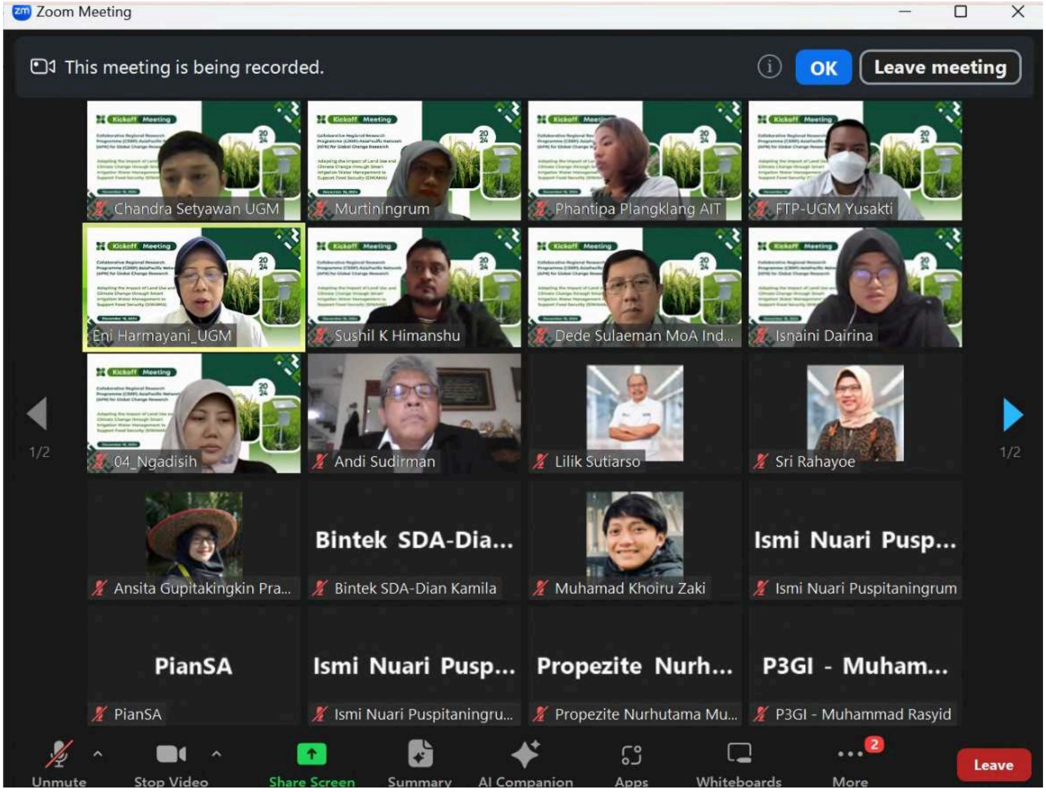

Figure 1 Online kick-off meeting of the CRRP-APN SIWAMA

- The documentation of Midterm Workshop CRRP-APN SIWAMA

Figure 2. Discussion session during the CRRP-APN SIWAMA midterm workshop

- The documentation of Final Workshop CRRP-APN SIWAMA

Figure 3. Presentation of the final project results by the CRRP-APN SIWAMA team

Figure 4. Presentation from collaborators

- The documentation of the Training of Machine Learning and GIS applications in water resource management

Figure 4. Group photo of participants and facilitators during the Training on Machine Learning and GIS Application

Figure 5. Training on Machine Learning and GIS Application

- The documentation of the Field Visit Activity

Figure 6. Field activity by the CRRP-APN SIWAMA team and collaborators

FULL REPORT

ASIA PACIFIC NETWORK FOR GLOBAL CHANGE RESEARCH (APN)
COLLABORATIVE REGIONAL RESEARCH PROGRAMME (CRRP)

ADAPTING THE IMPACT OF LAND USE AND CLIMATE CHANGE THROUGH SMART IRRIGATION WATER MANAGEMENT TO SUPPORT FOOD SECURITY (SIWAMA)

Project Reference Number: CRRP2024-10SY-Setyawan

PROJECT LEADER: DR. CHANDRA SETYAWAN

DEPARTMENT OF AGRICULTURAL AND BIOSYSTEMS ENGINEERING
FACULTY OF AGRICULTURAL TECHNOLOGY
UNIVERSITAS GADJAH MADA
2024

In collaboration with:

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Project Information:

Thematic Areas	:	Climate, Food, water and energy
Topic	:	Climate change and climate variability (CC&V) and disaster risk reduction
Duration	:	1 year
APN Funding	:	USD 12,500
Other Funding Secured	:	USD 11,000 (USD 4,000 cash, USD 7,000 in kind)
Total Combined Funding	:	USD 23,500
Countries Involved	:	Indonesia, Thailand, Vietnam

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PREFACE

Praise and gratitude are first and foremost extended to the Almighty for the blessings and guidance that have enabled the completion of this report on Smart Irrigation Water Management (SIWM). This report presents the outcomes of research focused on evaluating the impacts of land use changes and climate variability on irrigation systems in Southeast Asia, as well as exploring adaptive strategies to sustain agricultural productivity and food security. The adoption of intelligent irrigation technologies stands as a promising solution to enhance water use efficiency and resilience in tropical agricultural watersheds, especially for rice production.

The preparation and compilation of this report would not have been possible without the invaluable support and cooperation of many individuals and institutions. Special thanks are given to the project team members, academic advisors, and local stakeholders who contributed their expertise, data, and field knowledge. Their collaboration has been instrumental in applying innovative approaches and generating context-specific insights to improve irrigation management practices.

It is hoped that this report will serve as a scientific reference to guide future research and policy formulation toward sustainable water management. The integration of technology, community engagement, and adaptive governance illustrated herein underscores the potential to build climate-resilient agricultural systems in Indonesia, Thailand, Vietnam, and similarly vulnerable tropical regions. Constructive feedback and further discussions are welcomed to refine and advance the initiatives presented in this work.

ABSTRACT

Population growth, especially in tropical countries, increases food demand. To meet dietary needs, agricultural crop production is crucial. Land use changes in the upstream watershed for farming, mining, and others affect hydrologic characteristics, especially drought and flood. Middle and downstream areas witnessed farming converted to urbanization and various other purposes. Climate change worsens the situation and threatens food security and crop production. This circumstance altered irrigation, a crucial food production factor. This research seeks adaptation strategies to control the impact of land use and climate on food security through smart irrigation water management (SIWAMA) by achieving four objectives: (i) to evaluate the land use and climate change impacts on five pillars of irrigation water management, (ii) to develop a framework for smart irrigation water management that considers the combined impact of land use and climate change, (iii) to assess the influence of smart irrigation water management on agri-climate resilience and food security, and (iv) To disseminate research and empower stakeholders to adopt smart irrigation water management. Smart surface irrigation water management is unusual in Asia-Pacific. This offers a new opportunity to enhance SIWAMA's involvement in implementing the irrigation modernization initiative and enables opportunities for multinational collaboration involving researchers and stakeholders.

Keywords: *land use, climate, smart irrigation, water management, food security*

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CHAPTER 1. INTRODUCTION

1.1 Description of the Project

Population growth, especially in tropical countries, increases food demand. To meet dietary needs, agricultural crop production is crucial. Land use changes in the upstream watershed for farming, mining, and others affect hydrologic characteristics, especially drought and flood. Middle and downstream areas witnessed farming converted to urbanization and various other purposes. Climate change worsens the situation and threatens food security and crop production. This circumstance altered irrigation, a crucial food production factor. Irrigation modernization can help to address the challenges posed by climate change involving technology to improve the efficiency and effectiveness of irrigation systems through smart irrigation water management. This research seeks adaptation strategies to control the impact of land use and climate on food security through smart irrigation water management (SIWAMA) by achieving three objectives: (i) to evaluate the land use and climate change impacts on five pillars of irrigation water management, (ii) to develop a framework for smart irrigation water management that considers the combined impact of land use and climate change, and (iii) To disseminate research and empower stakeholders to adopt smart irrigation water management. Smart surface irrigation water management is unusual in Asia-Pacific.

This offers a new opportunity to enhance SIWAMA's involvement in implementing the irrigation modernization initiative and enables opportunities for multinational collaboration involving researchers and stakeholders. The project aims to conduct a specific case study in Indonesia following the aforementioned objectives and gather information regarding the advancement of smart irrigation water management in Thailand and Vietnam. Activities planned are structured into 3 Work Packages (WP), including (i) Evaluation of land use and climate change impacts on five pillars of irrigation that support rice production, (ii) Development of a framework for smart irrigation water management that takes into account the combined impact of land use and climate change, and (iii) Dissemination of research findings and build stakeholders' capacities to adopt and to upscale smart irrigation water management.

1.2 Concise Literature Review

Irrigation plays a crucial role in the advancement of Southeast Asia's agricultural sector. Implementing an efficient surface irrigation system helps enhance the agricultural sector's development while promoting food security (Darko et al., 2016; Pawlak & Kołodziejczak, 2020). Nevertheless, the efficiency of irrigation has deteriorated within a span of less than a century of its establishment and management in Indonesia. This decrease can be attributed to several factors, including unsatisfactory operation and maintenance of irrigation infrastructure services, an ineffective rehabilitation system, a weak management system, and insufficient funding (Tirtalistyani et al., 2022). The circumstance is exacerbated by the combination of land use and climate change, which is expected to impact on food security. The correlation between detrimental climate change and water and food security is associated with alterations in crop yields and levels of water consumption by agriculture and other industries. The anticipated rise in temperatures and decrease in precipitation would have an adverse impact on crops and water availability, significantly impacting the future patterns of agricultural production (Al-Bakri et al., 2013).

Developing strategies and implementing initiatives to enhance the ability of water management systems to withstand and adapt to climate variability is the most effective approach to proactively preparing for anticipated climate change (Darjee et al., 2023; Fedele et al., 2019). Enhanced water harvesting and storage methods are crucial for supplementing the water needs of rain-fed crops (LIU & JIN, 2017). Additionally, highly efficient irrigation systems and the implementation of best practices are essential for mitigating the adverse effects of unpredictable rainfall patterns and minimizing the impacts of extreme events such as floods and droughts (Nikolaou et al., 2020). The Indonesian government has been enacting an irrigation modernization program to address these concerns to develop a participatory irrigation management system that can effectively, efficiently, and sustainably provide irrigation services (Arif et al., 2019; Pradipta et al., 2019). Irrigation modernization can help to address the challenges posed by climate change involving technology to improve the efficiency and effectiveness of irrigation systems (Arif et al., 2019; Arif & Prabowo, 2014). This can help to reduce water use, improve crop yields, and make irrigation systems more resilient to climate change (Tarjuelo et al., 2015). Smart irrigation water management is a way to address irrigation modernization and is a crucial step toward improving food security. It is incorporating efficient monitoring and control mechanisms that significantly save water, energy, and labor (Ajayi et al., 2016).

1.3 Relevance to APN's Strategic Plan

This study supports APN's fifth Strategic Plan's Goals 1: Research, 2: Capacity development, and 4: Community engagement by strengthening research and community development.

Goal 1: Research: This study advances scientific understanding in land use and climate change impacts and adaptation, smart water management, food security, and sustainable agriculture. This study can also help implement and discuss international agendas like the Paris Agreement, Sustainable Development Goals (SDGs), and IPCC and UNFCCC scientific knowledge.

Goal 2: Capacity Development strengthens technical and institutional capacities for a wide range of stakeholders in the study areas by focusing on how smart irrigation water management can adapt to land use and climate change and potential food security. The project proposes training events for academia, government officials at multiple levels, NGOs working in the study areas, farmers, and community-based organizations. This project aims to help early-career professionals conduct training and lead focus group discussions with irrigation and agriculture producers.

Goal 4: Community Engagement can be achieved through stakeholder consultation and engagement, especially through team and external collaborators' co-design (research), co-production (data), and co-management (adaptation and response strategies). Every knowledge-creation activity integrates top-down expert-based and bottom-up community-based techniques to ensure scientific validity and policy relevance.

1.4 Objectives of the Project

The main objectives of the proposed project are to adapt the impacts of land use and climate change through smart irrigation water management to support food security via three specific objectives:

1. Objective 1: to evaluate the land use and climate change impacts on five pillars of irrigation water management i.e. (i) water availability, (ii) infrastructure, (iii) management system, (iv) institution, and (v) human capital that supports rice production.
2. Objective 2: to develop a framework for smart irrigation water management that takes into account the combined impact of land use and climate change.
3. Objective 3: to disseminate research findings and build stakeholders' capacities to adopt and upscale smart irrigation water management through (i) scientific publications, (ii) policy briefs, (iii) knowledge-sharing events, and (iv) social-media products.

The project aims to conduct a specific case study in Indonesia following the aforementioned objectives and gather information regarding the advancement of smart irrigation water management in Thailand and Vietnam.

1.5 Expected Deliverables/Outputs

This study aims to address land use and climate change impact through smart irrigation systems to enhance food security in the short and long term. Short-term outcomes include (i) creating and widely disseminating a novel and proactive knowledge framework on socially and environmentally sustainable smart irrigation water management strategies among partnering organizations, boundary partners, and end beneficiaries, and (ii) improving relevant parties' resilience to climate change and food security through smart irrigation water management methods. Long-term outcomes include (iii) identified potential and challenges in using smart irrigation water management methods in climate change adaptation initiatives in targeted countries, and (iv) improved collaboration and organization among involved countries and organizations (universities, research organizations, NGOs, and government agencies) through innovative promotional strategies on popular social media and communication platforms to popularize smart irrigation. These impressive outcomes are expected to draw domestic and international support, increasing financing for expansion.

CHAPTER 2. FRAMEWORK

This project investigates how smart irrigation water management might help tropical developing countries in Southeast Asia, adapt to land use and climate change to improve food security. The surface irrigation system helps the region's agriculture, notably rice, the staple food. Providing effective and efficient irrigation services is complicated by land use change, climate change, and population increase. Long-term land use and climate change will affect irrigation pillars: water availability, infrastructure, management systems, institutions, and human capital. Adapting to these difficulties requires maintaining effective and efficient irrigation services. With a modernization program, real-time irrigation operations, allocation, and losses can be achieved. Smart irrigation water management requires technology breakthroughs in data collecting, transmission, calculation, processing, and presentation for irrigation operations.

2.1 Study Area

We include a pilot site of the Kedung Putri Irrigation Scheme (IS) in Indonesia, with service area of 4,341 Ha. Kedung Putri is categorized as an irrigation scheme under the authority of the central government because its service area is above 3,000 Ha. The water supply for this irrigation scheme is obtained from the Bogowonto River through the Kedung Putri Weir, which is situated at 110°02’12,86” E and 7°41’12,1” S. Administratively, the irrigated area of Kedung Putri covers 52 villages and 7 sub-districts. Kedung Putri Irrigation System is managed by Large River Basin Organization of Serayu Opak (BBWS SO) in cooperation with Central Java Province and Purworejo’s Regency Governments. The planned planting pattern is rice-rice-upland crops start from November. However, the actual planting pattern is mostly rice-rice. The cropping intensity is approximately 220%. The location of Kedung Putri IS within the Bogowonto Watershed and the photograph of the Kedung Putri Weir is illustrated in Figure 1 In addition to the pilot project in Indonesia, we will also explore the application of smart irrigation water management in two other countries, namely Thailand and Vietnam.

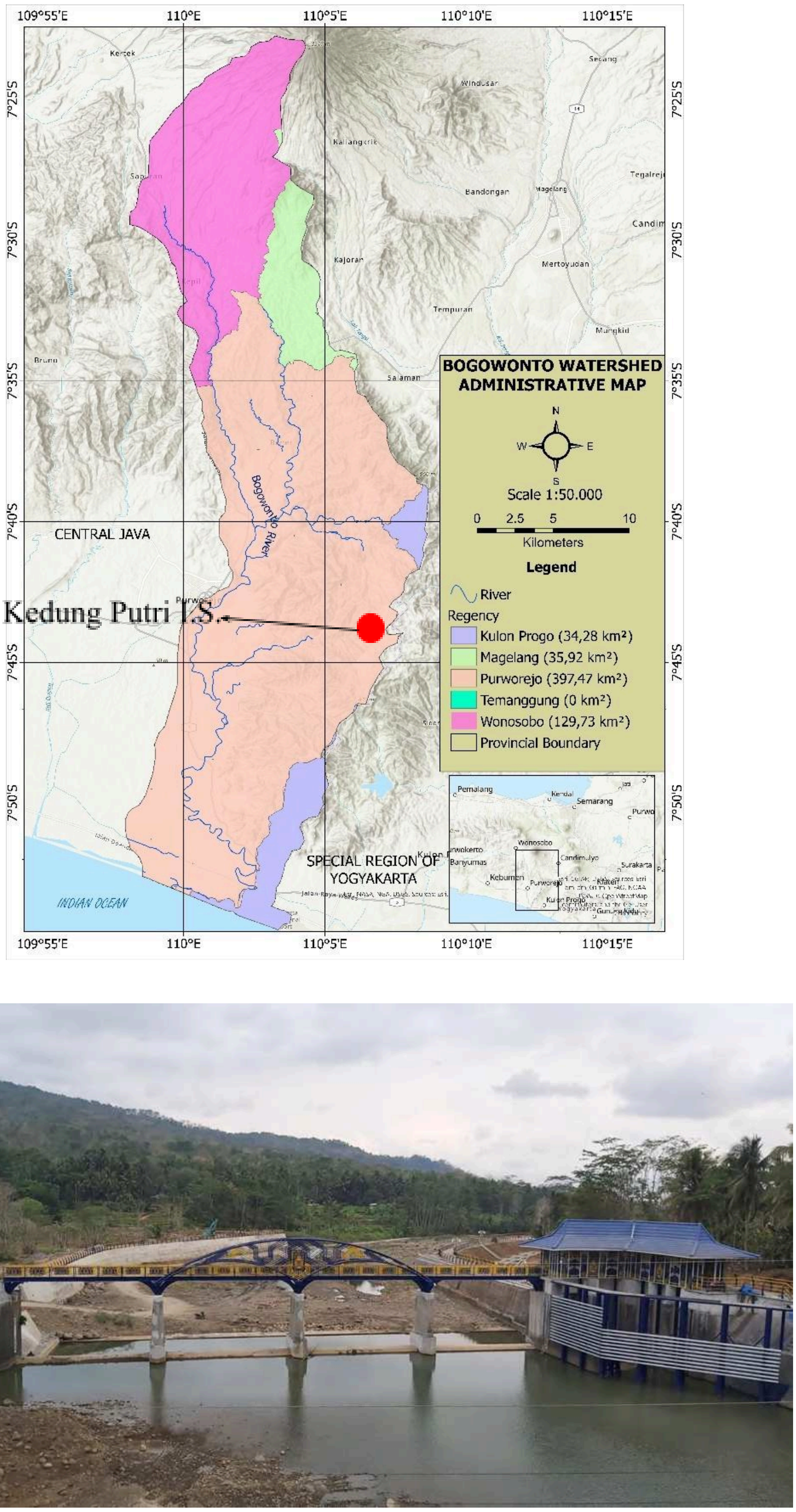


Figure 1 The location of Kedung Putri Irrigation Scheme within the Bogowonto Watershed and the photograph of the Kedung Putri Weir.

2.2 Logical Framework

From the pilot location we will examine smart irrigation water management from diverse perspectives and application contexts, generating discoveries for additional tropical developing countries in Southeast Asia, especially Thailand and Vietnam. This project has three work packages (WPs) where the logical framework is shown in Figure 2.

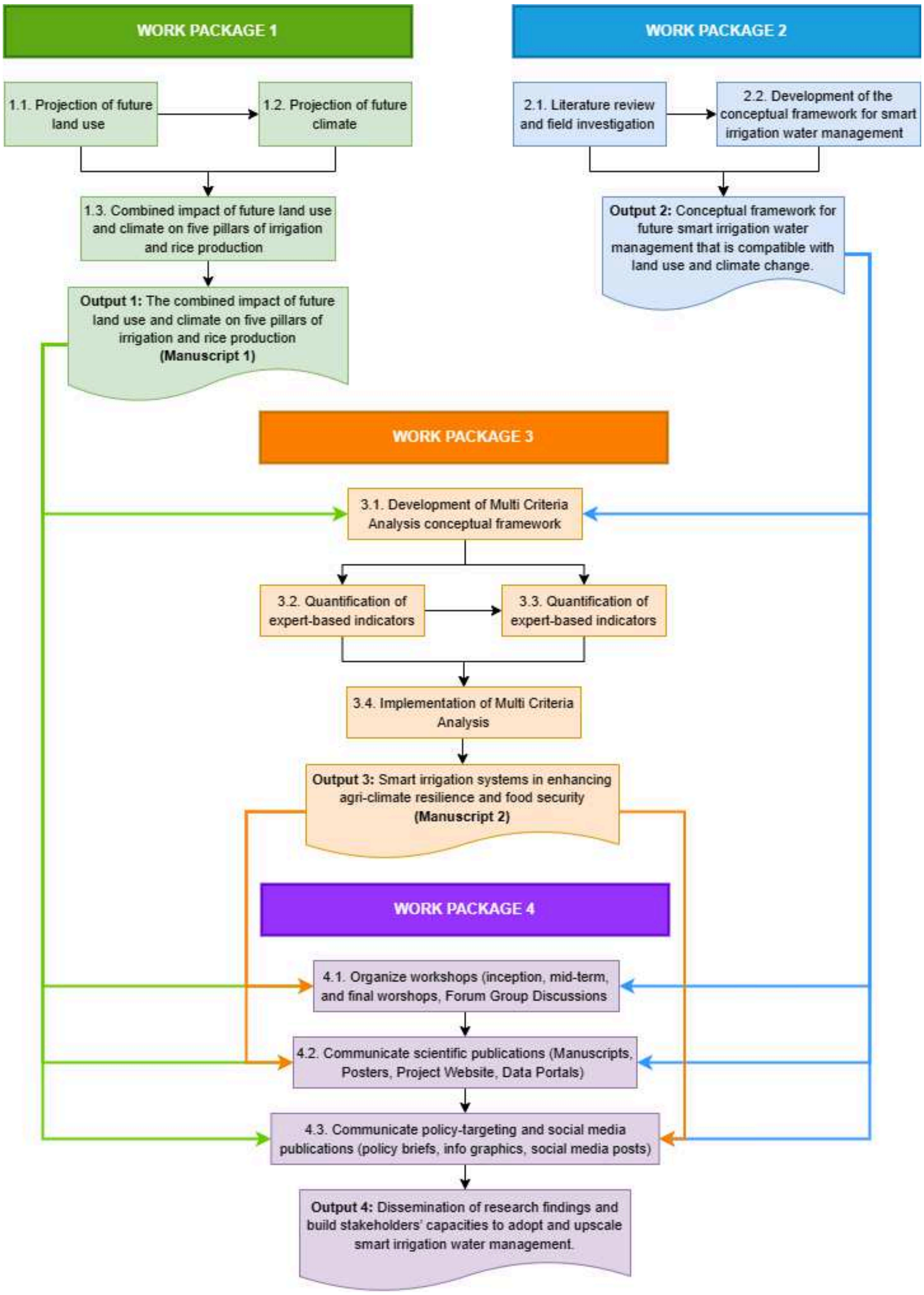


Figure 2 Logical Framework

2.3 Description of the Project Methodology

The description of the methods used in every work package (WP) that is divided into their multiple activities are described below.

WP 1: Evaluation of land use and climate change impacts on five pillars of irrigation that support rice production

Activity 1.1: Projection of future land use

The future land use will be projected using the Dynamic Conversion of Land Use and its Effects (DynaCLUE) model version 2.0, the improved version of the CLUE model. In this model, we require previous land use maps to set up, calibrate, and validate the model. The performance of the calibrated and validated model will be evaluated using Kappa statistical analysis, which includes parameters of observed relative agreement and hypothetical probability of change. After obtaining the validated model, we projected the future land use for three-time horizons, namely near future 2030s (2015-2045), middle future 2060s (2046-2076), and far future 2090s (2077-2100) under three scenarios. This study will examine four land-use scenarios that include the present and projected land use based on the current (CUR), business-as-usual trend (BAU), expansion of irrigation crop (EIC), and expansion of forestland (EFL). Based on the generated future land use maps, we can evaluate the trend of future land use change.

Activity 1.2: Projection of future climate

The future climate will be projected using the General Circulation Models (GCMs) of the latest Coupled Model Intercomparison Project Phase (CMIP6). Ten of the best-ranked GCMs will be occupied in this projection, and the selection is based on the literature review. The related climate parameters will be projected under three Shared Socio-economic Pathways (SSP) scenarios, namely SSP 1-2.6 (Sustainability), SSP 2-4.5 (Middle of the road), and SSP 5-8.5 (Fossil-fueled development). We will get the climate change projection downscaled for the region for three-time horizons (2030s, 2060s, and 2090s). The dataset needs to be bias-corrected using the quantile mapping method. Quantile mapping (QM) is commonly used for precipitation bias correction due to its ability to adjust the distribution characteristics of mean and variance effectively (Li et al., 2023). Before conducting the bias correction, we must select good performance datasets as the comparison parameters for the raw GCMs historical data (1981-2014). In this case, we will use Gridded Precipitation Products (GPPs), including the model-based reanalysis (CHIRPS25 and ERA5) and gauge-based datasets (APHRODITE), to compare them with the available observed ones. This is because the observed data in most developing countries are not completely available (Dhungana et al., 2023). The reanalysis and gauge-based datasets will be corrected with the observed data to evaluate their performance and suitability in the study areas using multiple performance indicators. The selected GPP will be used in bias correction, and after obtaining the bias-corrected dataset for historical and future climate data, we will continue to conduct performance evaluation of all GCMs. Finally, we can evaluate the trend of climate change in the future regarding GCMs and the scenarios.

Activity 1.3: Combined impact of future land use and climate on five pillars of irrigation and rice production

Climate change and land-use change are the critical drivers that alter various hydrological processes. Climate change impacts the water cycle by altering elements like precipitation, evapotranspiration, soil moisture, groundwater, and the scale and timing of runoff, while a land use change can modify factors such as canopy interception, surface roughness, soil characteristics, albedo, etc., ultimately affecting evapotranspiration (ET), soil moisture (SM), and runoff (Khadka et al., 2023; Teklay et al., 2021). The Soil and Water Assessment Tool (SWAT) will be utilized to simulate hydrological variables, particularly precipitation, evapotranspiration, soil moisture, surface runoff, and water yield that directly affect the surface irrigation system for paddy fields in terms of water availability, crop demand, and crop production. In the first step, we will prepare the observed climate, topography, land use, and soil input data. After modelling the hydrological system using SWAT, we need to calibrate and validate the model using SWAT-CUP. Based on the validated model, the simulation of water balance components for the baseline period (1981-2014) will be conducted. It is followed by the simulation of water balance for future conditions regarding three time horizons (2030s, 2060s, and 2090s) using the future data of land use and climate from sections 1.1 and 1.2. The comparison between baseline and future water balance conditions will be utilized to evaluate the combined impact of land use and climate change on irrigation systems (consisting of five pillars) and rice production.

WP 2: Development of a framework for smart irrigation water management that takes into account the combined impact of land use and climate change.

Activity 2.1: Literature review and field investigation of the current irrigation water management in study sites

In Indonesia, smart irrigation water management has been implemented in seven strategic irrigation schemes. Smart devices were developed to support data collection and system utilization, such as an automatic water level monitoring system (AWLMS), automatic weather station (AWS), and decision support system (DSS) for water management. The implemented smart irrigation water management in Indonesia does not yet accommodate land use and climate change factors. Through this project, we will develop the program with additional land use and climate change instruments and activities will focus on the Kedung Putri Irrigation Scheme in Indonesia. Firstly, we need to conduct a literature review and field investigations to better understand the proposed study sites and collect data and information about those ISs. The data and information that will be collected include schemes and details of irrigation networks/buildings, rice fields, water allocation, planting patterns, management systems, and historical hydro climatology data.

Activity 2.2: Development of the conceptual framework for smart irrigation water management that is compatible with land use and climate change

The framework that will be developed adopts the smart irrigation water management framework that has been implemented in Indonesia with the addition of land use and climate change instruments. The framework that will be used consists of seven main components grouped into three parts. The first group, namely input, consists of sensor technology components, water quality monitoring, as well as automation and remote sensing. The second group is process, consisting of data analysis and plant growth models. The third group is output consisting of intelligent irrigation control and precision irrigation. The linkages between the supporting components of smart irrigation water management will be realized in a Decision Support System (DSS) and the installation of smart devices such as AWLMS, AWS, and gate controllers.

WP 3: Dissemination of research findings and building stakeholders' capacities to adopt and upscale smart irrigation water management.

Activity 3.1: Organize workshops and trainings

Organizational arrangements will be made for the inception workshop during months 1-2, the mid-term workshop during months 6-7, and the final session during months 11-12. The initial phase of the project consists of a half-day event, during which the project's goals, tasks, outcomes, and schedule will be presented. We will also engage key boundary partners to facilitate the follow-up activities in WP2. The mid-term and final workshop, on the other hand, will last for 1.5 - 2 days. The interim results (WP1 and WP2) and comprehensive results (the whole project) will be communicated during the mid-term and final workshop, respectively. A training session will be integrated into each event, where we will offer training for utilizing the SWAT model and applying smart irrigation water management. In addition, a panel discussion with distinctive targets will be held during each workshop. For the mid-term workshop, the interim results will be discussed with decision-makers to gather recommendations for leveraging the policy relevance. For the final workshop, on the other hand, we will primarily target the exploration of opportunities to streamline key findings into climate change adaptation actions and policies. Both workshops will be regional events where we seek to streamline findings to other countries, especially other tropical developing countries in Southeast Asia.

Activity 3.2: Communicate scientific publications

We will produce at least two publications, delivering high-quality scientific research based on evidence, to submit them to peer-reviewed journals. Three presentations will be created for international conferences and symposiums to distribute important findings widely, share knowledge and expertise, and encourage active participation. The project consortium will construct and operate an open data repository as outlined in the data management plan.

Activity 3.3: Communicate policy-targeting and social media publications

We will publish three policy briefs to inform the audience, foster engagement, and contribute to important policy processes. The documents will be published on the project website and distributed across the websites and fan pages of the collaborators and boundary partners. To make the research findings more accessible to the public, the project participants will actively utilize social media platforms such as Instagram, Facebook, Twitter, and Linkedin to distribute the research findings and important messages.

2.4 Project Workplan and Timeline

The proposed project is scheduled for one year and will be organized into three work packages. The project starts from 1 October 2024 and ends on 30 September 2025 where the detailed timeline is indicated in Table 1.

