Heliyon 9 (2023) e19639

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

Evaluating the effect of climate change on rice production in Indonesia using multimodelling approach

Andrianto Ansari [a,*], Arin Pranesti [b], Mareli Telaumbanua [c], Taufan Alam [a], Taryono [a,d], Rani Agustina Wulandari [a], Bayu Dwi Apri Nugroho [e], Supriyanta [a]

[a] Department of Agronomy, Faculty of Agriculture, Universitas Gadjah Mada, Yogyakarta, Indonesia
[b] Department of Accounting, Faculty of Economics and Business, Universitas Negeri Yogyakarta, Yogyakarta, Indonesia
[c] Department of Agricultural Engineering, Faculty of Agriculture, University of Lampung, Bandar Lampung, Indonesia
[d] Agrotechnology Innovation Center, Universitas Gadjah Mada, Yogyakarta Indonesia
[e] Department of Agricultural and Biosystems Engineering, Faculty of Agricultural and Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia

A R T I C L E I N F O

Keywords:
Rice production
Climate model
Weather generator
Hydrological model
Crop model
Food security

A B S T R A C T

Achieving global food security in the face of climate change is a critical challenge, particularly in vulnerable countries like Indonesia. To effectively address this challenge, a systems-based approach utilizing climate-hydrological-crop models has emerged as an integral approach. These models integrate climate, hydrological, and crop components to understand and predict the complex interactions within agricultural systems and their responses to climate variables. By employing this approach, policymakers, researchers, and stakeholders can gain comprehensive insights into the potential consequences of climate change on crop growth, water availability, soil fertility, and overall crop yield. However, challenges exist in the implementation of this approach, including data reliability; scarcity of complete long-term data; lack of experimental information about crop species, especially local varieties; inadequate research resources; lack of expertise concerning modeling approaches; lack of testing; inaccurate testing; calibration; and model uncertainties. Furthermore, to address limitations and challenges in implementing this approach, improving the availability and reliability of data, collection method, and data quality should be conducted to ensure the accuracy of simulation and prediction. Finally, climate-hydrological-crop models, alongside improved data collection and modelling techniques, serve as essential tools for guiding the development of effective adaptation measures to mitigate the impacts of climate change on rice production in Indonesia.

1. Introduction

As the country placed fourth in population size, the agricultural sector plays a vital role in Indonesian's national economic growth through poverty alleviation, income and employment in rural areas, food security, and preservation of natural resources and the environment [1]. In 2021, the agricultural sector contributed to 13.28% of Indonesia's gross domestic product (GDP.) [2], and rice production holds particular significance as it serves as a staple food for over 90% of the population [3]. The development of rice production in Indonesia dates back to the 1960s. Notably, the country achieved rice self-sufficiency for the first time in 1984, following

* Corresponding author.
E-mail address: andrianto.ansari@mail.ugm.ac.id (A. Ansari).

https://doi.org/10.1016/j.heliyon.2023.e19639
Received 21 June 2022; Received in revised form 22 August 2023; Accepted 29 August 2023
Available online 31 August 2023
2405-8440/

substantial government investments in water facilities, including reservoirs and new irrigation systems. These efforts were complemented by introducing advanced agricultural machinery, fertilizer subsidies, the discovery of superior cultivars, expansions of agricultural land, and safeguards against price fluctuations [4,5]. Consequently, Indonesia transitioned from being one of the biggest rice importers in the world in the 1960s to one of the most self-sufficient countries in the world. This was recognized by an award from the Food and Agriculture Organization in 1985 in Rome [4,6]. During this period, agriculture played a crucial role in reducing farmers' poverty and increasing their income, as the government procured their products through the Indonesian Bureau of Logistics, known as "Bulog" [6,7].

Since achieving rice self-sufficiency in 1984, sustaining this success has proven challenging, resulting in increased total rice imports in recent decades [8]. The government implemented import policies with countries such as Vietnam, Thailand, India, China, and Pakistan to meet national demand,. Despite an increase in rice production since the 1970s (28.1 MT in 1973 and 71.3 MT in 2013), it has failed to keep pace with the growing population (124.2 million in 1970 and 251.8 million in 2013) [9,10]. This discrepancy can be attributed to the high per capita rice consumption, reaching to 160 kg per year [11]. Projections indicate that the Indonesian population will reach approximately 322 million by the end of the 2050s, leading to a corresponding 45% increase in rice consumption. The Indonesian government has adopted strategies at both ends of the supply chain: increasing rice production and promoting alternative food sources, such as the "one day without rice" campaign, encouraging the consumption of other staples once a week to achieve self-sufficiency [12]. Substantial government investments incentivize farmers to enhance production through the utilization of modern farming equipment, including advanced tractor technology, transplanter machines, large-medium combine harvesters, and state-of-the-art post-harvesting machinery, such as rice milling units, vertical and ultraviolet dryers, to improve both quantity and quality of the yield [13,14] Additionally, the government has expanded the rice production area on various islands, conducted repairs and construction of irrigation facilities, developed new high yielding cultivars, expedited the distribution of seeds and fertilizers, and established sustainable programs through collaborations with universities and students to facilitate knowledge and technology transfer to farmers [13,15].

The expansion of rice production areas by the government has been accompanied by a concerning trend of agricultural land conversion, particularly in Java, the primary centre of rice production in Indonesia. Approximately 26,900 ha of agricultural land have been converted into residential, industrial, and private land, resulting in a potential loss of around 2.2 million tons of rice production annually [16]. This land use conversion has predominantly occurred within watersheds, posing to water quality and quantity due to increased surface runoff and associated losses [17]. Furthermore, the changing climate, characterized by rising temperatures, variations in rainfall intensity, duration, and frequency, increased occurrences of extreme weather events, and escalating greenhouse gas (GHG) emissions, directly impacts agricultural productivity. Drought-affected areas (ranging from 25,580 to 867,930 ha) are estimated to lose 12,446 ha of rice fields and 885,430 tons of rice production [17,18]. The implications of climate change extend beyond agricultural productivity, as it contributes to the elevation of GHG levels, which can adversely affect human health and exacerbate environmental concerns [19,20]. Consequently, it becomes imperative to employ future climate predictions to formulate policies and adaptation strategies to mitigate climate change's effects on rice production [21,22]. Such measures are crucial for ensuring the sustainability and resilience of the rice farming sector in Indonesia.

Indonesia, as a country situated on the equator, has witnessed a significant rise in mean annual temperatures over the past few decades. Since 1990, the country has experienced an average increase of approximately 0.3 °C per decade, with projections indicating a further increase of 1.1–3.2 °C by the end of 2010 [23,24]. The implications of such temperature increases are far-reaching. Rising temperatures can lead to increase heatwaves and evaporation rates as well as alter precipitation patterns, significantly affecting Indonesian's ecosystems, water resources, and agriculture. Moreover, by the year 2100, changes in precipitation are estimated to range from a decrease of 1% to an increase of 5%., which means some areas may experience reduced rainfall, leading to water scarcity, while others may face more intense rainfall events, increasing the risk of flooding [23,24]. In addition, rising temperatures and changing rainfall patterns can influence the occurrence and distribution of pests and diseases that affect crops [21]. These alarming figures place Indonesia among the most vulnerable counties regarding climate change impacts and potentially decrease rice production, which in turn can have severe implications for food security [25]. To effectively address the challenges posed by climate change in the agricultural sector in Indonesia, adaptation strategies based on a modeling approach−including climate, hydrological, and crop model−is crucial for understanding and predicting the complex interactions between climate variables, agricultural systems, and their impacts. By utilizing modelling techniques, policymakers, researchers, and stakeholders can gain a comprehensive understanding of the potential effects of climate change on various aspects of agriculture, including crop growth, water availability, soil fertility, and crop yield. Therefore, this study aims to summarize potential climate, hydrological, and crop models that can be used for analyzing and evaluating rice production under different climate change scenarios for determining appropriate adaptation strategies.

2. Methods

This study employed a comprehensive literature search through Perish and Publish Software [26] based on four scientific databases (Scopus, Web of Science, Crossreff, and Google Scholar), employing the keywords "climate model," "hydrological model," "crop model" and "rice". A total of 267 papers were initially identified through the title screening process. These papers were further assessed by reviewing their abstracts in the second screening stage to determine their relevance to climate, hydrological, or crop models. After this screening process, 154 papers were deemed suitable for inclusion in the review. The review also included technical reports, government publications, conference proceedings, book chapters, and published reviews incorporating climate-hydrological-crop models to gather additional information and enhance the breadth of knowledge on the three modeling approaches. This broadened the scope of the review and ensured a comprehensive analysis of the available literature. Moreover, additional publications that met these criteria were incorporated to specifically focus on rice production in Indonesia and evaluate the use of climate-hydrological-crop models in different provinces. This facilitated a meta-analysis to gain insights into the distribution of research related to the utilized models across different regions of Indonesia. Overall, this systematic search and screening process resulted in a robust collection of papers, reports, and reviews that encompassed the relevant modeling approaches in the context of rice production, climate change, and hydrological factors in Indonesia. The review method employed in this study adhered to the PRISMA flowchart guidelines [27,28].

3. Modeling approach

In light of the substantial rise in global temperatures compared to the preindustrial era, which can primarily be attributed to human activities in industry and agriculture, it is imperative to acknowledge the challenges posed by climate change and its impacts on sustainable rice production in Indonesia. The significance of sustainable rice production cannot be overstated for the country, as it does not only contribute to the economy but also plays a vital role in ensuring food security and the overall well-being of local communities. To understand of the intricate factors affecting sustainable rice production, it is beneficial to consider the problem as a system and to represent it as a model. Models have been widely used for simulating natural phenomena in agricultural systems across various scales. Several advantages can be realized by employing modeling techniques, including the transfer of research knowledge to farmers and other users of agricultural systems [29]. Moreover, models provide a means for conducting foresight analysis, enabling the generation of different scenarios to predict future rice production. Such analyses play a pivotal role in making informed decisions regarding farm

Table 1
Summary of climate models.

Climate models	References	Description
BCC-CSM-1, BCC-CSM1-1-M	[34,35]	BCC-CSM-1 and BCC-CSM1-1-M are climate models developed by the Beijing Climate Center (BCC) of the China Meteorological Administration. These models are part of the larger BCC. Climate System Model (BCC-CSM) family, which includes various versions and configurations.
CSIRO-Mk3-6-0	[36,37]	CSIRO-Mk3-6-0 is a climate model developed by Australia's Commonwealth Scientific and Industrial Research Organisation (CSIRO) which is part of the Coupled Model Intercomparison Project Phase 5 (CMIP5). It uses a three-dimensional grid-system to represent the spatial distribution of atmosphere, oceans, land surface and sea ice by employing mathematical equations to describe physical processes.
FIO-ESM	[38,39]	FIO-ESM, developed by China's First Institute of Oceanography (FIO), is a climate model that combines various components to represent the earth systems including atmosphere, oceans land surface, sea ice, and carbon cycle for capturing the complex dynamics and feedback mechanisms that influence earth's cimate.
GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M	[40–42]	GFDL-CM3, GFDL-ESM2G, and GFDL-ESM2M are climate models developed by the Geophysical Fluid Dynamics Laboratory (GFDL) in the United States. These models are part of the CMIP5 (Coupled Model Intercomparison Project Phase 5) and CMIP6 initiatives, which involve collaboration among multiple climate modelling centers worldwide.
GISS-E2	[43,44]	GISS-E2 refers to the Goddard Institute for Space Studies Earth System Model (GISS-E2). It is a climate model developed by the NASA Goddard Institute for Space Studies (GISS) in collaboration with other institutions. GISS-E2 is designed to simulate and study various components of the Earth's climate system, including the atmosphere, oceans, land surface, sea ice, and the carbon cycle.
HadGEM	[45,46]	HadGEM stands for the Hadley Centre Global Environmental Model. It is a climate model developed by the Met Office Hadley Centre, a research institute based in the United Kingdom. HadGEM combines atmospheric, oceanic, and land surface components to simulate and study the Earth's climate system.
UKESM	[47,48]	UKESM stands for the U.K. Earth System Model. It is a state-of-the-art climate model developed by collaborating with the Met Office Hadley Centre and the Natural Environment Research Council (NERC) in the United Kingdom. UKESM integrates various Earth system components, including the atmosphere, oceans, land surface, and cryosphere, to simulate the complex interactions and feedback among these components.
IPSL-CM	[49,50]	IPSL-CM refers to the IPSL Climate Model developed by the Institute Pierre-Simon Laplace (IPSL), a consortium of French research institutions. IPSL-CM is a state-of-the-art Earth system model that simulates the behavior of the climate system, including the atmosphere, oceans, land surface, and sea ice.
MIROCS, MIROC-ESM, MIROC-ESM-CHEM	[51,52]	MIROCS, MIROC-ESM, and MIROC-ESM-CHEM are climate models developed by the Model for Interdisciplinary Research on Climate (MIROC) team, which consists of researchers from multiple institutions in Japan.
MRI-CHCM3	[53,54]	MRI-CHCM3 is a climate model developed by Japan's Meteorological Research Institute (M.R.I.). The model, also known as the M.R.I. Coupled General Circulation Model version 3 is designed to simulate the Earth's climate system and investigate various aspects of climate change.
NorESM	[55,56]	NorESM (Norwegian Earth System Model) is a comprehensive climate model developed by the Norwegian climate research community. It consists of several interconnected components that simulate various components of the Earth's climate system, including the atmosphere, ocean, sea ice, and land surface.
EC-Earth	[57,58]	EC-Earth (European Community Earth System Model) is a state-of-the-art climate model developed through collaboration between several European research institutions. It is designed to simulate the complex interactions between the atmosphere, oceans, land surface, and sea ice to represent the Earth's climate system comprehensively.
CNRM-CERFACS	[59,60]	CNRM-CERFACS (Centre National de Recherches Météorologiques - Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique) is a climate model developed in collaboration between the French National Center for Meteorological Research (CNRM) and the European Centre for Research and Advanced Training in Scientific Computation (CERFACS).
MPI-ESM	[61,62]	MPI-ESM (Max Planck Institute Earth System Model) is a comprehensive climate model developed by the Max Planck Institute for Meteorology in Germany. It is designed to simulate and study the Earth's climate system and its interactions between the atmosphere, ocean, land surface, and sea ice.

