Water Resources Management
https://doi.org/10.1007/s11269-023-03659-x

A Systematic Review of Methods for Investigating Climate Change Impacts on Water-Energy-Food Nexus

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Received: 22 August 2023 / Accepted: 7 November 2023

Abstract

Water, energy and food are important for human survival and sustainable development. With climate change, investigating climate change impacts on Water-Energy-Food nexus has been a topic of growing interest in recent years. However, there is a lack of a systematic review of the current state and methodologies of Water-Energy-Food nexus studies under climate change. Here, we review research articles investigating climate change impacts on Water-Food, Water-Energy and Water-Energy-Food nexus over last seven years. The existing methods and tools, spatial scales, and future climate scenarios setting in these articles are summarised and analysed. We found that the analyses methods could be divided into four categories (physics-based modelling, statistical methods, supervised learning and operation optimisation), among them, physics-based modelling accounts for the largest proportion. The reviewed studies cover a range of scales from site scale to global, with most studies focusing on the regional scale. Models used for small to middle scale are mainly related to hydrology and water resource, while large-scale modelling is based on interdisciplinary models. Future climate scenarios setting include emission scenarios and global warming scenarios based on Global Climate Models (GCMs). A number of future research challenges have been identified. These include spatial scale and resolution, internal physical mechanism, application of novel artificial intelligence models, extreme climate events, potential competition in nexus systems as well as data and model uncertainty.

Keywords PRISMA · Hydrology · Agriculture · Hydropower · Climate change

1 Introduction

Water, energy and food are three essential resources that human beings depend upon for survival and development. These three resources are interconnected in complex ways (Liang et al. 2020), necessitating a holistic approach to their evaluation. The Water-Energy-Food nexus concept was formally introduced in the Bonn 2011 Nexus Conference (Hoff 2011) as an integrated system that encapsulates the interdependencies between water, energy and food (Conway et al. 2015; Scanlon et al. 2017).

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The global temperature is likely to increase to 4.8℃ by 2100 compared to 1995–2014 in the high-emission scenario (IPCC 2021). The increased temperature may lead to more frequent extreme and compound events such as heatwaves and long-term droughts, which could significantly affect constrain food production and energy generation. Climate change may pose great uncertainties and risks to water security, energy security and food security in the future. Therefore, understanding climate change impacts on water, energy and food is crucial for achieving the SDG6 (clean water and sanitation), SDG7 (affordable and clean energy) and SDG2 (zero hunger) (Liu et al. 2018; UN 2018).

Significant efforts have been made to explore and evaluate the Water-Energy-Food nexus via various approaches (de Amorim et al. 2018; D'Odorico et al. 2018; Endo et al. 2020). Mannan et al. (2018) identified the capabilities and hindrances of applying the Life Cycle assessment on Water-Energy-Food nexus. Zhang et al. (2018) discussed the pros and cost of eight quantitative methods. Albrecht et al. (2018) emphasised the importance of integrating quantitative and qualitative methods with social science in studies that incorporate multiple methods. Zhang et al. (2019a) categorised eleven existing nexus methods and tools into three types according to research purposes. Namany et al. (2019) introduced three dynamic decision-making tools and proposed application examples during three decision-making process stages.

However, none of those reviews has analysed the methods and tools used for investigating climate change impacts to water, energy, and food. Several questions remain unanswered: What are existing state-of-the-art analytical methods and tools for studying Water-Energy-Food under climate change? Which ones are more widely used? What are their features and limitations? What is the focus of related research on different spatial scales and topics? How should models be selected according to research topic and spatial scale? How does the related research consider climate change scenarios? What are future prospects?

To address these questions, we have reviewed and analysed research articles published over the past seven years that investigated climate change impacts on Water-Food, Water-Energy and Water-Energy-Food nexus. Promising methods frequently used in each type of study, topics and models for different spatial scales, and climate change scenarios setting methods are identified and discussed. The research challenges and limitations are identified, suggesting potential directions for future research in the domain of Water-Energy-Food interactions under climate change.

2 Methods

We searched peer-reviewed journal articles on the subject of climate change in the Web of Science database that were published after 2017 and related to Water-Food, Water-Energy and Water-Energy-Food. The article selection procedure followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA, Page et al. 2021), and the flow chart of the selection process is shown in Fig. 1.