Table 1 Project timeline

Appendix 1. Detailed Timeline **Project Activities**	**Year 1 (2024/2025) (from 1 October 2024 – 30 September 2025)**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
WP1: Evaluation of land use and climate change impacts on five pillars of irrigation that support rice production												
1.1. Projection of future land use												
1.1.1. Prepare the current land use map	X	X	X									
1.1.2. Set up and calibrate the land use model (DynaCLUE)			X	X	X	X						
1.1.3. Generate future land use map				X	X	X						
1.2. Projection of future climate												
1.2.1. Review Global Climate Models (GCMS)	X	X	X									
1.2.2. Downscale and perform bias-correction			X	X	X	X						
1.2.3. Generate climate change scenarios			X	X	X	X						
1.3. Combined impact of future land use and climate on five pillars of irrigation												

Appendix 1. Detailed Timeline **Project Activities**	**Year 1 (2024/2025) (from 1 October 2024 – 30 September 2025)**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1.3.1. Prepare input data: climate, topography, land use, soil	X	X	X	X								
1.3.2. Model the hydrological system using SWAT		X	X	X	X							
1.3.3. Calibrate and validate the model using SWAT-CUP				X	X	X	X					
1.3.4. Simulate the water balance components for the baseline period							X	X				
1.3.5. Simulate the water balance for future conditions regarding three time horizons								X	X			
1.3.6. Evaluate the combined impact of land use and climate change on irrigation systems									X	X		
WP2: Adaptation of land use and climate change impacts through smart irrigation water management development												
2.1. Preparation of the conceptual framework for smart irrigation water management that is compatible with land use and climate change												
2.1.1. Conduct field surveys	X	X										
2.1.2. Prepare the framework		X	X	X	X							
2.1.3. Evaluate and Curate monitoring data			X	X	X	X						
2.2. Development of smart irrigation water management involving land use and climate change												
2.2.1. Conduct field surveys						X	X					

Appendix 1. Detailed Timeline **Project Activities**	**Year 1 (2024/2025) (from 1 October 2024 – 30 September 2025)**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
2.2.2. Calibrate the monitoring instruments							X	X	X			
2.2.3. Enhance the DSS with the integration of projected land use and climate							X	X	X	X	X	
2.3. Implementation of the developed smart irrigation water management												
2.2.1. Conduct daily observation from the WOC							X	X	X	X	X	
2.2.2. Evaluate the performance of enhanced DSS										X	X	
WP3: Dissemination of research findings and build stakeholders' capacities to adopt and to upscale smart irrigation water management												
4.1. Organization of workshops and regional events												
4.1.1. Kick-off Meeting including engagement of boundary partners (0.5 day)	X	X										
4.1.2. Mid-term workshop (1.5 - 2 days)						X	X					
4.1.3. Final workshop (1.5 - 2 days)											X	X
4.2. Scientific Publications and Communications												
4.2.1. Prepare manuscripts for submission									X	X	X	
4.2.2. Prepare presentations and posters for symposia and conferences										X	X	
4.2.3. Develop project website and data portals	X	X	X									

Appendix 1. Detailed Timeline **Project Activities**	**Year 1 (2024/2025) (from 1 October 2024 – 30 September 2025)**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
4.2.4. Conduct data sharing, storage and management			X	X	X	X	X	X	X	X	X	
4.3. Policy-relevant and Social-media Publications												
4.3.1. Develop policy-briefs										X	X	
4.3.2. Develop infographics and promote socio-media posts	X	X	X						X	X	X	
4.3.3. Prepare materials for training workshops									X	X	X	
4.3.4. Develop Final Report for submission											X	X

CHAPTER 3. PROJECTION OF FUTURE LAND USE

3.1 Developing Land Use Land Cover (LULC) Map

Projection of Future Land Use is the initial step in this research. Prediction of land use changes in the research area, namely D.I Kedung Putri, located in the Bogowonto Watershed, can be used as a reference in developing the Smart Irrigation Water Management To Support Food Security (Siwama) system. This study estimates land-use change prediction modeling using a combination of ANN (artificial neural network) and CA (Cellular Automata). Processing is carried out with the help of the MOLUSCE plugin on the QGIS Desktop software version 3.38.

The analysis stage is divided into two stages: developing a landcover map and landcover prediction. The developing landcover map stage prepares the Land Use Land Cover (LULC) base map. The LULC base map created is the 2015, 2019, and 2023 LULC maps. In simple terms, the Projection of the Future Land Use flow chart is shown in Figure 3.

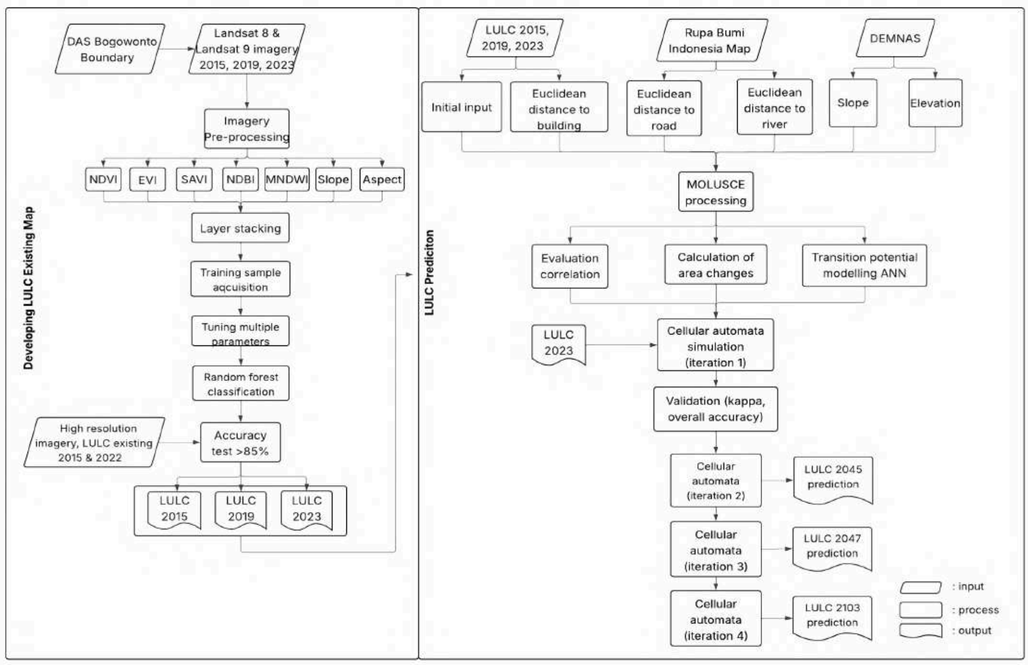


Figure 3 LULC overall framework

3.1.1 Developing Land Use Land Cover (LULC) Map

LULC classification is a stage to predict a previously unknown class using existing class groups. One of the aims of land cover classification is to produce a thematic map, where each pixel value in the image represents an object. The classification method used in this study is the random forest classification. LULC classification in this study consists of 6 classes: rice field, moorland, high-density vegetation, built-up, bare land, and water body. This classification is carried out on each Landsat 8 OLI image in 2015, 2019, and 2023.

a. Layer stacking method

LULC maps for 2015, 2019, and 2023 were produced using Landsat 8 imagery. Several remote sensing indices were computed namely NDVI, EVI, AWEI, MNDWI, and BUI (Table 3.1) and subsequently integrated through a layer-stacking technique. These indices improve the discrimination of LULC classes by highlighting the spectral properties of major surface features. NDVI and EVI were employed to represent vegetation vigor and biomass (Kwan et al., 2020), while BUI and NDBI were used to identify built-up areas (Benkoider et al., 2019). MNDWI and AWEI were effective for delineating water bodies, especially within complex urban settings (Ali et al., 2019). The mathematical expressions for each index are provided below.

Table 2 Remote sensing index

Vegetation Index	Formulation
Normalized Difference Vegetation Index (NDVI)	
Enhanced Vegetation Index (EVI)	$EVI = G \times \frac{NIR-RED}{NIR+C1+RED-C2\times BLUE+L}$ Where: G=2.5, C_1=6, C_2= 7.5, L=1
Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{GREEN-SWIR\ 1}{GREEN+SWIR\ 2}$

Automated Water Extraction Index (AWEI)	AWEI = 4 × GREEN - SWIR 1 - (0.25 × NIR + 2.75 ×SWIR)
Built Up Index (BUI)	$NDVI = \frac{NDBI-NDVI}{NDBI+NDVI}$
Normalized Difference Built Up Index (NDBI)	$NDBI = \frac{SWIR-NIR}{SWIR+NIR}$

In addition, topographic parameters such as slope and aspect were incorporated to account for terrain effects. The layer-stacking approach combining multispectral bands, vegetation indices, and topographic variables has been widely recognized for enhancing classification performance (Lee et al., 2019). Image classification was then carried out using a stratified random sampling approach followed by supervised classification with the Random Forest algorithm.

b. Supervised classification random forest algorithm

Random Forest is a supervised learning algorithm issued by Breiman in 2001. Random Forest is commonly used to solve problems related to classification, regression, etc. Machine learning is a branch of artificial intelligence that imitates the work of the human brain in solving problems and making decisions (Piralilou et al., 2019). In geospatial analysis, machine learning can overcome the limitations of GIS (Geographic Information System) when conducting analysis.

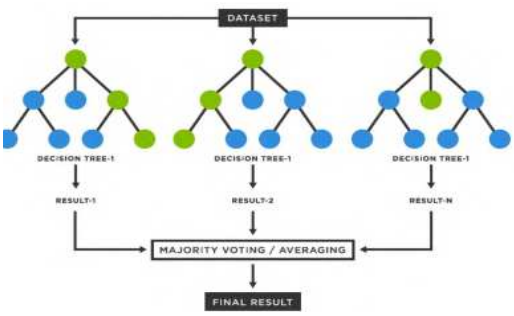


Figure 4 Random forest scheme

c. Accuracy test use Google Earth Pro and LULC Map from Government

The accuracy test was held by employing high-resolution imagery from Google Earth Pro (2015, 2019, and 2023)(Figure 5) and LULC existing map produced by Geospatial Information Agency (BIG) year 2022 and Wonosobo's Local Government year 2015. Accuracy test used Google Earh Pro is illustrated in Figure 5.

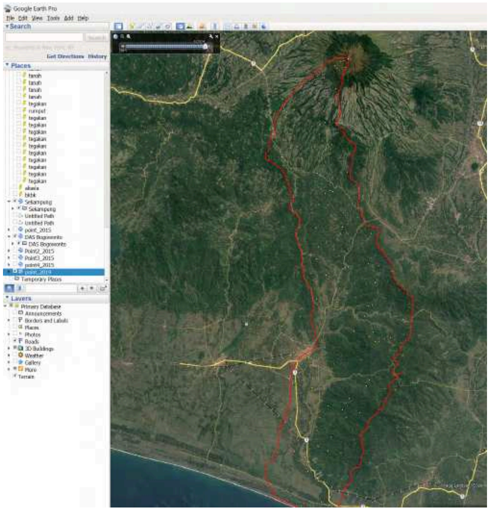


Figure 5 Accuracy test used Google Earth Pro

The sample acquisition method utilized stratified random sampling, in which number of population samples was based on each class area. This method considers the probability of each LULC class will be equal while also deliberating length area every class (McCoy, 2005). Stratified random sampling is illustrated in Figure 6.

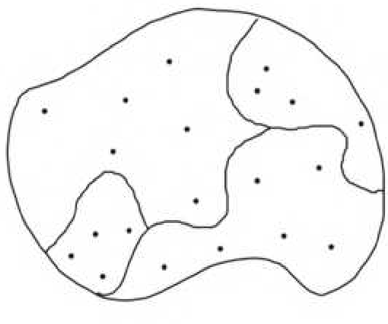


Figure 6 Stratified random sampling model

Source: McCoy (2005)

LULC samples which was being identified are rice field, moorland, barren land, high density vegetation, built up, and water body (Table 3). Sample from rice field and high density vegetation were more than others because of the area of its classes, and research aims to predict rice field area in Bogowonto Watershed.

Table 3 Number of Sampling

Class	Number of sample point		
	2015	2019	2023
Moorland	12	12	12
Barren land	10	10	10
Built up	13	13	14
Rice field	20	20	20
High densitiy vegetation	43	42	41
Water body	11	10	11
Total sampel	108	108	108

Source: Data processed (2025)

The LULC accuracy test was aimed for find out the accuracy resulted from multispectral classification by employing confusion matrix. Confusion matrix is defined as a matrix consisting of a number of omissions in the context of comparison between multispectral classification and field data (Aranoff, 1993). If the kappa coefficient value approaches 1, then the possibility of the accuracy occurring by chance is close to zero (Sutanto 1993 in Murti (2014)). Level accuracy from all of classes is calculated by utilizing Formula xx.

$$\text{Overall accuracy} = \frac{Number\ of\ sampel\ from\ all\ classes\ which\ classified\ correctly}{Total\ of\ accuracy\ sampel} \times 100$$

$$\text{Producer's accuracy} = \frac{Number\ of\ sampel\ which\ classified\ correctly\ in\ certain\ class}{Total\ of\ accuracy\ sampel\ in\ certain\ class} \times 100$$

$$\text{User's accuracy} = \frac{Number\ of\ sampel\ which\ classified\ correctly\ in\ certain\ class}{Number\ of\ accuracy\ samples\ classified\ as\ that\ class} \times 100$$

$$\text{Kappa coeficient} = \frac{N\sum_{i=1}^{r} \text{xii} - N\sum_{i=1}^{r}(x_i + x_{+i})}{N^2 - N\sum_{i=1}^{r}(x_{i+} \,.\, x_{+i})} \ldots (8)$$

Where:

N = Total sampel

r = Number of row

x_{ii} = number of samples in row I and column i

x_{i+} = number of samples in row i

x_{+1} = number of samples in column i

Table 4 Confussion matrix LULC Bogowonto Watershed 2015

Class	Moorland	Barren Land	Built up	Rice field	High density vegetation	Water body	Rows total	Users Accuracy	Kappa
Moorland	10	0	0	0	2	0	12	83.33	120
Barren land	0	10	0	0	0	0	10	100	100
Built up	0	0	13	1	0	0	13	100	195
Rice field	0	0	2	17	1	0	20	85	360
High density vegetation	0	0	0	1	41	1	43	95.35	1892
Water body	0	0	0	0	0	11	11	100	132
Columns total	10	10	15	19	44	12	109		2799
Producers Accuracy	100	100	86.67	89.47	93.18	91.67	**Overall accuracy**	**93.58**	102

Kappa Index	**0.92**

Source: Data processed (2025)

Table 5 Confussion matrix LULC Bogowonto Watershed 2019

Class	Moorland	Barren Land	Built up	Rice field	High density vegetation	Water body	Rows total	Users Accuracy	Kappa
Moorland	11	0	0	0	1	0	12	91.67	144.00
Barren land	0	6	0	0	3	1	10	60.00	60.00
Built up	0	0	12	1	0	0	13	92.31	169.00
Rice field	0	0	1	17	2	0	20	85.00	380.00
High density vegetation	1	0	0	1	40	0	42	95.24	1932
Water body	0	0	0	0	0	10	10	100.00	110.00
Columns total	12	6	13	19	46	11	107		2795.00
Producers Accuracy	91.67	100.00	92.31	89.47	86.96	90.91	**Overall accuracy**	**89.72**	96
Kappa Index									**0.86**

Source: Data processed (2025)

Table 5 Confussion matrix LULC Bogowonto watershed 2023

Class	Moorland	Barren Land	Built up	Rice field	High density vegetation	Water body	Rows total	Users Accuracy	Kappa
Moorland	12	0	0	0	0	0	12	100.00	144.00
Barren land	0	8	0	1	2	0	11	72.73	88.00
Built up	0	0	14	0	0	0	14	100.00	238.00
Rice field	0	0	2	18	0	0	20	90.00	380.00
High density vegetation	0	0	1	0	40	0	41	97.56	1722
Water body	0	0	0	0	0	11	11	100.00	121.00
Columns total	12	8	17	19	42	11	109		2693.00
Producers Accuracy	100.00	100.00	82.35	94.74	95.24	100.00	**Overall accuracy**	**94.50**	103
Kappa Index									**0.93**

Source: Data processed (2025)

The accuracy test result is shown in Table 3, Table 4, and Table 5. According to those confusion matrixes, the overall accuracy for LULC map years 2015, 2019, and 2023 are 93,58%, 89,72%, and 94,50%, respectively. Based on Vierra & Garret (2005) and Murti (2014), our accuracy results indicate that every LULC map are classified as almost perfect agreement (81% - 99%). Moreover, LULC maps can be employed for further processing because the overall accuracy exceeds 85%.

d. Existing Landcover Result

After performing accuracy, the existing land use map for 2015, 2019, and 2023 can be made. These three maps will be the basis for making model predictions using Mollusc. The accuracy obtained on each map is 93.58% in 2015, 89.72% for 2019, and for 2023 is 94.50% (Figure 5). The changes in each class are shown in Table 6.

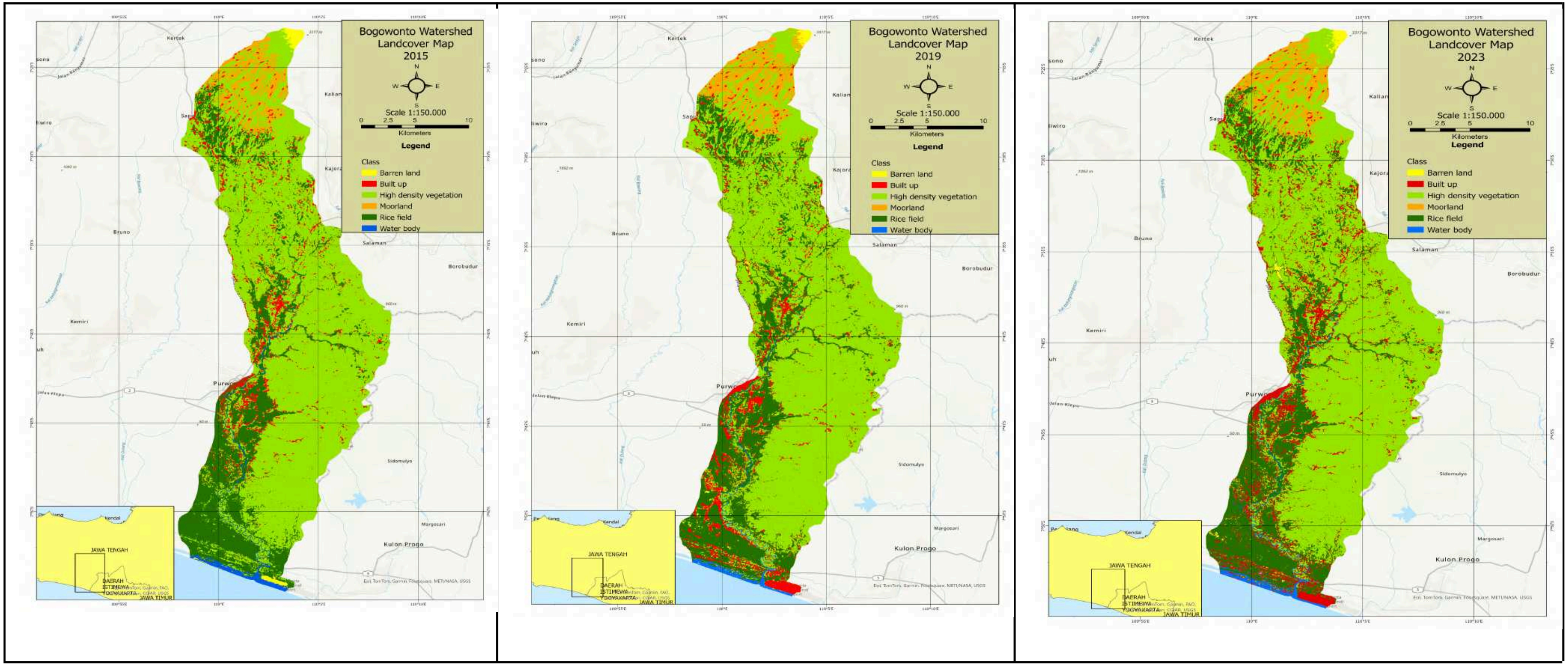


Figure 7 LULC existing map (2015, 2019, 2023) Source: Data processed (2025)

Table 6 Changes in Land Use Areas

Class	Area (ha)		
	2015	2019	2023
Barren land	392.78	325.24	379.45
Built up	3136.28	3962.71	5523.56
High density vegetation	40612.21	39590.10	38496.13
Moorland	2456.04	3006.86	2758.61
Rice field	12461.76	12282.51	11904.72
Water body	693.16	584.81	689.76

Source: Data processed (2025)

Between 2015 and 2023, rice fields declined around 557,04 ha primarily in zones adjacent to expanding urban areas where farmlands were converted into residential and commercial spaces. This reduction poses potential challenges for regional food security. Similarly, high-density vegetation decreased considerably by about 2116,08 ha mainly in the mid-watershed, where forest patches were transformed into mixed gardens or settlements, leading to impacts on slope stability and sediment regulation. Moorlands showed fluctuating trends, peaking in 2019 before declining again by 2023, likely influenced by variations in cropping cycles or land preparation stages. Barren land remained nearly constant, while water bodies slightly contracted, possibly due to sediment buildup in small reservoirs or natural river course changes. Overall, these dynamics indicate intense human pressure on agricultural and vegetated lands, especially in easily accessible lowland regions, whereas upper watershed areas remained relatively stable under both physical and regulatory constraints.

As illustrated in Figure 3.5, the land use and land cover changes highlight clear transformation trends within the watershed. Built-up areas exhibited the most significant absolute and relative increase, expanding about 2387,28 ha The most rapid development occurred in downstream zones with gentle slopes, close to transport routes and urban centers, which naturally attract infrastructure and investment. A key catalyst of this urban expansion was the construction of the New Yogyakarta International Airport (New YIA), which began in 2017 and started limited operations in 2019. The airport's development spurred rapid urbanization in its surroundings through the establishment of supporting infrastructure, commercial hubs, and residential neighborhoods.

3.1.2 Prediction of future LULC map using MOLUSCE

The next step is to create a LULC prediction map with Molusce software. MOLUSCE is a plugin in QGIS software that allows land change analysis. MOLUSCE can be used to visualize and validate land change prediction results obtained from ANN (Blissag, Yebdri, and Kessar 2024) In Molusce, various modeling functions, including artificial neural network (ANN), can be used. MOLUSCE also provides a kappa index as a validity function to show the suitability of the actual map and predicted maps' suitability. The capabilities of this plugin are that it can effectively calculate land use changes spatiotemporally, perform transition potential modeling, and simulate future scenarios (Alipbeki, 2024). ANN consists of neurons with the same mechanism as the human brain and using them to recognize data trends (Kufel et al., 2023). In the MOLUSCE plugin found in QGIS Desktop version 3.38, the ANN algorithm recognizes potential changes with output as a transition potential matrix.

The transition potential model used in this study was trained with a momentum of 0.050 and a learning rate of 0.006 to stabilize the learning graph. Furthermore, the number of iterations was set to 1000 to prevent overfitting problems in the model. Then, the land use change simulation was processed using the MOLUSCE plugin based on the CA-ANN model. The CA-ANN simulation selects raster data, such as land use class, spatial parameter raster, and transition potential model, based on the ANN algorithm. The simulation checks a fixed number of pixels, with the greatest certainty for each transition corresponding to the most likely transition, and then adjusts the pixel class. Several simulation iterations were carried out to achieve the next prediction maps in 2043, 2075, and 2103. The land use change prediction results were validated by comparing the 2023 prediction map with the actual map in 2023. The method used is using Kappa, with the minimum accuracy criteria achieved presented in Table 7. If the simulation results have a strong Kappa value, then the modeling for prediction can be carried out for the desired target year.

Table 7 Kappa value classification

Kappa Coefficient Value	Interpretation of Kappa Value

<0,20	Poor
0,21 – 0,40	Fair
0,41 – 0,60	Moderate
0,61 – 0,80	Good
>0,80	Very Good

Source: Kunz (2017)

Before starting the modeling, the first thing to do is prepare the driving factors as input material. In this study, the driving factors used are road, river, slope, building, and elevation.

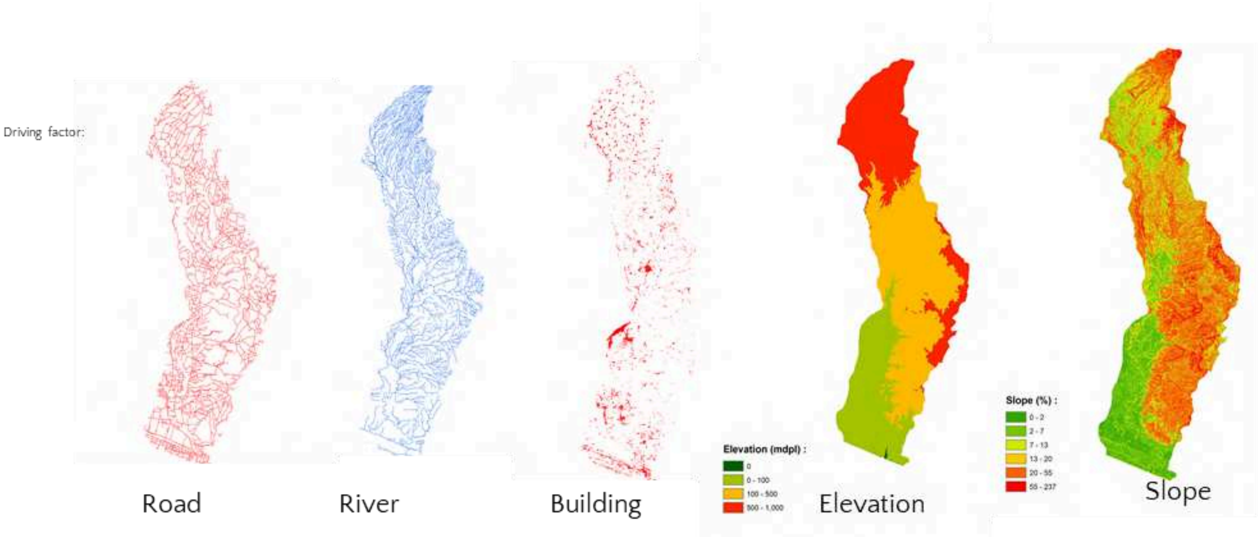


Figure 8 Driving factors

Source: Data processed (2025)

Several stages in MOLUSCE, among others:

a) Input Model,

Input data is used to calculate the initial year and the final year of the prediction, where 2015 is the initial year and 2019 is the final year. The driving factors of road, river, slope, building, and elevation are also input data in this process.

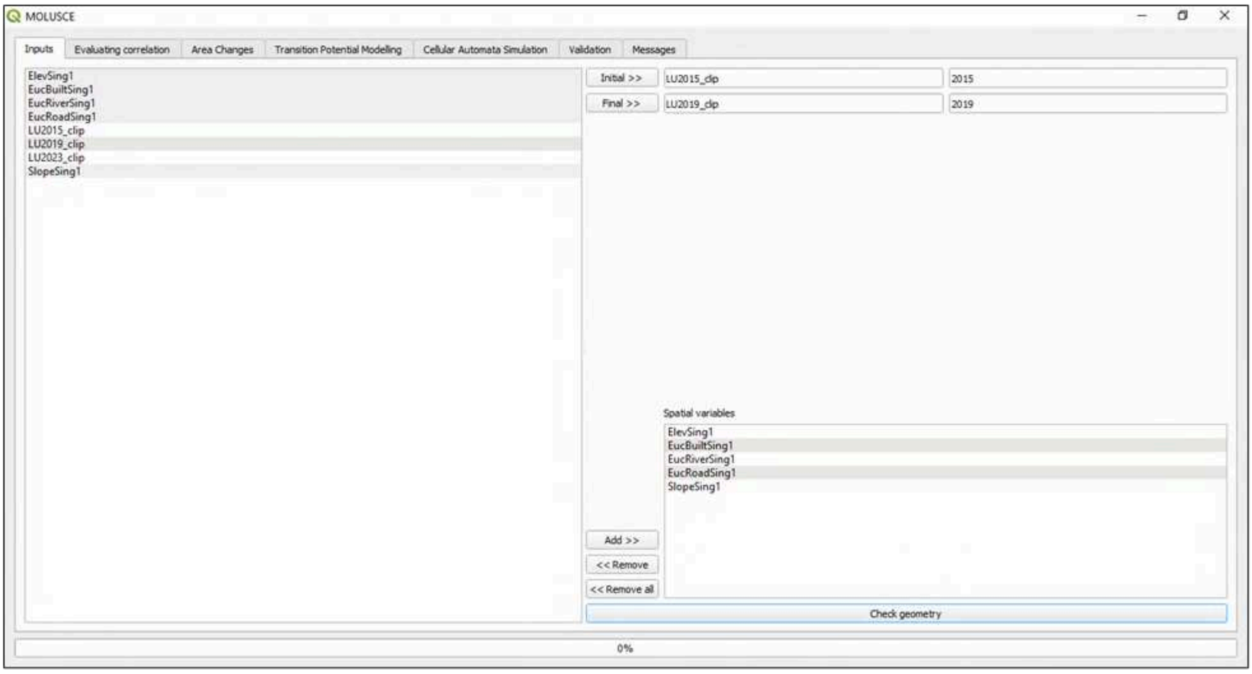


Figure 9 Input model process

b) Evaluating Corellation,:

MOLUSCE has a feature to calculate the correlation between a factor and the initial and final year data entered, namely the driving factor at the evaluating correlation stage. This driving factor results from calculating the Euclidean distance (linear distance) between each pixel or area in a particular region with the road and coastline features around it. The Pearson's Correlation test between variables shows that the driving factors have a positive correlation.