management, including planting schedules, fertilization, irrigation, pesticide use, and harvesting. Through leveraging modelling, the quantity of rice production can be evaluated to ensure food security [21,30].

Accurate predictions of future climate are paramount for evaluating the far-reaching impacts of climate change. On the one hand, climate models have emerged as invaluable tools in this endeavor, serving as extensions of weather forecasting techniques. Among these models, General Circulation Models (GCMs) stand out as mathematical representations of atmospheric, oceanic, and continental processes, incorporating their intricate interactions [31]. It becomes possible to simulate climate change patterns on a global scale and regional scale by subsequently using regional climate model. These models facilitate the study of localized phenomena, enabling researchers to delve into the intricacies of specific regions and assess their vulnerability, impacts, and potential adaptation strategies (VIA) assessments [32,33]. On the other hand, weather models, often referred to as weather generators, complement climate models by simulating daily weather variables such as precipitation, maximum and minimum temperatures, solar radiation, relative humidity, and wind speed. According to data from climateknowledgeportal.org, for instance, provided by the world bank, the climate projections indicate an increase in rainfall from 2040 to 2100 during the November to May period, while the June to September period is expected to be drier. These changes may result in more frequent flooding and drought events. Moreover, the maximum projected temperature is estimated to exceed 31 °C by the end of the 21st century, significantly higher than the current mean temperature of around 26 °C–27 °C in Indonesia. To achieve more precise and realistic results at various scales (from local to national), a comprehensive summary of climate models and weather generators suitable for predicting climate change in Indonesia is provided in Tables 1 and 2. These tables aims to provide informations regarding climate and weather models that suitable applied in Indonesia since these models are crucial inputs for hydrological and crop models.

Climate change exerts a profound influence on hydrological processes, causing significant alterations in precipitation, evaporation, groundwater levels, runoff, evapotranspiration, and other factors that vary across different watersheds [74]. Changes in water availability due to climate change have wide-ranging impacts on energy supplies, industry, transportation, agriculture, social well-being, environment, and the economy. Moreover, the water balance in agricultural systems is disturbed by climate change, affecting water availability and subsequently impairing crop growth and yield. Precipitation serves as the primary resource within the hydrological system and plays a vital role in agriculture by providing water for plant growth and irrigation. However, climate change leads to temporal and spatial reductions in the frequency and quantity of precipitation, resulting in increased occurrences of droughts and floods that directly impact rice production. Understanding the intricate relationship between hydrological processes and rice production is paramount. Specifically, it is necessary to determine the water availability in each irrigation area, the capacity for surface and groundwater reservoirs to store water during drought, and the development of a crop calendar based on water availability. Assessing the seasonal and long-term water availability holds immense significance for agriculture, water authorities, and farmers, as well as the sustainability of human life, the environment, and biodiversity [74,75]. Table 3 summarizes hydrological models that can simulate the water balance and its associated variables in agricultural systems. By utilizing these models, researchers and stakeholders can gain valuable insights into the complex dynamics of water resources, enabling informed decision-making and implementing sustainable agriculture practices.

Exploring the impact of climate change on rice production is crucial for determining appropriate adaptation strategies to mitigate harmful effect from its effects. Crop models offer a valuable tool to simulate various aspects of crop development, growth, yield, nutrient uptake, water use, and emissions as a result of changing rainfall pattern and elevating temperature and CO_2. These models

Table 2
Summary of weather generator.

Weather generator	References	Description
MarkSIM	[63,64]	MarkSIM is a software tool and web-based application that simulate daily weather variables, such as precipitation, temperature, solar radiation, and wind speed, based on statistical relationships and historical weather data.
Lars-WG	[65,66]	LARS-WG is a stochastic weather generator to simulate daily weather variables such as precipitation, temperature, and solar radiation at a regional scale, considering the spatial variability of weather conditions across different locations
SIMMETEO	[67,68]	SIMMETEO is a program developed for generating daily rainfall data using statistical methods.
WGEN	[69,70]	WGEN is a weather generator model to generate synthetic daily weather variables, including precipitation, maximum and minimum temperatures, and solar radiation, based on statistical characteristics derived from historical weather data. WGEN allows for the generation of long-term weather data that can be used in crop simulations, hydrological modelling, and other applications requiring weather input.
ClimGen	[71,72]	ClimGen is a weather generator model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma) to generate synthetic daily weather data. The ClimGen model uses a statistical approach to generate weather variables such as precipitation, temperature, solar radiation, humidity, and wind speed. ClimGen allows for the generation of weather data at specific locations or for larger spatial scales
WeaGETS	[73,74]	WeaGETS is designed to generate synthetic precipitation and temperature data at a daily time step. It can be used for various applications, including hydrological modelling, climate change impact assessment, and water resources management.
AAFC-WG	[75,76]	AAFC-WG is indeed a weather generator developed at Agriculture and Agri-Food Canada (AAFC) and is designed to preserve the Richardson-type structure while incorporating empirical distributions to account for the diverse climates. This approach allows AAFC-WG to capture the relationships between weather variables and generate realistic synthetic weather data.
PRECIS	[77]	PRECIS (Providing REgional Climates for Impacts Studies) is a regional climate modelling system developed by the Met Office Hadley Centre. It is designed to generate high-resolution climate projections for regional and local-scale assessments of climate change impacts. PRECIS uses a regional climate model (RCM) to downscale global climate model (GCM) output, providing more detailed information at a regional level.

Table 3
Summary of hydrological model.

Hydrological models	References	Description
SWAT	[78,79]	SWAT (Soil and Water Assessment Tool) was developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS.). It is a comprehensive river basin-scale model that simulates a watershed's hydrological processes, water quality, and land management practices.
HBV	[80,81]	HBV (Hydrologiska Byråns Vattenbalansavdelning) is a hydrological model developed by the Swedish Meteorological and Hydrological Institute (SMHI). It is a lumped-parameter, conceptual model for simulating a watershed's hydrological processes.
BTOPMC	[82,83]	The BTOPMC hydrological model is an extension of the TOPMODEL (Topographic Model) and Muskingum-Cunge methods for simulating hydrological in large ungauged basins. It incorporates a block-wise approach to simulate the hydro environmental processes in large ungauged basins.
WATBAL	[84,85]	WATBAL, short for Water Balance Model, is a hydrological model used to estimate water balance components in a specific area or watershed. It is designed to assess the water availability and distribution within a hydrological system by accounting for various inputs and outputs.
WaSim-ETH	[86,87]	WaSim-ETH, developed by the Water Resources Management Group at ETH Zurich, is a hydrological simulation model for water resource assessment and management. It is designed to simulate the water balance components of a watershed or river basin using a combination of physically-based and data-driven approaches
TWBM	[88,89]	The TWBM (Two-Parameter Monthly Water Balance Model) aims to provide a simple and computationally efficient approach for estimating water balance in hydrological modelling. It can be used when limited data are available or as a preliminary analysis tool. The model parameters are typically calibrated using observed data to improve its performance and accuracy
MIKESHE	[90,91]	MIKESHE is a hydrodynamic and water quality model developed by the Danish Hydraulic Institute (DHI) for simulating the flow and transport processes in river systems, estuaries, and coastal areas. MIKESHE is based on the finite element method and solves the governing equations of fluid flow, including the continuity equation and the Navier-Stokes equations.
VIC	[92,93]	VIC (Variable Infiltration Capacity) is a hydrological model developed by the University of Washington's Climate Impacts Group. VIC is a physically based model representing the complex interactions between land surface and hydrological processes. It simulates the water and energy balances within a grid cell by considering factors such as precipitation, snow accumulation and melt, soil moisture, vegetation dynamics, and evapotranspiration.
DHSVM	[94]	DHSVM (Distributed Hydrology Soil Vegetation Model) is a physically based hydrological model that simulates the water and energy balance in a spatially distributed manner. The model incorporates modules for simulating vegetation dynamics, snow accumulation and melt, infiltration, surface and subsurface flow, and channel routing.
TOPLATS	[95]	The TOPLATS (TOPOgraphic-LAndscape-Templates) model is a hydrological model designed to simulate catchment water balances and analyze the impact of spatial data resolution on model performance.
PRMS	[96]	PRMS (Precipitation-Runoff Modelling System) is a distributed hydrological model to simulate the hydrological processes and water movement. The model operates on a grid or subbasin scale, dividing the watershed into smaller spatial units and simulating each unit's water balance processes independently.
SLURP	[97]	The SLURP (Semi-distributed Land Use-based Runoff Processes) is a macroscale hydrological model developed for simulating the hydrological processes at large spatial scales. The model incorporates various components such as snow accumulation and melt, soil moisture dynamics, evapotranspiration, and runoff generation.
LASCAM	[98]	The LASCAM (Large Scale Catchment Model) is a physically-based conceptual model that operates at a daily time-step. It is designed to simulate hydrological processes in large catchments, taking into account the physical characteristics and processes that influence water movement and storage. It represents the catchment as a series of interconnected conceptual components, each representing a specific hydrological process.
IHACRES	[99]	IHACRES (Identification of Hydrographs And Component flows from Rainfall, Evaporation, and Streamflow data) is a conceptual rainfall-runoff model used for hydrological analysis and streamflow simulation. The model operates at a daily time-step and uses a set of linear reservoirs to represent the storage and release of water within the catchment.
DREAM	[100]	DREAM (Distributed model for Runoff, Evapotranspiration, and Antecedent soil Moisture simulation) is a hydrological model developed for simulating daily streamflow and other hydrological processes in a watershed. The DREAM model is based on a lumped conceptual approach, where the watershed is represented as a single unit with input and output flows.
DRAINMOD	[101]	DRAINMOD is a computer simulation model developed to simulate poorly drained agricultural lands' hydrology and water management. The model focuses on simulating water flow and solute transport in artificially drained agricultural fields, particularly in areas with subsurface drainage systems.
WaSSI	[102]	WaSSI (Water Supply Stress Index) is a modelling framework developed by the U.S. Geological Survey (USGS) to assess water availability and water stress at regional and national scales. It combines hydrological and climatological data with landscape characteristics to estimate water supply and demand dynamics.
WEP	[103]	WEP (water and energy transfer processes) model is a distributed hydrological model designed to simulate the spatially variable water and energy processes in watersheds with complex land covers. The model incorporates various state variables and processes to represent the hydrological and energy dynamics within the watershed.
C.M.F.	[104]	CMF (Catchment Modelling Framework) is a hydrological programming language extension developed to facilitate the integration of various components and models within an integrated catchment modelling framework. The C.M.F. framework provides a flexible and modular approach for building integrated catchment models, allowing for the representation of multiple hydrological processes and their interactions.
WEAP	[105]	WEAP (Water Evaluation and Planning System) is a software tool used for integrated water resources planning and management. It is designed to assist decision-makers in understanding and evaluating the complex interactions between water supply, demand, and environmental systems.
APEX	[106]	Agricultural Policy/Environmental eXtender (APEX) is a widely used watershed simulation model developed by USDA and Texas A&M University, to simulates the movement of water, sediment, nutrients and pesticides across agricultural landscapes and provides insights into the impacts of various land management practices on water quality, soil erosion, and crop production.

utilize weather, soil, agronomic data, and information on rice management practices, allowing for simulations in the field or larger areas. Crop models can capture crop-soil-atmosphere relationships under different conditions, including treatments, seasons, locations, and scenarios. Since the population issues that require double food demand in 2050, crop models also play a vital role in preventing food shortages through its contributions on simulating food demand-supply gaps, required agricultural land area, and the environmental suitability of agroecology for crop production [107]. Essential data must be incorporated to simulate rice production effectively using crop models. This includes weather variables such as precipitation, temperature, solar radiation, and wind speed; soil characteristics such as texture, initial conditions, and cultivar information; crop management practices such as tillage, irrigation, fertilizer application, pest control, organic amendments, and harvesting; and agronomic traits like physiological characteristics, leaf area index, yield, and grain weight. Collectively, these data enable accurate and comprehensive simulations of rice production dynamics. For a comprehensive overview of crop models suitable for simulating rice growth, yield, and related variables, Table 4 provides a valuable resource.