2.1 Review Process

In Web of Science, we used 'climate change', 'water', 'food' and'irrigation' as the keywords to search the abstract, title and keywords of publications between 2017 and 2022, 1676 articles were found. By replacing the keywords with 'climate change', 'soil moisture' and 'crop yield', 1155 articles were selected; when searching keywords 'climate change

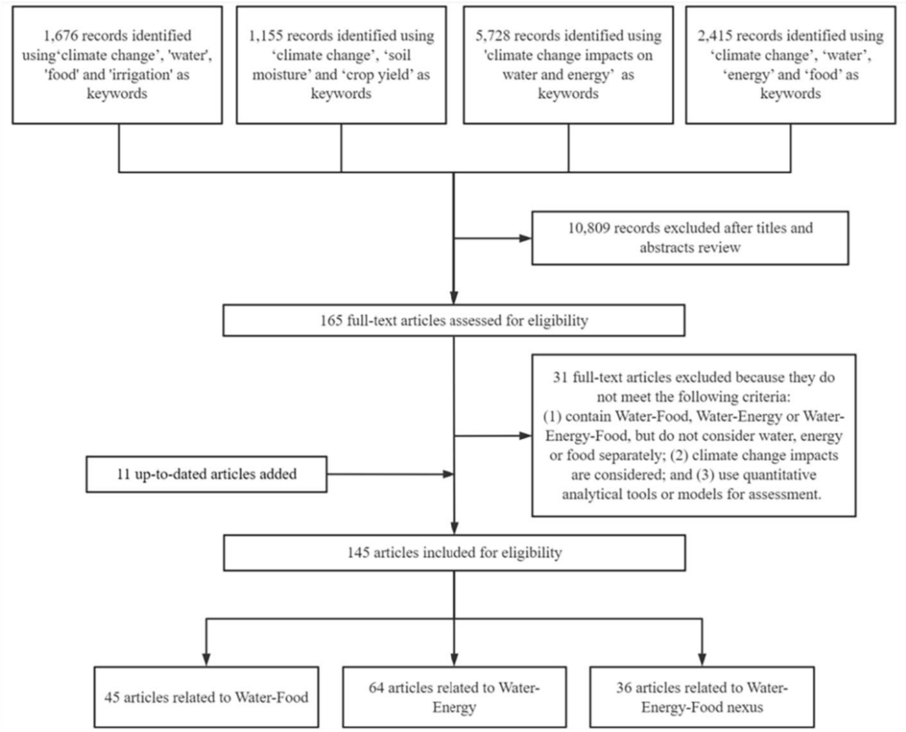

Fig. 1 Flow chart of articles selection process following PRISMA

impacts on water and energy', 5728 articles were found; and 2415 articles were listed through keywords 'climate change', 'water', 'energy' and 'food'. Altogether, 10,974 articles were selected after the initial search.

2.2 Inclusion and Exclusion Criteria

Articles that met all the following criteria were selected: (1) they contain Water-Food, Water-Energy or Water-Energy-Food, but do not consider water, energy or food separately; (2) the consider climate change impacts; and (3) they use quantitative analytical tools or models for assessment. Besides, eleven articles published in 2023 were added during the revision of the paper.

Based on these criteria, we obtained 45 articles related to Water-Food and climate change, identified 64 articles studying climate change impacts on Water-Energy, and selected 36 articles about climate change and Water-Energy-Food nexus. Thus, a total of 145 articles were identified as suitable.

2.3 Information Extraction

After full-text reading of the 145 relevant articles, we extracted the following information: (1) the purpose of the study (2) the scale of study area; (3) methods used in the study area, based on statistical methods, physics-based modelling, supervised learning or operation optimisation; (4) whether the article used models, combined multiple models or used a single model; (5) whether the article claimed a new method; (6) whether there was a simulation under future scenarios and how the scenarios were set up; and (7) characteristics, major challenges and limitations in the application of methods and models.

3 Diversity of Nexus Methods

Numerous and diverse methods have been used or proposed for evaluating climate change impacts on Water-Food, Water-Energy and Water-Energy-Food nexus. while some studies have combined multiple methods. In this review, we divided the approaches into four categories: Statistical methods, Physics-based modelling, Supervised learning and Operation optimisation.

Methods based on statistics such as formula calculations, regression and statistical tests were grouped into Statistical methods; methods using models based on the representation of physical mechanisms were grouped into Physics-based modelling; methods using machine learning to do simulation were classified into Supervised learning; and methods using optimisation algorithm to determine optimal solution under constraints were classified into Operation optimisation.

3.1 Water-Food Nexus Analysis Methods

In the Water-Food nexus research, 53% of studies (24 of 45) used statistical methods, 64% (29 of 45) used physics-based modelling methods and 9% (4 of 45) used operation optimisation methods. We tabulate and categorise Water-Food analytical methods and tools from the selected 45 articles based on method categorisation and discipline in Table 1.

Studies investigating the influence of climate change on Water-Food nexus mainly focused on how climate change may impact water availability for irrigation, soil moisture and crop yield. Most Water-Food studies utilised multiple methods or coupled models from different disciplines. The input data of the models were commonly multidisciplinary from the areas of meteorology (precipitation, temperature, wind speed, humidity, solar radiation, etc.), environment (CO_2 concentration, etc.), geospatial (vegetation, landuse, etc.), economics (GDP, etc.) and society (population, etc.).