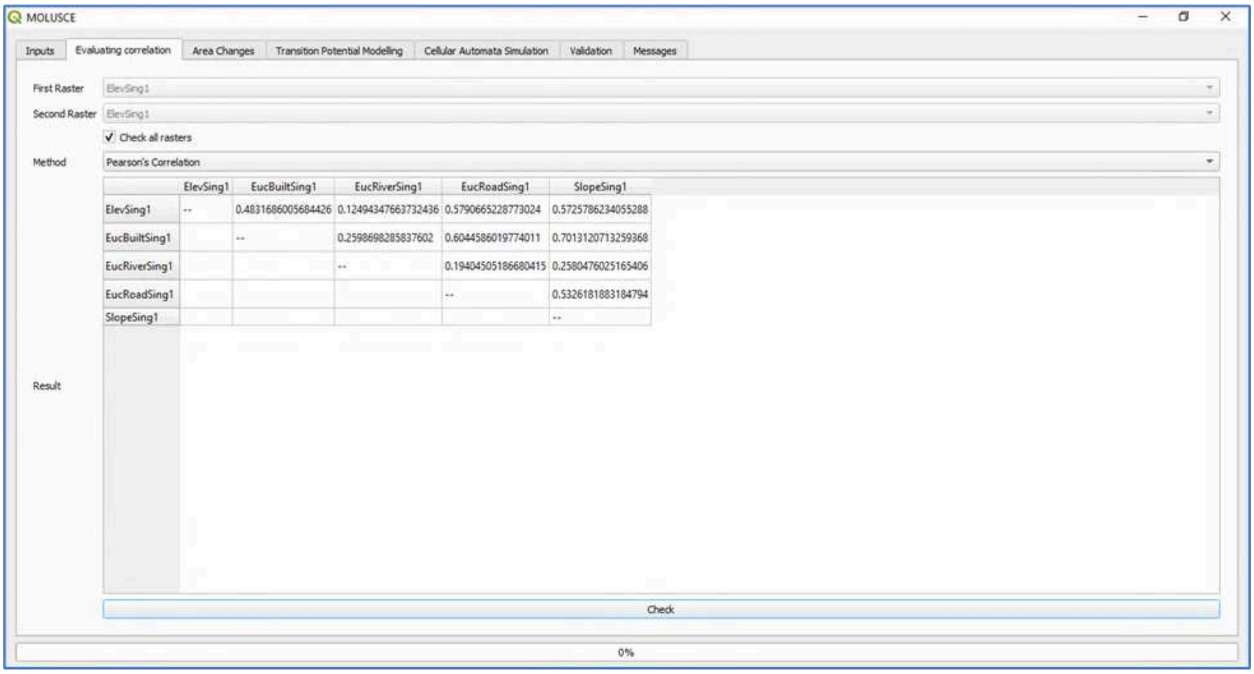
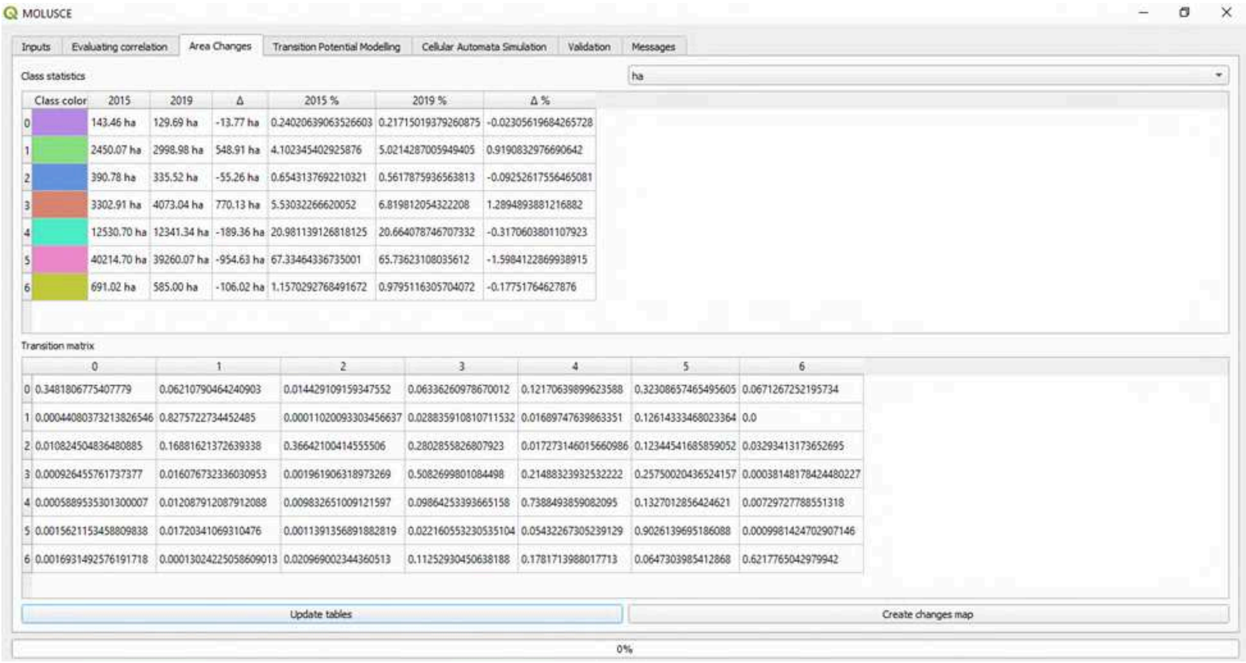


Figure 10 Evaluating correlation

c) Area Changes

In the area change stage in MOLUSCE, the transition matrix describes the probability of pixel changes from the initial land use/land cover class (LULC) to the final LULC class over a certain period. This transition matrix contains values from 0 to 1, reflecting pixel change probability. The range of 0 or 1 is unchanged, but 0.1–0.9 is a change. Thus, the difference between the probability values of 0.1 and 0.9 in the transition matrix will reflect how likely the change is to occur, where a value of 0.9 will indicate a higher probability of change than a value of 0.1. A change with a probability value of 0.9 tends to be more likely than a change with a probability value of 0.1.



	Class color	2015	2019	Δ	2015 %	2019 %	Δ %
0		143.46 ha	129.69 ha	-13.77 ha	0.24020639063526603	0.21715019379260875	-0.02305619684265728
1		2450.07 ha	2998.98 ha	548.91 ha	4.102345402925876	5.0214287005949405	0.9190832976690642
2		390.78 ha	335.52 ha	-55.26 ha	0.6543137692210321	0.5617875936563813	-0.09252617556465081
3		3302.91 ha	4073.04 ha	770.13 ha	5.53032266620052	6.819812054322208	1.2894893881216882
4		12530.70 ha	12341.34 ha	-189.36 ha	20.981139126818125	20.664078746707332	-0.3170603801107923
5		40214.70 ha	39260.07 ha	-954.63 ha	67.33464336735001	65.73623108035612	-1.5984122869938915
6		691.02 ha	585.00 ha	-106.02 ha	1.1570292768491672	0.9795116305704072	-0.17751764627876

	0	1	2	3	4	5	6
0	0.3481806775407779	0.0621079046424090 3	0.014429109159347552	0.06336260978670012	0.12170639899623588	0.32308657465495605	0.0671267252195734
1	0.00044080373213826546	0.827572273445248 5	0.00011020093303456637	0.028835910810711532	0.01689747639863351	0.12614333468023364	0.0
2	0.010824504836480885	0.16881621372639338	0.36642100414555506	0.2802855826807923	0.017273146015660986	0.12344541685859052	0.03293413173652695
3	0.000926455761737377	0.016076732336030953	0.001961906318973269	0.5082699801084498	0.21488323932532222	0.2575002043652415 7	0.00038148178424480227
4	0.0005889535301300007	0.012087912087912088	0.009832651009121597	0.09864253393665158	0.7388493859082095	0.1327012856424621	0.007297277885513 18
5	0.0015621153458809838	0.01720341069310476	0.0011391356891882819	0.022160553230535104	0.05432267305239129	0.9026139695186088	0.0009981424702907146
6	0.0016931492576191718	0.00013024225058609013	0.020969002344360513	0.11252930450638188	0.1781713988017713	0.0647303985412868	0.6217765042979942

Figure 11 Area changes

d) Train Neural-Network

The training stages using MOLUSCE containing the ANN algorithm include determining the neighborhood, setting the maximum iteration, configuring the learning rate, selecting the number of hidden layers, and selecting the momentum factor. These hyperparameters can be adjusted based on the complexity of the input data and the desired level of generalization. The Artificial Neural Network (ANN) algorithm involves initializing weights and biases, receiving input data, processing it through hidden layers, and generating predictions. The error is calculated, and the weights and biases are adjusted to minimize the error through the backpropagation process. Iterative updates are performed, and the ANN predicts new data. Performance is evaluated with appropriate metrics.

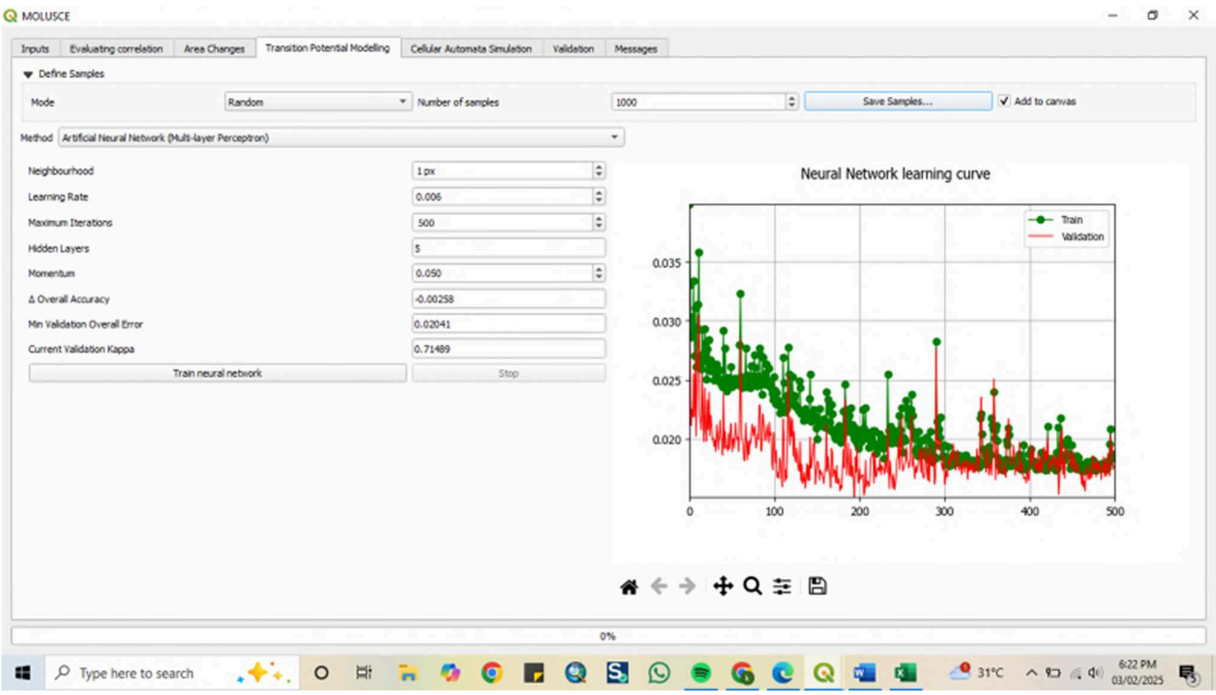


Figure 12 Transition potential modelling

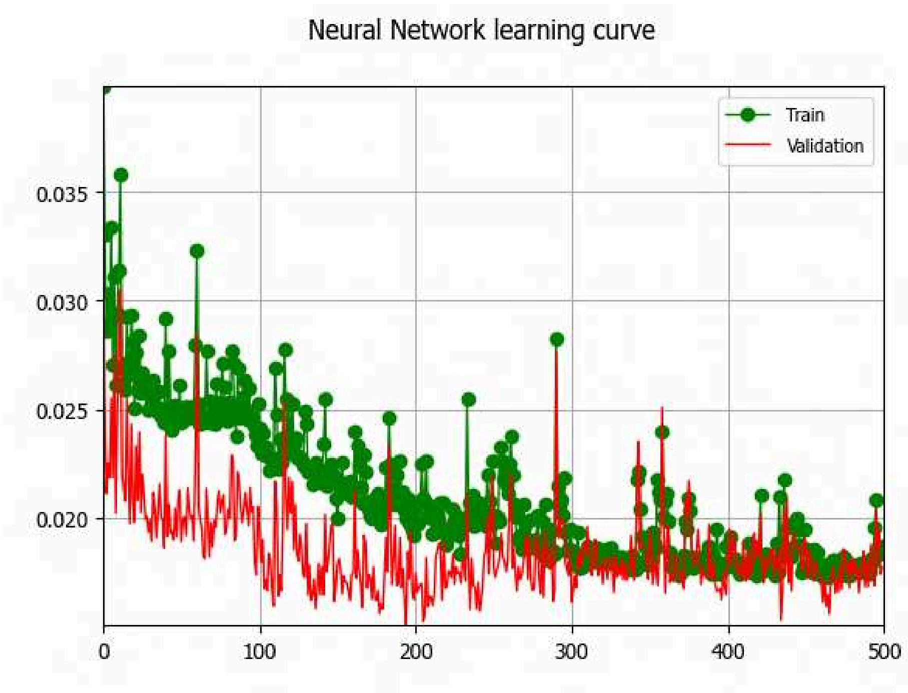


Figure 13 Neural network learning curve

e) Validation

MOLUSCE has a validation stage to measure the performance of the prediction model, where there are "& of correctness" and "Kappa (overall)". & of correctness measures the accuracy of the prediction in percentage. In contrast, kappa (overall) measures the suitability of the prediction with the actual data using the kappa coefficient. & of correctness only provides information about the accuracy of the prediction in general. In contrast, kappa (overall) provides information about the suitability of the prediction with the actual data as a whole.

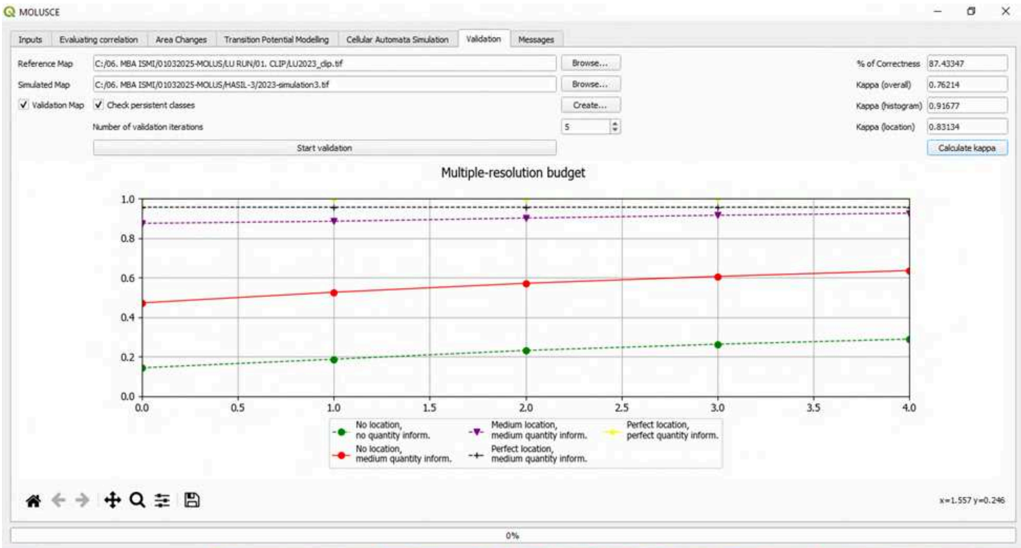


Figure 14 Multiple resolution budget graph

At this stage, there is a Multiple-resolution Budget Graph. The Multiple-resolution Budget graph at the validation stage in MOLUSCE is used to evaluate the spatial accuracy of the land use change prediction model at various resolutions. On the graph there is a purple line, which shows Quantity Accuracy, Location Accuracy is shown by the Green Line, and the red line shows Combined Accuracy which is the combined accuracy of quantity and location. The higher the red line, the better the overall model. So based on the Figure above, it can be shown that:

1. Quantity Accuracy: Quite good, with a value close to 1 at all resolutions.
2. Location Accuracy: Quite good, with a value close to 1 at all resolutions.
3. Combined Accuracy: Quite good, with a value close to 1 at all resolutions.
4. Consistency: The model's accuracy looks consistent at all spatial resolutions, which shows the model is quite robust.

So, it can be concluded that the land use change prediction model is quite accurate in predicting the quantity and location of changes. The model also looks consistent at various spatial resolutions.

3.1.3 Accuracy Test Results

The results of the classification are then evaluated for accuracy. One way to evaluate the accuracy of the classification results is to conduct an accuracy evaluation, namely by creating an error matrix. The error matrix is a square matrix that functions to see classification deviations in excess pixels from other classes or a lack of pixels in each class. Ideally, all non-diagonal elements in the matrix must be zero, meaning there are no deviations. This matrix can calculate the magnitude of producer accuracy, user accuracy, overall accuracy, and kappa accuracy. Kappa accuracy in Molusce consists of three accuracies, namely: Kappa (overall), Which measures the overall suitability between prediction and observation maps; Kappa (histo), Which measures suitability based on the distribution of land use categories; and Kappa (loc), Which measures suitability based on the location of land use changes.

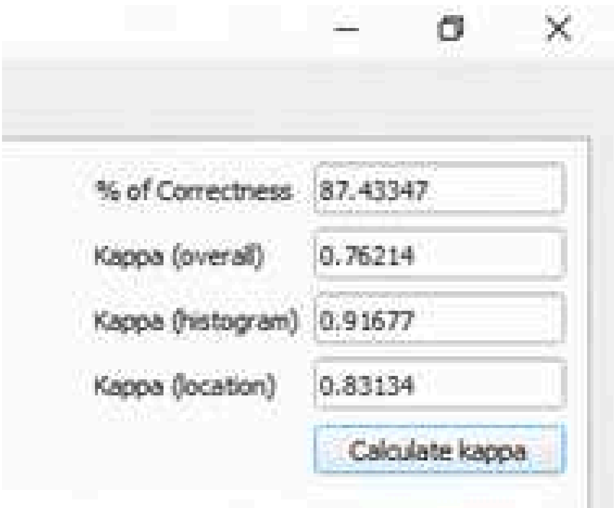


Figure 15 Kappa validation

Based on the kappa validation shown in Figure 15, it can be concluded as follows:

• % of Correctness: 87.43347 – Shows the percentage of areas correctly predicted by the model.

• Kappa (overall): 0.76214 – Shows a good overall agreement between the prediction and observation maps.

• Kappa (histo): 0.91677 – Shows a very good agreement in the distribution of land use categories.

• Kappa (loc): 0.83134 – This shows a very good agreement regarding the location of land use changes.

3.1.4 Prediction Model Validation

In this study, validation was carried out with the default input from the MOLUSCE plugin on two maps: the predicted map of 2023 and the actual map (classification results) of 2023. Model validation was carried out to check how the developed model can describe actual land use changes. Model validation results can be evaluated using indexes or other metrics.

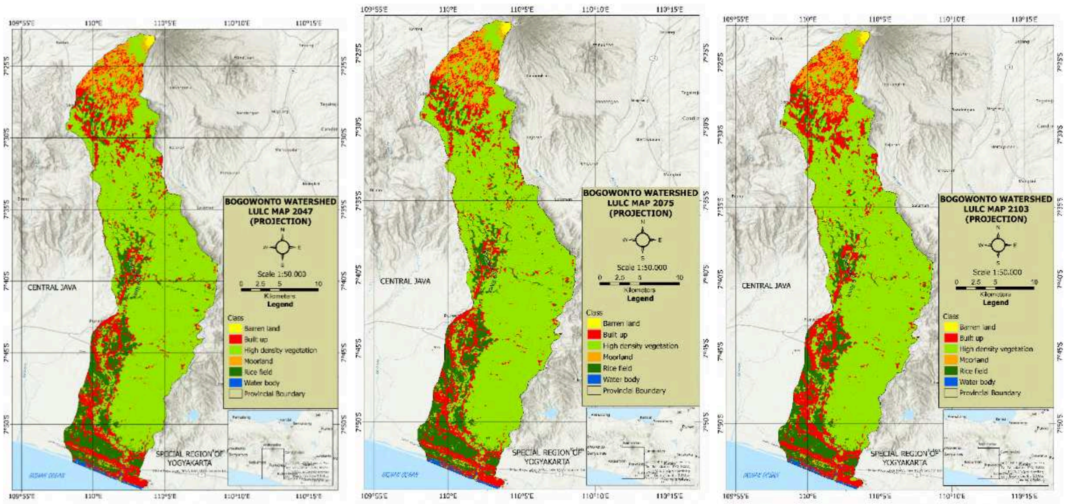


Figure 16 LULC Model Prediction Results for 2047, 2075, and 2103

Based on the results of the prediction map modeling in Figure 16, there is an increase in the settlement area from 2047 to 2103. This indicates regional development and population growth in the Bogowonto Watershed. The increase in settlements is more significant in the downstream part of the watershed. The open land area has also changed. There is a tendency to increase in several areas, which may be related to agricultural activities or infrastructure development. In general, high vegetation areas still dominate the Bogowonto Watershed. However, there is a decrease in several areas, especially around the settlement area. This indicates a change in land function from vegetation areas to built-up areas. The pattern of land use change shows a shift from natural areas (high vegetation) to built-up areas (settlements and open land). Various factors, such as population growth, economic development, and changes in spatial planning policies, can influence this change. Details of land changes are shown in Table 8.

Table 8 Land area changes predicted by LULC model

Class	Area (ha)		
	2047-2075	**2075-2103**	**2047-2103**
Barren land	256.42	255.11	254.45
Built up	8984.91	9998.58	10435.07
High density vegetation	40087.75	39778.25	39624.12
Moorland	2512.71	2476.63	2464.73
Rice field	7607.68	6953.02	6686.96
Water body	302.75	290.64	286.90

Based on the prediction map modeling results in Table 8, it can be seen that there has been a significant decrease in the area of rice field. This decrease continues from the period 2047-2075 to 2075-2103. This indicates a change in land function or rice field degradation. There has been a decrease in barren land, although not as large as rice field and moorland. This indicates land rehabilitation efforts or changes in land use. On the other hand, there has been a significant increase in land area on built-up land. This increase indicates rapid regional development and urbanization in the Bogowonto Watershed. The highest increase occurred in 2047-2075 and continued to increase relatively high in 2075-2103. Then, there was a significant decrease in the area of rice fields. This decrease indicates the conversion of rice fields into built-up areas or other land uses. The decrease occurred relatively high in 2047-2075 and continued to decrease in 2075-2103. Then, there was a decrease in the use of high-density vegetation land. This decrease may be related to deforestation or other changes in land function. Finally, there is a decrease in the area of water bodies, although relatively minor. This may indicate a change in hydrology or drying of water bodies. Thus, land use changes in the Bogowonto watershed indicate a strong urbanization trend, marked by a significant increase in the built-up land area.

3.2 Integration of LULC Projection with The Regional Spatial Planning Policy (RTRW) 2024

The comparative analysis reveals that much of the projected expansion of built-up areas aligns with RTRW-designated settlement and industrial zones, especially in the downstream region surrounding New YIA. This consistency indicates that urban growth is generally in line with the existing spatial plan, though the projected rate of expansion offers important insights for assessing infrastructure and service capacity. Similarly, the projected persistence of rice fields in several downstream and mid-watershed areas corresponds with the RTRW's agricultural zones, supporting the policy aim of preserving productive farmland.

Integrating LULC projections with the RTRW Map (Figure 3.15) serves two primary planning purposes. First, it provides a forward-looking perspective on land cover trajectories, helping anticipate future development directions. Second, it enables preventive spatial management by identifying potential risks—such as the accelerated conversion of rice fields—that warrant protective interventions. During the 2024–2044 period, the RTRW is scheduled for review every five years, allowing the planning document to adapt to emerging land use dynamics. The simulated decline in rice field areas underscores the need to reinforce their protected status within future revisions. Such adaptive adjustments enhance the role of spatial planning as a mechanism to balance development objectives with long-term food security.

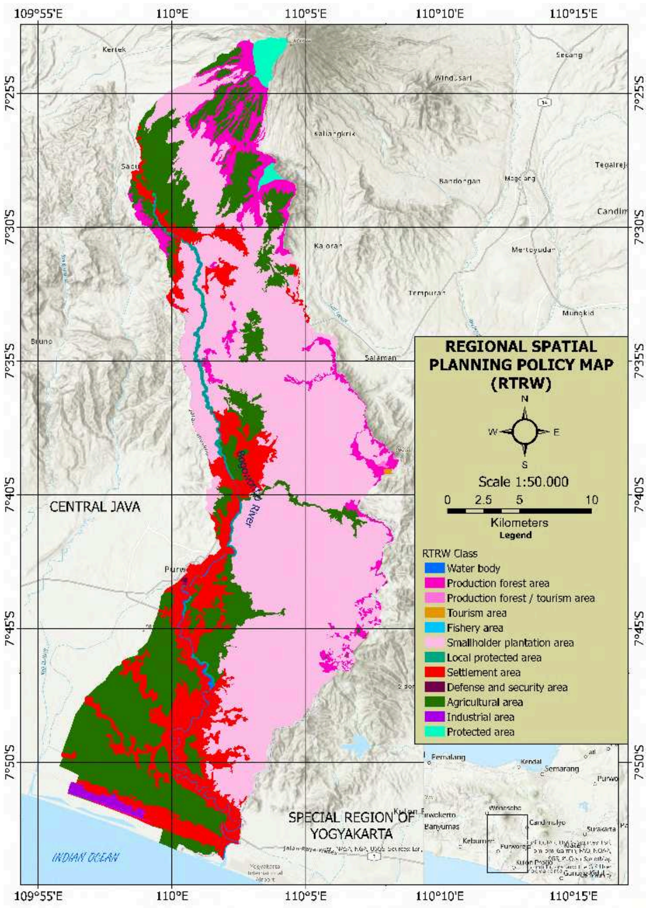


Figure 17 Regional spatial planning policy map (RTRW) 2024-2044

Source: Central Java Public Works and Public Housing Agency

CHAPTER 4. IMPACT OF LAND USE AND CLIMATE CHANGE ON IRRIGATION SYSTEM (WATER BALANCE AND RICE PRODUCTIVITY)

4.1 INTRODUCTION

Water is a critical resource for global food security, supporting agricultural production such as crop irrigation, livestock management, and fisheries. Notably, the agricultural sector accounts for approximately 70% of global freshwater consumption. This trend is also evident in Indonesia, where in 2021 about 80% of the country's total freshwater withdrawals were allocated to agriculture. Within this sector, water use primarily involves irrigation, particularly for rice cultivation and other water-intensive crops. Figure 18 presents the volume of water withdrawals in Indonesia's agricultural sector.

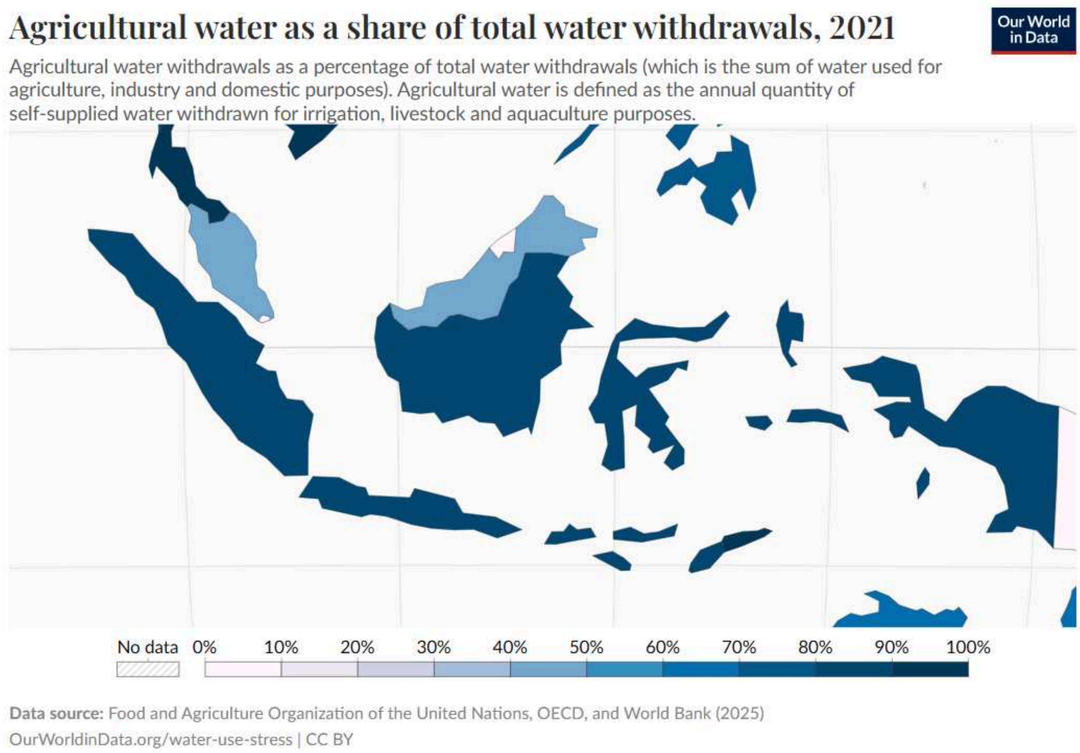


Figure 18 Agricultural water withdrawals in Indonesia in 2021 (source: Ritchie and Roser, 2024)

Water balance prediction is pivotal in managing water resources to sustain agricultural irrigation, especially in Indonesia, where rice production underpins national food security. Rice yield directly influences food availability, and efficient water management is critical given the highly variable climate and distribution of water resources. Accurate water balance prediction models are essential for optimizing irrigation scheduling and ensuring a sustainable water supply, accounting for evapotranspiration, rainfall variability, and crop water demand. It supports efficient water use, reducing waste and enhancing the resilience of rice production systems to climate uncertainties.

Integrated assessment is required to evaluate water balance in regions with complex river basins and diverse land uses. The Soil and Water Assessment Tool (SWAT), developed by the Agricultural Research Service (ARS) of the US Department of Agriculture (USDA), is a semi-distributed hydrological model designed to simulate water, sediment, and agrochemical dynamics in large watersheds. SWAT facilitates the evaluation of land management practices and climate change impacts on long-term water availability (Arnold et al., 2012; Gassman et al., 2014). The model quantifies the effects of land management on water, sediment, and nutrient fluxes, including nitrogen and phosphorus, thereby supporting land-use planning and conservation initiatives. Applications of SWAT in Indonesia, such as those by Sujarwo et al. (2022) and Junaidi (2012), highlight its effectiveness in sensitivity analysis and modeling erosion and sedimentation in the Brantas and Cisadane watersheds. Additionally, SWAT has been used to assess water availability and reservoir management in the Bajulmati and Semantok watersheds (Sujarwo et al., 2020; Kurniawati et al., 2024).