Previous studies have implemented integration between climate-hydrological-crop models in several countries [25,133–148]. For example, a study from Becker et al. (2023) [133] in Pakistan's Punjab region utilized an agro-hydrological model (SWAT) and

Table 4
Summary of crop models for simulating rice growth and yield.

Crop models	References	Description
DSSAT	[108,109]	The DSSAT (Decision Support System for Agrotechnology Transfer) provides a comprehensive framework for simulating crop growth, yield, and various agroecosystem processes, enabling the user to assess the impact of different management practices, climate scenarios, and environmental factors on crop productivity.
APSIM	[110,111]	APSIM (Agricultural Production Systems sIMulator) is designed to simulate and analyze various aspects of agricultural systems. The modelling capabilities of APSIM are based on a modular approach, allowing users to choose and configure different modules based on their specific research objectives and agricultural systems.
Wofost	[112,113]	WOFOST (World Food Studies), developed by Wageningen University and Research in the Netherlands, is a crop growth simulation model that is used for assessing and analyzing agricultural production and crop yield under different environmental conditions. It is a process-based model that simulates various field crops' growth, development, and yield.
DNDC	[114,115]	DNDC (DeNitrification and DeComposition) is a process-based biogeochemical model focusing on plant growth, carbon assimilation, litter decomposition, soil organic matter dynamics, nitrogen transformations, and denitrification.
WARM	[116,117]	The Water Accounting Rice Model (WARM) is a specialized crop model designed to assess rice production systems' water dynamics and management strategies. WARM integrates hydrological processes, agronomic practices, and environmental factors to simulate rice growth and yield under varying conditions.
MCWLA-Rice	[118,119]	MCWLA-Rice is an extension of the Model to Capture the Crop-Weather Relationship over a Large Area (MCWLA), specifically tailored for rice crops. It utilizes Bayesian probability inversion and a Markov chain Monte Carlo (MCMC) technique to analyze parameter estimation and model prediction uncertainties while optimizing the rice production model.
RiceGrow	[120]	RiceGrow is a comprehensive rice growth and productivity model that integrates relationships between rice growth and development and the environment. The model comprises seven sub-models that simulate different aspects of rice growth and development, including phenology, morphology and organ formation, photosynthesis and biomass production, dry matter partitioning, yield and quality formation, water relation, and nutrient balance.
GeCROS	[121]	GeCROS (Genotype-by-Environment interaction on CROp growth Simulator) is an ecophysiological simulation model developed to study the interactions between genotypes and their environment on crop growth. It provides a comprehensive framework for analyzing the dynamics of crop systems and how they are influenced by genotype-by-environment interactions. The model considers climate, soil properties, and crop management practices to simulate crop growth and development over time.
GEMRICE	[122,123]	The development of GeCROS is based on published studies and field data, providing a robust foundation for modelling crop systems dynamics. It serves as a valuable tool for researchers and practitioners in agriculture and crop science to better understand and predict the responses of crop genotypes to varying environmental conditions. It incorporates a range of physiological processes, including photosynthesis, biomass accumulation, leaf area development, nitrogen uptake and allocation, and grain filling.
AquaCrop	[124,125]	AquaCrop is a crop model developed by the FAO that simulates crop yield response to water availability. AquaCrop operates on the concept of crop water productivity, which is the crop yield ratio to the amount of water consumed by the crop. It considers the crop's growth stages, canopy cover, root development, and transpiration rates to estimate its water requirements and potential yield.
CropSyst	[126,127]	CropSyst is a cropping systems simulation model that simulates various crops' growth, development, and yield in response to environmental factors, management practices, and cropping system interactions. The model is process-based and incorporates a range of biological, physical, and chemical processes that influence crop growth and development.
InfoCrop	[128,129]	InfoCrop is a dynamic simulation model for assessing crop yields, pest losses, and environmental impacts in tropical agroecosystems. It provides a comprehensive framework to simulate various crops' growth, development, and yield under different management and environmental conditions. The model incorporates the interactions between climate, soil, crop physiology, pests, and management practices to simulate crop performance.
SIMRIW	[130]	SIMRIW is a simplified process model specifically designed to simulate the growth and yield of irrigated rice crops in relation to weather conditions. The model achieves this by rationalizing and simplifying the underlying physiological and physical processes involved in the growth of rice crops. By focusing on key growth processes and their interaction with weather variables, SIMRIW provides a practical tool for understanding and predicting the response of rice crops to different weather scenarios.
CARICE	[131]	CARICE is a rice model specifically developed for scheduling and evaluating management actions in rice production systems under a continuously flooded, direct water-seeded culture. By incorporating information on planting dates, irrigation scheduling, fertilizer application, and other management practices, CARICE allows users to assess the potential impacts of different management scenarios on crop performance and resource utilization
Shierary Rice	[132]	Shierary Rice model is a rice model simulation that can describe the relation of climate, hydrology, soil, and management with rice growth and development processes as well as estimates the harvest
EPIC	[106]	The EPIC (Environmental Policy Integrated Climate) model, developed by USDA, is cropping systems model that is developed to simulates crop growth, soil dynamics, water management, nutrient cycling, and climate interactions. It helps assess the impacts of management practices, climate variability, and climate change on crop productivity and environmental outcomes.

biophysical crop models (APSIM) to predict future crop production, including rice, cotton, and maize, under future climate change scenarios (RCP 4.5 and RCP 8.5). Their study revealed that increased heat stress due to climate change is likely to significantly impact crop yields in Pakistan's Punjab region, despite intensified irrigation efforts. Another study by Ruane et al. (2013) [140] using a combination of MIKE BASIN hydrologic and biophysical Crop (CERES) model under future climate change scenarios mentioned that climate change is expected to reduce production in Bangladesh for all three rice seasons by 2050s, with boro rice is expected to be most severely impacted, even when irrigation is unconstrained for existing boro areas. In addition, a study by Wei et al. (2009) [134], simulated future cereal production using CERES and VIC models in China under climate change scenarios derived from PRECIS. Their result showed that by the 2040s, the absolute effects of climate change were relatively modest and highly dependent on climate scenarios, socio-economic development pathways, and the effects of CO_2, as well as fertilization on crop yields which may almost totally offset the decreases in production. Additionally, a study from Geethalakshmi et al. (2016) in the Cauvery River Basin India, used a multimodelling approach, comprising hydrological (SWAT) and crop (DSSAT and APSIM) models to assess the impact of climate change on water availability and rice production [149]. Their approach predicted a decline in rice yield in the Cauvery Delta region due to temperature increments caused by climate changes. Result show a projected decrease of 6.7% in the mid-century and 25.3% in the end-century.

According to previous studies, the multimodelling approach offers numerous benefits in studying the impacts of climate change on agricultural systems, as illustrated in Fig. 1 [133,134,136,139,149]. Firstly, this approach provides a comprehensive understanding of the complex interactions between climate variables, hydrological processes, and crop growth. Climate models simulate changes in temperature, precipitation, solar radiation, and other climate variables, while hydrological models capture the effects of these changes on water availability, runoff, and groundwater recharge. Crop models then simulate the response of crops to these hydrological and climate conditions, including growth, yield, water use, and nutrient uptake. Through the combination these models, researchers can simulate and analyze how changes in climate variables propagate through the hydrological system and ultimately affect crop production. Secondly, this integrated approach allows for assessing potential risks and vulnerabilities in agricultural systems. Considering the combined impacts of climate and hydrological factors on crops, researchers can identify regions or specific crops that may be particularly susceptible to climate change. For example, the models can help identify areas with reduced water availability or increased risk of drought, which can significantly impact crop productivity. This information can then inform targeted adaptation strategies based on regional analysis, such as selecting drought-flood-salt-tolerant crop varieties, implementing efficient irrigation systems, soil and water conservation practices, improved water management infrastructure, coastal zone management plant, and developed early warning systems to enhance resilience and mitigate potential losses in agricultural productivity (see Fig. 2).

Additionally, integrating these models facilitates the exploration of different future scenarios. Researchers can simulate and compare various climate change scenarios and their potential implications for agriculture by incorporating climate model projections into hydrological and crop models,. This allows for assessing different potential adaptation and mitigation strategies and can aid in decision-making processes for policymakers and stakeholders. Several consideration factors such as climate change mitigation strategies, land suitability, and agricultural productivity, policymakers can make informed decisions and develop favorable policies to enhance rice production in a sustainable manner. For example, policy makers can evaluate the effectiveness of different land

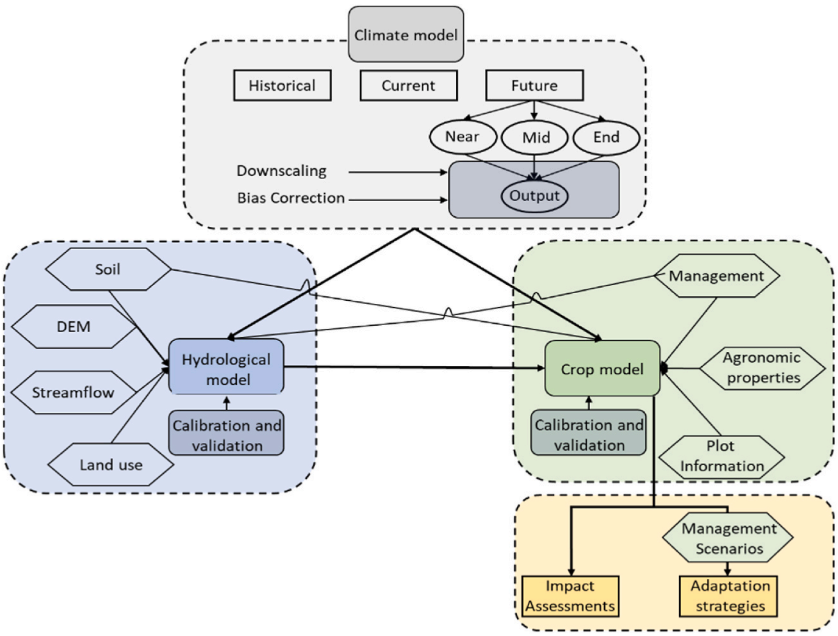

Fig. 1. Multimodelling approach for evaluating and adapting impact of climate change on rice production. Adopted from Geethalakshmi et al. (2016) [149].