Generally, in model coupling studies, a hydrological model was used to simulate runoff or soil moisture, and an agricultural model or a statistical calculation method was used to calculate irrigation water requirements and parameters related to crop yields. For example, Akoko et al. (2020) used Soil & Water Assessment Tool (SWAT) to estimate the current and future water resources availability and Cropwat to calculate irrigation water requirements. Meanwhile, many interdisciplinary models were developed to study the Water-Food nexus. Blanc et al. (2017) integrated water resources model and a crop yield reduction module into the Integrated Global System Modelling framework (IGSM) to assess the influence of climate and socioeconomic changes on irrigation water availability as well as subsequent impacts on crop yields by 2050. Malek et al. (2018) integrated a process-based irrigation module into VICCropSyst to assess the influence of climate change on irrigation losses.

Some model-based studies only utilised a single discipline model or a series of equations. This kind of research mostly focused on soil moisture, irrigation and crop parameters rather than simulations of water availability. He et al. (2021) projected the amount of agricultural water for food production during peak population period (2029–2033) based on a series of equations including FAO's Penman–Monteith equation. Jha et al. (2020) utilised

Table 1 Catalogue of methods used in the climate change impacts on Water-Food studies sample set, categorised by Physics-based modelling (a), Statistical methods (b) and Operation optimisation (c)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Cryosphere, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 29) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Hydrology					**11 studies (38%)**
Lund-Potsdam-Jena managed Land (LPJmL)	Simulation of the global terrestrial carbon and water cycle	Spatially explicit time series of climate, human land use, soil properties, and river flow directions	Global	Daily	Langerwisch et al. 2018; Pastor et al. 2019; Lutz et al. 2022
Soil & Water Assessment Tool (SWAT)	Simulation of the quality and quantity of surface and ground water	Meteorological data, DEM, land use, and soil characteristics	Watershed	Daily	Akoko et al. 2020; Paul et al. 2020; Piniewski et al. 2020; Haro-Monteagudo et al. 2023; Tan et al. 2023
Spatial Processes in Hydrology (SPHY)	Hydrological process simulation	Spatially explicit DEM, land use type, glacier cover, lakes/reservoirs and soil characteristics, as well as climate data with time series	Watershed	Daily	Lutz et al. 2022
The mesoscale Hydrologic Model (mHM)	Hydrological process simulation	Spatially explicit data of physiographic land surface and meteorological forcings	Watershed	Hourly	Peichl et al. 2019
Modular three-dimensional groundwater flow model (MODFLOW)	Groundwater simulation	Site data of geological and other characteristics of the aquifer	Watershed	Undefined or secondly	Goodarzi et al. 2019
IHACRES	Streamflow simulation	Time series data of observed rainfall, temperature and streamflow	Watershed	Minutely	Ashofteh et al. 2017
Cryosphere					**1 study (3%)**
Glacier Bed Topography model version 2 (GlabTop2)	Estimation of glacier volumes	DEM, glacier outlines and a set of branch lines for each glacier	Regional	-	Lutz et al. 2022
Agriculture					**8 studies (28%)**

Table 1 (continued)

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Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Decision Support System for Agrotechnology Transfer (DSSAT)	Simulation of crops growth, development and yield	Meteorological data, soil surface and profile information, and detailed crop management	Site	Daily	Ashofteh et al. 2017; Mitchell et al. 2017; Xu et al. 2019; Jha et al. 2020
ORYZA	Simulation of rice growth and development	Experiment data, crop data, soil data (required only for water-limited simulation) and weather data	Site	Daily	Wang et al. 2017; Ding et al. 2020
Agro-ecological Zone (AEZ)	Crop productivity assessment	Climate data, topography and soil characteristics	Global to regional	Daily	Xu et al. 2019
APEX-paddy model	Simulation of water balance components from paddy fields under ponded conditions	Meteorological data, soil type, crop definition, management system and watershed definition	Field	Daily	Kim et al. 2021
Interdisciplinary					**11 studies (38%)**
VIC-CropSyst	Simulation of the interactions between hydrology, crop growth and phenology, and crop and water resource management decisions	Grided climate data, soil data, crop patterns, characteristics and management data	Global to regional	Daily	Malek et al. 2018; Rajagopalan et al. 2018
Global Crop Water Model (GCWM)	Simulation of crop water use and crop yields in rainfed and irrigated agriculture	Cropping pattern, cropping seasons and average crop productivity, climate data, soil properties, trade and population density	Global	Daily	Qin et al. 2020b
Irrigation Management System Model (IManSys)	Calculation of irrigation water requirement for any annual or perennial crop	Climate data, soil hydrologic parameters, crop water uptake parameters	Regional	Daily	Cooper et al. 2022
IGSM-WRS-US	Assessment of climate change effects on managed water-resource systems	Economic, climatic, and hydrologic drivers	Global to regional	Annually	Blanc et al. 2017