The Soil and Water Assessment Tool (SWAT) directly links water availability to food production by modeling key hydrological variables such as river discharge and groundwater flow, using climate, soil, and land cover data. Adequate water supply, as predicted by SWAT, supports well-irrigated agricultural land and maximizes the yield of crops including rice, corn, and vegetables. In the Bogowonto watershed for Kedung Putri, SWAT analysis focuses on maintaining a sufficient and sustainable irrigation water supply for rice fields throughout the planting season, thereby supporting regional rice availability. This study applies the SWAT model to predict the effects of climate and land-use changes on future water balance and to evaluate the effectiveness of various land and water management strategies.

4.2 STUDY AREA

The Kedung Putri Irrigation Area, located in Trirejo Village, Loano District, Kabupaten Purworejo, Central Java, Indonesia, was established around 1925 as a surface irrigation system. This system supplies water to agricultural land across seven subdistricts: Ngombol, Banyuurip, Bayan, Purwodadi, Purworejo, Loano, and Gebang. The irrigation network comprises a main canal approximately 20.81 kilometers in length, supported by 123 mechanical regulation structures, including regulators and diversion weirs. These components enable efficient water distribution to approximately 3,875 hectares of productive agricultural land.

Kedung Putri lies within the Bogowonto watershed, a significant river basin that provides the primary water source for the irrigation system through the intake at Bendung Kedung Putri. The watershed plays a critical role in sustaining water availability by collecting rainfall and runoff that feed the irrigation canals. Land use is primarily dedicated to paddy fields for rice cultivation, reflecting rice's vital role as a staple food and economic backbone in the region. Secondary crops and limited sugarcane production are also present. The predominantly flat to gently undulating terrain is well-suited for surface irrigation.

Consequently, the Kedung Putri irrigation system functions as an integrated water and land management unit within the Bogowonto watershed, supporting rice production and local food security. Figure 19 shows the location of Kedung Putri Reservoir.

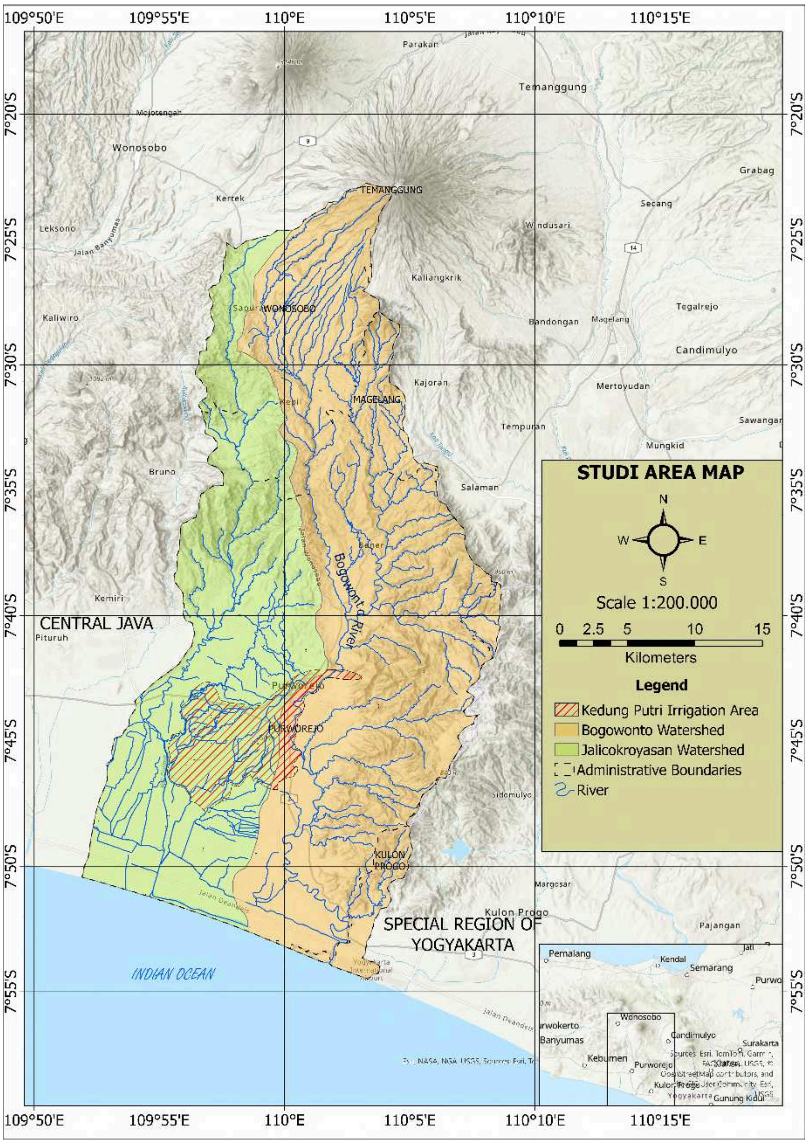


Figure 19 Location of Kedung Putri Reservoir

4.3 METHODS

This section outlines the methodology and model configuration for estimating the water balance using the Soil and Water Assessment Tool (SWAT). The SWAT model is applied to predict water availability and water demand within the Bogowonto Watershed, with a focus on the Kedung Putri Irrigation Area. The model evaluates hydrological components, such as discharge at the Kedungputri Reservoir and watershed conditions in the Bogowonto region. Figure 20 illustrates the SWAT-based water balance framework.

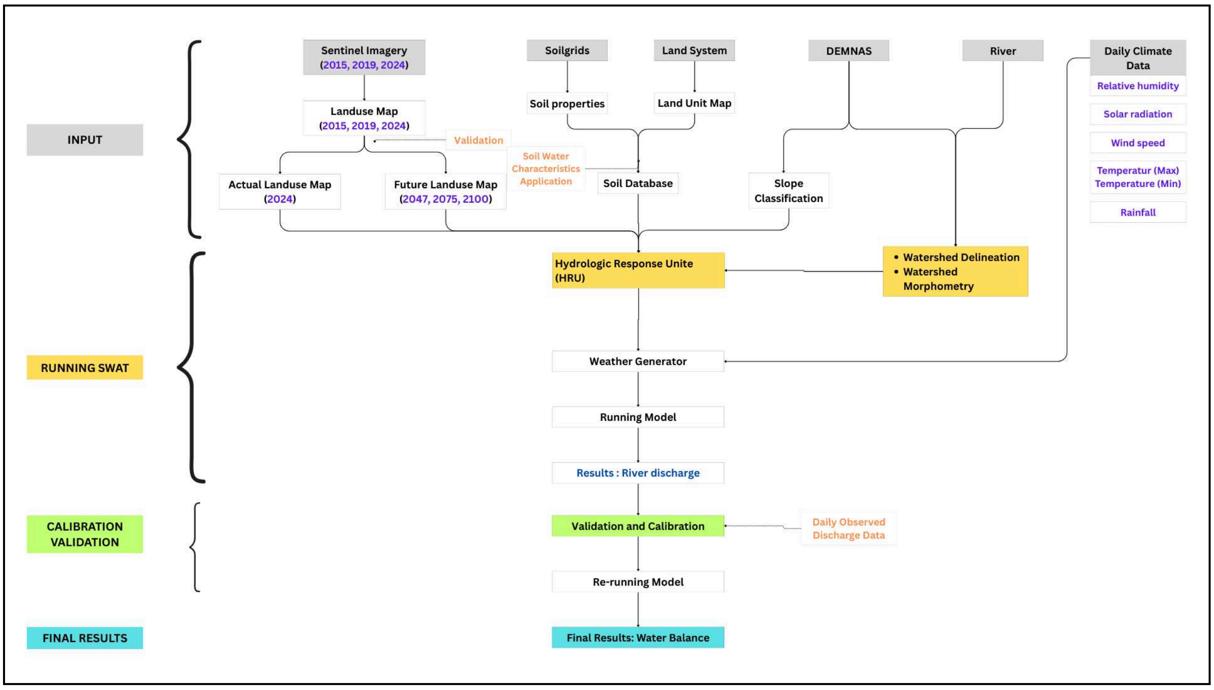


Figure 20 Water balance framework

4.3.1 SWAT Input Model

Climate Input

Climate data are organized into two primary formats: the station format, which encompasses stations measuring precipitation, temperature, relative humidity, solar radiation, and wind velocity, and the annual measurement data format. The standard ArcSWAT climate data formats are summarized in Table 9 and Table 10.

Table 9 Climate Station Format for Precipitation, Temperatur, Relative Relative Humidity, Solar Radiation dan Wind Velocity

ID	*NAME*	*LAT*	*LONG*	*ELEVATION*
Integer	*String max 8 chars*	*Floating point*	*Floating point*	*Integer*

Table 10 Database Format for Daily Data of Precipitation, Temperature, Relative Humidity, Solar Radiation and Wind Velocity Every Station

Row	*Coloumn Format*	*Description*
First	*yyyymmdd (string)*	*First date of the data*

Next - End	*Floating point, free format*	*Daily data of precipitation, solar radiation, temperature, wind, and relative humidity*

ArcSWAT accepts input data in the .txt file format. Data prepared in Microsoft Excel should be saved as .csv files and subsequently converted to .txt files to ensure compatibility with ArcSWAT database requirements.

After data preparation, the model uses climate variables such as maximum and minimum temperatures, precipitation, relative humidity, solar radiation, and wind speed, all derived from the EC-Earth3, EC-Earth CC, and NonESM2 satellite datasets. The data collection period spans from 1980 to 2100, and data acquisition continues beyond 2010. Simulations are conducted for Shared Socioeconomic Pathways (SSP) 2.45 and 5.85 scenarios using the EC-Earth3, EC-Earth CC, and NonESM2 models. Data for relative humidity, solar radiation, and wind speed remain under collection in Table 11.

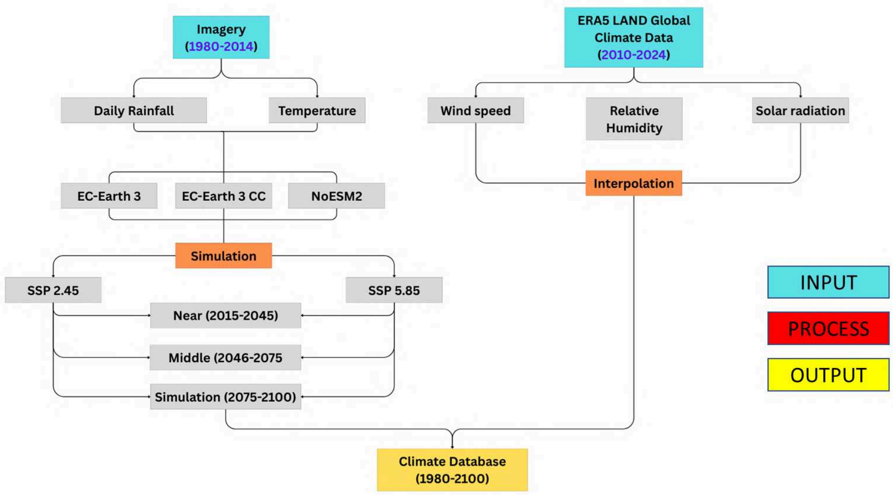
Table 11 Data for relative humidity, solar radiation, and wind speed remain under collection

Id	Name	Lat	Long	Elevation (msl)
1	St Panungkulan	-7.63	110.02	320
2	St Sapuran	-7.73	110.683	18
3	St Sawangan	-7.52359	110.3487	497
4	Global Data	-7.5631	110.0551	480

Figure 21 Climate station

Table 12 Temperature Input in SWAT

No	Simulation	Model	Temperature			Rain		
			Min	Max	Avg	Min	Max	Avg
1	SSP 2.45	EC-Earth 3	17.78	36.53	26.90	0	47.64	5.37
		EC-Earth CC	17.78	37.32	26.98	0	44.70	5.34
		NonESM2	17.78	35.40	27.03	0	109.95	6.99
2	SSP 5.85	EC-Earth 3	17.78	39.26	27.06	0	68.68	5.68
		EC-Earth CC	17.78	39.74	27.52	0	79.24	5.67
		NonESM2	17.78	40.55	27.86	0	92.16	6.90



Soil Data Input

Soil data derived from laboratory test results are compiled into a database that adheres to the User Soil database format. Once compiled, the dataset is transferred to the SWAT 2012.mdb database within the User Soil section. At each stage, the data status can be tracked as: compiled, transferred, and verified. To verify completion, users access ArcSWAT, select Edit SWAT Input, proceed to Edit Database, and choose User Soil. When soil classification data appears, the input process is complete. For soil data supplied as shapefile (.shp) or grid files, a personal database format must be used to enable automatic naming within ArcSWAT. The required data format is detailed in Table 13, and soil data input codes are listed in Table 14.

Table 13 Format basis data SWAT

VALUE	*STMUID*
String	*String (5 chrac)*

Table 14 Soil input code of SWAT model

Kode SWAT	**Description**
SNAME	Soil name *(required)*
NLAYERS	Number of soil horizon
HYDGRP	Hydrological Soil Group, based on SCS-CN classification *(required)*
SOL_ZMX	Maximum Root Depth (mm) *(required)*
ANION_EXCL	Fraction of porosity (void space) from which anions are excluded *(optional)*
SOL_CRK	Potential or maximum crack volume of the soil profile expressed as a fraction of the total soil volume *(optional)*
TEXTURE	Soil texture classification every soil layer, number of soil texture is based on the number of soil layer *(required)*
SOL_Z	Soil layer depth (mm) *(required)*
SOL_BD	Bulk Density (gr/cm^3) *(required)*
SOL_AWC	Available Water Holding Capacity (%) *(required)*
SOL_CBN	Soil Organic Carbon (%) *(required)*
SAND	Percentage of Sand (%) *(required)*
CLAY	Percentage of Clay (%) *(required)*
SILT	Percentage of Silt (%) *(required)*
ROCK	Percentage of coarse fragment (%) *(required)*
SOL_ALB	Moist soil albedo *(required)*

Kode SWAT	**Description**
SNAME	Soil name *(required)*
	$Soil\ Albedo\ =\ 0.069\ *\ (color\ value) -\ 0.144$
K_USLE	Soil Erodibility *(required)* $K\ =\ 0.2\ +\ 0.3\ \exp exp\left(0.0256\ x\ Sa\ x\left(1\ -\ \frac{Si}{100}\right)\right)x\left(\frac{Si}{Cl+Si}\right.$ Sa : % sand Si : % silt Cl : % sand C : % soil organic carbon SN : permeability factor or structure factor

Source: Gijsman et al 2007; Gies and Merwade, 2009; Neitshc et al, 2009

FAO Texture Class	**Texture Code**	**%Clay**	**%Sand**	**%Silt**
C	Clay	50	30	20
CL	Clay Loam	34	33	33
L	Loam	18	42	40
LS	Loamy Sand	6	82	12
Sa	Sand	5	92	3
SC	Sandy Clay	42	52	6
SCL	Sandy Clay Loam	28	60	12
SL	Sandy Loam	10	65	25

FAO Texture Class	Texture Code	%Clay	%Sand	%Silt
Si	Silt	6	7	87
SiC	Silty Clay	47	7	46
SiCL	Silty Clay Loam	34	10	56
SiL	Silty Loam	20	20	60

Source: Gijsman et al 2007; Gies and Merwade, 2009

Hydrologic Soil Group	Description
A	% sand >86, depth >= 1500 mm
B	%sand >50, %clay <35, depth >500 mm
C	% clay >= 28, % sand <= 44, and depth <= 800 mm
D	% clay >= 50

Source: Gijsman et al 2007; Gies and Merwade, 2009

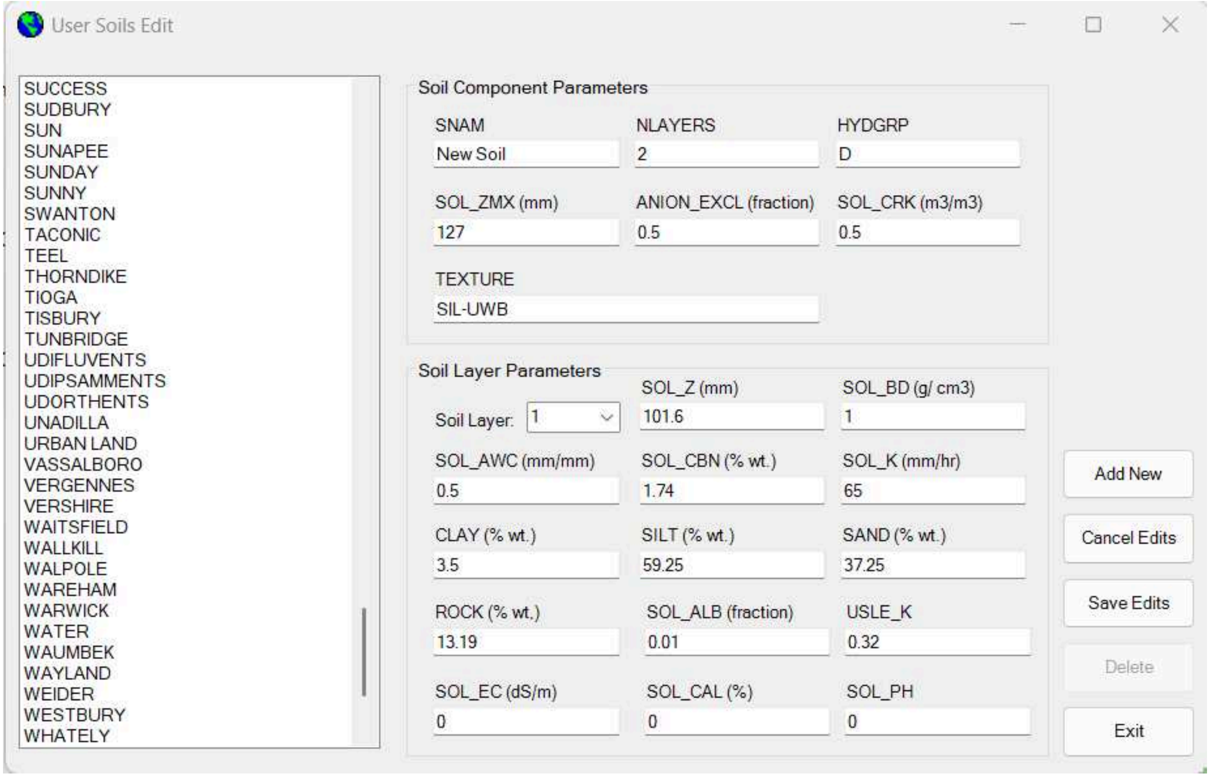


Figure 22 User soil data base

The study classified 22 distinct soil types present at the site. Each soil type is assigned a unique code and characterized by specific attributes, including hydrologic soil group (HSG), which quantifies water infiltration rates, and soil texture, defined by the proportions of sand, silt, and clay. For instance, the soil type coded AHK1 is categorized as HSG C and exhibits a clay loam to clay texture (CL-CL). These data are essential for simulating water infiltration, subsurface flow, and sediment transport processes.

These classifications require robust soil data inputs, which for this project were obtained from two primary sources: a spatial dataset and a global dataset. The spatial dataset consists of a 1:50,000-scale Soil Type Map from Indonesia's Geospatial Information Agency, while the global dataset is SoilGrids, which provides spatially explicit soil property data. The compiled parameters include physical, hydrological, and soil classification properties.

1. The parameters derived encompass several categories. Physical properties include soil texture, organic matter content, soil depth, coarse material fraction, and bulk density.

2. In addition to physical properties, hydrological properties are crucial. These include permeability, defined as the rate at which water moves through the soil; available water capacity (AWC), which quantifies the volume of water soil can store and release for plant uptake; and soil erodibility, representing the susceptibility of soil to erosion.

3. Finally, classification relies on the hydrologic soil group, which categorizes soils according to infiltration capacity and associated runoff potential.

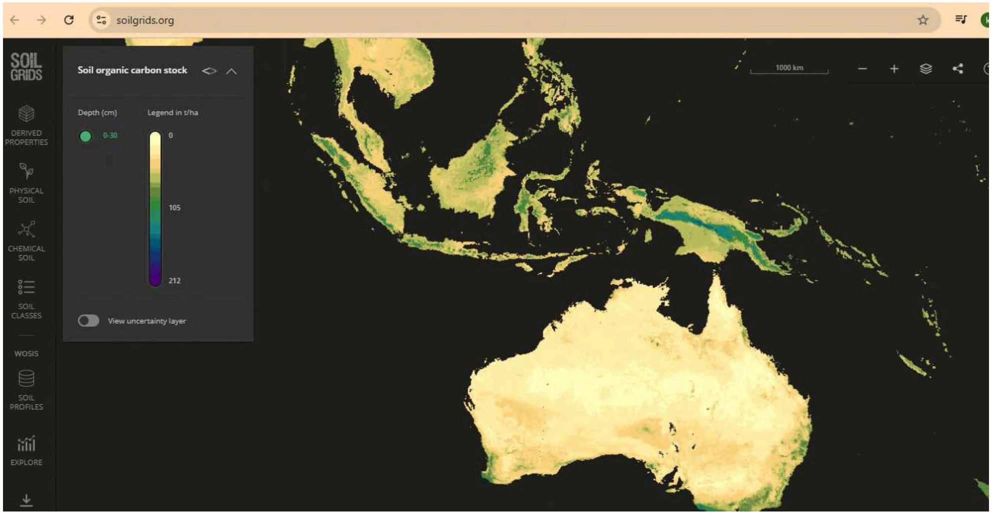


Figure 23 Soil data parameterization

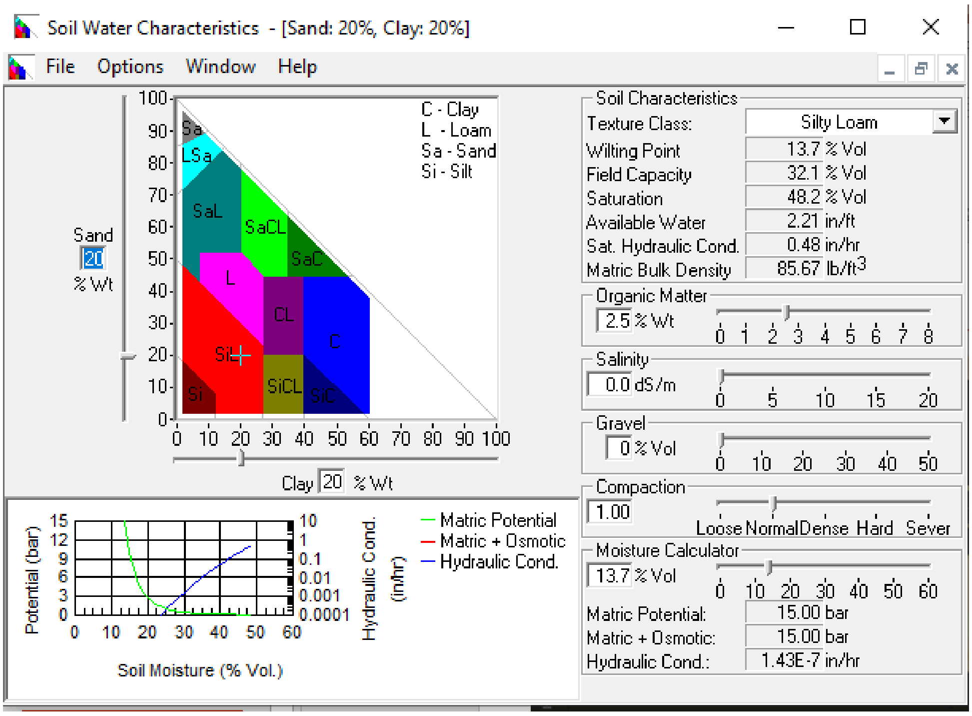
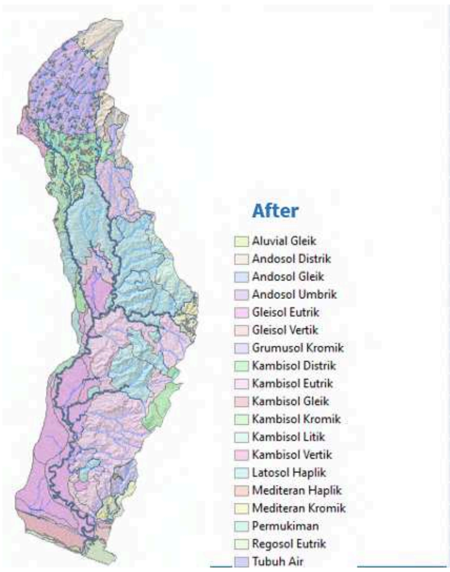


Figure 24 Soilgrid.Org

A comparative analysis evaluated conditions before and after updating soil data to determine the impact of revised soil information. This method aimed to improve the accuracy of infiltration and water flow simulations.



No	Kode	HSG	Texture
1	AHK1	C	CL-CL
2	BBG1	C	CL-CL
3	BBG2	C	CL-C
4	BBG3	C	CL-CL
5	BBG4	C	CL-C
6	BKN1	C	CL-CL
7	BMS1	C	CL-CL
8	BMS2	C	CL-C
9	BMS3	C	CL-CL
10	BMS4	C	CL-C
11	CBN1	C	CL-C
12	DTA1	C	CL-CL
13	DTA2	C	CL-C
14	GRO1	C	CL-CL
15	HBU1	C	CL-CL
16	KHY1	C	CL-CL
17	MPT1	C	CL-CL
18	PTG1	C	CL-C
19	PTG2	C	CL-C
20	PTG2	C	CL-CL
21	RTG1	C	CL-CL
22	TGM1	C	CL-C
23	TGM2	C	CL-CL
24	TGM3	C	CL-C
25	TGM4	C	CL-CL

Figure 25 Soil map and soil classification table

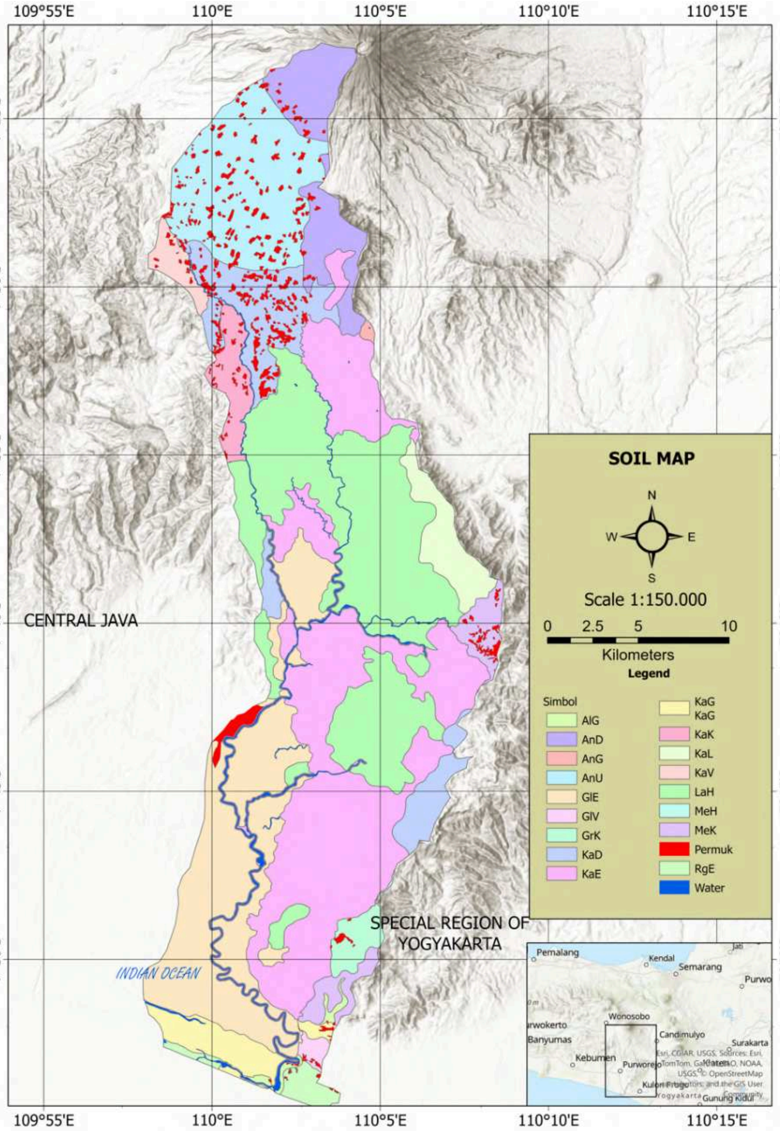
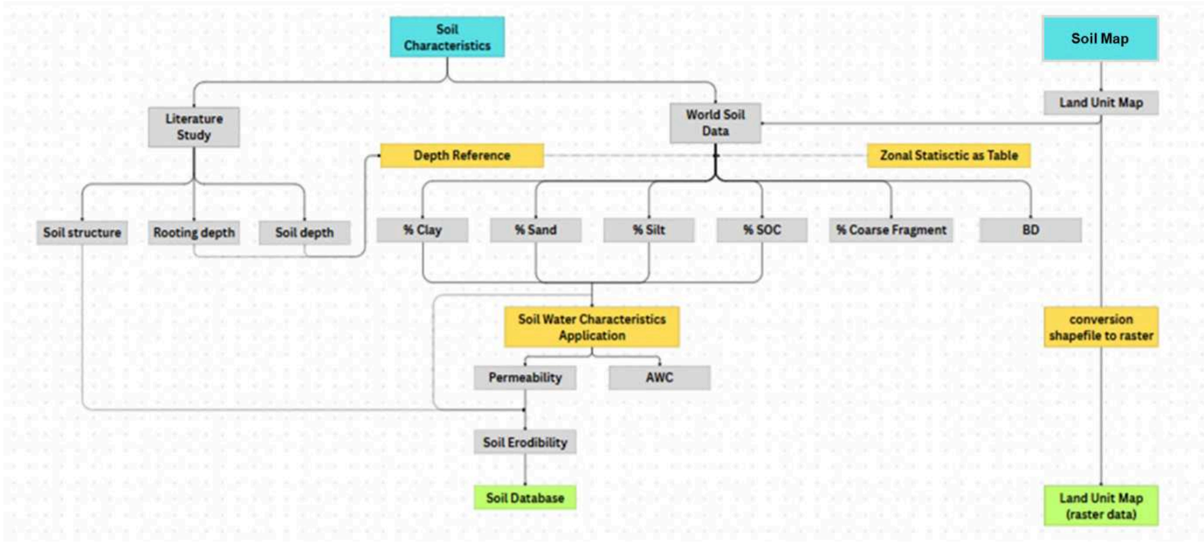


Figure 26 Soil Tyep Map of Bogowonto Watershed

Table 15 Soil parameter data table for hydrological modeling

C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
SEQN	SNAM	S5ID	CMPPCT	NLAYERS	HYDGRP	SOL_ZMX	ANION_EXCL	SOL_CRK	TEXTURE	SOL_Z1	SOL_BD1	SOL_AWC1	SOL_K1	SOL_CBN1	CLAY1	SILT1	SAND1	ROCK1	SOL_ALB1	USLE_K1	SOL_EC1	SOL_Z2
1	AlG	AlG	100	1	C	350	0,5	0,5	SaC	1000	0,76	0,19	14	3,97	25	28	47	5,35	0,13	0,161	0	0
1	AnD	AnD	100	1	C	600	0,5	0,5	CL	1000	0,87	0,19	5,52	4,61	36	37	27	15,09	0,13	0,162	0	0
1	AnG	AnG	100	1	C	600	0,5	0,5	CL	1000	0,88	0,25	6,88	6,20	39	34	27	14,55	0,13	0,157	0	0
1	AnU	AnU	100	1	C	600	0,5	0,5	C	1500	1,12	0,18	8,77	2,47	40	38	22	12,70	0,13	0,164	0	0
1	GlE	GlE	100	1	C	300	0,5	0,5	CL	1000	1,16	0,25	5,31	6,25	37	32	31	7,86	0,13	0,156	0	0
1	GlV	GlV	100	1	C	300	0,5	0,5	CL	1000	1,23	0,26	5,73	6,61	40	33	27	6,23	0,13	0,156	0	0
1	GrK	GrK	100	1	C	600	0,5	0,5	CL	1500	1,21	0,21	7,1	5,08	37	35	28	13,42	0,13	0,159	0	0
1	KaD	KaD	100	1	C	600	0,5	0,5	C	1500	1,20	0,25	8,26	6,31	40	36	24	12,20	0,13	0,16	0	0
1	KaE	KaE	100	1	C	600	0,5	0,5	CL	1500	1,20	0,22	7,2	5,56	39	35	26	12,16	0,13	0,159	0	0
1	KaG	KaG	100	1	C	600	0,5	0,5	CL	1500	1,10	0,32	15,59	8,16	36	38	26	6,92	0,13	0,163	0	0
1	KaK	KaK	100	1	C	600	0,5	0,5	C	1500	1,22	0,26	8,2	6,54	41	36	23	12,92	0,13	0,161	0	0
1	KaL	KaL	100	1	C	200	0,5	0,5	CL	500	1,14	0,31	12,55	7,87	39	37	24	14,18	0,13	0,162	0	0
1	KaV	KaV	100	1	C	600	0,5	0,5	C	1500	1,23	0,21	5,12	5,05	42	36	22	10,96	0,13	0,161	0	0
1	LaH	LaH	100	1	C	600	0,5	0,5	C	1500	1,20	0,30	5,74	7,11	45	31	24	12,70	0,13	0,152	0	0
1	MeH	MeH	100	1	C	600	0,5	0,5	C	1500	1,18	0,27	2,61	6,08	50	30	20	12,35	0,13	0,151	0	0
1	MeK	MeK	100	1	C	600	0,5	0,5	C	1500	1,18	0,24	7,74	6,08	40	35	25	12,35	0,13	0,159	0	0
1	Permuk	Permuk	100	1	C	500	0,5	0,5	L	500	1,03	0,21	4	4,80	35	32	33	10,69	0,13	0,157	0	0
1	RgE	RgE	100	1	C	300	0,5	0,5	L	500	0,85	0,22	31,79	5,51	19	30	51	5,76	0,13	0,168	0	0
1	Water	Water	100	1	C	100	0,5	0,5	SiL	500	1,13	0,18	4	6,20	20	57	23	10,11	0,13	0,199	0	0



Land use Data Input

A significant limitation of the ArcSWAT program is its requirement for land-use data. The software requires users to match local land use data to a predefined, non-modifiable database. This alignment demands a detailed assessment of crop characteristics and land management practices. Table 2.10 presents the personal database format, and Figure 2.4 illustrates the data input interface.