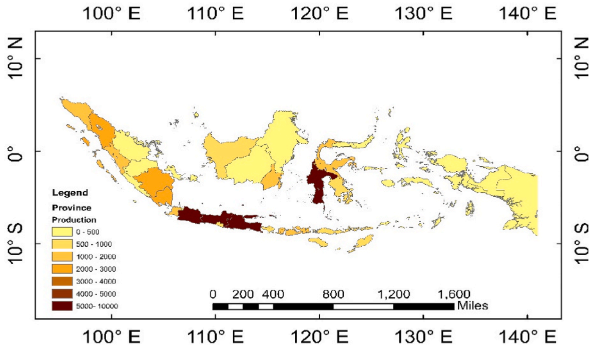

Fig. 2. Rice production in 2021 (M T./ha). Data derived from bps.go.id [150].

management practices or irrigation strategies in mitigating the adverse impacts of climate change on crop production. Moreover, the joint application provides a valuable tool for forecasting and planning in the agricultural sector by providing site-specific information on crop growth and yield predictions. Through utilizing historical climate data, coupled with hydrological and crop models, it becomes possible to develop predictive models that can assist in optimizing resource allocation, minimizing wastage, and improving overall productivity while reducing environmental impacts. For instance, farmers can use these models to make informed decisions regarding water management, crop planting schedules, and fertilizer application, considering expected climate conditions. These models can also support early warning systems for extreme weather events such as floods or heatwaves, helping farmers and policy makers to take timely actions to minimize crop losses and ensure food security.

4. Challenges and opportunities of modelling approaches in Indonesia

The agricultural sector plays a vital role in achieving the United Nations' Sustainable Development Goals (SDGs), particularly in ending global hunger and malnutrition, ensuring food security by 2030 (SDGs. 2), and adapting to climate change (SDGs 13) [151, 152]. Climate change has become a prioritized challenge for national development in Indonesia since 1990, as the country is expected to experience severe impacts in the coming decades, posing a threat to national food security. Notably, Fig. 1 provides a comprehensive visualization of the distribution of rice production across various provinces in Indonesia, shedding light on the spatial patterns and highlighting the key regions involved in rice cultivation. Among these regions, West Java, Central Java, East Java, and South Sulawesi emerge as prominent areas for rice production, signifying their significant contributions to the country's overall output. Java, with its favorable climatic conditions, fertile soils, and well-established agricultural infrastructure, has long been considered the heartland of rice cultivation in Indonesia. The provinces of West Java, Central Java, and East Java, in particular, have been traditionally recognized as major rice-producing regions owing to their vast rice fields and high agricultural productivity. These provinces benefit from favorable rainfall patterns, suitable temperatures, and a long-standing agricultural tradition, collectively supporting robust rice production. Additionally, South Sulawesi emerges as another key player in rice cultivation, reflecting its significant contribution to Indonesia's overall rice output. Located in the eastern part of the country, South Sulawesi boasts favorable agro-climatic conditions, including abundant rainfall and fertile soils, which make it conducive to rice cultivation. Nevertheless, climate change seems to hinder efforts to achieve rice self-sufficiency and meet the SDGs in Indonesia, which needs appropriate adaptation strategies to mitigate climate change's effect on rice production.

Nevertheless, climate change has several effects on agricultural systems, including drought, salinity, submergence (flooding), sea level rise, and higher temperatures [153,154]. Droughts are becoming more frequent and severe, leading to reduce water availability and decrease crop yields. Rising sea levels and changes in precipitation patterns contribute to increase soil salinity, affecting crop growth and freshwater availability. Intense and prolonged rainfall events result in flooding, damaging crops and hindering their growth. Sea level rise exacerbates coastal erosion, storm surges, and saltwater intrusion into agricultural lands. Higher temperatures pose heat stress on crops and alter pest and disease dynamics, further impacting rice production. Moreover, elevated nighttime temperature can have significant effects on plant physiology, including altered metabolic processes, increased respiration rates, and reduced growth and yield [129]. These impacts can be particularly relevant in the context of rice production, as rice crops are known to be sensitive to temperature variations, especially during critical growth stages. In addition, elevated nighttime temperature can disrupt the delicate balance between daytime and nighttime temperatures, leading to imbalances in plant development and nutrient uptake. This can further exacerbate the potential negative impacts on rice growth and productivity.

By employing a multimodelling approach, researchers can effectively identify the specific regions with the potential for increasing rice production, particularly outside of Java island. However, there need to be more research or publications that comprehensively integrate the climate-hydrological-crop model to assess the impact of climate change on rice production in Indonesia. Most studies have focused on either a single or a combination of two models. For instance, Naylor et al. (2007) employed a climate model to assess climate risks and variability for rice agriculture in Indonesia, focusing solely on the central rice production region without incorporating hydrological and crop models for future rice predictions. Yuliawan and Handoko (2016) [132] utilized the Shierary Rice model to evaluate the impact of temperature rise on rice crop yield in Indonesia, revealing a reduction in yield of up to 11.1% and 14.4% in rainfed and irrigated areas, respectively, for a 1 °C temperature increase. Achyadi et al. (2019) [155] analyzed water requirements for irrigation units in Barito Kuala, South Kalimantan, under climate change scenarios, concerning local rice cultivation. The study revealed that the impact of climate change on water irrigation requirements for local paddy cultivation during the 2050s and 2090s would be 56% and 25% higher than current conditions in July and September–October, respectively. Lastly, Kinose et al. (2020) [156] utilized a combination of climate and process-based crop models to assess the impact of climate change on the major rice cultivar Ciherang in Indonesia. The results demonstrated reduced production under all climate scenarios due to significantly increased temperatures affecting photosynthesis, respiration, and phenological processes. To address these challenges and achieve the SDGs in Indonesia, adopting climate-hydrological-crop models by researchers, policymakers, and decision-makers is crucial. Such modelling approaches offer a cost-effective, time-efficient, and labor-saving means to mitigate the potential decreases in rice production caused by climate change. Nonetheless, the utilization of climate-hydrological-crop models in Indonesia comes with challenges and opportunities, which we will discuss in the following section.

4.1. *Climate models*

Climate models offer numerous benefits for agriculture, including their ability to determine crop calendars, predict water availability for irrigation, anticipate pests, diseases, and viruses, and support the development of heat-resistant crop varieties [21]. Various climate modelling using GCMs provide a reasonable basis for estimating future climate projections [31,141,144,145]. However, it is important to note that the output generated by GCMs cannot be directly applied to regional studies. The reliability of results obtained from climate models is influenced by several factors, including the chosen scenarios, models, time periods, and number of predicted generations [139]. This limitation arises from the inherent challenges in adequately representing and simulating local-scale processes and the coarse spatial resolution of GCMs, resulting in high uncertainties results. Various techniques have been developed to address and reduce uncertainties in climate modelling, including ensemble models, calibration and validation, downscaling techniques, bias correction, uncertainty quantification, and data assimilation [32,141,144,157,158]. These techniques are often required to bridge the gap between the large-scale output of GCMs and the local-scale processes and conditions that are crucial for accurate assessments and decision-making to better represent the specific characteristics of a region or location [32,157]. For example, multimodel ensembles (MMEs)—a combination of multiple climate models to generate a range of possible outcomes by involving multiple instances of models with slight variations in input parameters, initial conditions, or model configurations—enables a more objective quantification of uncertainty, leading to improved predictions, compared to single model simulations [45,119]. MMEs involve conducting simulation experiments using multiple climate models and utilizing the variance of the results as an estimate of uncertainty. Combining the outputs of different models, MMEs provide a more comprehensive and robust perspective when simulating future climate change, reducing reliance on individual model simulations [159]. In addition. downscaling methods, such as statistical downscaling, dynamical downscaling, or hybrid approaches, can help refine the GCMs output to represent better the specific characteristics of a region or location [32,157].

In developing countries like Indonesia, one of the challenges in studying climate change impacts is the limited availability of reliable and comprehensive long-term weather data [160,161]. The distribution of meteorological stations is often sparse, making it difficult to capture accurate and representative data across the nationwide. This scarcity of weather data poses significant challenges for climate modelling, impact assessments, and the development of effective adaptation strategies [159]. The scarcity of long-term weather data hampers the generation of reliable future climate projections at regional and local scales, especially in remote areas with limited data availability. The lack of historical and climate projections for specific areas poses challenges in developing location-specific adaptation strategies and conducting accurate calibration and validation processes [162]. This limitation hinders efforts to enhance resilience and effectively manage climate risks in those areas since, without comprehensive data and projections, decision-makers may struggle to make informed choices and implement targeted measures to address the unique climate challenges faced by these regions. Moreover, climate data collection is fragmented, with different agencies gathering data for specific purposes [162]. This fragmented approach limits the accessibility and integration of climate data from various sources, hindering comprehensive analysis and the ability to make informed decisions. Consequently, there is a need for enhanced coordination and collaboration among agencies to improve the availability and accessibility of climate data for researchers, policy makers and stakeholders. To facilitate precise decision-making processes related to climate evaluation, adaptation, and mitigation, enhancing the reliability of climate data through various measures, such as increasing the number of meteorological stations, upgrading climate instruments, enhancing the frequency of data collection, and standardizing data formats may increase the accuracy of climate predictions [158,159,162].

4.2. *Hydrological models*

Hydrological models are essential for comprehending the complex hydrological processes within a watershed, encompassing various physical, chemical, biological, and human activities associated with agriculture, industry, and residential sectors [163]. However, the effective utilization of hydrological models is hindered by several challenges, including data availability, modelling techniques, parameter selection, and calibration and validation issues [164]. The accuracy and reliability of hydrological models heavily rely on the quality of input data, particularly rainfall data, which significantly impacts other processes such as infiltration, runoff, groundwater flow, and streamflow [165]. Unfortunately, there are often challenges associated with rainfall data, such as incomplete and inconsistent data provided, incompatible data collection methods, variations in rain gauge types, improper gauge placement, or malfunctioning instruments [159]. Similarly, long-term and comprehensive streamflow data are often limited, despite their significance in representing the overall outcomes of watershed processes. This data scarcity poses significant obstacles to accurate hydrological modelling and water resource management. Nevertheless, in some cases, valuable data and information can be acquired through rigorous data validation and expansion, which proves beneficial for future water resource planning endeavours [166].

The selection of hydrological models can be driven by specific needs or available resources [164]. When selecting a model, consideration should be given to its functionality and complexity, as these are key criteria. A simple hydrological model may be suitable for addressing specific needs in cases where data limitations exist. On the other hand, resource-driven selections may involve complex models that incorporate multiple factors influencing hydrological processes. It is important to emphasize that all models should undergo calibration against observed data by adjusting the parameters to minimize the overall discrepancy [164,167]. This calibration process ensures that the model accurately represents real-world conditions and Improves its capabilities for future simulations and predictions. However, challenges may arise in applying hydrological models due to limited resources for supporting hydrological research, insufficient expertise in hydrological modelling, and a lack of understanding regarding the underlying driving forces in hydrologic modelling. Enhancing data quality, improving result accuracy, and using satellite imagery can be utilized to gather essential data such as rainfall and streamflow data [168,169]. Satellite imagery provides high quality, accuracy, and precision of spatiotemporal data, enhancing the overall data quality for hydrological modelling. Additionally, the Internet of Things (IoT) can be utilized for real-time streamflow data through online systems, minimizing human error and providing reliable streamflow data for simulation and the calibration of hydrological processes [170]. These technological advancements offer opportunities to enhance data collection, improve modelling accuracy, and advance the understanding of hydrological processes, leading to more effective water resource management and planning.

4.3. Crop models

Crop models are crucial in understanding the complex interplay between crops, soil, water, and the atmosphere, providing valuable insights for research, crop management, policy formulation, and adaptation strategies [135,139,158]. The global significance of crop models is evident in their application for assessments, evaluations, mitigation strategies, and the identification of favorable policies to address climate change [21,110,161]. Decision-making processes have benefited from utilizing crop models, enabling the quantification of gaps between food demand and crop yields, risk assessments, and predictions of future land requirements for food production [171]. For example, a study by Arunrat et al. (2021) have utilized EPIC model to estimated rice production and carbon footprint under CMIP6 climate projections using four future climate scenarios (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) [172]. The result showed increasing rice production and soil organic carbon (SOC) for all scenarios, except RCP8.5. Moreover, a study by Arunrat et al. (2022), have assessed the effect of climate change on major crop yield and water footprint using two different pathways namely Shared socioeconomic pathways (SSP245 and SSP585) in Thailand. Their results were consistent with previous study which showed increasing temperature and precipitation would be increased in the study area, affecting on increasing rice production on SPP245, but decrease on SSP585. However, it's worth to note that water footprint will also change due to an increase in crop yield and vice-versa.