Table 1 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Cryosphere, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 29) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Aral Sea Basin management model (ASBmm)	Calculation of the future water balance and water allocation in the Aral Sea Basin	Population data, water use, climate data, and socio-economic data	Watershed	Annually	Duan et al. 2019
MIROC-INTEG-LAND	Simulation of the interactions among coupled natural–human earth system components	Socioeconomic variables, atmospheric variables, soil and vegetation properties	Global	Different time step in submodels	Yokohata et al. 2020
Global Food and Water System (GFWS)	Assessment of the disparity between food production and demands, as well as the difference between water usage for irrigation and the fresh water supply	Population and demographic data, weather data, crop characteristics, land use and water resource	Global	Annually	Grafton et al. 2017
WATNEEDS	Simulation of crop-specific green and blue water requirements	Spatially and temporally distributed information on climate, soil, and crop characteristics	Global	Monthly	Rosa et al. 2020
Crop-river coupled model (CROVER)	Assessment of crop production under varying water availability	Climate data, soil properties, agricultural management, socioeconomic water demand, reservoir operation management, and land use	Watershed	Daily	Okada et al. 2018
Global Biosphere Management Model (GLOBIOM)	Assessment of climate change mitigation policies impact on land-based sectors	Spatially explicit land cover, production, population, GDP, demand, prices and trade, livestock data, crops data and forest data	Global	10-year	Pastor et al. 2019

Table 1 (continued)

b. Statistical methods

Method	Main purpose	Data required	Reference studies
Penman–Monteith equation and crop coefficient approach recommended by the FAO/Cropwat	Calculation of crop water requirements and irrigation requirements	Site location, air temperature, humidity, radiation, wind speed, and crop coefficient	Acharjee et al. 2017; Ashofteh et al. 2017; Zhou et al. 2017; Sylla et al. 2018; Goodarzi et al. 2019; Zhang et al. 2019b; Akoko et al. 2020; Zhang et al. 2020; Abdoulaye et al. 2021; He et al. 2021; Mostafa et al. 2021
Mann–Kendall test	Determining whether a time series has a monotonic upward or downward trend	A series of data with no autocorrelation	Ding et al. 2017; Duan et al. 2019
Regression	Attempting to determine the relationship between dependent variable and independent variables and predicting for the future	A series of dependent variables values and independents variables values	Ding et al. 2017; Kirby et al. 2017; Lu et al. 2019
Cobb–Douglas production function	Modelling the correlation between production output and inputs	Production and input parameters	Lu et al. 2019
Logarithmic Mean Divisia Index (LMDI)	Decomposing and quantifying the different effects of factors on a variable	Data of factors and variable	Zhang et al. 2020

c. Operation optimisation methods

Method	Purpose in related research	Description	Reference studies
Nonlinear optimisation	Determing optimal crop production strategies / Optimizing hydro-economic framework	It solves optimisation problems where the constraints or the objective functions are nonlinear	Mitchell et al. 2017; Gohar and Cashman 2018
Multiobjective genetic programming (MOGP)	Optimizing reservoir-operating rules	MOGP considers the accuracy and the tree complexity as the fitness objectives based on Pareto dominance relations, which can reduce the overfitting effectively while optimizing the solution	Ashofteh et al. 2017

DSSAT to project the changes in rice yield, water demand and phenological growth due to climate change.

A small number of studies did not use or depend on models but used statistical methods to analyse climate change impacts on Water-Food nexus. Zhang et al. (2020) distinguished the different effects of climate change, planted area crop mix on irrigation water demand based on the LMDI method. Kirby et al. (2017) analysed the historical trends of water use, crop production, food availability and population growth, and project them forward to 2050. Madadgar et al. (2017) developed a multivariate probabilistic model to estimate the probability distribution of crop yields under projected climate conditions.

Operation optimisation methods were less used in the climate change impacts on Water-Food studies, in which more studies using nonlinear optimisation framework (Mitchell et al. 2017; Gohar and Cashman 2018). These studies optimised water or food related strategies under climate change conditions.

3.2 Water-Energy Nexus Analysis Methods

In the Water-Energy nexus research, 33% of studies (21 of 64) used statistical methods, 92% (59 of 64) used physics-based modelling methods, 25% (16 of 64) used operation optimisation methods, and 9% (6 of 64) used supervised learning methods. Most studies utilised models and hydrological models accounted for a large part. The catalogue of Water-Energy analytical methods and tools from the selected 64 articles are tabulated and categorised based on method categorization and discipline in Table 2.

Studies analysing climate change impacts on Water-Energy mainly focused on hydropower. Hydropower is vulnerable to the impacts of climate change due to its direct dependence on the timing and magnitude of streamflow. Most studies projected future hydropower generation to evaluate how climate change will affect energy production, or optimised the reservoir operation schemes to minimise the impacts of climate change on streamflow. Generally, hydrological models or supervised learning were adopted to simulate and project future streamflow/inflow to hydropower reservoirs, then energy models or equations were employed to calculate potential hydropower generation, optimisation algorithms or water management models were employed to solve the optimal reservoir operation. For example, Rahmati et al. (2021) simulated future runoff with Artificial Neural Network (ANN) and optimised hydropower generation by Grasshopper Optimisation Algorithm (GOA). Guo et al. (2021) used Genetic Algorithm (GA) to solve the robust optimisation model with the inflows simulated by SWAT under climate and land use change scenarios in the future. Anghileri et al. (2018) contributed a modelling framework combining hydrological modelling, hydropower modelling and multi-objective optimisation technique to assess climate change and energy policies impacts on the operations of hydropower reservoir systems in the Alps.