Table 16 Format Personal Data Base Landuse

VALUE	*LANDUSE*
String	*String (4 chrac)*

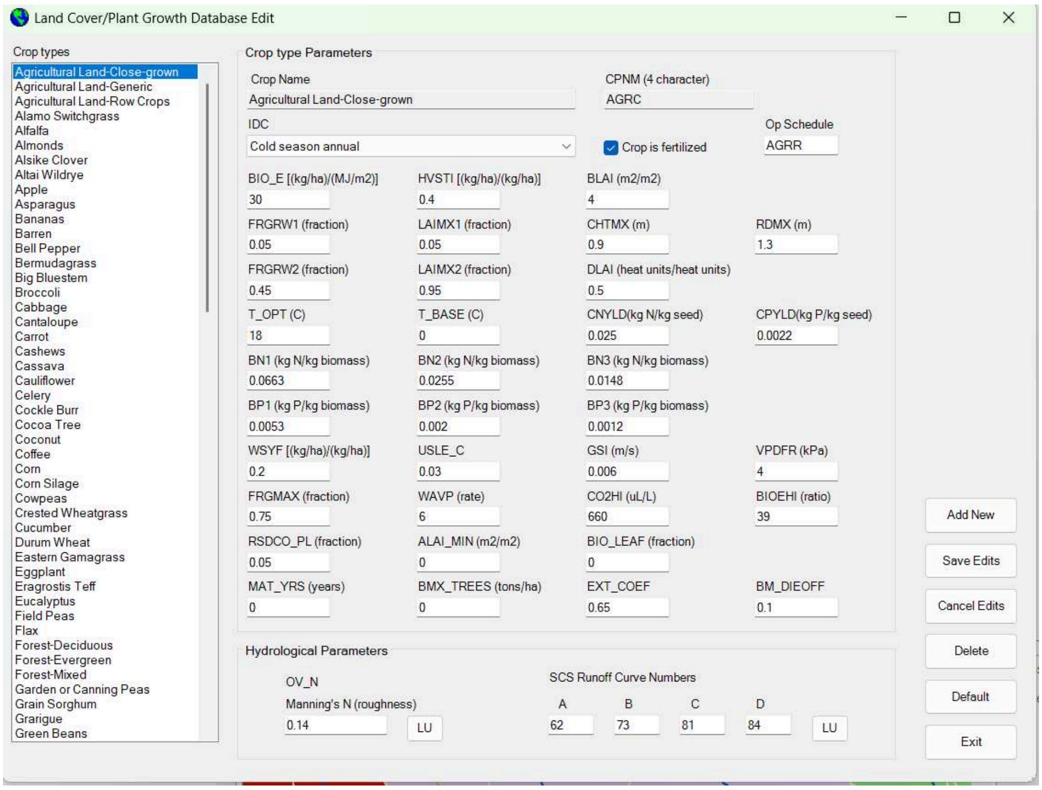


Figure 27 Land Cover/Plant Grow Data Base

Land cover data is used to characterize the watershed surface, specifically to differentiate between agricultural and forestry land uses. During this phase, a land use parameterization process assigns land cover types to categories defined in the SWAT (Soil and Water Assessment Tool) model. The land-use information used in this analysis is based on 2023 spatial data. Previously, the team produced a 2023 land use map, but following a review, it was determined that the land use dataset input for SWAT modeling would be the version reconciled with the approved Regional Spatial Planning (RTRW) regulations.

No	Landuse in Classification	Code
0	Water Body	WATR
1	Forest	FRSE
2	Production Forest Area	FRST
3	Conservation Area	FRSE
4	Community Plantation Area	FRSD
5	Local Protection Area	FRST
6	Area Providing Protection to the Area Below	FRST
7	Built-up Land	URHD
8	Open Land	BARR
9	Rice Field	RICE
10	Dryland Agriculture (Tegalan)	AGRL

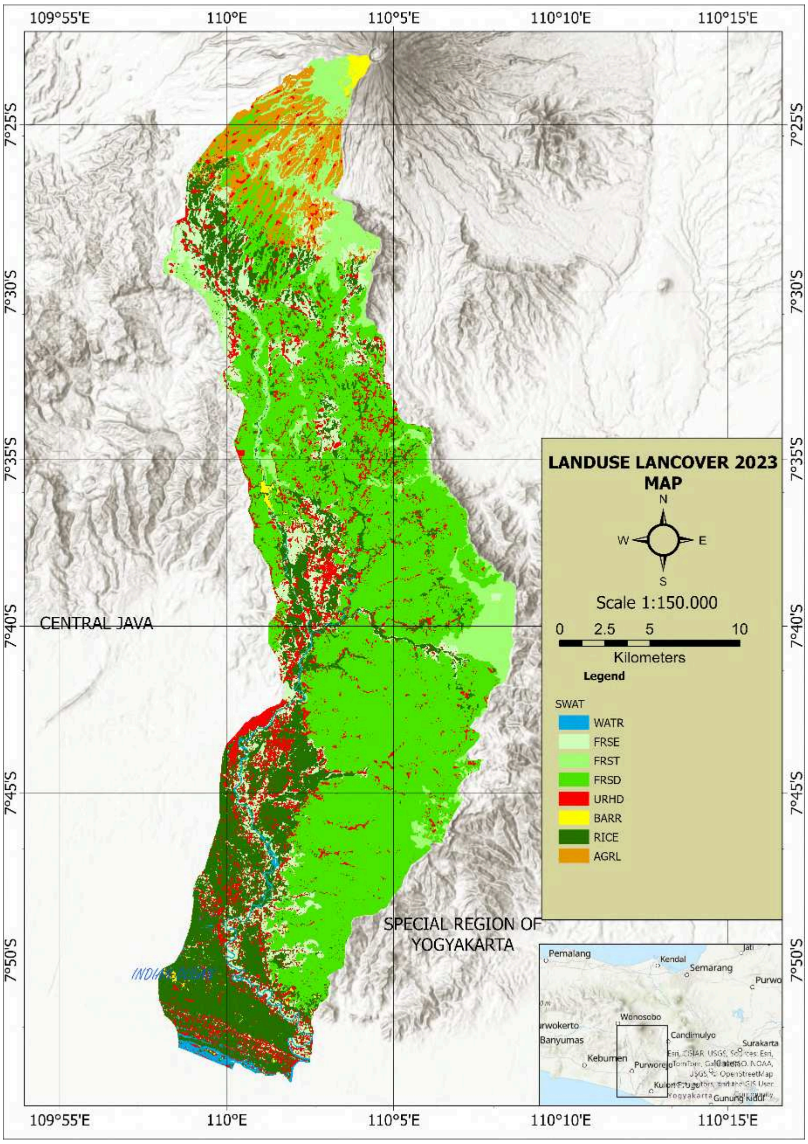


Figure 28 Landuse Input in 2023 (Baseline Year)

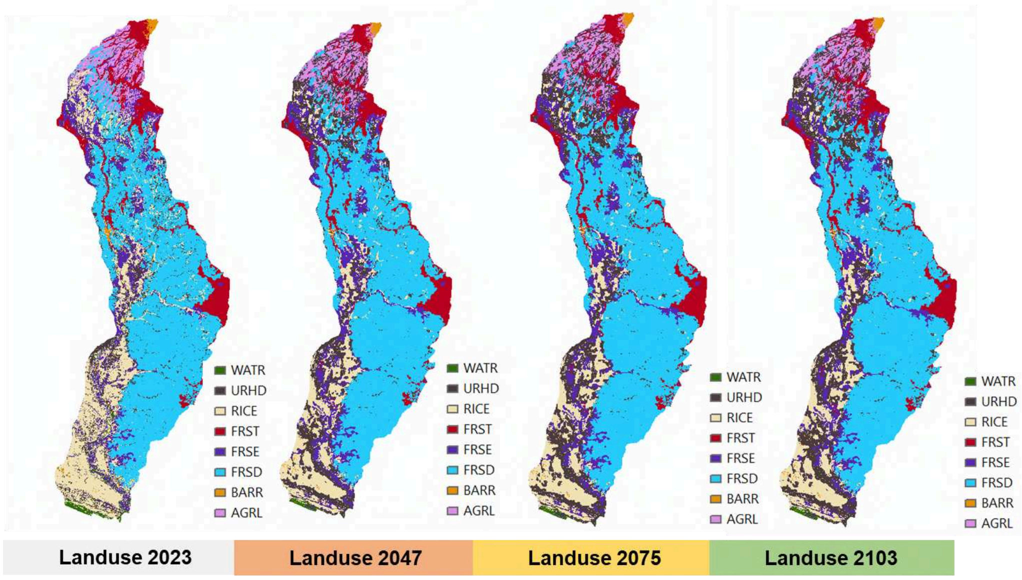
Figure 28 compares 2023 land use inputs in the Bogowonto watershed before and after integration with the Regional Transport and Roadway (RTRW) Plan. The upper table presents the land use and land cover (LULC) classification based on the 2023 RTRW and the associated Soil and Water Assessment Tool (SWAT) codes. The lower diagram depicts land use composition before and after RTRW implementation. Integration with the RTRW Plan provides a more precise representation of land use, consistent with regional planning objectives. This improvement increases the reliability of SWAT model simulations for predicting the effects of land use change on hydrological processes in the Bogowonto watershed.

The analysis indicates substantial changes in land-use classification following integration with the RTRW Plan.

a) Forest is detailed, with areas now categorized as FRSE (Forest and Conow categorized as), FRST (Production Forest and Protection Areas), and FRSD (Smallholder Plantation Areas).

b) A new class, AGRI, has been introduced to represent non-rice-field agricultural land that was previously included in AGRL (Garland).

c) The URHD (Built-Up Land) class has been refined to more specifically represent the (Open Land) class, which has undergone boundary adjustments based on the RTRW delineation.



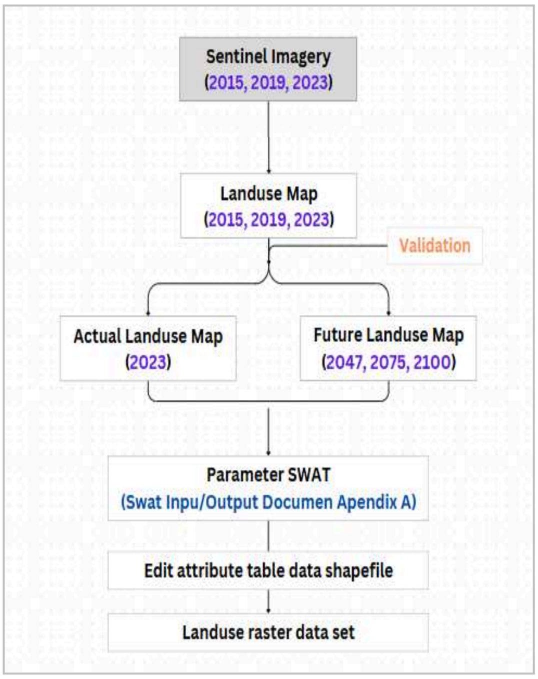


Figure 29 Land use change projection maps and data processing workflow

4.3.2 SWAT Model Run

The Soil Water Assessment Tool (SWAT) is a semi-distributed hydrological model designed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large and complex watersheds. The workflow in ArcSWAT (ArcGIS interface for SWAT) generally involves the following steps:

1. Watershed Delineation

Watershed delineation constitutes the initial step in the application of the Soil and Water Assessment Tool (SWAT) model. This procedure divides the study area into hydrologically relevant sub-basins using topographic features and drainage patterns derived from a Digital Elevation Model (DEM). In this study, the DEMNAS dataset with an 8-meter spatial resolution served as the input model. The delineation establishes spatial boundaries for simulating hydrological processes, including surface runoff, infiltration, and channel flow. Parameters utilized in this step include river channels, the DEM, and watershed boundaries. Figure 30 presents the parameter inputs for Step 1: Watershed Delineation.

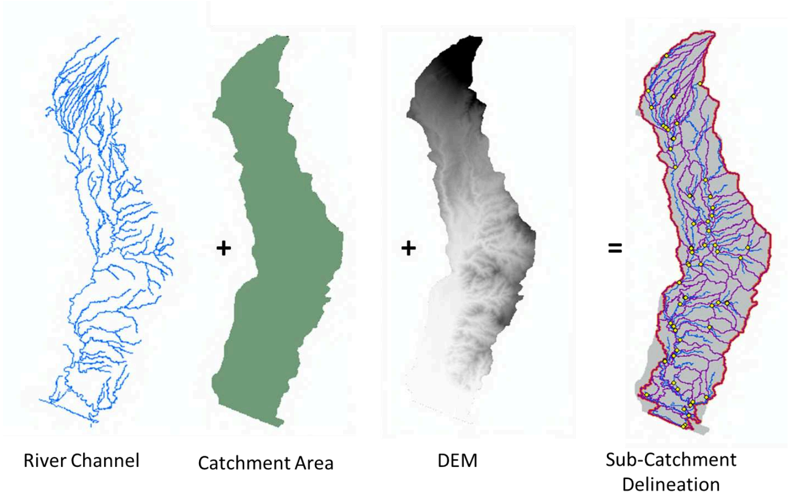


Figure 30 Watershed delineation

Watershed delineation is completed automatically using digital elevation model (DEM) data. DEM supplies essential elevation information for determining flow direction and flow accumulation. The model uses this data to identify stream networks and drainage divides. The delineation process consists of several key steps (**Figure 30**):

1. DEM Setup
2. The digital elevation model (DEM) is imported and changed to remove any low spots that could stop water from flowing across the surface.
3. Flow Direction and Accumulation
4. Tools in ArcSWAT determine how water moves from each cell and show where it collects.
5. Stream Definition and Outlet Selection
6. A threshold value for flow accumulation is used to generate the stream network. Outlets subdivide the main watershed into multiple sub-basins. In this study, the threshold area parameter is set to 300 hectares. This is the minimum contributing area needed to define the drainage network. This parameter controls stream network density and the number of sub-basins. It affects the model's spatial resolution and hydrological response. A smaller threshold area produces more streams and additional sub-basins.

7. Watershed Delineation
8. Using the selected outlets and the stream network, ArcSWAT automatically divides the watershed into sub-basins, each acting as a separate water area.
9. Calculation of Sub-basin Parameters

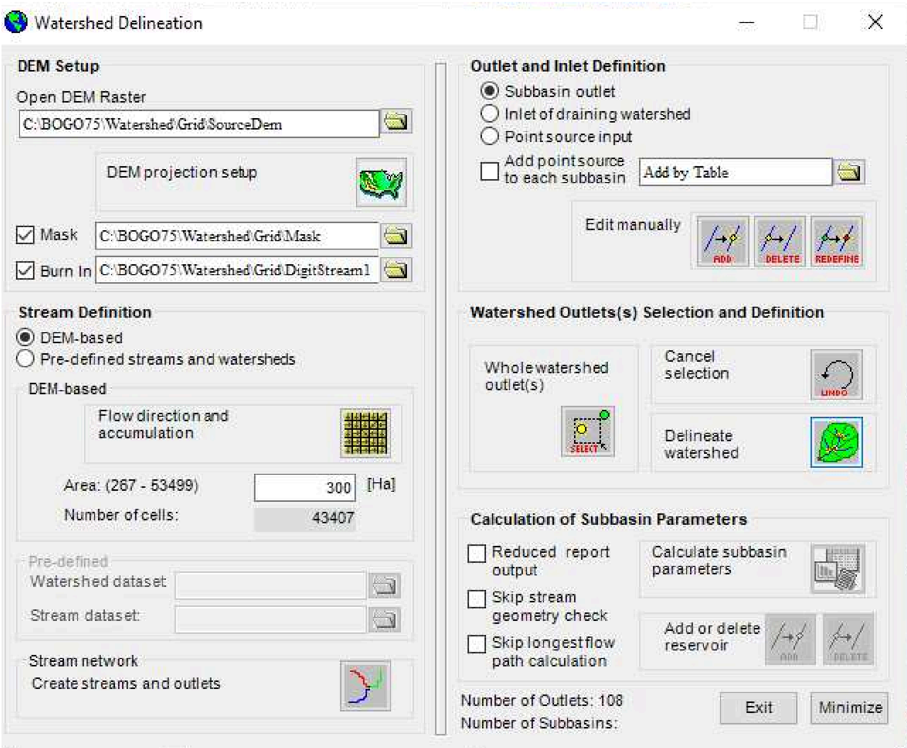


Figure 31 The SWAT model automatically calculates basic features for each sub-basin

This process produces spatial data layers. These include flow direction, flow accumulation, stream networks, sub-basin boundaries, outlet locations, and sub-basin morphometric parameters. Precise watershed delineation is crucial for reliable hydrological simulations. Inaccuracies in the definition of drainage boundaries can propagate through the model, resulting in substantial errors in flow and sediment yield predictions. Selecting a high-resolution digital elevation model (DEM) and carefully parameterizing flow thresholds are essential for achieving accurate watershed delineation.

2. Hydrologic Response Unit Definition

Hydrologic Response Units (HRUs) serve as the primary spatial units in the Soil and Water Assessment Tool (SWAT). These units help simulate hydrological and biogeochemical processes in watersheds. Each HRU represents a homogeneous area within a sub-basin. It is defined by a specific combination of land use, soil type, and slope class. This delineation enables the SWAT model to efficiently represent spatial heterogeneity.

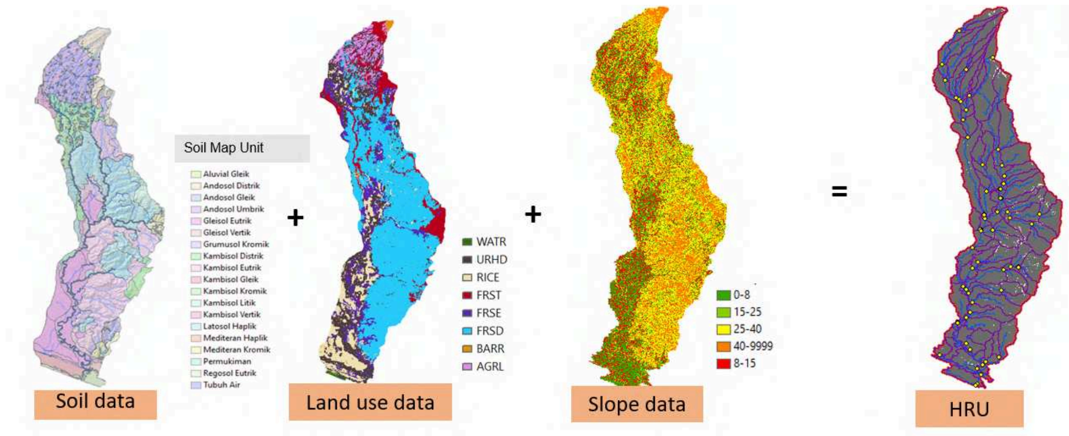


Figure 32 Overlay Process of Soil, Land Use, and Slope Data to Generate Hydrologic Response Units (HRU)

HRU delineation follows watershed and sub-basin delineation. In ArcSWAT, this step uses three main spatial datasets.

1. The land use map classifies areas into crop types, forests, urban areas, and other cover types.
2. The soil map shows soil texture, hydraulic traits, and fertility.
3. The third dataset is the slope map, typically derived from a digital elevation model (DEM) and classified into distinct slope categories.

The intersection of these three spatial layers defines the HRUs within each sub-basin. To minimize computational demands and exclude minor spatial units, threshold percentages are established for land use, soil type, and slope. Combinations that do not meet these thresholds are omitted from the simulation.

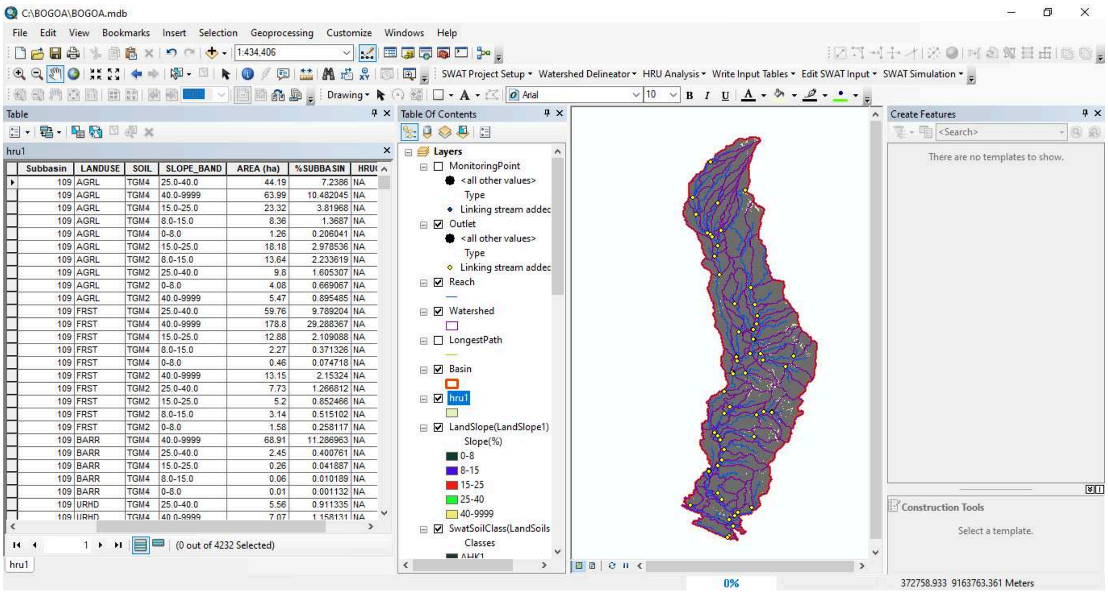


Figure 33 HRU analysis in arcgis for SWAT model

3.Run Model

The Soil and Water Assessment Tool (SWAT) modeling framework allows a comprehensive evaluation of how anthropogenic land-use changes and climate variability affect watershed hydrology and agricultural productivity in the twenty-first century. During the baseline period (2010–2023), the model uses 2023 land-use data with observed climate data from 2010 to 2023. This simulates current hydrological conditions. This calibration and validation stage ensures the model replicates observed streamflow, evapotranspiration, and related hydrological processes under existing conditions. These steps adjust sensitive parameters and confirm the model's reliability before applying it to future scenarios.

In future simulations, the model integrates projected land-use and climate datasets to evaluate long-term hydrological changes. Future land-use maps for 2045, 2075, and 2100 reflect anticipated land-cover shifts driven by regional development and planning. Climate data for each projection period (2023–2045, 2045–2075, and 2075–2100) come from Earth Climate Change (CC) datasets under the SSP5-8.5 high-emission scenario. This scenario reflects a trajectory of intensified greenhouse gas emissions. These datasets enable the model to simulate future components of the water balance, including runoff, evapotranspiration, and groundwater flow. They also support estimates of crop yield and plant water demand under evolving climatic and land-use conditions.

No	***Landuse Data***	***Climate Data***	***Model Result***
1.	*Landuse 2023*	*2010-2023*	*Baseline Year (Calibration & Validation)*
2.	*Future Landuse 2045*	*2023-2045*	*Future Prediction 2045-2075*
3.	*Future Landuse 2075*	*2045-2075*	*Future Prediction 2075-2100*
4.	*Future Landuse 2100*	*2075-2100*	*Future Prediction 2020-2045*

The SWAT model simulation setup window defines the parameters for the hydrological simulation of the Kedung Putri watershed. The simulation period runs from January 1, 2020, to December 31, 2045, enabling 26 years of continuous hydrological computation. Rainfall distribution is set as skewed normal, which models daily precipitation with a non-symmetric distribution to better reflect tropical rainfall. The output frequency is daily, enabling detailed analysis of streamflow and water balance. Options like Print Velocity/Depth Output and Print Calendar Dates record daily flow depth, discharge, and calendar dates for easier interpretation of results. Output options for nutrient or management simulations are unchecked, indicating the focus is on hydrological response rather than water quality or management. The 64-bit SWAT executable enables faster, more stable, long-term, large-scale simulations. This setup aims to deliver high-resolution hydrological outputs for analyzing future discharge trends and climate change impacts over an extended period.

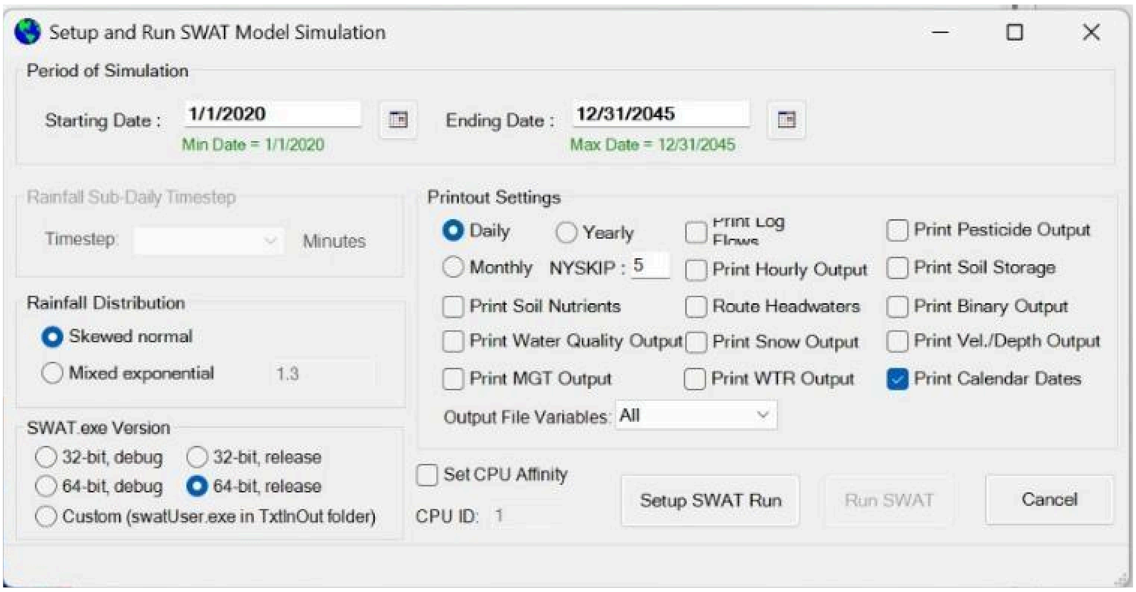


Figure 34 Setup and run SWAT model simulation

4.3.3 SWAT Output Model

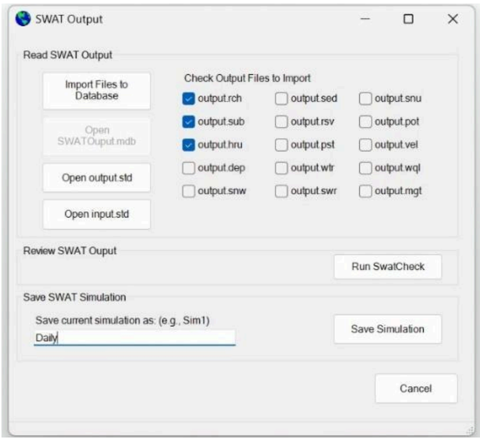
The model computes the water balance components (precipitation, evapotranspiration, infiltration, surface runoff, percolation, and baseflow) for each HRU and aggregates them to the sub-basin and watershed scales. The simulation produces daily, monthly, or annual time series of discharge, sediment yield, and nutrient loads. SWAT Output Window demonstrates the post-processing stage in SWAT modelling, where users select relevant hydrological output files for analysis and preserve the simulation configuration for subsequent validation or scenario comparison. It is used to manage, review, and save the results of a completed SWAT model simulation. This interface allows the user to select specific output files for import and analysis, open standard output tables, and save the simulation setup for future reference or comparison.