Despite the benefit of using crop models in term of evaluating the effect of climate change, the application of this model is challenges. Incomplete and unavailable long-term input data, such as weather information, soil data, crop management practices, and agronomic properties domains, can impede crop models' accurate simulation and prediction capabilities [159,161,166,173]. For instance, a lack of historical and reliable weather data can hinder the precise estimation of crop growth and development, as weather variables play a critical role in determining crop response to environmental conditions [159]. Similarly, limited access to detailed soil data, including soil properties and fertility, can affect the accuracy of crop models' predictions, as soil conditions directly impact crop growth, nutrient availability, and water-holding capacity [166]. Moreover, incomplete information about agricultural management practice data, including planting dates, fertilizer usage, tillage practices, irrigation amounts, organic amendments, and harvesting schedules, are often not adequately recorded, which can introduce uncertainties into the model simulation, as these factors significantly influence crop performance and yield [161]. Additionally, the lack of experimental information on crop species, inadequate testing, inaccuracies in testing, and uncertainties in sampling certain factors further contribute to the challenges associated with crop models. Different crops have distinct physiological and growth characteristics, and using generic models may not capture the specific responses of individual crops to varying environmental factors. Therefore, it is essential to consider crop-specific models that have been validated and calibrated using local experimental data [143]. The lack of available data often leads users to opt for simpler models that require less comprehensive information to address specific phenomena [174].

Before conducting climate change impact assessments on rice production using a crop model that incorporates hydrological processes, it is crucial to calibrate the model using observed data. The calibration process involves adjusting the model parameters to minimize the discrepancies between simulated and observed data, thereby enhancing the accuracy and reliability of the model's prediction for rice production under different scenarios [161]. Proper calibration of the model is crucial for generating reliable results and providing insights for agricultural planning, policy-making, and adaptation strategies in changing climate conditions. Nevertheless, it is important to acknowledge that different crop models can exhibit varying degrees of uncertainty and potential errors in their parameters and variables. The sensitivity of crop models to environmental factors, such as temperature, rainfall, and pH can also impact other parameters used for yield simulations, leading to potential inaccuracies in the results, potentially leading to misperception of the result [117]. This is attributed to mechanistic or empirical interaction among model parameters [161,175]. Sensitivity analysis and validation against observed data can help identify the source of uncertainties and improve the reliability of the model's predictions [117,176]. Sensitivity analysis involves systematically varying input parameters to evaluate their impact on the model outputs, while validation against observed data involves comparing the model's output with actual field measurements or experimental data. These sensitivity analysis and validation processes help identify potential sources of uncertainties in the model, such as parameter values, model assumptions, or quality of input data. Additionally, users need to be familiar with the characteristics of each crop model they employ, including model responses, limitations, data requirements, and factors that the model does not account for [174]. Such knowledge is crucial for informed decision-making and proper interpretation of model outputs.

5. Conclusions

Climate-hydrological-crop models are crucial in understanding and predicting the complex interactions between climate variables, hydrological processes, and crop growth. These models are essential for assessing the impacts of climate change on rice production, particularly ion counties like Indonesia that face significant challenges due to their vulnerability to climate change. The multi-modelling approach provides a comprehensive framework for analyzing and evaluating rice production under different climate change scenarios. The use of this approach can give better understand the potential effects of climate change on various aspects of agriculture, including crop growth, water availability, soil fertility, and crop yield. However, the application of this approach is challenging in developing country. The limited availability of reliable and comprehensive long-term weather and streamflow data poses obstacles in accurately capturing the local-scale processes and critical conditions for robust modelling. More efforts are needed to improve data availability, collection method, and data quality to address these challenges and enhance the reliability of climate-hydrological-crop models. Moreover, continuous model updates and improvements based on thorough testing and quantifying errors and uncertainties are necessary. Integration of satellite imagery and IoT technologies can provide valuable spatiotemporal data, while calibration and validation can help identify and reduce uncertainties. It also depends on the willingness of model users to adapt to modularity and model standardization. Effective communication and collaboration among different user groups are essential for mitigating the effects of climate change on rice production in Indonesia. Overall, the development and utilization of climate-hydrological-crop models, along with advancements in data collection, calibration, and validation techniques, are essential for accurately assessing the impact of climate change on rice production and informing appropriate adaptation strategies.

Author contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

Data availability statement

Data included in article/supplementary material/referenced in article.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Department of Economic and Social Affairs, P.D. World Population Prospects 2022; vol. 2022; ISBN 978-92-1 -148373-4.
[2] World Bank Indonesia Economic Prospects: Trade for Growth and Economic Transformation, 2022, pp. 1–61.
[3] H.E. Hara, R.A.S. Uwignyo, J.S. Akagami, Swamp rice cultivation in South sumatra, Indonesia, Trop. Agric. Dev. 59 (2015) 35–39, https://doi.org/10.11248/jsta.59.35.
[4] A. Booth, Indonesian agricultural development in comparative perspective, World Dev. 17 (1989) 1235–1254, https://doi.org/10.1016/0305-750X(89)90235-0.
[5] J.S. Davidson, Then and Now: campaigns to achieve rice self-sufficiency in Indonesia, Bijdr. tot Taal-, Land- en Volkenkd 174 (2018) 188–215, https://doi.org/10.1163/22134379-17402001.
[6] J.H. McGlynn, H. Sulistyo, Indonesia in the Soeharto Years: Issues, Incidents, and Images, NUS Press, 2007. ISBN 9971693585.
[7] G. Hansen, Rural administration and agricultural development in Indonesia, Pac. Aff. 44 (1971) 390–400.
[8] L. Peter Rosner, N. McCulloch, A note on rice production, consumption and import data in Indonesia, Bull. Indones. Econ. Stud. 44 (2008) 81–92.
[9] Ministry of Agriculture of Republic Indonesia *Rice Production In Indonesia 2018*, Indonesia, Jakarta, Indonesia, 2019.
[10] Indonesia, Statistics Indonesia; Indonesia, S.; Statistics Indonesia *Statistics Of 70th Indonesia Independence*, Badan Pusat Statistik, Jakarta, Indonesia, 2015. ISBN 9789790648586.
[11] S. Mohanty, Trends in global rice consumption, Rice Today 12 (2013) 44–45.
[12] A. Widyanti, I. Sunaryo, A.D. Kumalasari, Reducing the dependency on rice as staple food in Indonesia–a behavior intervention approach, J. ISSAAS 20 (2014) 93–103.
[13] Asian Development Bank *Policies To Support Investment Requirements Of Indonesia's Food And Agriculture Development during 2020-2045*, 2019. ISBN 9789292617479.
[14] Organization for Economic Cooperation and Development *Managing Food Insecurity Risk*: Analytical Framwork and Application to indonesia, 2015. ISBN 9789264233867.
[15] Z. Zulfitriyana, I.W. Syarfi, H. Hasnah, The application of UPSUS PAJALE program technology on rice, Eur. J. Agric. Food Sci. (2020) 2.
[16] B. Irawan, S. Friyanto, Dampak konversi lahan sawah di jawa terhadap produksi beras dan kebijakan pengendaliannya, SOCA Socioecon. Agric. Agribus. 2 (2002) 1–33.