Meanwhile, a small number of studies used interdisciplinary models to study Water-Energy nexus. Miara et al. (2017) simulated river discharge and temperature as well as electricity generation under climate change using the coupled Water Balance Model and Thermoelectric Power and Thermal Pollution Model (WBM TP2M). Graham et al. (2020) utilised Global Change Assessment Model (GCAM) to investigate the relative contributions of climate and human systems on water scarcity regionally and globally.

Table 2 Catalogue of methods used in the climate change impacts on Water-Energy studies sample set, categorised by Physics-based modelling (a), Statistical methods (b) and Supervised learning (c) and Operation optimisation (d)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Water management) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 60) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Hydrology					**45 studies (75%)**
SWAT	Simulation of the quality and quantity of surface and ground water	Meteorological data, DEM, land use, and soil characteristics	Small watershed to river basin-scale	Daily	de Oliveira et al. 2017; Abera et al. 2018; Goodarzi et al. 2020; Qin et al. 2020a; Bahati et al. 2021; Guo et al. 2021; Shrestha et al. 2021; Wang et al. 2021a; Qin et al. 2022; Ramião et al. 2023
Variable Infiltration Capacity (VIC)	Simulation of land–atmosphere fluxes, and the land surface process	Meteorological data, elevation band data, land cover information	Global to regional	Daily	Forrest et al. 2018; Zhong et al. 2019; Li et al. 2020; Zhong et al. 2020; Yun et al. 2021; Zhao et al. 2021b; Zhao et al. 2022
Hydrologiska Byråns Vattenbalansavdelning (HBV)	Streamflow simulation	Meteorological data, DEM, land use/cover data	Watershed	Hourly	Mousavi et al. 2018; Adera and Alfredsen 2020; Jakimavicius et al. 2020; Carlino et al. 2021; Mutsindikwa et al. 2021
Xinanjiang Model	Streamflow simulation	Meteorological data	Watershed	Daily	Feng et al. 2018, 2021
Hydrological Predictions for the Environment (HYPE)	Water flow and substances simulation	Climate data, elevation, stream network, soil type and land use	Watershed	Daily	Skoulikaris 2021
NedborAfstromnings Model (NAM)	Streamflow and soil moisture content simulation	Meteorological data	Watershed	Daily	Yimere and Assefa 2021
MIKE NAM	Rainfall-runoff processes simulation	Meteorological data	Watershed	Daily	Adynkiewicz-Piragas and Miszuk 2020

Table 2 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Water management) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 60) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
IHACRES	Streamflow simulation	Meteorological data	Watershed	Minutely	Zolghadr-Asti et al. 2019
Veralgemeend Conceptueel Hydrologisch (VHM)	Rainfall-runoff processes simulation	Meteorological data	Watershed	Daily	Donk et al. 2018
ABCD water balance model	Streamflow simulation	Meteorological data	Watershed	Daily	Khalkhali et al. 2018
Topkapi-ETH	Hydrological process simulation suitable for glacierized mountain areas	Climate data, topography, soil type and vegetation	Watershed	Hourly	Anghileri et al. 2018
HEC-HMS	Hydrological process simulation	Meteorological data, DEM, land use type and soil characteristics	Watershed	10-min	Goodarzi et al. 2020
WaterGAP	Water flows, storages, water withdrawals and consumptive uses simulation	Climate data, population data, land cover, soil type, topography, water storage data and water use data	Global	Daily	Turner et al. 2017
The PCRaster GLOBal Water Balance model (PCR-GLOBWB)	Hydrological process simulation and water resource assessment	Soil characteristics, land cover, topography, meteorological data	Global	1 day for hydrology and water use, sub-daily time stepping for hydrodynamic river routing	Meng et al. 2020
Finnish Environment Institute's Watershed Simulation and Forecasting System (WSFS)	Hydrological process simulation	Meteorological data, topography, soil characteristics, land use and vegetation	Watershed	Daily	Jaaskelainen et al. 2018
Integrated Catchment Hydrological Model (ICHYMOD)	Rainfall-runoff processes simulation	Meteorological data	Watershed	Hourly	Francois et al. 2018
GR2M+	Streamflow simulation	Meteorological data	Watershed	Monthly	Wagner et al. 2017