- In this setup, several key output files are chosen: output.rch, output.sub, output.hru, and output.std. Each file gives a specific level of hydrological output.
- output.rch shows reach-level results, including streamflow, sediment load, and nutrient transport, for each river segment.

- output.sub provides sub-basin-scale data that summarize components of the water balance, such as surface runoff, baseflow, and evapotranspiration.
- output.hru provides HRU-scale data that summarize water balance, nutrients, crop yield, and sediment components.
- output.std stores overall watershed statistics and performance summaries.

These files help evaluate model behavior and analyze how hydrological responses vary across the watershed. Unchecked options, like output.mgt and output.SWR, this simulation focuses on hydrological discharge, not management or detailed HRU data.

The 'Save SWAT Simulation' section lets users name and save the simulation configuration for later use. Here, the simulation is saved as 'Daily,' meaning it ran on a daily time step. This helps organize runs, especially when comparing scenarios or time resolutions.



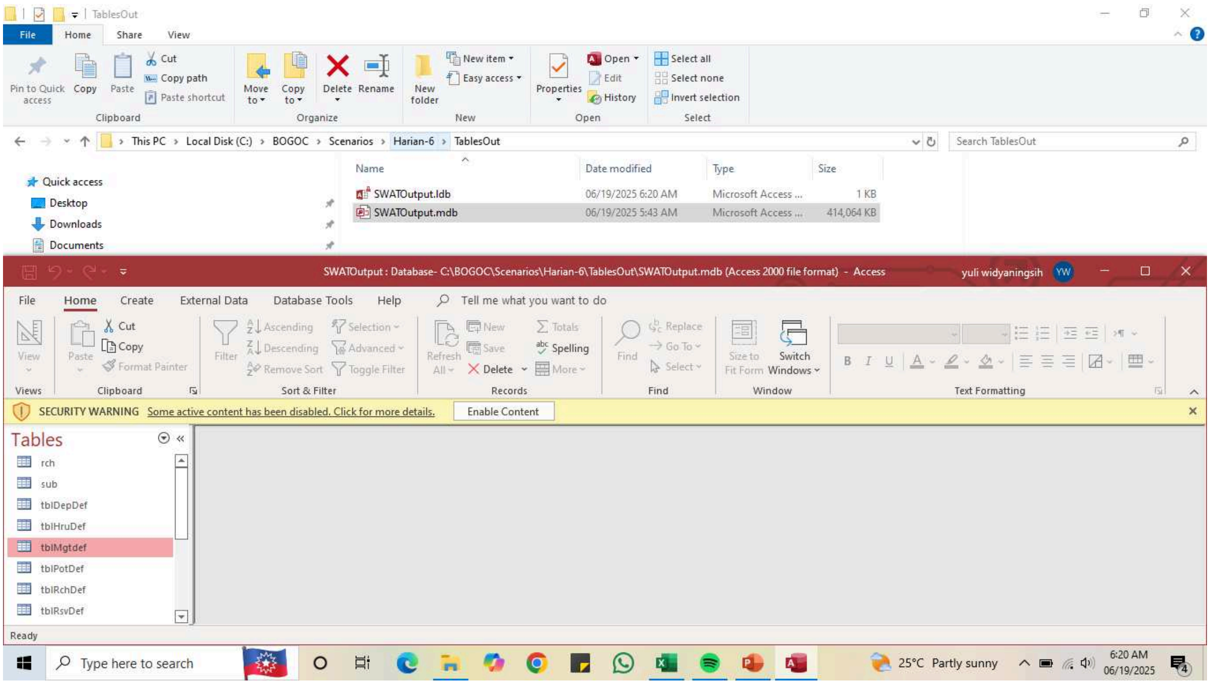


Figure 35 SWAT Model

4.3.4 Water Availability

The water balance is a fundamental notion in hydrology. It applies the law of conservation of mass to a specific hydrological system over a defined timeframe (Huang et al., 2021). The water balance includes all inflows, outflows, and changes in storage within a specified region, like a catchment area, aquifer, or lake. The concept states that water entering the system must match water exiting it, plus any change in storage within the borders (Ochoa-Tocachi et al., 2019). This approach helps hydrologists and water managers understand the local hydrological cycle, assess water availability, and identify issues such as scarcity, groundwater depletion, and flooding. The water balance is essential for sustainable management and planning. It provides a quantitative framework for assessing climate change and human impacts on water systems (Healy, 2010; Asdak, 2018).

The comprehensive water balance equation is mathematically articulated as

$P - Q - ET - G \pm \Delta S = 0$

wherein

P : precipitation

Q : total runoff

ET : evapotranspiration

G : net groundwater flow

ΔS : the alteration in storage (including soil moisture, groundwater, and surface reservoirs).

4.3.5 Plant Water Demand

Plant water demand, or crop water requirement, is an essential term in agronomy, hydrology, and irrigation research. It is the water required for a crop to satisfy its evapotranspiration demands and attain its maximum yield potential (Cai et al., 2023). This requirement is influenced by evapotranspiration, encompassing water loss by evaporation and transpiration. Precisely assessing plant water requirements is crucial for formulating effective irrigation schedules, maximizing water utilization, and guaranteeing sustained agricultural output, particularly in arid areas (Pereira et al., 2020).

The reference evapotranspiration (ET_0) and crop coefficient (Kc) approach is the most widely accepted method for quantifying plant water demand, standardized by the Food and Agriculture Organization (FAO). The core formula is:

$ETc = Kc \times ET_0$,

where

ETc : plant water demand

Kc : specific crop characteristics and growth stages

ET_0 : atmospheric demand.

$$ET_{plant} = PET \times \frac{LAI}{LAI + e^{-k}}$$

In the SWAT model, plant water demand is the water crops need for optimal growth in given climate and soil conditions. The figure shows management parameters for a rice (Oryza sativa) subbasin. The schedule outlines key operations—auto-irrigation start, planting, growth onset, auto-fertilization, and harvest. Irrigation uses the “Schedule by Heat Units” option, triggering events based on accumulated thermal time rather than calendar dates, to match water applications with critical crop growth phases.

The auto-irrigation parameter (**WSTRS_ID**) is set to 'Plant Water Demand.' This directs the model to irrigate when the soil water deficit exceeds the crop's transpiration demand. SWAT computes plant water demand dynamically using potential evapotranspiration (**PET**), soil moisture, and crop leaf area. The model calculates this demand as the difference between potential (**Tpot**) and actual transpiration (Tact). This value indicates the amount of water required for optimal plant function. The irrigation efficiency (**IRR_EFF**) and maximum irrigation volume (**IRR_MX**) parameters reflect local irrigation performance. In this configuration, both are set to zero, using the model's default efficiency.

This setup enables SWAT to simulate demand-based irrigation, which is essential for paddy rice systems. These systems require continuous water to maintain flooded conditions. The model estimates plant water demand and irrigation volumes in response to climate and soil. This approach is key to modeling crop water balance, evapotranspiration, and yield under various climate scenarios. **Figure 36** displays the irrigation setup in SWAT.

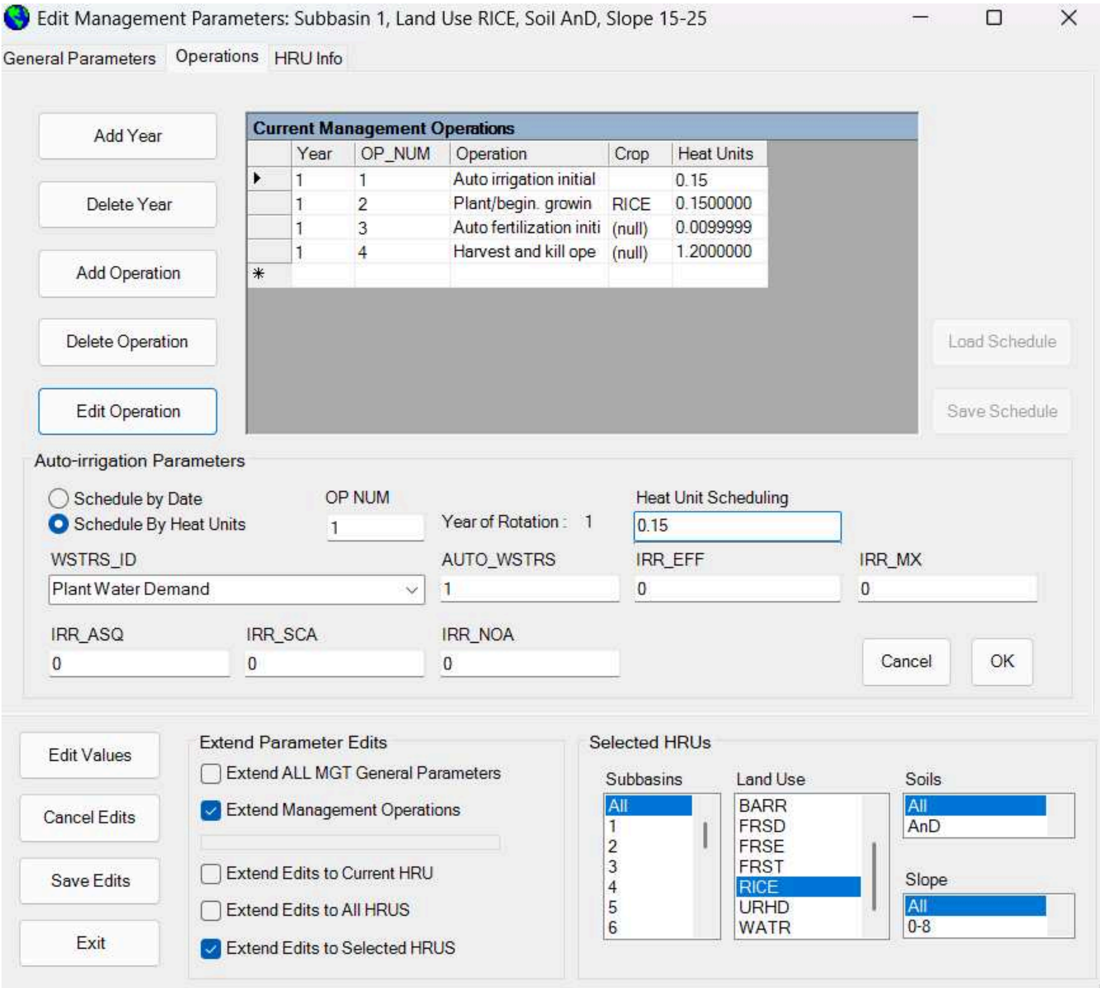


Figure 36 Plant Water Demand Setup in the SWAT Model

4.3.6 Crop Productivity

Crop productivity is a vital component of agronomy and food security, emphasizing the efficacy of agricultural systems in transforming inputs such as light, water, nutrients, and management into harvestable output. It is regulated by photosynthesis and biomass buildup, wherein plants transform solar radiation into dry matter. The conversion efficiency, quantified as energy Use Efficiency (RUE), represents the biomass generated per unit of solar energy absorbed by the crop canopy (Lobell et al., 2022; van Ittersum et al., 2013).

Land Cover/Plant Growth Database Edit step (Figure x) defines how crops grow and produce yield. This interface contains parameters for each crop's physiological, phenological, and hydrological characteristics. These parameters are used by SWAT's

EPIC (Environmental Policy Integrated Climate) plant growth model. For example, BIO_E (radiation use efficiency) measures how effectively a crop converts sunlight into biomass. HVSTI (harvest index) sets the fraction of total biomass that becomes harvestable yield. LAIMX (leaf area index), T_OPT (optimal temperature), and RDMX (maximum root depth) affect canopy development, growth rate, and water or nutrient uptake.

Crop yield in SWAT is calculated from total biomass using the equation:

Harvest Index Calculation:

$$HI = HI_{opt} \cdot \frac{100 \cdot fr_{PHU}}{\left(100 \cdot fr_{PHU} + \exp\left[11.1 - 10 \cdot fr_{PHU}\right]\right)}$$

Above Ground Biomass:

$$bio_{ag} = \left(1 - fr_{root}\right) \cdot bio$$

Crop Yield Calculation:

$$yld = bio_{ag} \cdot HI \qquad \text{when } HI \leq 1.00$$

$$yld = bio \cdot \left(1 - \frac{1}{\left(1 + HI\right)}\right) \qquad \text{when } HI > 1.00$$

where biomass (bio_{ag}) is determined by solar radiation, radiation-use efficiency, and stress factors related to temperature, water, and nutrients.

Additionally, hydrological parameters like **Manning's roughness (OV_N)** and **SCS Curve Numbers (CN2)** describe how vegetation affects runoff and infiltration. Saving edits in this step updates SWAT's crop database, ensuring these characteristics are applied in all simulated areas where the crop is grown. In short, this process is essential for accurately modelling crop growth, water use, and yield within SWAT. Figure 37 showed the steps to modify the crop yield factor in the plant database.

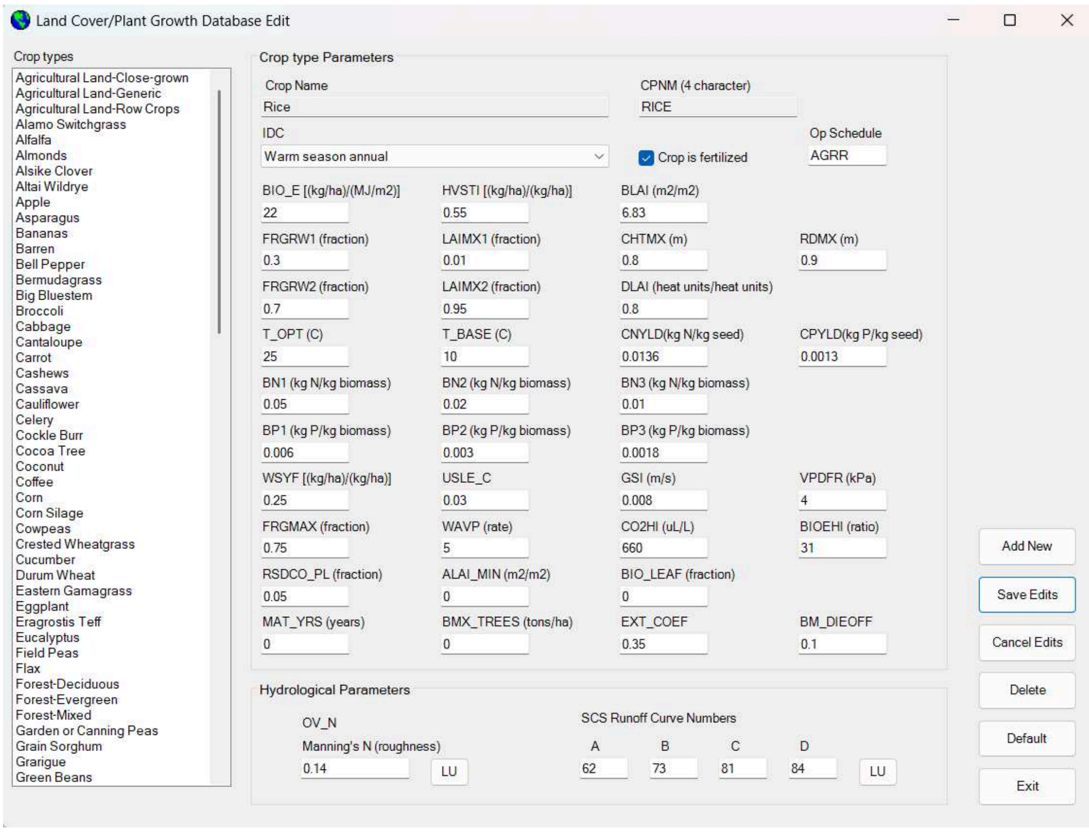


Figure 37 Modified plant database for rice

4.3.7 Calibration and Validation Using RSWAT

R-swat for calibration is SWATdoctR, a R programming language package that offers utilities to facilitate the calibration of the SWAT+ hydrological model. This package includes utilities for conducting guided model calibration, assessing model performance, and displaying and diagnosing simulation results to enhance model correctness (Mengistu, et al., 2019).

Reasons for Using RSWAT for Validation (Nguyen, et al., 2022).

1. R-SWAT was validated against SWAT-CUP, a widely used calibration and validation tool, to ensure it produces consistent results.
2. The validation revealed R-SWAT's reliability and efficiency, achieving a high correlation (R^2 = 0.99994) with SWAT-CUP while correctly updating input files.

3. R-SWAT demonstrated superior speed, processing in just 0.10 seconds compared to SWAT-CUP's 0.52 seconds, ensuring performance improvements do not compromise accuracy.
4. The validation showcased R-SWAT's capability to fully integrate with R and utilize various R packages for enhanced computation, uncertainty analysis, and result visualization.

4.3.8 RSWAT Setting

Several stages to setting RSWAT are:

a. General Setting

The general setting constitutes the initial stage in configuring RSWAT. During this phase, the working folder, TxtInOut folder, executable SWAT file, and the file containing the list of SWAT parameters are specified according to the system configuration. The working folder functions as the directory for storing all project files. The TxtInOut folder contains climate data, specifically daily records. The HRU option is selected to enable visibility of Hydrologic Response Unit (HRU) data. The executable SWAT file is the core model responsible for conducting hydrological simulations based on the provided input text files. The list of SWAT parameters is then prepared for use in subsequent steps.

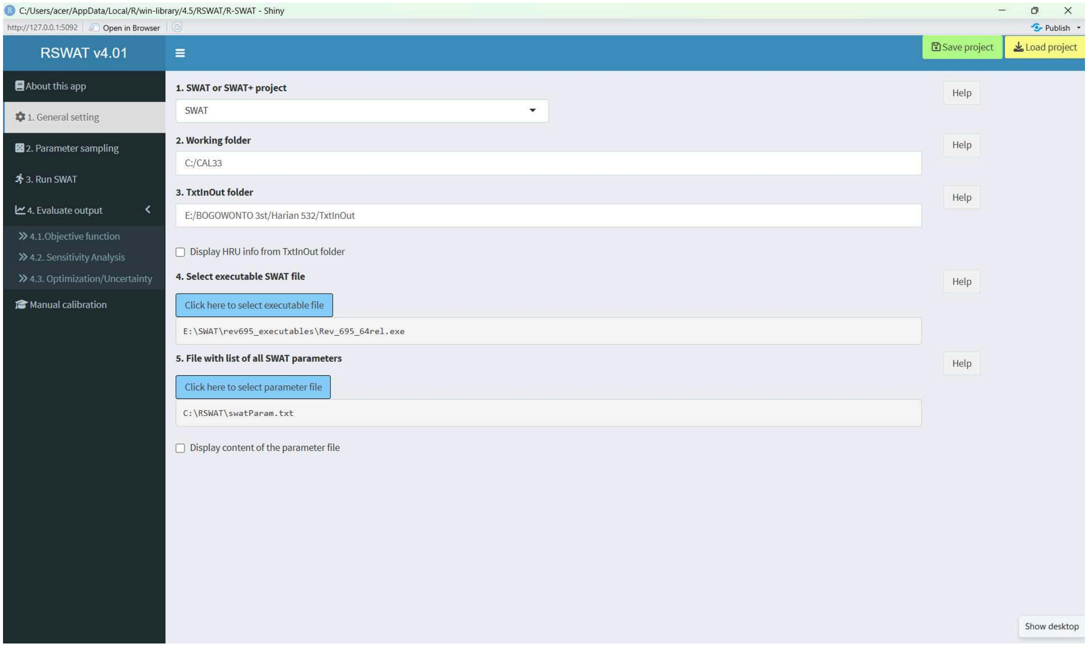


Figure 38 General setting

b. Parameter Sampling

All SWAT parameters are displayed in this section. Parameter sampling is the stage in which we select parameters along with their minimum and maximum values and define settings for sub-basins, land use, soil, and slope. The parameter range (min–max) is usually determined from a literature review. The process is iterated up to 500 times. This stage involves a trial-and-error approach, particularly in deciding the appropriate number of iterations. The higher the number of iterations, the longer the processing time required.

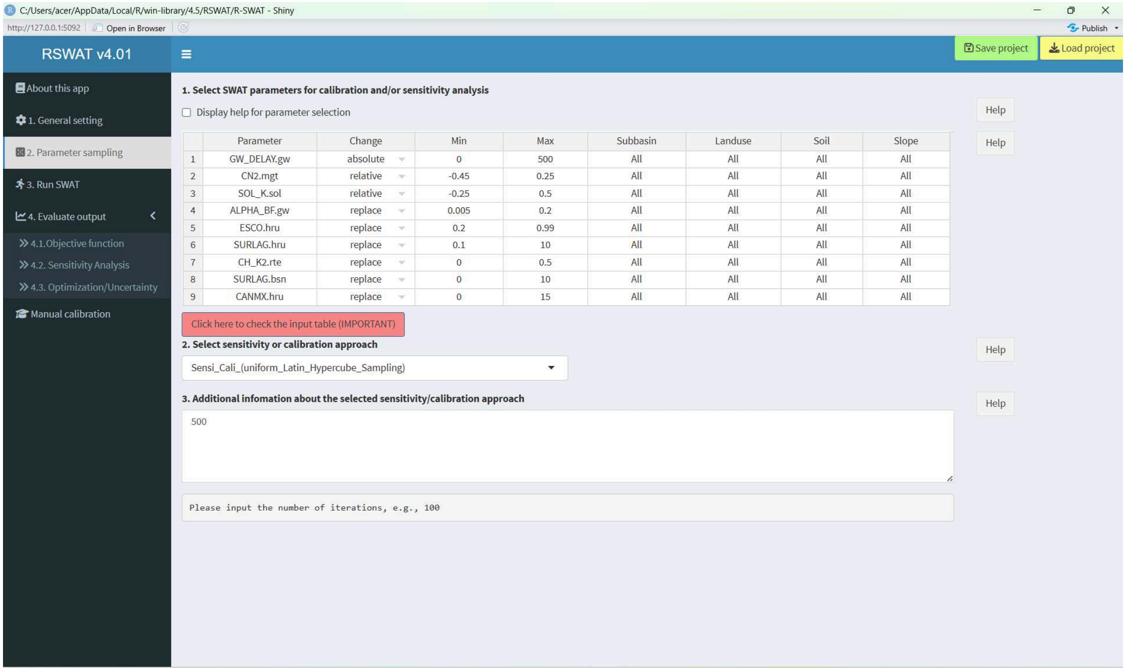


Figure 39 Parameter sampling

c. Run SWAT

In this stage, we define the simulation period, for example, from 2015 to 2020. We also set the number of parallel runs to 20, and then execute the SWAT simulation. The progress of the process can be monitored in the status box at the bottom-right corner of the screen. Once the simulation is complete, we can open the Current Simulation Report, display all parameter sets, and save the simulated results.

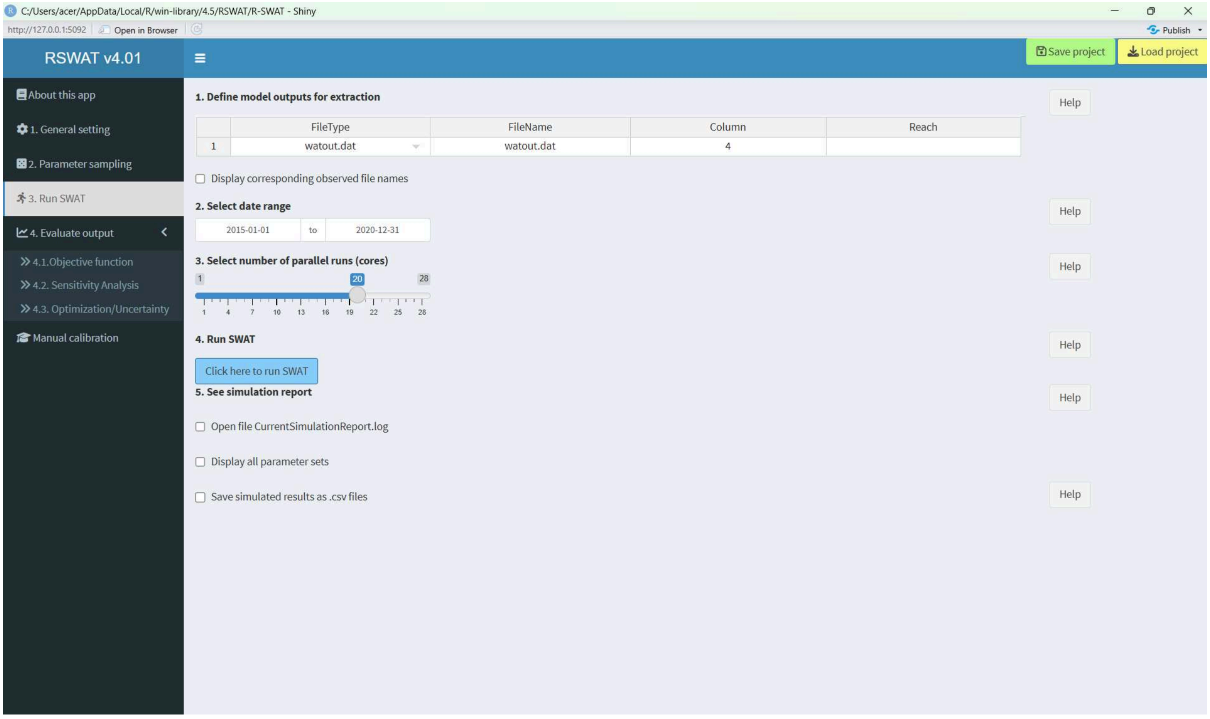


Figure 40 Run SWAT

d. Evaluate Output

The *Evaluate Output* stage is used to analyze the SWAT results, for instance using the NSE value. We first load the observed data file and then calculate the objective function.

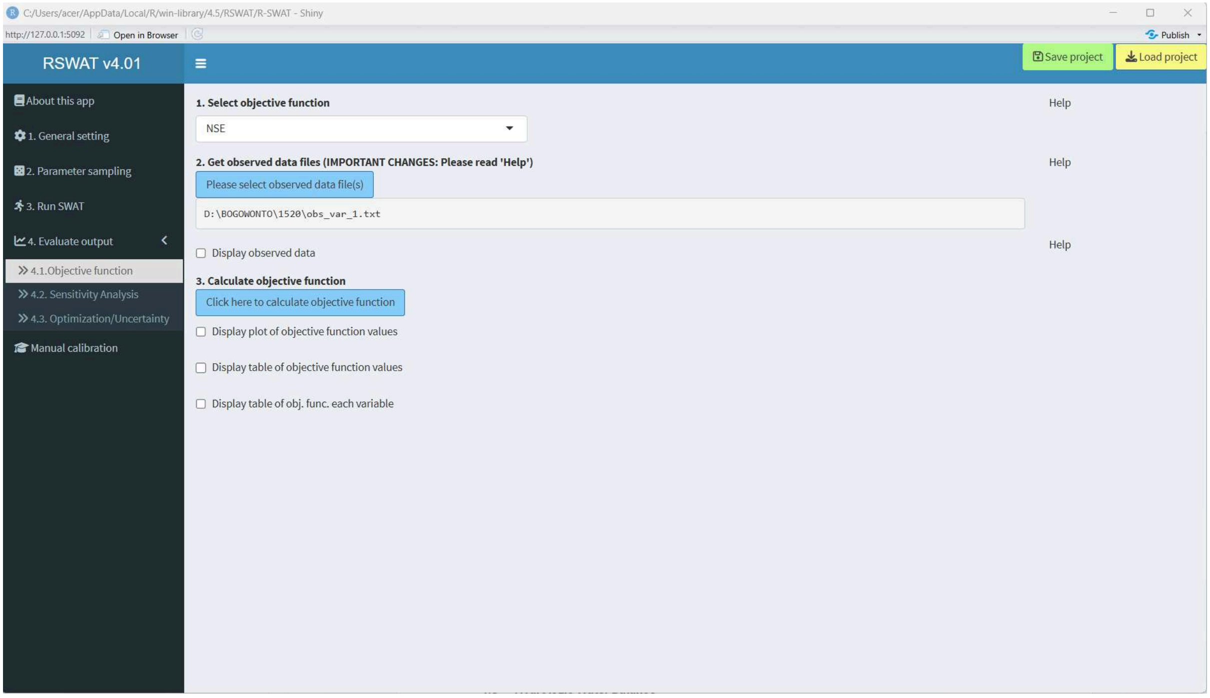


Figure 41 Objective function

This figure shows how the Nash–Sutcliffe Efficiency (NSE) assesses model performance. The scatter plots depict the impact of parameters ALPHA_BF.gw, CN2.mgt, and SOL_K.sol on NSE during calibration. CN2.mgt and SOL_K.sol are highly sensitive; small changes greatly affect accuracy.