[17] H. Förster, T. Sterzel, C.A. Pape, M. Moneo-Lain, I. Niemeyer, R. Boer, J.P. Kropp, Sea-level rise in Indonesia: on adaptation priorities in the agricultural sector, Reg. Environ. Chang. 11 (2011) 893–904, https://doi.org/10.1007/s10113-011-0226-9.
[18] B.P.P. Nasional, A. Strategy, Indonesia adaptation strategy: improving capacity to adapt, Bappenas. Jakarta. hlm 7 (2011) 39.
[19] Y.-P. Lin, A. Ansari, T. Ngoc-Dan Cao, Y.-J. Shiau, H.-S. Lur, A. Muzaffar, R.F. Wunderlich, H. Mukhtar, Using inhibitors to trade greenhouse gas emission for ammonia losses in paddy soil: a zero-sum game, Environ. Technol. Innov. 28 (2022), 102547, https://doi.org/10.1016/j.eti.2022.102547.
[20] H. Mukhtar, R.F. Wunderlich, A. Muzaffar, A. Ansari, O.V. Shipin, T.N.-D. Cao, Y.-P. Lin, Soil microbiome feedback to climate change and options for mitigation, Sci. Total Environ. (2023), 163412, https://doi.org/10.1016/j.scitotenv.2023.163412, 882.
[21] A. Ansari, Y.-P. Lin, H.-S. Lur, Evaluating and adapting climate change impacts on rice production in Indonesia: a case study of the keduang subwatershed, central Java, Environments 8 (2021) 117.
[22] Ansari, A.; Pranesti, A.; Telaumbanua, M.; Ngadisih, N.; Hardiansyah, M.Y.; Alam, T.; Supriyanta, S.; Martini, T.; Taryono, T. Optimizing water-energy-food nexus: achieving economic prosperity and environmental sustainability in agriculture. Front. Sustain. Food Syst. 7, 1207197, doi:DOI: 10.3389/fsufs.2023.1207197.
[23] Ministry of Foreign Affairs of the Netherlands Climate Change Profile: Indonesia. Minist. Foreign Aff. Netherlands 2018, vol. 14.
[24] R.L. Naylor, D.S. Battisti, D.J. Vimont, W.P. Falcon, M.B. Burke, Assessing risks of climate variability and climate change for Indonesian rice agriculture, Proc. Natl. Acad. Sci. U. S. A. 104 (2007) 7752–7757, https://doi.org/10.1073/pnas.0701825104.
[25] D. Gupta, N. Gujre, S. Singha, S. Mitra, Role of existing and emerging technologies in advancing climate-smart agriculture through modeling: a review, Ecol. Inform. 71 (2022), 101805, https://doi.org/10.1016/j.ecoinf.2022.101805.
[26] A.-W. Harzing, The Publish or Perish Book, Tarma Software Research Pty Limited Melbourne, 2010. ISBN 0980848512.
[27] D. Moher, L. Shamseer, M. Clarke, D. Ghersi, A. Liberati, M. Petticrew, P. Shekelle, L.A. Stewart, Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement, Syst. Rev. 4 (2015) 1–9.
[28] M. Subirana, I. Solá, J.M. Garcia, I. Gich, G. Urrútia, A nursing qualitative systematic review required MEDLINE and CINAHL for study identification, J. Clin. Epidemiol. 58 (2005) 20–25.
[29] P.S.L. Kothari, M. Ali, Soft Computing : Theories and Applications, 2016. ISBN 9198291424.
[30] T. Alam, P. Suryanto, N. Susyanto, B. Kurniasih, P. Basunanda, A. Ansari, Performance of 45 Non-linear Models for Determining Critical Period of Weed Control and Acceptable Yield Loss in Soybean Agroforestry Systems, 2022.
[31] D. Hillel, C. Rosenzweig, Desertification in relation to climate variability and change, Adv. Agron. 77 (2002) 1–38.
[32] F. Giorgi, Thirty years of regional climate modeling: where are we and where are we going next? J. Geophys. Res. Atmos. 124 (2019) 5696–5723, https://doi.org/10.1029/2018JD030094.
[33] S.L. Grotch, M.C. MacCracken, The use of general circulation models to predict regional climatic change, J. Clim. 4 (1991) 286–303.
[34] T. Wu, A mass-flux cumulus parameterization scheme for large-scale models: description and test with observations, Clim. Dyn. 38 (2012) 725–744.
[35] T. Wu, Y. Lu, Y. Fang, X. Xin, L. Li, W. Li, W. Jie, J. Zhang, Y. Liu, L. Zhang, The Beijing Climate Center climate system model (BCC-CSM): the main progress from CMIP5 to CMIP6, Geosci. Model Dev. (GMD) 12 (2019) 1573–1600.
[36] H.B. Gordon, L.D. Rotstayn, M. J.L, D. M.R, S. Kowalczyk, O. P, W. L.J, H. A.C, W. S.G, C. M.A, et al., The CSIRO Mk3 climate system model, Asoendale CSIRO Atmos. Res. Tech. Pap. 130 (2002).
[37] S. Jeffrey, L. Rotstayn, M. Collier, S. Dravitzki, C. Hamalainen, C. Moeseneder, K. Wong, J. Syktus, Australia's CMIP5 submission using the CSIRO-Mk3. 6 model, Aust. Meteor. Ocean. J 63 (2013) 1–14.
[38] Y. Bao, Z. Song, F. Qiao, FIO-ESM version 2.0: model description and evaluation, J. Geophys. Res. Ocean. 125 (2020) 1–21, https://doi.org/10.1029/2019JC016036.
[39] X. Chunmei, C. Liping, C. Song, C. Guang, W. Danying, Z. Xiufu, Rhizosphere aeration improves nitrogen transformation in soil, and nitrogen absorption and accumulation in rice plants, Rice Sci. 27 (2020) 162–174, https://doi.org/10.1016/j.rsci.2020.01.007.
[40] S.M. Griffies, M. Winton, L.J. Donner, L.W. Horowitz, S.M. Downes, R. Farneti, A. Gnanadesikan, W.J. Hurlin, H.-C.C. Lee, Z. Liang, et al., The GFDL CM3 coupled climate model: characteristics of the ocean and sea ice simulations, J. Clim. 24 (2011) 3520–3544, https://doi.org/10.1175/2011JCLI3964.1.
[41] J.P. Dunne, J.G. John, S. Shevliakova, R.J. Stouffer, J.P. Krasting, S.L. Malyshev, P.C.D. Milly, L.T. Sentman, A.J. Adcroft, W. Cooke, et al., GFDL's ESM2 global coupled climate-carbon earth system models. Part II: carbon system formulation and baseline simulation characteristics, J. Clim. 26 (2013) 2247–2267, https://doi.org/10.1175/JCLI-D-12-00150.1.
[42] J.P. Dunne, J.G. John, A.J. Adcroft, S.M. Griffies, R.W. Hallberg, E. Shevliakova, R.J. Stouffer, W. Cooke, K.A. Dunne, M.J. Harrison, et al., GFDL's ESM2 global coupled climate-carbon earth system models. Part I: physical formulation and baseline simulation characteristics, J. Clim. 25 (2012) 6646–6665, https://doi.org/10.1175/JCLI-D-11-00560.1.
[43] D.T. Shindell, O. Pechony, A. Voulgarakis, G. Faluvegi, L. Nazarenko, J.-F. Lamarque, K. Bowman, G. Milly, B. Kovari, R. Ruedy, Interactive ozone and methane chemistry in GISS-E2 historical and future climate simulations, Atmos. Chem. Phys. 13 (2013) 2653–2689.
[44] M. Kelley, G.A. Schmidt, L.S. Nazarenko, S.E. Bauer, R. Ruedy, G.L. Russell, A.S. Ackerman, I. Aleinov, M. Bauer, R. Bleck, et al., GISS-E2.1: configurations and climatology, J. Adv. Model. Earth Syst. 12 (2020), https://doi.org/10.1029/2019MS002025.
[45] C.D. Jones, J.K. Hughes, N. Bellouin, S.C. Hardiman, G.S. Jones, J. Knight, S. Liddicoat, F.M. O'Connor, R.J. Andres, C. Bell, et al., The HadGEM2-ES implementation of CMIP5 centennial simulations, Geosci. Model Dev. (GMD) 4 (2011) 543–570, https://doi.org/10.5194/gmd-4-543-2011.
[46] G.M. Martin, N. Bellouin, W.J. Collins, I.D. Culverwell, P.R. Halloran, S.C. Hardiman, T.J. Hinton, C.D. Jones, R.E. McDonald, A.J. McLaren, et al., The HadGEM2 family of met office unified model climate configurations, Geosci. Model Dev. (GMD) 4 (2011) 723–757, https://doi.org/10.5194/gmd-4-723-2011.
[47] J.P. Mulcahy, C. Jones, A. Sellar, B. Johnson, I.A. Boutle, A. Jones, T. Andrews, S.T. Rumbold, J. Mollard, N. Bellouin, Improved aerosol processes and effective radiative forcing in HadGEM3 and UKESM1, J. Adv. Model. Earth Syst. 10 (2018) 2786–2805.
[48] J.P. Mulcahy, C. Johnson, C.G. Jones, A.C. Povey, C.E. Scott, A. Sellar, S.T. Turnock, M.T. Woodhouse, N.L. Abraham, M.B. Andrews, Description and evaluation of aerosol in UKESM1 and HadGEM3-GC3. 1 CMIP6 historical simulations, Geosci. Model Dev. (GMD) 13 (2020) 6383–6423.
[49] J.-L.L. Dufresne, M.-A.A. Foujols, S. Denvil, A. Caubel, O. Marti, O. Aumont, Y. Balkanski, S. Bekki, H. Bellenger, R. Benshila, et al., Climate change projections using the IPSL-CM5 earth system model: from CMIP3 to CMIP5, Clim. Dyn. 40 (2013) 2123–2165, https://doi.org/10.1007/s00382-012-1636-1.
[50] O. Boucher, J. Servonnat, A.L. Albright, O. Aumont, Y. Balkanski, V. Bastrikov, S. Bekki, R. Bonnet, S. Bony, L. Bopp, et al., Presentation and evaluation of the IPSL-CM6A-LR climate model, J. Adv. Model. Earth Syst. 12 (2020) 1–52, https://doi.org/10.1029/2019MS002010.
[51] S. Watanabe, T. Hajima, K. Sudo, T. Nagashima, T. Takemura, H. Okajima, T. Nozawa, H. Kawase, M. Abe, T. Yokohata, et al., MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments, Geosci. Model Dev. (GMD) 4 (2011) 845–872, https://doi.org/10.5194/gmd-4-845-2011.
[52] T. Hajima, M. Watanabe, A. Yamamoto, H. Tatebe, M.A. Noguchi, M. Abe, R. Ohgaito, A. Ito, D. Yamazaki, H. Okajima, Development of the MIROC-ES2L Earth system model and the evaluation of biogeochemical processes and feedbacks, Geosci. Model Dev. (GMD) 13 (2020) 2197–2244.
[53] S. Yukimoto, H. Yoshimura, M. Hosaka, T. Sakami, H. Tsujino, M. Hirabara, T.Y. Tanaka, M. Deushi, A. Obata, H. Nakano, Meteorological research institute-earth system model version 1 (MRI-ESM1)-Model description, Meteorol. Res. Inst. Tech. Rep. 92 (2011).
[54] Y. Adachi, S. Yukimoto, M. Deushi, A. Obata, H. Nakano, T.Y. Tanaka, M. Hosaka, T. Sakami, H. Yoshimura, M. Hirabara, Basic performance of a new earth system model of the Meteorological Research Institute (MRI-ESM1), Pap. Meteorol. Geophys. 64 (2013) 1–19.
[55] M. Bentsen, I. Bethke, J.B. Debernard, T. Iversen, A. Kirkevåg, Ø. Seland, H. Drange, C. Roelandt, I.A. Seierstad, C. Hoose, The Norwegian Earth System Model, NorESM1-M–Part 1: description and basic evaluation of the physical climate, Geosci. Model Dev. (GMD) 6 (2013) 687–720.
[56] T. Iversen, M. Bentsen, I. Bethke, J.B. Debernard, A. Kirkevåg, Ø. Seland, H. Drange, J.E. Kristjansson, I. Medhaug, M. Sand, The Norwegian earth system model, NorESM1-M–Part 2: climate response and scenario projections, Geosci. Model Dev. (GMD) 6 (2013) 389–415.
[57] W. Hazeleger, C. Severijns, T. Semmler, S. Ştefănescu, S. Yang, X. Wang, K. Wyser, E. Dutra, J.M. Baldasano, R. EC-Earth Bintanja, A seamless earth-system prediction approach in action, Bull. Am. Meteorol. Soc. 91 (2010) 1357–1364.