Table 2 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Water management) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 60) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
GR4J	Rainfall-runoff processes simulation	Meteorological data	Watershed	Daily	Zhong et al. 2021
Poli-hydro	Hydrological balance and flow routing simulation	Grided meteorological data, DEM and land cover	Watershed	Daily	Bombelli et al. 2021
Coupled routing and excess storage model (CREST)	Land surface, subsurface water fluxes and storages simulation	Meteorological data, DEM, soil characteristics and land cover	Global to regional	Daily	Zhao et al. 2021b
1 K-DHM	Rainfall-runoff processes simulation	Meteorological data and topography	Watershed	10-min	Meema et al. 2021
Modelo de Grandes Bacias (MGB)	Hydrological process simulation	Meteorological data, topography, soil characteristics and land cover	Watershed (generally in South America)	Daily	Almeida et al. 2021
Soil Moisture Accounting Procedure (SMAP)	Rainfall-runoff processes simulation	Meteorological data and drainage area	Watershed	Daily	da Silva et al. 2021
HYMOD	Rainfall-runoff processes simulation	Meteorological data	Watershed	Daily	Chilkoti et al. 2017
Water management					**11 studies (18%)**
Water Evaluation and Planning system (WEAP)	Water resources planning	DEM, demand data, supply data, hydrology, groundwater and reservoirs	Watershed	Monthly	Spalding-Fecher et al. 2017; Sun et al. 2018; Goodarzi et al. 2020; Obahoundje et al. 2021; Shirsat et al. 2021

Table 2 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Water management) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 60) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
The Reservoir System Simulation (HEC-ResSim)	Reservoir operations modelling at one or more reservoirs for a variety of operational goals and constraints	Reservoir properties, control and operational characteristics, river routing properties	Reservoir and cascade series of reservoirs	5-min	Beheshti et al. 2019; Shrestha et al. 2021; Skoulikaris 2021; Wang et al. 2021a
The Information System for Water Allocation Management (SIGA)	Planning and operation simulation of water resources systems	Demands and priorities, river routing properties	Reservoir and cascade series of reservoirs	Monthly	da Silva et al. 2021
Reservoir Evaluation System Perspective Reservoir Model (HEC-ResPRM)	Reservoir management strategies evaluation	Network connectivity, hydrological flows and penalty functions for reservoirs and links	Multi-reservoir river system	Monthly	Abera et al. 2018
Energy					**10 studies (17%)**
Long-Range Energy Alternatives Planning (LEAP)	Energy policy analysis and climate change mitigation assessment	Energy data, climate data, social and economic data	National to regional	Annual	Spalding-Fecher et al. 2017; Sun et al. 2018; Zhou et al. 2019
TIMES_PT	Optimisation of a least-cost energy system to satisfy the demand for energy services and user constraints	Socio-economic data, resource potentials and prices of primary energy supply, policy constraints and energy services	Portugal	5-year	Teotonio et al. 2017
Regional Integration and Planning Assessment (RIPA) tool	Optimisation of mix of generation and transmission	Hydropower generation, shadow prices of constraints for hydropower capacity and energy spill	Regional	Monthly	Yimere and Assefa 2021
The Generation Evaluation System (GENESYS) model	Assessment of the adequacy of power supply	Technology data, cost data, demands and energy data	The Pacific Northwest	Hourly	Turner et al. 2019

Table 2 (continued)

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Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
EnergyPLAN	Operation simulation of energy systems	Technical data, economic data and energy demands	National	Hourly	Jaaskelainen et al. 2018
PRIMES-IEM power system model	Simulation of electricity system	Plant capacities, demands, load, fuel and carbon prices, reserves, networks and market rules	European	Hourly	Carlino et al. 2021
Hydropower simulator nMAG	Hydropower systems simulation	Inflow, production information, operational strategy and power market	Multiple reservoir hydropower systems	Daily	Adera and Alfredsen 2020
Poli-power	Hydropower production optimisation	Stream flows, prices, demand of hydropower and geometry of the reservoir	Multiple reservoir hydropower systems	Daily	Bombelli et al. 2021
Interdisciplinary					**2 studies (3%)**
The coupled Water Balance Model and Thermoelectric Power and Thermal Pollution Model (WBM TP2M)	Power plant operations simulation	hydrologic flows, climate conditions including air temperature and humidity	Power plants	Daily and 3-min river network resolution	Miara et al. 2017
Global Change Assessment Model (GCAM)	Simulation of interactions among various systems between society-earth-climate	Energy resources, technologies and users, agriculture and land use information, greenhouse gas emissions, climate feedback parameters, socioeconomics, policies information	Global	5-year	Graham et al. 2020

Table 2 (continued)

b. Statistical methods

Method	**Main purpose**	**Data required**	**Reference studies**
Hydropower calculation	Calculating hydropower generation	Streamflow, hydraulic head, water density, gravitational acceleration and total plant efficiency	Chilkoti et al. 2017; de Oliveira et al. 2017; Donk et al. 2018; Francois et al. 2018; Khalkhali et al. 2018; Adynkiewicz-Piragas and Miszuk 2020; Jakimavicius et al. 2020; Almeida et al. 2021; Bahati et al. 2021; Jung et al. 2021; Meema et al. 2021; Mutsindikwa et al. 2021; Yimere and Assefa 2021; Qin et al. 2022; Ramião et al. 2023
Blue water footprint calculation	Calculating evaporative water losses per unit of net power generation	Allocating factor for hydropower, evaporation rate, surface area and net power generation	Zhao et al. 2021a
Regression	Attempting to determine the relationship between dependent variable and independent variables and predicting for the future	A series of dependent variables values and independents variables values	da Silva et al. 2021; Suo et al. 2021; Zhao et al. 2021a
Mann–Kendall test	Determining whether a time series has a monotonic upward or downward trend	A series of data with no autocorrelation	da Silva et al. 2021
Two flood series extraction methods: mean annual flood (MAF) and peak over threshold (POT)	Calculating the average maximum streamflow to evaluate the flood magnitude in a selected period and evaluating flood frequency in other comparative periods	A series of streamflow in selected period	Yun et al. 2021