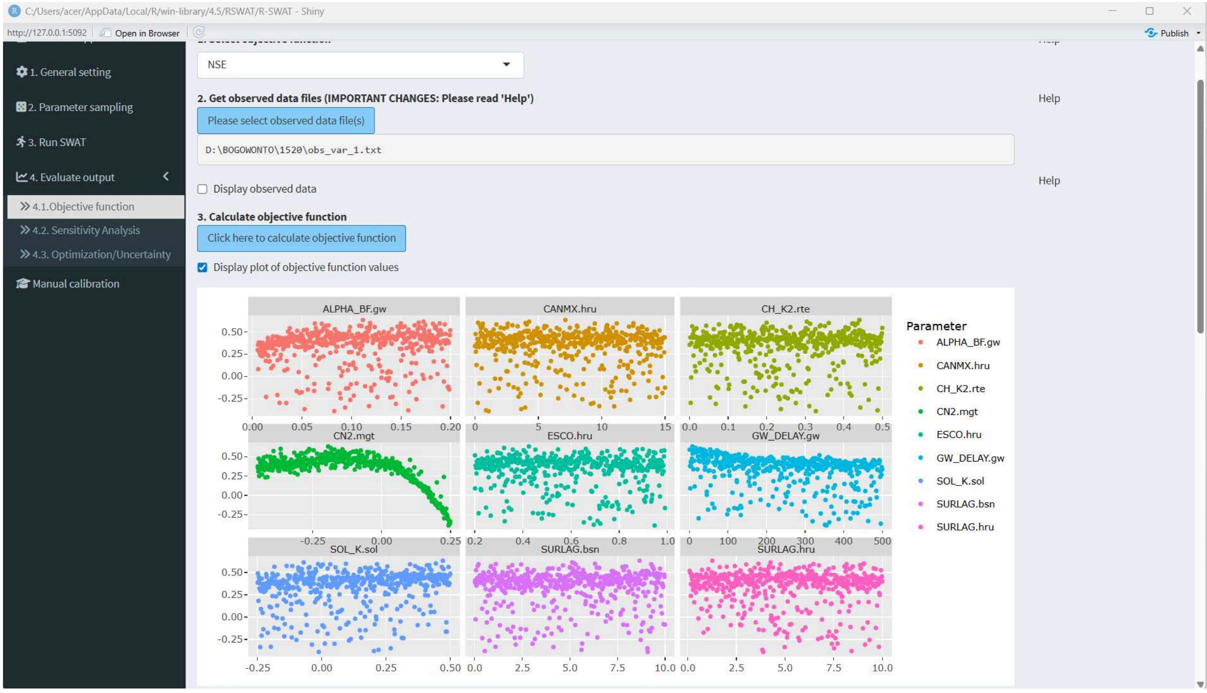


Figure 42 Scatter plot of object function

Sensitivity analysis is the process of determining how changes in model input parameters influence the simulation results. The main goal is to identify which parameters have the most significant impact on model outputs.

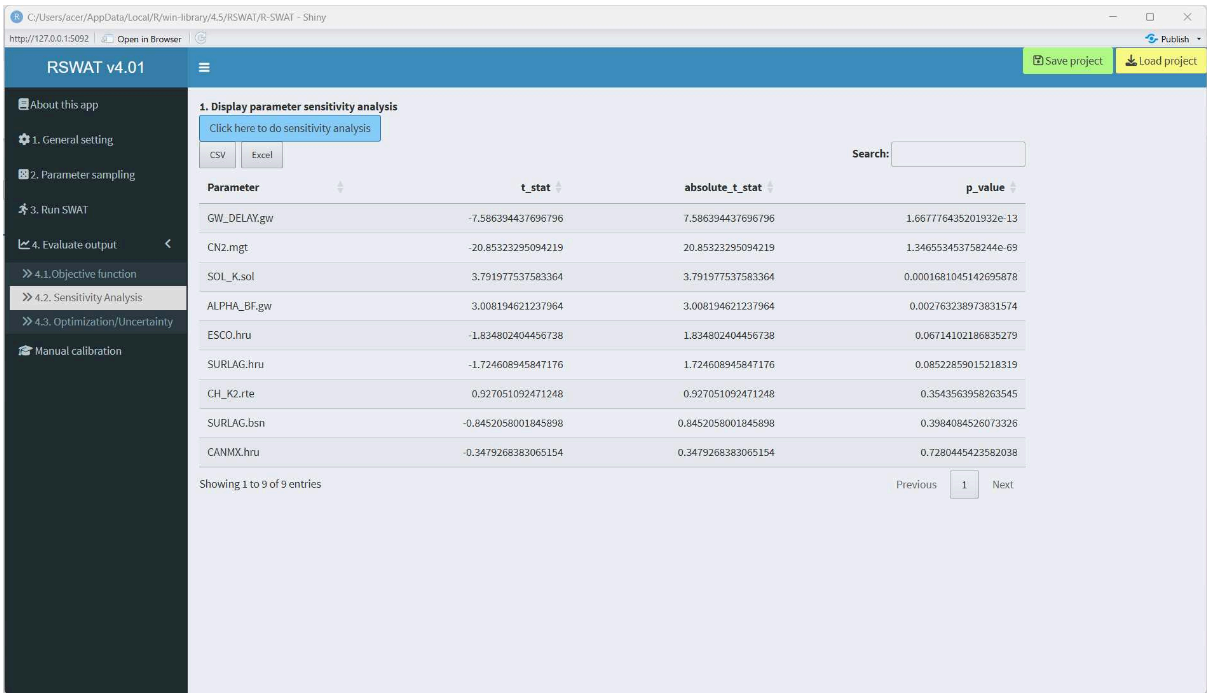


Figure 43 Sensitivity analysis

This figure summarizes the behavioral parameter range obtained from the uncertainty analysis. It lists parameters such as GW_DELAY.gw, CN2.mgt, and ALPHA_BF.gw along with their lower, median, and upper limits of the 95PPU. The displayed p-factor (0.47 for calibration) and r-factor (0.78 for calibration) indicate that the model successfully captures most observed data within an acceptable uncertainty range, reflecting a reliable calibration performance.

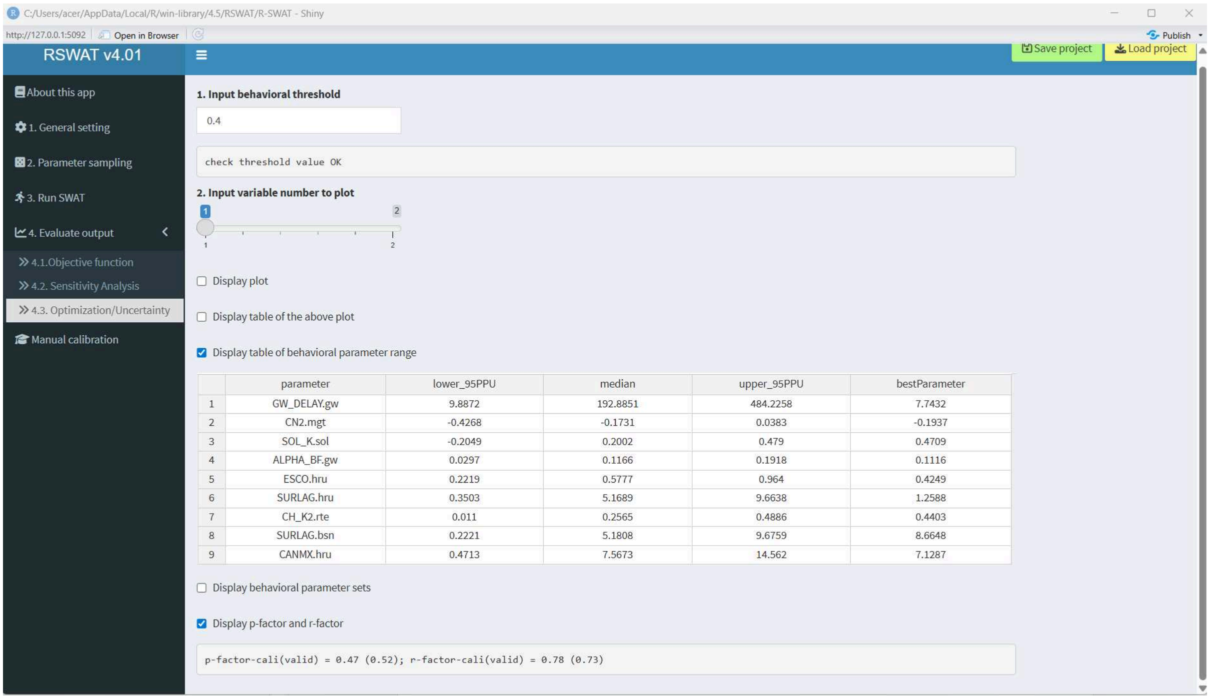


Figure 44 Optimization/uncertainty

This plot represents the uncertainty evaluation in the RSWAT model using the 95 Percent Prediction Uncertainty (95PPU) band. The red area indicates the 95PPU range, while the green, blue, and black lines represent the best simulation, observed, and median flow values, respectively. The close alignment between simulated and observed data suggests that the model has been well-calibrated with acceptable uncertainty levels.

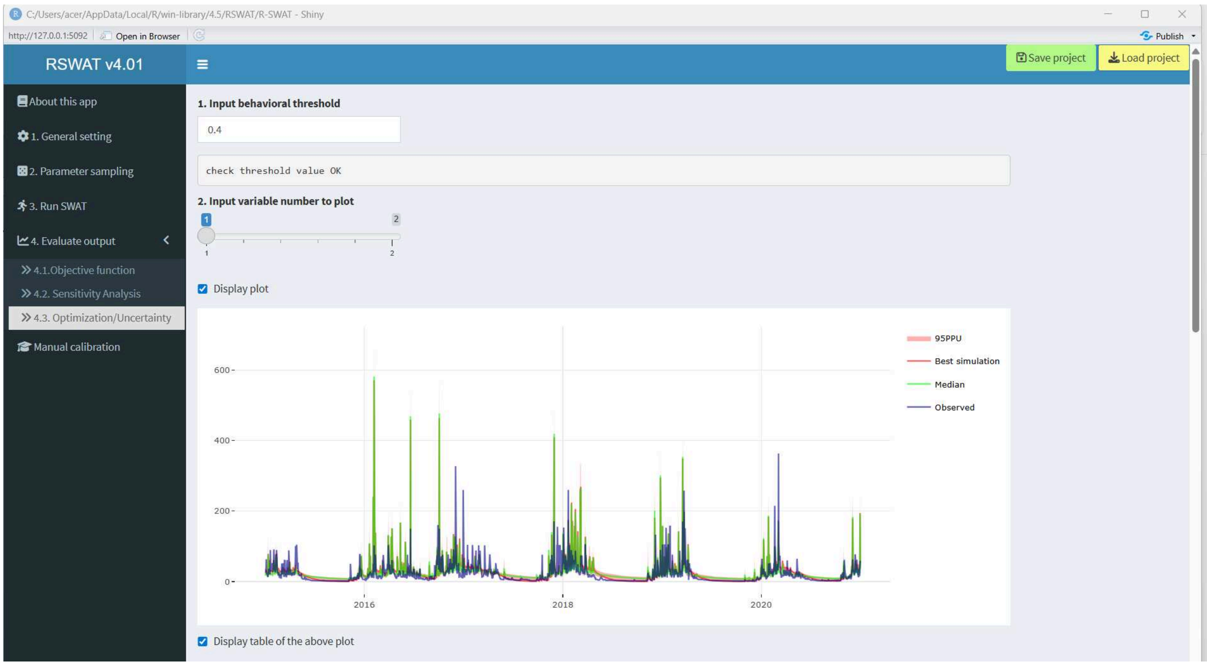


Figure 45 Graphic of optimization/uncertainty

Calibration and Validation Result

The calibration and validation results of the SWAT model using RSWAT are presented in Table X. Model performance was evaluated under different climate model inputs (Earth3 and NorESM) and emission scenarios (RCP 2.45 and RCP 5.85) using statistical indices including Nash–Sutcliffe Efficiency (NSE), Kling–Gupta Efficiency (KGE), coefficient of determination (R^2), Root Mean Square Error (RMSE), and absolute bias (aBIAS). During the calibration period, NSE values ranged from 0.535 to 0.632, and KGE from 0.624 to 0.758, indicating that the model performed satisfactorily to very well according to common hydrological standards. The R^2 values (0.573–0.758) indicate a strong correlation between simulated and observed streamflow, while the relatively low RMSE and aBIAS values suggest limited deviation and acceptable error magnitudes. Among the tested scenarios, the Earth CC 5.85 simulation produced the best calibration performance (NSE = 0.632, KGE = 0.758, RMSE = 8.931, aBIAS = 0.162), suggesting strong model consistency under high-emission conditions.

During the validation period, model performance remained stable, with NSE values between 0.413 and 0.536 and KGE values between 0.599 and 0.727. Although a slight reduction in accuracy was observed compared to calibration—as reflected by marginally higher RMSE values (14.998–16.863)—the overall performance still meets acceptable thresholds for hydrological simulation reliability. The persistence of satisfactory KGE and R^2 values during validation indicates that the model parameters are robust and transferable over different temporal conditions. Overall, the RSWAT calibration–validation results confirm that the model effectively reproduces observed discharge dynamics in the study area, demonstrating its suitability for assessing water balance and hydrological responses under future climate scenarios.

Table 17 Calibration and validation statistics

No	Scenario	Calibration					Validation				
		NSE	KGE	R2	RMSE	aBIAS	NSE	KGE	R2	RMSE	aBIAS
1	Earth 3 245	0.535	0.624	0.573	14.543	0.236	0.499	0.599	0.521	15.582	0.177
2	Earth CC 245	0.591	0.727	0.657	9.414	0.196	0.499	0.696	0.595	15.57	0.196
3	NorESM 245	0.541	0.739	0.588	9.971	0.11	0.413	0.681	0.598	16.863	0.114
4	Earth 3 585	0.611	0.739	0.656	9.184	0.174	0.518	0.717	0.599	15.274	0.168
5	Earth CC 585	0.632	0.758	0.676	8.931	0.162	0.536	0.727	0.615	14.998	0.163
6	NorESM 585	0.595	0.689	0.636	9.375	0.209	0.513	0.685	0.581	15.353	0.205

Based on the calibration and validation statistics presented in Table 17, the Earth CC 5.85 scenario shows the best overall model performance among the six configurations tested. This scenario achieved the highest NSE (0.632) and KGE (0.758) during calibration, along with a strong R^2 (0.676) and the lowest RMSE (8.931), indicating excellent agreement between observed and simulated streamflow. During the validation phase, this scenario also maintained consistent performance with NSE (0.536) and KGE (0.727), confirming the model's robustness and reliability across different periods. The combination of high efficiency coefficients and low error metrics suggests that the Earth CC 5.85 setup most accurately captures the watershed's hydrological dynamics under future high-emission conditions. Therefore, this configuration is identified as the best-performing and most reliable model for subsequent water balance and climate impact analyses.

Model Uncertainties

Climate data uncertainty represents one of the most critical sources of error in SWAT (Soil and Water Assessment Tool) simulations, as hydrological and crop growth processes are highly sensitive to variations in precipitation, temperature, and other climatic inputs. Inaccuracies in observed or projected climate data—such as measurement errors, spatial interpolation biases, or inconsistencies in downscaled Global Climate Model (GCM) outputs—can propagate through the model, affecting water balance components, evapotranspiration, and crop yield estimations (Abbaspour et al., 2015; Ficklin & Barnhart, 2014). Moreover, differences among GCMs, emission scenarios, and downscaling methods contribute additional uncertainty, particularly in long-term climate impact studies (Kingston et al., 2011). These uncertainties highlight the need for ensemble simulations, bias correction, and sensitivity analysis to ensure reliable interpretation of SWAT results under future climate projections (Zhang et al., 2017).

The time series analysis revealed a temporal mismatch between rainfall and observation streamflow data, indicating that discharge fluctuations did not consistently correspond with rainfall variations. This discrepancy may result from differences in measurement frequency, hydrological response lag, or errors in data synchronization. Such inconsistency significantly affects the validation and calibration of the SWAT model, as accurate temporal alignment between rainfall input and streamflow response is essential for reliable parameter estimation. When rainfall and discharge data are not synchronized, model performance tends to deteriorate, leading to lower statistical indicators (R^2 and NSE) and higher bias and error metrics (PBIAS and RMSE). Therefore, ensuring proper synchronization of climatic and hydrological datasets is crucial to enhancing the robustness and credibility of SWAT simulations.

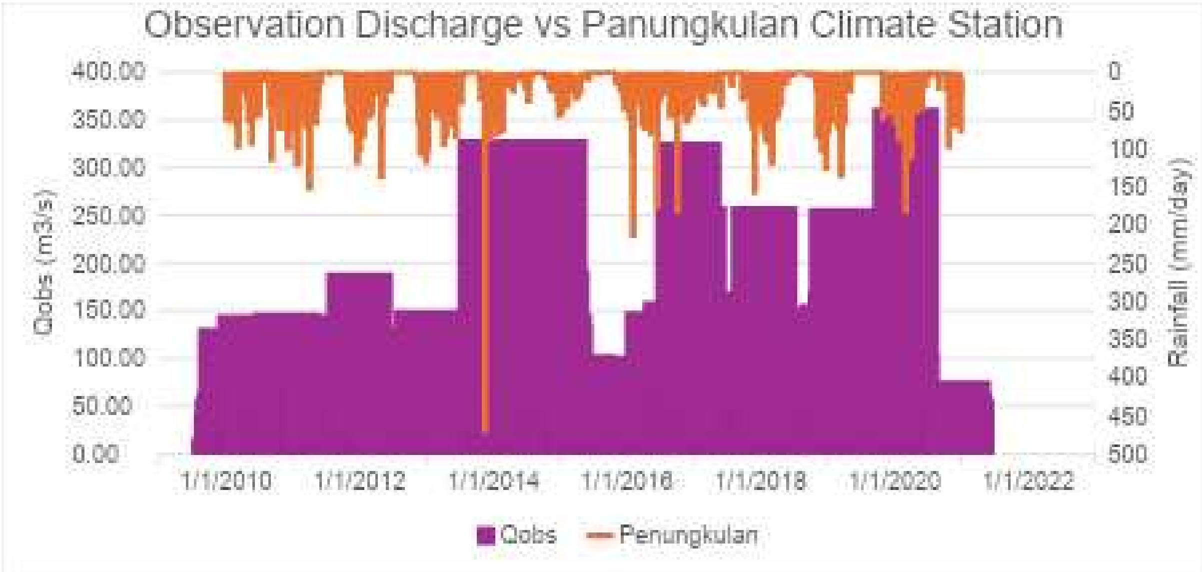


Figure 46 Observation discharharge vs panungkulan climate station

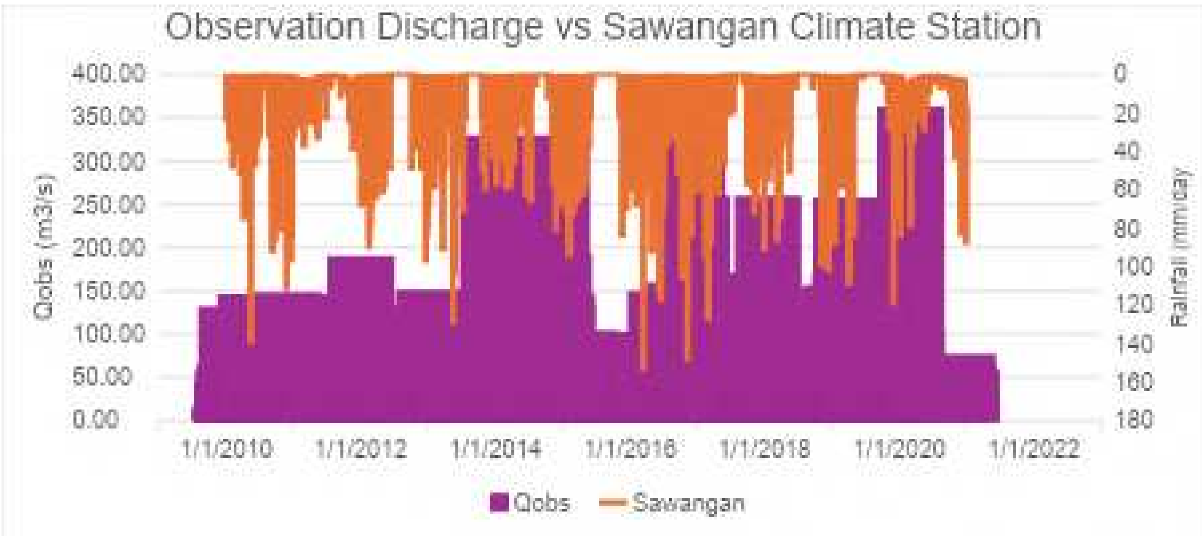


Figure 47 Observation discharharge vs sawangan climate station

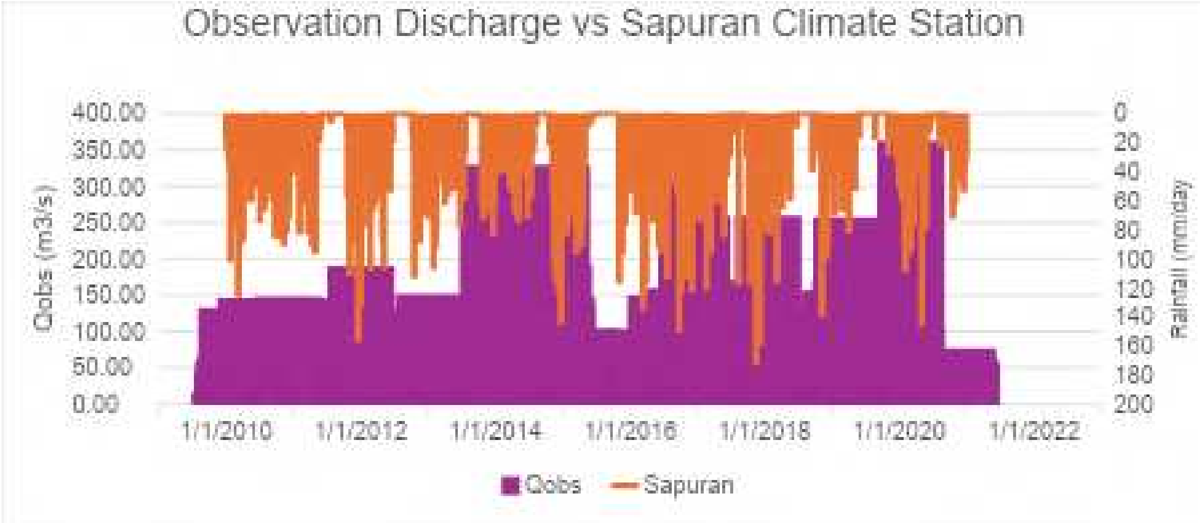


Figure 48 Observation discharharge vs sapuran climate station

4.4 RESULTS AND DISCUSSION

Water Availability

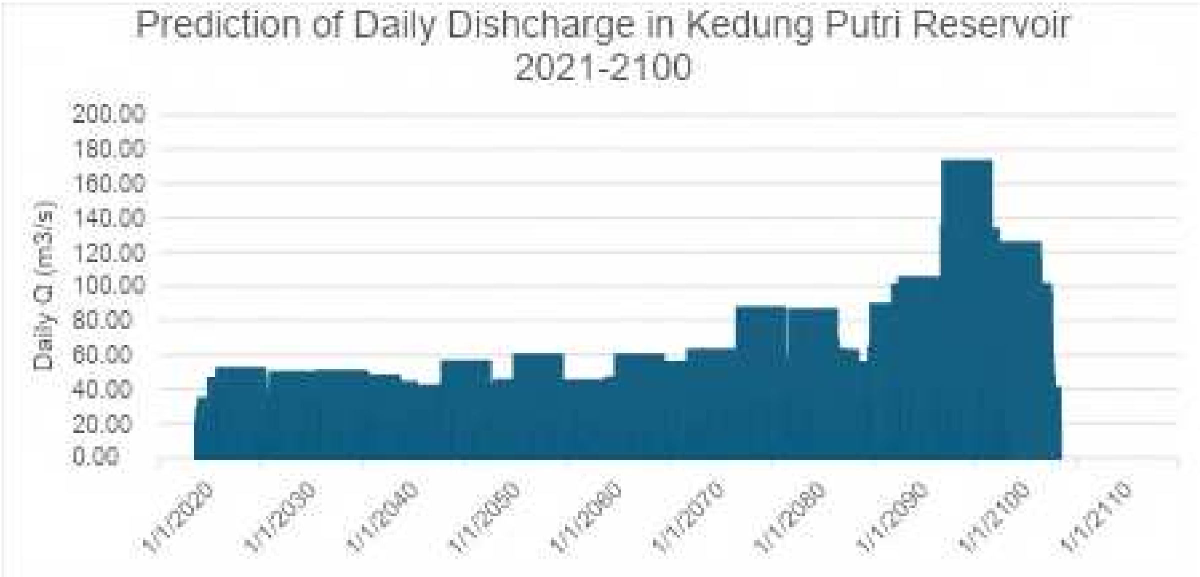


Figure 49 Prediction of daily discharge in Kedung Putri reservoir 2021-2100

The graph illustrates the simulated daily streamflow under the SSP5-8.5 high-emission climate scenario. The results show a clear temporal pattern: streamflow fluctuates annually, with moderate discharge peaks of approximately 20–40 m^3/s during the early projection period (2021–2050). However, starting in the mid-century (around 2060), the amplitude of peak discharges increases noticeably, and by the end of the century (2080–2100), the predicted peak flows rise dramatically, reaching values close to or exceeding 150–200 m^3/s. This pattern indicates a distinct upward trend in extreme discharge events, despite relatively stable baseflow conditions throughout the simulation period.

The increasing discharge trend can be attributed mainly to changes in precipitation intensity and distribution under the SSP5-8.5 scenario. This high-emission pathway is characterized by rapid economic growth and heavy reliance on fossil fuels, leading to increased greenhouse gas concentrations and significant global warming. As global temperatures rise, atmospheric moisture capacity also increases, enhancing evaporation and intensifying the global hydrological cycle. Consequently, rainfall events become more frequent and extreme, particularly in tropical regions such as Indonesia. The Intergovernmental Panel on Climate Change (IPCC, 2021) reports that extreme precipitation intensity in Southeast Asia may increase by 20–30% by the end of the twenty-first century under this scenario.

In addition to climate factors, the hydrological response of the Kedung Putri watershed is critical. Catchments with elongated morphology and moderate to steep slopes tend to respond rapidly to rainfall events, producing sharp increases in runoff and streamflow. If land use changes, such as urban expansion or deforestation, occur within the basin, infiltration capacity would decrease, further amplifying surface runoff and streamflow. Therefore, the observed increase in simulated discharge likely reflects the combined effects of enhanced rainfall intensity, a stronger hydrological response, and possible land cover alterations.

Overall, the projection suggests that future hydrological conditions in the Kedung Putri Reservoir will be increasingly dominated by higher and more variable discharges. This trend underscores the need for adaptive water management strategies, including improved flood-control infrastructure, early warning systems, and watershed conservation efforts, to mitigate risks associated with climate-induced hydrological extremes.

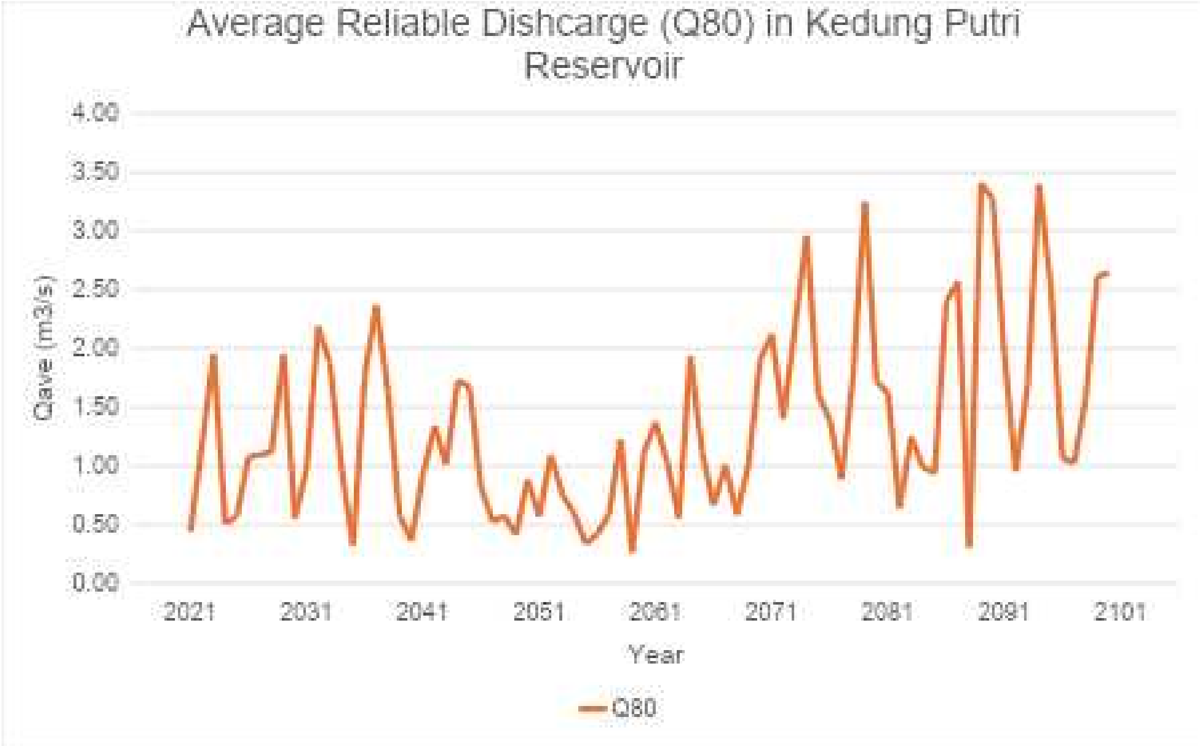


Figure 50 Average reliable discharge (Q80) in Kedung Putri reservoir

The Figure illustrates the projected temporal dynamics of simulated streamflow from 2021 to 2100 generated by the SWAT (Soil and Water Assessment Tool) model under a high-emission (Earth CC) scenario. The discharge (Qave) fluctuates between approximately 0.50 and 3.50 m³/s, exhibiting pronounced interannual variability that reflects the combined influence of climate change and natural climate oscillations. SWAT simulates discharge through a continuous water balance process that integrates precipitation, surface runoff, lateral and groundwater flow, and channel routing at the sub-basin scale (Neitsch et al., 2011; Arnold et al., 2012). The mid-century period (2040–2060) shows a relative decline in average flow, potentially linked to projected reductions in rainfall and increased evapotranspiration, while the late-century period (2070–2099) displays enhanced hydrological extremes with sharp discharge peaks and deep troughs. This behavior may be influenced by the intensification of ENSO events under high-emission scenarios, which are known to drive alternating wet and dry periods in Indonesia (Cai et al., 2020; Hermawan et al., 2022). These results suggest that both anthropogenic climate forcing and ENSO variability contribute to increased hydrological uncertainty in the Kedung Putri Reservoir, with important implications for water availability, reservoir management, and climate adaptation planning.