[58] W. Hazeleger, X. Wang, C. Severijns, S. Ştefănescu, R. Bintanja, A. Sterl, K. Wyser, T. Semmler, S. Yang, B. Van den Hurk, EC-Earth V2. 2: description and validation of a new seamless earth system prediction model, Clim. Dyn. 39 (2012) 2611–2629.
[59] R. Séférian, P. Nabat, M. Michou, D. Saint-Martin, A. Voldoire, J. Colin, B. Decharme, C. Delire, S. Berthet, M. Chevallier, Evaluation of CNRM earth system model, CNRM-ESM2-1: role of earth system processes in present-day and future climate, J. Adv. Model. Earth Syst. 11 (2019) 4182–4227.
[60] A. Voldoire, D. Saint-Martin, S. Sénési, B. Decharme, A. Alias, M. Chevallier, J. Colin, J. Guérémy, M. Michou, M. Moine, Evaluation of CMIP6 deck experiments with CNRM-CM6-1, J. Adv. Model. Earth Syst. 11 (2019) 2177–2213.
[61] C.H. Reick, T. Raddatz, V. Brovkin, V. Gayler, Representation of natural and anthropogenic land cover change in MPI-ESM, J. Adv. Model. Earth Syst. 5 (2013) 459–482, https://doi.org/10.1002/jame.20022.
[62] V. Brovkin, L. Boysen, T. Raddatz, V. Gayler, A. Loew, M. Claussen, Evaluation of vegetation cover and land-surface albedo in MPI-ESM CMIP5 simulations, J. Adv. Model. Earth Syst. 5 (2013) 48–57, https://doi.org/10.1029/2012MS000169.
[63] P.G. Jones, P.K. Thornton, Generating downscaled weather data from a suite of climate models for agricultural modelling applications, Agric. Syst. 114 (2013) 1–5, https://doi.org/10.1016/j.agsy.2012.08.002.
[64] P.G. Jones, P.K. Thornton, MarkSim: software to generate daily weather data for Latin America and Africa, Agron. J. 92 (2000) 445–453, https://doi.org/10.2134/agronj2000.923445x.
[65] M.A. Semenov, E.M. Barrow, Use of a stochastic weather generator in the development of climate change scenarios, Clim. Change 35 (1997) 397–414, https://doi.org/10.1023/A:1005342632279.
[66] M.A. Semenov, R.J. Brooks, Spatial interpolation of the LARS-WG stochastic weather generator in Great Britain, Clim. Res. 11 (1999) 137–148.
[67] S. Geng, F.W.T.P. de Vries, I. Supit, A simple method for generating daily rainfall data, Agric. For. Meteorol. 36 (1986) 363–376.
[68] S. Geng, J. Auburn, E. Brandstetter, B. Li, A program to simulate meteorological variables: documentation for SIMMETEO, Agron. Prog. Rep (1988) 204.
[69] CW Richardson, DA Wright, WGEN: A model for generating daily weather variables. Report ARS-8 August 1984, 1984, p. 83, 3 Fig, 12 Tab, 13 Ref, 4 App.
[70] A. Soltani, N. Latifi, M. Nasiri, Evaluation of WGEN for generating long term weather data for crop simulations, Agric. For. Meteorol. 102 (2000) 1–12.
[71] C.O. Stöckle, G.S. Campbell, R. Nelson, ClimGen Manual. *Biol. Syst. Eng. Dep. Washingt*, . State Univ. Pullman, WA, 1999, p. 28.
[72] T.J. Osborn, C.J. Wallace, I.C. Harris, T.M. Melvin, Pattern scaling using ClimGen: monthly-resolution future climate scenarios including changes in the variability of precipitation, Clim. Change 134 (2016) 353–369.
[73] J. Chen, F.P. Brissette, R. Leconte, Downscaling of weather generator parameters to quantify hydrological impacts of climate change, Clim. Res. 51 (2012) 185–200.
[74] J. Chen, F.P. Brissette, R. Leconte, WeaGETS–a Matlab-based daily scale weather generator for generating precipitation and temperature, Procedia Environ. Sci. 13 (2012) 2222–2235.
[75] B. Qian, S. Gameda, H. Hayhoe, R. De Jong, A. Bootsma, Comparison of LARS-WG and AAFC-WG stochastic weather generators for diverse Canadian climates, Clim. Res. 26 (2004) 175–191.
[76] B. Qian, H. Hayhoe, S. Gameda, Evaluation of the stochastic weather generators LARS-WG and AAFC-WG for climate change impact studies, Clim. Res. 29 (2005) 3–21.
[77] R.G. Jones, M. Noguer, D.C. Hassell, D. Hudson, S.S. Wilson, G.J. Jenkins, J.F.B. Mitchell, Generating high resolution climate change scenarios using PRECIS, Met Off. Hadley Centre, Exet. UK 40 (2004).
[78] J.G. Arnold, R. Srinivasan, R.S. Muttiah, J.R. Williams, Large area hydrologic modeling and assessment part I: model development 1, JAWRA J. Am. Water Resour. Assoc. 34 (1998) 73–89.
[79] A. Ansari, T. Kato, A. Fitriah, Simulating streamflow through the SWAT model in the keduang sub-watershed, wonogiri regency, Indonesia, agriTECH 39 (2019) 60–69.
[80] S. Bergström, The HBV model, Comput. Model. watershed Hydrol. (1995) 443–476.
[81] G. Lindström, A simple automatic calibration routine for the HBV model, Hydrol. Res. 28 (1997) 153–168.
[82] K. Takeuchi, T. Ao, H. Ishidaira, Introduction of block-wise use of TOPMODEL and Muskingum-Cunge method for the hydroenvironmental simulation of a large ungauged basin, Hydrol. Sci. J. 44 (1999) 633–646.
[83] K. Takeuchi, P. Hapuarachchi, M. Zhou, H. Ishidaira, A BTOP model to extend TOPMODEL for distributedhydrological simulation of large basins, Hydrol. Process. 22 (2008) 3236–3251.
[84] D.N. WatBal Yates, An integrated water balance model for climate impact assessment of river basin runoff, Int. J. Water Resour. Dev. 12 (1996) 121–140, https://doi.org/10.1080/07900629650041902.
[85] D.E. Welch, P. Eng, Tailings Basin Water Balance Modelling and Watbal Manual, Gtci-Camisea.Com.Pe, 1997.
[86] J. Schulla, K Jasper, Model description wasim-eth, Institute for Atmospheric and Climate Science, Swiss Federal Institute of Technology, Zurich, 2007 Feb.
[87] J. Cullmann, V. Mishra, R. Peters, Flow analysis with WaSiM-ETH–model parameter sensitivity at different scales, Adv. Geosci. 9 (2006) 73–77.
[88] C. Deng, P. Liu, S. Guo, Z. Li, D. Wang, Identification of hydrological model parameter variation using ensemble Kalman filter, Hydrol. Earth Syst. Sci. 20 (2016) 4949–4961.
[89] L. Xiong, S. Guo, A two-parameter monthly water balance model and its application, J. Hydrol. 216 (1999) 111–123.
[90] D.N. Graham, M.B. Butts, Flexible, integrated watershed modelling with MIKE SHE, Watershed Model 849336090 (2005) 245–272.
[91] J.C. Refshaard, B. Storm, S.H.E. Mike, Comput. Model. watershed Hydrol. (1995) 809–846.
[92] D. Lohmann, E. Raschke, B. Nijssen, D.P. Lettenmaier, Regional scale hydrology: I. Formulation of the VIC-2L model coupled to a routing model, Hydrol. Sci. J. 43 (1998) 131–141.
[93] S. Guo, J. Guo, J. Zhang, H. Chen, VIC distributed hydrological model to predict climate change impact in the Hanjiang basin, Sci. China Ser. E Technol. Sci. 52 (2009) 3234–3239.
[94] M.S. Wigmosta, B. Nijssen, P. Storck, D.P. Lettenmaier, The distributed hydrology soil vegetation model, Math. Model. small watershed Hydrol. Appl. (2002) 7–42.
[95] H. Bormann, Impact of spatial data resolution on simulated catchment water balances and model performance of the multi-scale TOPLATS model, Hydrol. Earth Syst. Sci. 10 (2006) 165–179.
[96] D. Koller, N. Friedman, S. Džeroski, C. Sutton, A. McCallum, A. Pfeffer, P. Abbeel, M.-F. Wong, C. Meek, J. Neville, Introduction to Statistical Relational Learning, MIT press, 2007. ISBN 0262072882.
[97] A.G. Barr, G.W. Kite, R. Granger, C. Smith, Evaluating three evapotranspiration methods in the SLURP macroscale hydrological model, Hydrol. Process. 11 (1997) 1685–1705.
[98] N.R. Viney, M. Sivapalan, Modelling catchment processes in the Swan–Avon river basin, Hydrol. Process. 15 (2001) 2671–2685.
[99] B.F.W. Croke, F. Andrews, A.J. Jakeman, S. Cuddy, A. Luddy, Redesign of the IHACRES rainfall-runoff model, in: Proceedings of the 29th Hydrology and Water Resources Symposium, 2005, pp. 21–23.
[100] S. Manfreda, M. Fiorentino, V. Iacobellis, DREAM: a distributed model for runoff, evapotranspiration, and antecedent soil moisture simulation, Adv. Geosci. 2 (2005) 31–39.
[101] R.W. Skaggs, A Water Management Model for Shallow Water Table Soils, Water Resources Research Institute of the University of North Carolina, 1978.
[102] K. Averyt, J. Meldrum, P. Caldwell, G. Sun, S. McNulty, A. Huber-Lee, N. Madden, Sectoral contributions to surface water stress in the coterminous United States, Environ. Res. Lett. 8 (2013), 35046.
[103] Y. Jia, G. Ni, Y. Kawahara, T. Suetsugi, Development of WEP model and its application to an urban watershed, Hydrol. Process. 15 (2001) 2175–2194.
[104] P. Kraft, K.B. Vaché, H.-G. Frede, L. Breuer, CMF: a hydrological programming language extension for integrated catchment models, Environ. Model. Softw. 26 (2011) 828–830.
[105] D. Yates, J. Sieber, D. Purkey, A. Huber-Lee, WEAP21—a demand-, priority-, and preference-driven water planning model: part 1: model characteristics, Water Int. 30 (2005) 487–500.

[106] X. Wang, J.R. Williams, P.W. Gassman, C. Baffaut, R.C. Izaurralde, J. Jeong, J.R. Kiniry, EPIC and APEX: model use, calibration, and validation, Trans. ASABE (Am. Soc. Agric. Biol. Eng.) 55 (2012) 1447–1462.
[107] K.I. Ngoy, D. Shebitz, Potential impacts of climate change on areas suitable to grow some key crops in New Jersey, USA, Environments 7 (2020) 76.
[108] J.W. Jones, G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, P.W. Wilkens, U. Singh, A.J. Gijsman, J.T. Ritchie, The DSSAT cropping system model, Eur. J. Agron. 18 (2003) 235–265.
[109] G. Hoogenboom, C.H. Porter, K.J. Boote, V. Shelia, P.W. Wilkens, U. Singh, J.W. White, S. Asseng, J.I. Lizaso, L.P. Moreno, The DSSAT crop modeling ecosystem, Adv. Crop Model. a Sustain. Agric. (2019) 173–216.
[110] D.P. Holzworth, N.I. Huth, P.G. deVoil, E.J. Zurcher, N.I. Herrmann, G. McLean, K. Chenu, E.J. van Oosterom, V. Snow, C. Murphy, et al., Apsim – evolution towards a new generation of agricultural systems simulation, Environ. Model. Softw. 62 (2014) 327–350, https://doi.org/10.1016/j.envsoft.2014.07.009.
[111] B.A. Keating, P.S. Carberry, G.L. Hammer, M.E. Probert, M.J. Robertson, D. Holzworth, N.I. Huth, J.N.G. Hargreaves, H. Meinke, Z. Hochman, et al., An overview of APSIM, a model designed for farming systems simulation, Eur. J. Agron. 18 (2003) 267–288, https://doi.org/10.1016/S1161-0301(02)00108-9.
[112] A. de Wit, H. Boogaard, D. Fumagalli, S. Janssen, R. Knapen, D. van Kraalingen, I. Supit, R. van der Wijngaart, K. van Diepen, 25 years of the WOFOST cropping systems model, Agric. Syst. 168 (2019) 154–167, https://doi.org/10.1016/j.agsy.2018.06.018.
[113] H. Boogaard, A.J. De Wit, J. te Roller, C. Van Diepen, User Manual for WOFOST and the WOFOST Control Centre, vol. 133, 2014.
[114] D.L. Giltrap, C. Li, S.D.N.D.C. Saggar, A process-based model of greenhouse gas fluxes from agricultural soils, Agric. Ecosyst. Environ. 136 (2010) 292–300, https://doi.org/10.1016/j.agee.2009.06.014.
[115] T. Fumoto, K. Kobayashi, C. Li, K. Yagi, T. Hasegawa, Revising a process-based biogeochemistry model (DNDC) to simulate methane emission from rice paddy fields under various residue management and fertilizer regimes, Glob. Chang. Biol. 14 (2008) 382–402.
[116] R. Confalonieri, M. Acutis, M. Donatelli, G. Bellocchi, L. Mariani, M. Boschetti, D. Stroppiana, S. Bocchi, F. Vidotto, D. Sacco, et al., WARM: a scientific group on rice modelling, Riv. Ital. di Agrometeorol. 2 (2005) 54–60.
[117] R. Confalonieri, G. Bellocchi, S. Bregaglio, M. Donatelli, M. Acutis, Comparison of sensitivity analysis techniques: a case study with the rice model WARM, Ecol. Modell. 221 (2010) 1897–1906, https://doi.org/10.1016/j.ecolmodel.2010.04.021.
[118] F. Tao, S. Zhang, Z. Zhang, Changes in rice disasters across China in recent decades and the meteorological and agronomic causes, Reg. Environ. Chang. 13 (2013) 743–759.
[119] F. Tao, M. Yokozawa, Z. Zhang, Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis, Agric. For. Meteorol. 149 (2009) 831–850, https://doi.org/10.1016/j.agrformet.2008.11.004.
[120] L. Tang, Y. Zhu, D. Hannaway, Y. Meng, L. Liu, L. Chen, W. Cao, RiceGrow: a rice growth and productivity model, NJAS - Wageningen J. Life Sci. 57 (2009) 83–92, https://doi.org/10.1016/j.njas.2009.12.003.
[121] Y. Xinyou, H.H. Van Laar, Crop Systems Dynamics: an Ecophysiological Simulation Model of Genotype-By-Environment Interactions, Wageningen Academic Publishers, 2005. ISBN 9076998558.
[122] H. Yoshida, T. Horie, K. Nakazono, H. Ohno, H. Nakagawa, Simulation of the effects of genotype and N availability on rice growth and yield response to an elevated atmospheric CO2 concentration, F. Crop. Res. 124 (2011) 433–440.
[123] H. Yoshida, T. Horie, A model for simulating plant N accumulation, growth and yield of diverse rice genotypes grown under different soil and climatic conditions, F. Crop. Res. 117 (2010) 122–130.
[124] P. Steduto, T.C. Hsiao, D. Raes, E. Fereres, AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles, Agron. J. 101 (2009) 426–437.
[125] F.A.O. AquaCrop, The Crop Water Productivity Model, vol. 4, 2017.
[126] C.O. Stöckle, M. Donatelli, R. CropSyst Nelson, A cropping systems simulation model, Eur. J. Agron. 18 (2003) 289–307.
[127] R. Confalonieri, S. Bocchi, Evaluation of CropSyst for simulating the yield of flooded rice in northern Italy, Eur. J. Agron. 23 (2005) 315–326.
[128] P.K. Aggarwal, N. Kalra, S. Chander, H. Pathak, InfoCrop: a dynamic simulation model for the assessment of crop yields, losses due to pests, and environmental impact of agro-ecosystems in tropical environments. I. Model description, Agric. Syst. 89 (2006) 1–25, https://doi.org/10.1016/j.agsy.2005.08.001.
[129] P. Krishnan, D.K. Swain, B.C. Bhaskar, S.K. Nayak, R.N. Dash, Impact of elevated CO2 and temperature on rice yield and methods of adaptation as evaluated by crop simulation studies, Agric. Ecosyst. Environ. 122 (2007) 233–242.
[130] T. Horie, H. Nakagawa, H.G.S. Centeno, M.J. Kropff, The rice crop simulation model SIMRIW and its testing, Model. impact Clim. Chang. rice Prod. Asia (1995) 51–66.
[131] B.C. Miller, T.C. Foin, J.E. Hill, CARICE: a rice model for scheduling and evaluating management actions, Agron. J. 85 (1993) 938–947.
[132] T. Yuliawan, I. Handoko, The effect of temperature rise to rice crop yield in Indonesia uses shierary rice model with geographical information system (GIS) feature, Procedia Environ. Sci. 33 (2016) 214–220, https://doi.org/10.1016/j.proenv.2016.03.072.
[133] R. Becker, C. Schüth, R. Merz, T. Khaliq, M. Usman, T. Beek, der aus, R. Kumar, S. Schulz, Increased heat stress reduces future yields of three major crops in Pakistan's Punjab region despite intensification of irrigation, Agric. Water Manag. 281 (2023), 108243, https://doi.org/10.1016/j.agwat.2023.108243.
[134] W. Xiong, D. Conway, E. Lin, Y. Xu, H. Ju, J. Jiang, I. Holman, Y. Li, Future cereal production in China: the interaction of climate change, water availability and socio-economic scenarios, Glob. Environ. Chang. 19 (2009) 34–44, https://doi.org/10.1016/j.gloenvcha.2008.10.006.
[135] D. Wallach, D. Makowski, J.W. Jones, F. Brun, Chapter 12 - multimodel ensembles, in: D. Wallach, D. Makowski, J.W. Jones, F. Brun (Eds.), Working with Dynamic Crop Models, third ed., Academic Press, 2019, pp. 425–443. ISBN 978-0-12-811756-9.
[136] K. McNeill, K. Macdonald, A. Singh, A.D. Binns, Food and water security: analysis of integrated modeling platforms, Agric. Water Manag. 194 (2017) 100–112, https://doi.org/10.1016/j.agwat.2017.09.001.
[137] J.W. Jones, J.M. Antle, B. Basso, K.J. Boote, R.T. Conant, I. Foster, H.C.J. Godfray, M. Herrero, R.E. Howitt, S. Janssen, et al., Toward a new generation of agricultural system data, models, and knowledge products: state of agricultural systems science, Agric. Syst. 155 (2017) 269–288, https://doi.org/10.1016/j.agsy.2016.09.021.
[138] D.P. Holzworth, V. Snow, S. Janssen, I.N. Athanasiadis, M. Donatelli, G. Hoogenboom, J.W. White, P. Thorburn, Agricultural production systems modelling and software: current status and future prospects, Environ. Model. Softw. 72 (2015) 276–286, https://doi.org/10.1016/j.envsoft.2014.12.013.
[139] K.J.-Y.N. Guessan, B.A. Dahi, A.K.O. Aidhet, S.M. Asayoshi, N.E.A. Ssidjo, Assessment of climate change impact on water requirement and rice productivity, Rice Sci. 30 (2023) 276–293, https://doi.org/10.1016/j.rsci.2023.03.010.
[140] A.C. Ruane, D.C. Major, W.H. Yu, M. Alam, S.G. Hussain, A.S. Khan, A. Hassan, B.M.T. Al Hossain, R. Goldberg, R.M. Horton, et al., Multi-factor impact analysis of agricultural production in Bangladesh with climate change, Glob. Environ. Chang. 23 (2013) 338–350, https://doi.org/10.1016/j.gloenvcha.2012.09.001.
[141] K. Tsujimoto, N. Kuriya, T. Ohta, K. Homma, M.S. Im, Quantifying the GCM-related uncertainty for climate change impact assessment of rainfed rice production in Cambodia by a combined hydrologic - rice growth model, Ecol. Modell. (2022) 464, https://doi.org/10.1016/j.ecolmodel.2021.109815.
[142] V. Geethalakshmi, K. Bhuvaneswari, A. Lakshmanan, N.U. Sekhar, S. Mcdermid, A.P. Ramaraj, R. Gowtham, K. Senthilraja, Multimodeling approach to assess the impact of climate change on water availability and rice productivity: a case study in Cauvery River Basin, Tamil nadu, India, in: Groundwater Assessment, Modeling, and Management, CRC Press, 2016, pp. 479–497. ISBN 1315369044.
[143] S. Masia, A. Trabucco, D. Spano, R.L. Snyder, J. Sušnik, S. Marras, A modelling platform for climate change impact on local and regional crop water requirements, Agric. Water Manag. (2021) 255, https://doi.org/10.1016/j.agwat.2021.107005.
[144] M.B. Masud, T. McAllister, M.R.C. Cordeiro, M. Faramarzi, Modeling future water footprint of barley production in Alberta, Canada: implications for water use and yields to 2064, Sci. Total Environ. 616–617 (2018) 208–222, https://doi.org/10.1016/j.scitotenv.2017.11.004.
[145] F. Tao, M. Yokozawa, Y. Hayashi, E. Lin, Future climate change, the agricultural water cycle, and agricultural production in China, Agric. Ecosyst. Environ. 95 (2003) 203–215, https://doi.org/10.1016/S0167-8809(02)00093-2.
[146] J.M. Winter, J.R. Lopez, A.C. Ruane, C.A. Young, B.R. Scanlon, C. Rosenzweig, Representing water scarcity in future agricultural assessments, Anthropocene 18 (2017) 15–26, https://doi.org/10.1016/j.ancene.2017.05.002.