Table 2 (continued)

c. Supervised learning

Algorithm	Purpose in related research	Description	Reference studies
Feedforward Neural Network	Rainfall-runoff process simulation	Each neuron is arranged in layers, and only connected to the neuron in the previous layer. Outputs are received and sent to the next layer, without feedback between layers	Beheshti et al. 2019; Huangpeng et al. 2021; Jung et al. 2021; Rahmati et al. 2021
Backpropagation Neural Networks (BPNN)	Streamflow simulation	BPNN is a multi-layer feedforward neural network trained according to error backpropagation algorithm	Liu et al. 2020
Elman Neural Network (ENN)	Streamflow simulation	ENN is a feedback neural network based on BPNN	Wang et al. 2021a
Multivariate tree boosting	Predicting the interconnected water and electricity demand in the residential sector	It is an extension of gradient tree boosting, which improve prediction accuracy by the meta-algorithm boosting	Obringer et al. 2020

d. Operation optimisation methods

Method	Purpose in related research	Description	Reference studies
Dynamic programming (DP)	Optimising hydropower output	The storage volume of reservoir at each stage is divided into a finite number of points. The global optimum is determined by enumerating all possible combinations of these discrete points	Li et al. 2020
Progressive optimality algorithm (POA)	Calculating operation scheduling under climate change	POA is a variant of DP, dividing the multi-stage decision problem into a sequence of two-stage subproblems to reduce computation burden	Liu et al. 2020
Multiobjective optimisation technique	Estimating current hydropower system operations and future possible evolution under scenarios	Multiobjective optimisation explores alternative hydropower operating strategies, diversely balancing the different operating purposes	Anghileri et al. 2018

Table 2 (continued)

d. Operation optimisation methods

Method	Purpose in related research	Description	Reference studies
Grasshopper Optimisation Algorithm (GOA)	Optimising hydropower generation	GOA is a population-based meta-heuristic optimisation method inspired by grasshopper group behaviour	Rahmati et al. 2021
Particle swarm optimisation (PSO)	Optimising hydropower generation	PSO is inspired by social behaviour of birds and fish. PSO introduces a number of variables called particles that are scattered in search space	Rahmati et al. 2021
Gravitational Search Algorithm (GSA)	Solving long-term hydropower generation problem of cascade hydropower stations	GSA is an evolutionary method based on Newton's gravitational law. In GSA, agents are considered as objects, and the gravitational interaction between them leads to a global movement of all objects towards those with heavier masses, which represents an optimum solution in the search space	Feng et al. 2018
Stochastic Dynamic Programming (SDP)	Optimising the turbine release decision by the human	SDP combines stochastic programming and dynamic programming, explicitly considering stream flow uncertainty in its recursive equation	Turner et al. 2017
Discrete differential dynamic programming (DDDP) combined with the large-scale system decomposed coordinating (LSSDC) method	Hydropower generation prediction for large-scale reservoirs considering climate change and specific reservoir operation processes	DDDP is an improved DP algorithm, alleviating the influence of "cruse of dimensionality" and simplifying the modelling process	Zhong et al. 2020
Nondominated Sorting Genetic Algorithm-II (NSGA-II)	Quantifying the hydropower-ecology trade-offs	NSGA-II is based on the Pareto optimum solution that has several advantages, including high calculation speed, good convergence of solutions, high diversity of solution sets, and adaptability to high-dimensional inputs	Zhong et al. 2021

Table 2 (continued)

d. Operation optimisation methods			
Method	**Purpose in related research**	**Description**	**Reference studies**
Improved dynamic programming (IDP) algorithm	Optimising Reservoir operation	IDP is developed based on the monotonic relationship in the reservoir optimisation and can greatly enhance the computational efficiency as compared to DP algorithm	Zhao et al. 2021b
Genetic Algorithm (GA)	Optimising Reservoir operation	GA is a metaheuristic derived from the principles of natural selection that belongs to the larger class of evolutionary algorithms	Guo et al. 2021
Improved multi-objective cuckoo search algorithm (MoCS)	Optimisation of multi-objective long-term hydropower generation	MoCS is based on the NSGA-II algorithm and the improved cuckoo search algorithm	Feng et al. 2021
Threshold Accepting (TA)	Optimising hydropower generation	TA is a local search algorithm, exploring the search space by affecting the turbine schedule. It avoids staying stuck in a local optimum, while staying efficient	Bonato et al. 2019
An optimisation framework with interval-parameter programming (IPP)	Supporting sustainable development of China's energy system	IPP reflects uncertainty derived from data collection, parameter estimation and policy formulation	Suo et al. 2021