Plant Water Demand

The *Plant Water Demand* illustrates the simulated annual rice water demand from 2021 to 2099 generated by the SWAT (Soil and Water Assessment Tool) model. The results show that rice water demand fluctuates between approximately 0.6 and 1.6 m3/s per year, indicating inter-annual variability influenced by climatic factors such as precipitation and temperature. In SWAT, plant water demand is estimated as the amount of water required to meet potential transpiration, which is determined based on potential evapotranspiration (PET) and soil moisture availability. PET is calculated using methods such as the Penman–Monteith or Hargreaves, which represent the atmospheric water demand under non-limiting soil moisture conditions. The model then partitions PET into soil evaporation and plant transpiration based on canopy cover and leaf area index, while actual transpiration is adjusted by a soil water stress factor that reflects root-zone moisture conditions. The simulation results suggest that, throughout the projection period, rice water demand remains relatively stable, with occasional peaks likely corresponding to drier or warmer years that increase evapotranspiration demand. Toward the end of the century, a slight increase in water demand is observed, implying that future climatic warming may elevate irrigation requirements to sustain optimal rice growth conditions.

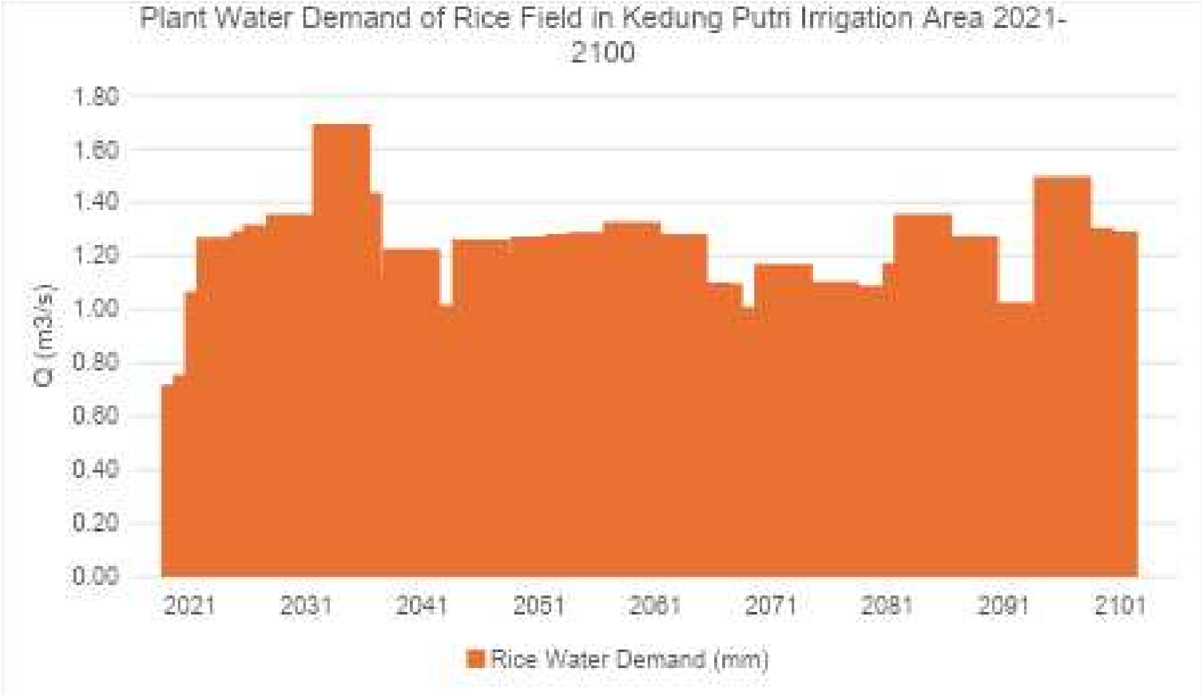


Figure 51 Plant water demand of rice field in Kedung Putri Irrigation Area (2021-2100)

Hydrologic Water Balance

The temporal variability and mid-century deficit pattern of the predicted water balance in the Kedung Putri Irrigation Area (2021–2100), as illustrated in the figure, are attributed to climate-induced hydrological responses simulated with the SWAT model under the high-emission scenario (RCP 8.5). In this study, the reliable discharge (Q80) represents the dependable streamflow—defined as the flow exceeded 80% of the time—which serves as a conservative estimate of available water for irrigation. The simulation results show that Q80 exhibits significant interannual and decadal fluctuations, with a pronounced reduction between approximately 2045 and 2075, when Q80 values frequently fall below the rice crop water demand. This deficit pattern reflects the combined effects of increasing air temperatures, changing rainfall distribution, and enhanced evapotranspiration, as projected under the RCP 8.5 scenario.

According to global and regional climate projections, the mid-21st century is expected to experience a marked rise in mean temperature (up to 2–3 °C in Southeast Asia) accompanied by a shift in precipitation patterns toward shorter wet seasons and prolonged dry spells (IPCC, 2021; Chattopadhyay & Hulme, 2022). These climatic changes reduce effective rainfall and baseflow recharge, leading to lower Q80 discharge. Within the SWAT model framework, which dynamically simulates surface runoff, infiltration, and evapotranspiration processes, such climatic alterations translate into declining low-flow conditions. Simultaneously, increased evapotranspiration driven by higher temperatures accelerates soil moisture loss and reduces catchment water yield (Ficklin et al., 2014). Consequently, during 2045–2075, the reliable discharge becomes insufficient to meet the relatively constant irrigation demand of rice cultivation.

This mid-century deficit thus represents a critical phase where hydrological supply diminishes more rapidly than agricultural demand due to climatic stressors. After 2075, a partial recovery in Q80 is observed, possibly due to hydrological stabilization or adaptation measures in the watershed. The temporal variability and mid-century deficit patterns observed in this study are consistent with findings from previous research indicating that tropical basins under the RCP 8.5 scenario will experience increased low-flow variability and irrigation water shortages around the mid-21st century (Cruz et al., 2017; Ficklin & Novick, 2017).

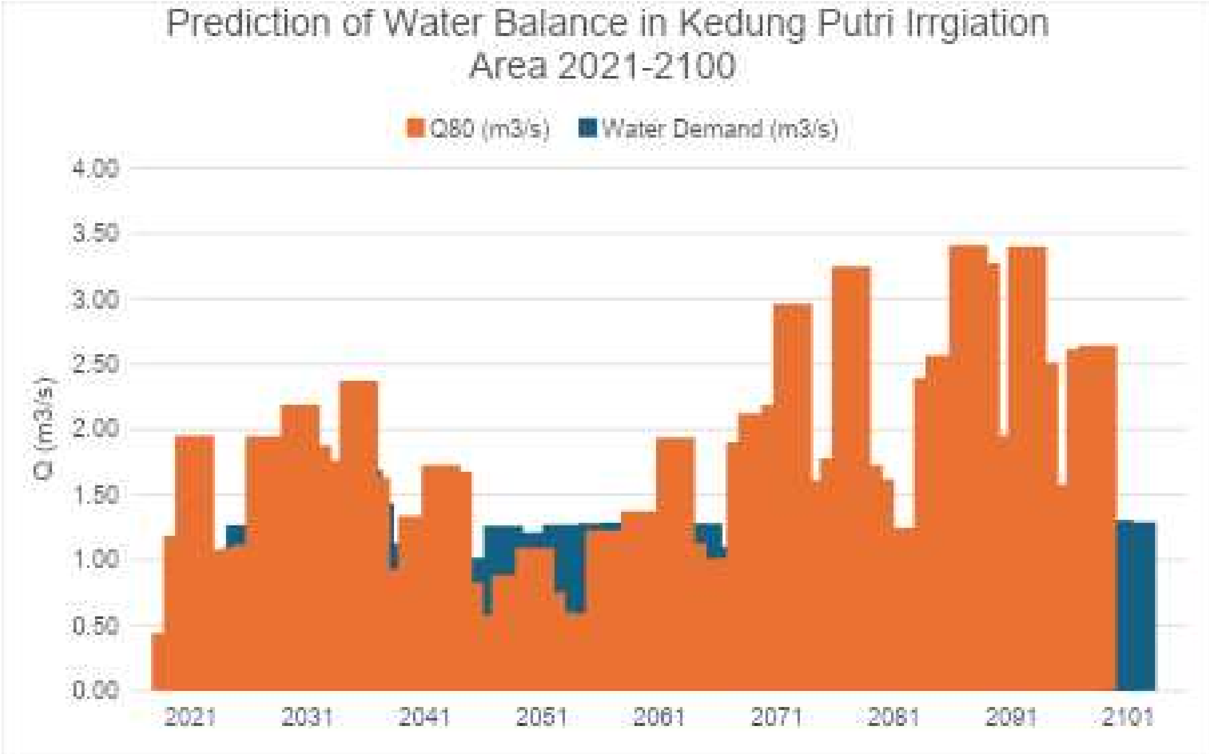


Figure 52 Prediction of water balance in Kedung Putri irigation area (2021-2100)

Crop Productivity

Rice productivity is simulated using a biophysical growth model that accounts for photosynthesis, biomass accumulation, and harvest index. This study modified the rice plant database in rice crop production using 0,55 Harvest Index and 6,83 Leaf Area Index (LAI). The study indicates a gradual decline in rice productivity throughout the projection period. At the beginning of the simulation (around 2021), rice yield is approximately 4.0 t/ha, but it shows a consistent downward trend toward the end of the century, reaching about 2.5-3.0 t/ha by 2099. This reduction suggests an increasing influence of environmental stressors—such as rising temperature, altered precipitation patterns, and water availability constraints—on rice growth. The pattern implies that, under future climate conditions, potential decreases in soil moisture and enhanced thermal stress could reduce photosynthetic efficiency and biomass accumulation, ultimately lowering grain yield. Thus, the chart reflects the modelled long-term vulnerability of rice production to climatic variations within the simulated watershed system.

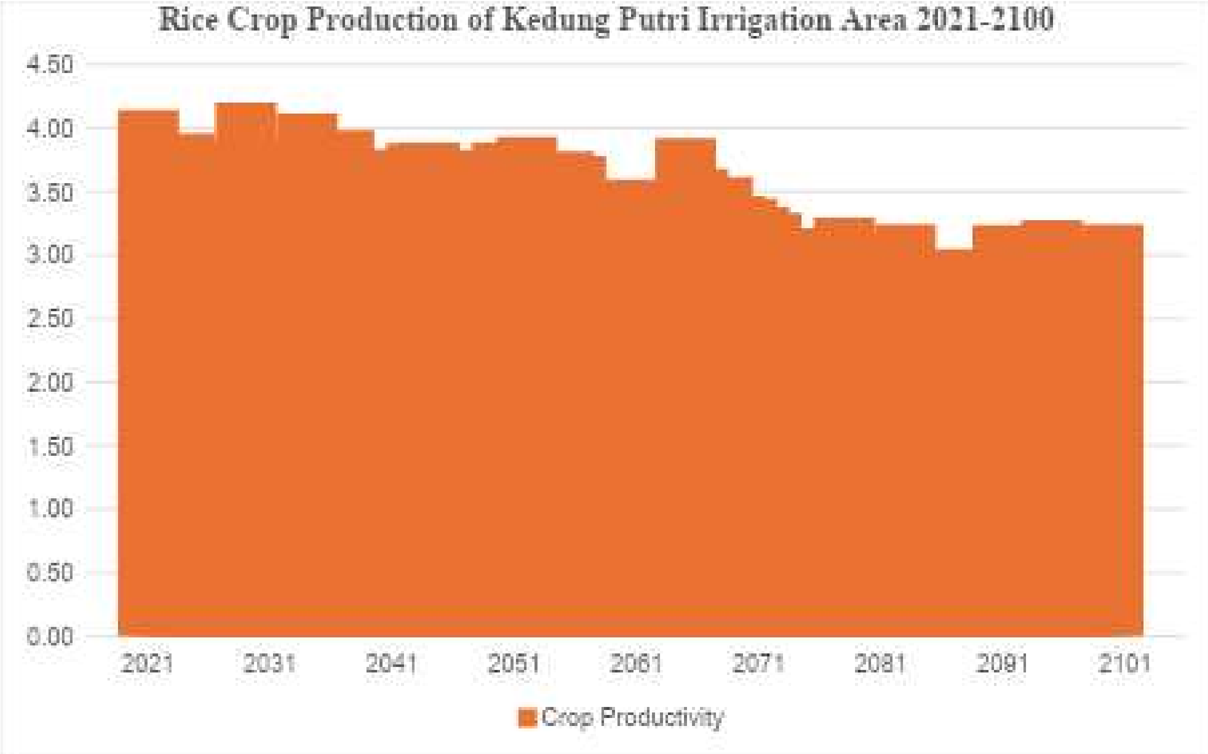


Figure 53 Rice crop production of Kedung Putri irrigation area 2021-2100

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ACTIVITY REPORT

ASIA PACIFIC NETWORK FOR GLOBAL CHANGE RESEARCH (APN)
COLLABORATIVE REGIONAL RESEARCH PROGRAMME (CRRP)

ADAPTING THE IMPACT OF LAND USE AND CLIMATE CHANGE THROUGH SMART IRRIGATION WATER MANAGEMENT TO SUPPORT FOOD SECURITY (SIWAMA)

Project Reference Number: CRRP2024-10SY-Setyawan

PROJECT LEADER: DR. CHANDRA SETYAWAN

DEPARTMENT OF AGRICULTURAL AND BIOSYSTEMS ENGINEERING
FACULTY OF AGRICULTURAL TECHNOLOGY
UNIVERSITAS GADJAH MADA
2024

In collaboration with:

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CHAPTER 1
KICK OFF- MEETING CRRP-APN

A research group led by Dr. Chandra Setyawan collaborated with researchers from several universities across Asia and representatives from the Indonesian government. The research team members from Universitas Gadjah Mada (UGM) include Prof. Dr. Sigit Supadmo, Dr. Murtiningrum, Dr. Ansita Gupitakingkin Pradipta, Dr. Ngadisih, Dr. Hanggar Ganara Mawandha, and Dr. Muhamad Khoiru Zaki. Researchers from higher education institutions in the Asia-Pacific region who participated in this collaboration are Dr. Sushil Kumar Himansu and Ms. Phantipa Plangklang from the Asian Institute of Technology (AIT), Dr. Tran Dang An from Thuy Loi University (TLU), Vietnam, Dr. Ha Thi Hoa Dari from Thai Nguyen University of Agricultural and Forestry (TUAF), Vietnam, and Mr. Muhammad Rasyid Ridho from Flinders University, Australia.

Government representatives serving as policy stakeholders include Dr. Andi Sudirman from the Ministry of Public Works and Dr. Dede Sulaiman from the Ministry of Agriculture. This research is supported by the Asia-Pacific Network (APN) for Global Change Research under the Collaborative Regional Research Programme (CRRP) scheme. To initiate the 2023–2024 research activities, an online kick-off meeting was held on Monday, December 16, 2024. The meeting aimed to align the understanding of all research members regarding the objectives of the study and the implementation framework of the project.

The event began with an opening remark delivered by the Dean of the Faculty of Agricultural Technology, Prof. Dr. Eny Harmayani. In her address, Prof. Harmayani emphasized that collaboration to anticipate the impacts of climate change on water resources and food production is essential. She expressed her strong support for integrative solutions that combine cutting-edge technology, local wisdom, and policy frameworks.

Following the remarks, Dr. Chandra Setyawan introduced all team members and presented the overarching three-year research theme and the focus of the first year.

Subsequently, Dr. Ansita Gupitakingkin Pradipta presented the overall research framework and the progress achieved during the October–December 2024 period. The session was moderated by Dr. Ngadisih and concluded with a discussion involving all team members to refine the research objectives and outline the next steps to be undertaken.

The documentation of this activity is presented as follows.

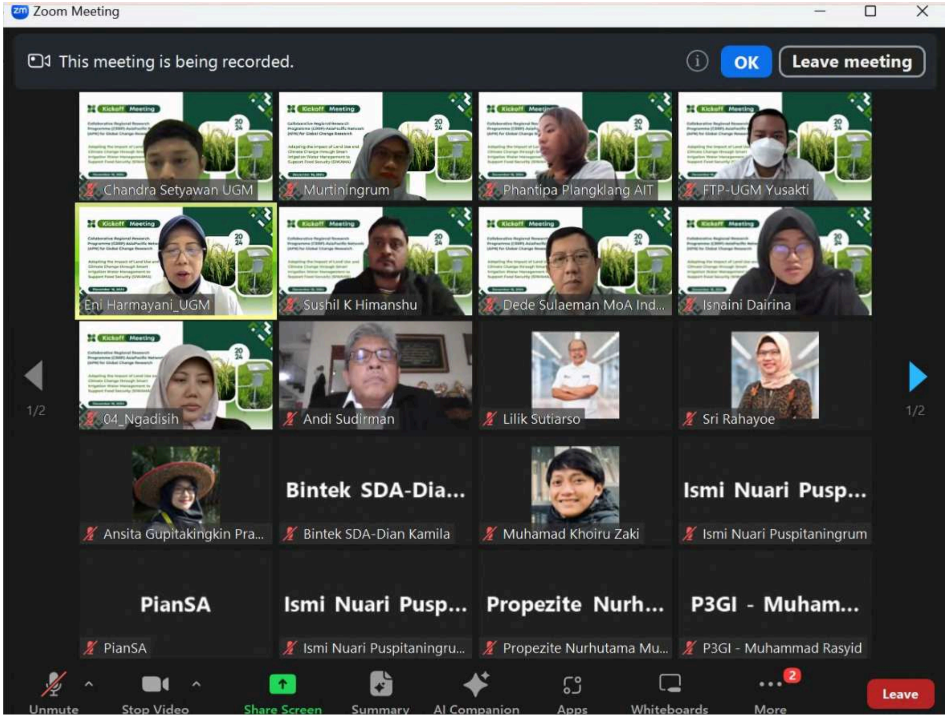

Figure 1. Online Kick-off Meeting of the CRRP-APN Project

CHAPTER 2
MIDTERM WORKSHOP CRRP-APN

The Collaborative Regional Research Programme–Asia Pacific Network (CRRP-APN) team from the Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, organized the "Midterm Workshop CRRP-APN" on Friday (May 16) in Conference Room I. This event represented the second phase of a series of forums for discussion and presentation of research findings from the project titled Adapting the Impact of Land Use and Climate Change through Smart Irrigation Water Management to Support Food Security (SIWAMA), which received an international research seed grant from the Asia Pacific Network (APN) for Global Change Research.

The workshop, led by Dr. Chandra Setyawan, was conducted in a hybrid format and attended by members of the CRRP-APN team, including:

- Prof. Dr. Sigit Supadmo Arif (Department of Agricultural and Biosystems Engineering, FTP UGM)
- Propezite Nurhutama Mustain, S.T., M.T. (Ministry of Public Works and Housing, Republic of Indonesia)
- Dede Sulaeman (Ministry of Agriculture, Republic of Indonesia)
- Andri Prima Nugroho, Ph.D. (DTPB FTP UGM)
- Muhammad Rosyid Ridlo, M.Sc. (Flinders University, Australia)
- Eng. Ansita Gupitakingkin Pradipta (DTPB FTP UGM)
- Muhamad Khoiru Zaki, Ph.D. (DTPB FTP UGM)
- Phantipa Plangklang (Asian Institute of Technology, Thailand)
- Teguh Triyana (DTPB FTP UGM)
- Isnaini Dairina (DTPB FTP UGM)

as well as several undergraduate students of Agricultural Engineering. The workshop was also attended in person by Prof. Dr. Eny Harmayani, Dean of the Faculty of Agricultural Technology, and Prof. Dr. Ir. Lilik Sutiarso, Head of the Department of Agricultural and Biosystems Engineering.

The main agenda of the workshop included presentations of the Kedung Putri Irrigation Scheme case study in Indonesia, along with reviews of smart irrigation developments in Thailand and Vietnam. Each researcher presented their respective methodologies and preliminary findings, ranging from field data collection to analyses of land-use change impacts. The forum also highlighted the importance of integrating sensor technology and automated control systems to enhance water distribution efficiency during both dry and wet seasons.

The Midterm Workshop is expected to accelerate the implementation of technical recommendations, foster innovation in monitoring methods, and advance the development of predictive models for smart irrigation water management. Consequently, the SIWAMA project aims to directly contribute to strengthening national food security amidst the challenges of climate change.

The outcomes and recommendations generated from the Midterm Workshop CRRP-APN align with several Sustainable Development Goals (SDGs)—notably SDG 2: Zero Hunger, through improved agricultural productivity supported by smart irrigation systems; SDG 6: Clean Water and Sanitation, through efficient and sustainable water management; and SDG 13: Climate Action, by promoting adaptation and mitigation strategies through innovative technologies. Moreover, the multi-sectoral collaboration fostered in this program embodies the spirit of SDG 17: Partnerships for the Goals, strengthening regional academic and institutional networks in food security research.

The documentation of this activity is presented as follows.

Figure 2. Presentation of progress during the CRRP-APN coordination meeting

Figure 3. Presentation of progress during the CRRP-APN coordination meeting

Figure 4. Participants of the CRRP-APN coordination meeting

CHAPTER 3
FINAL WORKSHOP CRRP-APN

On Thursday, September 25, 2025, the Collaborative Regional Research Programme–Asia-Pacific Network for Global Change Research (CRRP–APN) team from the Department of Agricultural and Biosystems Engineering (DTPB), Faculty of Agricultural Technology, Universitas Gadjah Mada (FTP UGM) held the Final Workshop under the theme *"Adapting the Impact of Land Use and Climate Change through Smart Irrigation Water Management to Support Food Security (SIWAMA)"*.

The event was officially opened by Prof. Dr. Ir. Lilik Sutiarso, Head of DTPB FTP UGM, who delivered welcoming remarks and emphasized the importance of cross-country collaboration in addressing the challenges of climate change and land degradation that threaten food security.

The workshop consisted of two main sessions. The first session featured presentations of collaborative research findings by the CRRP–APN research team of DTPB FTP UGM, led by Dr. Chandra Setyawan, S.T.P., M.Sc. The team—comprising Dr. Chandra Setyawan (Principal Investigator), Dr. Ansita Gupitakingkin Pradipta, Dr. Muhamad Khoiru Zaki, Dr. Andri Prima Nugroho, and Isnaini Dairina, M.Sc.—presented the outcomes of their research on smart irrigation water management as a climate change adaptation strategy to support sustainable food systems.

The second session was a guest lecture moderated by Dr. Ngadisih, featuring four distinguished speakers from both international and national institutions:

- Dr. Sushil Kumar Himanshu (Asian Institute of Technology, Thailand)
- Dr. Ha Thi Hoa (Thai Nguyen University of Agricultural and Forestry, Vietnam)
- Dr. Dede Sulaeman (Ministry of Agriculture, Republic of Indonesia)

- Propezite Nurhutama M., S.T., M.T. (Ministry of Public Works, Republic of Indonesia)

The speakers shared their perspectives on climate change adaptation strategies, innovations in irrigation technology, and sustainable agricultural and infrastructure policies relevant to implementation in the Southeast Asian region.

This activity aligns closely with several Sustainable Development Goals (SDGs), particularly:

- SDG 2 – Zero Hunger: supporting food security through adaptive and efficient irrigation systems;
- SDG 6 – Clean Water and Sanitation: promoting sustainable water resource management;
- SDG 13 – Climate Action: developing research-based adaptation strategies to address climate change impacts;
- SDG 17 – Partnerships for the Goals: strengthening cross-national collaboration in academia, research, and policy.

Through this workshop, DTPB FTP UGM not only expanded its international research network and strengthened its capacity in smart irrigation research, but also demonstrated its academic excellence and research leadership in contributing tangible solutions toward building resilient, adaptive, and sustainable agricultural and food systems at both national and regional levels.

The documentation of this activity is presented as follows.

Figure 5. Participants of the CRRP-APN coordination meeting

Figure 6. Guest Lecture Session

Figure 7. Group Photo of Participants of the Final Workshop CRRP-APN

CHAPTER 4
TRAINING MACHINE LEARNING AND GIS

Yogyakarta, September 25, 2025 – The Collaborative Regional Research Programme–Asia Pacific Network for Global Change Research (CRRP–APN) team from the Department of Agricultural and Biosystems Engineering (DTPB), Faculty of Agricultural Technology, Universitas Gadjah Mada (FTP UGM) organized a training program entitled *"Training on the Application of Machine Learning and GIS for Future Land Use Projection."* The event was held in Room 384, FTP UGM, and attended by students of DTPB UGM as well as participants from the general public.

The training was opened by Dr. Ngadisih, who delivered welcoming remarks emphasizing the importance of mastering spatial technology in addressing the challenges of climate change and future land management. The main session was then facilitated by Isnaini Dairina, M.Sc., along with other members of the teaching team. During the training, participants received technical instruction on utilizing various machine learning and geographic information system (GIS) software applications, including Google Earth Engine, ArcGIS Pro, and QGIS (MOLUSCE Plugin). Through these platforms, participants were trained to generate land use maps based on remote sensing satellite imagery, which were subsequently used to project future land use patterns. This approach is expected to provide a more comprehensive perspective for spatial planning, environmental risk mitigation, and sustainable development.

This activity is closely aligned with several Sustainable Development Goals (SDGs), namely:

- SDG 4 – Quality Education: providing learning opportunities and capacity building for students and the public.

- SDG 9 – Industry, Innovation, and Infrastructure: promoting the use of geospatial and machine learning technologies for land use planning and innovation.
- SDG 13 – Climate Action: supporting adaptation and mitigation efforts against climate change through more accurate land use projections.
- SDG 15 – Life on Land: contributing to ecosystem sustainability through environmentally balanced land use planning.

Through this training, DTPB FTP UGM aims for participants not only to gain theoretical knowledge, but also to develop practical skills that can be directly applied in research, regional planning, and community engagement initiatives.

The documentation of this activity is presented as follows.

Figure 8. Participants engaging in practical sessions during the *Training on Machine Learning and GIS*

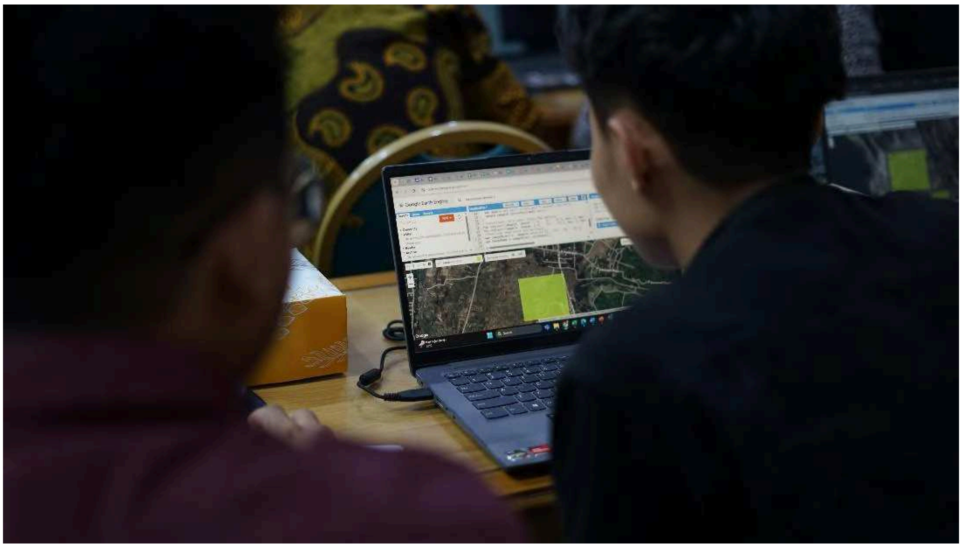

Figure 9. Participants engaging in practical sessions during the *Training on Machine Learning and GIS*

Figure 10. Group photo of participants and instructors after the *Training on Machine Learning and GIS*

CHAPTER 5
FIELD VISIT CRRP-APN

On September 25, 2025, the Collaborative Regional Research Programme–Asia Pacific Network for Global Change Research (CRRP–APN) team from the Department of Agricultural and Biosystems Engineering (DTPB), Faculty of Agricultural Technology, Universitas Gadjah Mada (FTP UGM) conducted a field visit together with Dr. Sushil Kumar Himanshu from the Asian Institute of Technology (AIT), Thailand.

Dr. Sushil was accompanied by several DTPB faculty members, namely Dr. Murtiningrum, Dr. Chandra Setyawan, Dr. Andri Prima Nugroho, and Dr. Ansita Gupitakingkin Pradipta. The visit began at the Sapon Weir, where the team observed the implementation of irrigation modernization within the Sapon Irrigation Area. The irrigation system has adopted electrically operated intake gates and an Automatic Water Level Monitoring System (AWLMS) developed by the SIPASI UGM (Irrigation Management System) research team.

The AWLMS is integrated with a Decision Support System (DSS), enabling efficient monitoring of water surface levels and providing predictive capabilities by comparing real-time data with historical records. This technology offers valuable insights for policymakers in planning precise and sustainable water allocation across irrigation zones. In addition, the team visited demonstration sites showcasing the application of this system on water gates capable of automatically adjusting water distribution volumes according to agricultural land requirements.

The visit continued to the sandy agricultural land at Samas Beach, Bantul, which is managed by partner farmers collaborating with the Department of Agricultural and Biosystems Engineering (DTPB), Faculty of Agricultural Technology, Universitas Gadjah Mada (FTP UGM).

At this site, mist, drip, and sprinkler irrigation systems have been implemented. These systems offer several advantages, including the ability to optimize water distribution directly to the plant root zone, minimize water loss due to evaporation, and maintain stable soil moisture levels around the crops. Consequently, such irrigation technologies not only enhance plant growth in marginal sandy soils, but also promote sustainable agricultural practices through improved water-use efficiency.

This field visit is closely aligned with several Sustainable Development Goals (SDGs), particularly:

- SDG 2 (Zero Hunger): supporting food security through innovations in sustainable agricultural technology;
- SDG 6 (Clean Water and Sanitation): optimizing water resource management for efficient irrigation;
- SDG 9 (Industry, Innovation, and Infrastructure): applying modern technologies in irrigation systems;
- SDG 13 (Climate Action): adapting to climate change impacts through smart irrigation systems;
- SDG 17 (Partnerships for the Goals): strengthening international collaboration in agricultural technology research and development.

Through this field visit, DTPB FTP UGM aims to continuously demonstrate its competence and tangible contribution to the advancement of smart irrigation technologies that address global challenges. Moreover, the activity is expected to reinforce international research networks while providing direct benefits to partner farmers, enabling them to manage their land more productively, efficiently, and sustainably.

The documentation of this activity is presented as follows.

Figure 11. A member of the research team explaining the function of an automatic weather station powered by a solar panel during the CRRP-APN field visit

Figure 12. A member of the research team providing an explanation during the CRRP-APN field visit at a water monitoring station

Figure 13. Field visit activity by the CRRP-APN team