[147] E. Monaco, A. Bonfante, S.M. Alfieri, A. Basile, M. Menenti, F. De Lorenzi, Climate change, effective water use for irrigation and adaptability of maize: a case study in southern Italy, Biosyst. Eng. 128 (2014) 82–99, https://doi.org/10.1016/j.biosystemseng.2014.09.001.
[148] A.G. Kamalamma, M.S. Babel, V. Sridhar, G. Vellingiri, A novel approach to vulnerability assessment for adaptation planning in agriculture: an application to the Lower Bhavani Irrigation Project, India, Clim. Serv. 30 (2023), 100358, https://doi.org/10.1016/j.cliser.2023.100358.
[149] V. Geethalakshmi, K. Bhuvaneswari, A. Lakshmanan, N.U. Sekhar, S. McDermid, A.P. Ramaraj, R. Gowtham, K. Senthilraja, Multimodeling approach to assess the impact of climate change on water availability and rice productivity: a case study in Cauvery River Basin, Tamil nadu, India, Groundw. Assessment, Model. Manag. (2016) 479–497, https://doi.org/10.1201/9781315369044-32.
[150] I.N. Khasanah, S. Haryanto, Paddy harvested area and production in Indonesia 2021, Stat. Indones. 5203031 (2022) 104–116.
[151] G.A. Un, Resolution Adopted by the General Assembly on 25 September 2015, 70/1. Transforming Our World: the 2030 Agenda for Sustainable Development, 2015. A/RES/70/1, 21 October.
[152] A.V. Pastor, A. Palazzo, P. Havlik, H. Biemans, Y. Wada, M. Obersteiner, P. Kabat, F. Ludwig, The global nexus of food–trade–water sustaining environmental flows by 2050, Nat. Sustain. 2 (2019) 499–507.
[153] R. Wassmann, S.V.K. Jagadish, K. Sumfleth, H. Pathak, G. Howell, A. Ismail, R. Serraj, E. Redona, R.K. Singh, S. Heuer, Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation, Adv. Agron. 102 (2009) 91–133.
[154] R. Wassmann, S.V.K. Jagadish, S. Heuer, A. Ismail, E. Redona, R. Serraj, R.K. Singh, G. Howell, H. Pathak, K. Sumfleth, Climate change affecting rice production: the physiological and agronomic basis for possible adaptation strategies, Adv. Agron. 101 (2009) 59–122.
[155] M.A. Achyadi, K. Ohgushi, T. Morita, Impacts of climate change on agriculture for local paddy water requirement irrigation Barito Kuala, South Kalimantan, Indonesia, J. Wetl. Environ. Manag. 7 (2019) 140–150.
[156] Y. Kinose, Y. Masutomi, F. Shiotsu, K. Hayashi, D. Ogawada, M. Gomez-Garcia, A. Matsumura, K. Takahashi, K. Fukushi, Impact assessment of climate change on the major rice cultivar ciherang in Indonesia, J. Agric. Meteorol. 76 (2020) 19–28, https://doi.org/10.2480/agrmet.D-19-00045.
[157] B. Ahrens, A. Dobler, Regional climate projections, Appl. Geoinformatics Sustain. Integr. L. Water Resour. Manag. Brahmaputra River Basin Results From Ec-Project Brahmatwinn (2015) 11–15, https://doi.org/10.1007/978-81-322-1967-5_4.
[158] A.J. Challinor, F. Ewert, S. Arnold, E. Simelton, E. Fraser, Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation, J. Exp. Bot. 60 (2009) 2775–2789, https://doi.org/10.1093/jxb/erp062.
[159] M. Beniston, Grand challenges in climate research, Front. Environ. Sci. 1 (2013) 1–4, https://doi.org/10.3389/fenvs.2013.00001.
[160] A. Becker, P. Finger, A. Meyer-Christoffer, B. Rudolf, K. Schamm, U. Schneider, M. Ziese, A description of the global land-surface precipitation data products of the Global Precipitation Climatology Centre with sample applications including centennial (trend) analysis from 1901–present, Earth Syst. Sci. Data 5 (2013) 71–99.
[161] J.V. Silva, K.E. Giller, Grand challenges for the 21st century: what crop models can and can't (yet) do, J. Agric. Sci. 158 (2020) 794–805, https://doi.org/10.1017/S0021859621000150.
[162] V. Ramanathan, Y.A.N. Feng, On avoiding dangerous anthropogenic interference with the climate system: formidable challenges ahead, Proc. Natl. Acad. Sci. 105 (2008) 14245–14250.
[163] A.J. Guswa, K.A. Brauman, C. Brown, P. Hamel, B.L. Keeler, S.S. Sayre, Hydrologic modeling to support decision making, Water Resour. Res. 50 (2014) 1–10, https://doi.org/10.1002/2014WR015497.Received.
[164] A.W. Jayawardena, Recent Developments and Challenges Ahead in Hydrological Modelling Recent Developments and Challenges Ahead in Hydrological Modelling, 2015.
[165] B.A. Ebel, B.B. Mirus, Disturbance hydrology: challenges and opportunities, Hydrol. Process. 28 (2014) 5140–5148, https://doi.org/10.1002/hyp.10256.
[166] S.K. Mishra, S. Rupper, S. Kapnick, K. Casey, H.G. Chan, E. Ciraci', U. Haritashya, J. Hayse, J.S. Kargel, R.B. Kayastha, et al., Grand challenges of hydrologic modeling for food-energy-water nexus security in high mountain asia, Front. Water 3 (2021) 1–18, https://doi.org/10.3389/frwa.2021.728156.
[167] A. Bárdossy, Calibration of hydrological model parameters for ungauged catchments, Hydrol. Earth Syst. Sci. 11 (2007) 703–710.
[168] B. Collischonn, W. Collischonn, C.E.M. Tucci, Daily hydrological modeling in the Amazon basin using TRMM rainfall estimates, J. Hydrol. 360 (2008) 207–216.
[169] J.K. Thakur, S.K. Singh, V.S. Ekanthalu, Integrating remote sensing, geographic information systems and global positioning system techniques with hydrological modeling, Appl. Water Sci. 7 (2017) 1595–1608.
[170] A. Salam, Internet of things for water sustainability, in: Internet of Things for Sustainable Community Development, Springer, 2020, pp. 113–145.
[171] D. Gerten, V. Heck, J. Jägermeyr, B.L. Bodirsky, I. Fetzer, M. Jalava, M. Kummu, W. Lucht, J. Rockström, S. Schaphoff, Feeding ten billion people is possible within four terrestrial planetary boundaries, Nat. Sustain. 3 (2020) 200–208.
[172] N. Arunrat, S. Sereenonchai, C. Wang, Carbon footprint and predicting the impact of climate change on carbon sequestration ecosystem services of organic rice farming and conventional rice farming: a case study in Phichit province, Thailand, J. Environ. Manage. 289 (2021), 112458.
[173] A. Maiorano, P. Martre, S. Asseng, F. Ewert, C. Müller, R.P. Rötter, A.C. Ruane, M.A. Semenov, D. Wallach, E. Wang, et al., Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles, F. Crop. Res. 202 (2017) 5–20, https://doi.org/10.1016/j.fcr.2016.05.001.
[174] K.J. Boote, J.W. Jones, N.B. Pickering, Potential uses and limitations of crop models, Agron. J. 88 (1996) 704–716.
[175] A.S. Gardner, I.M.D. Maclean, K.J. Gaston, L. Bütikofer, Forecasting future crop suitability with microclimate data, Agric. Syst. 190 (2021), 103084, https://doi.org/10.1016/j.agsy.2021.103084.
[176] D. Wallach, P.J. Thorburn, Estimating uncertainty in crop model predictions: current situation and future prospects, Eur. J. Agron. 88 (2017) A1–A7, https://doi.org/10.1016/j.eja.2017.06.001.