3.3 Water-Energy-Food Nexus Analysis Methods

There are relatively fewer selected studies about evaluating climate change impacts on Water-Energy-Food nexus. In the selected research, 36% of studies (13 of 36) used statistical methods, 78% (28 of 36) used physics-based modelling methods, 36% (13 of 36) used operation optimisation methods, and 6% (2 of 36) used supervised learning. Most studies evaluated climate change impacts on Water-Energy-Food through physics-based modelling, among them most utilised interdisciplinary models with the proportion of 44%. Besides, many studies in Water-Energy-Food utilised operation optimisation method. The catalogue of Water-Energy-Food analytical methods and tools from the selected 36 articles are tabulated and categorised in Table 3.

Studies investigating climate change impacts on Water-Energy-Food nexus can be divided into three categories: (1) simulations of future Water-Energy-Food nexus change under future climate change scenarios, (2) optimal management options for mitigating future climate change impacts, (3) historical attribution or trend analysis of climate change impacts.

For future simulation research, studies generally utilised interdisciplinary models or coupled different models from multiple disciplines. Sridhar et al. (2021) presented an integrated modelling framework combining Variable Infiltration Capacity (VIC) and System Dynamics (SD) model for analysing the impacts of future climate on irrigation, hydropower, and other supply and demand through a feedback loop. Yang et al. (2018) adopted a two-way coupled agent-based model (ABM-SWAT) to evaluate the water availability for irrigation, hydropower generation, and riverine ecosystem health under joint effect of climate change and water infrastructure development.

Operation optimisation research mainly focused on addressing complex contradictions of Water-Energy-Food nexus to find an optimal strategy and aid sustainable development. Optimisation programming was used in this kind of research, sometimes combining physics-based modelling, supervised learning or statistical methods. Yuan et al. (2018) integrated Life Cycle Assessment (LCA) and linear programming to assess the feasibility of bioenergy and consider future circumstances under climate change impacts. Giuliani et al. (2022) combined HBV hydrological model, ANN and evolutionary multi-objective direct policy search method to demonstrate how local dynamics across Water-Energy-Food systems are impacted by climate change mitigation policies.

Research focused on historical trend utilised statistical methods to analyse datasets. Barik et al. (2017) investigated the Water-Energy-Food nexus in India under drought and monsoon rainfall in the last few decades based on GLDAS and GRACE data.

4 Studies for Different Spatial Scales

According to spatial scale of study area, these selected studies were categorised into large scale studies and small to middle scale studies. The research objectives and typical models of each scale and topic of research are summarised in Table 4. The selected studies related to Water-Food and Water-Energy occupy a higher proportion, while research on water-energy-food is relatively less. This is because the research on this topic involves more interdisciplinary science, so related research is not easy to conduct. Besides there were fewer studies of water-energy-food at global and national scales than at regional scales, because the larger the study area, the more complex the water-energy-food nexus is, the access to the required data also becomes more difficult.

Table 3 Catalogue of methods used in the climate change impacts on Water-Energy-Food studies sample set, categorised by Physics-based modelling (a), Statistical methods (b) and Supervised learning (c) and Operation optimisation (d)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 28) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Interdisciplinary					**15 studies (54%)**
System Dynamics (SD) model	Simulation of complex systems	Variables and equations in the systems	The space where the simulation systems located	Second	Berardy and Chester 2017; Hussien et al. 2018; Sušnik et al. 2018; Bakhshianlamouki et al. 2020; Sridhar et al. 2021; Wang et al. 2021b; Wu et al. 2022
TIMES-WEF	Investigation of the climate change impacts and policies on the agricultural system	Land use, energy demand, primary energy supply, techno-economic factors, environmental variables and other policy parameters	Reginal	Annual	Tortorella et al. 2020
WEF Nexus Tool 2.0	Identifying sustainable resource management strategies informed by the water-energy-food nexus	Local characteristic data and scenario components	Regional	Annual	Schull et al. 2020
Irrigation Management System Model (IManSys)	Calculation of irrigation water requirement for any annual or perennial crop	Climate data, soil hydrologic parameters, crop water uptake parameters	Regional	Daily	Cooper et al. 2022

Table 3 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 28) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Food-Energy-Water Calculator (FEWCalc)	Addressing multi-scale, multi-stakeholder food-energy-water problems	Crop characteristic data, irrigation practices, water availability, renewable energy investment, and environmental conditions	Regional	Annual	Phetheet et al. 2021
A systematic approach	Analysing resilience in the security of water-energy-food nexus in areas that present significant climatic variations throughout the year	Water, food and energy demand, possible failures modes including hurricanes, freezing, and drought	Regional	Monthly	Núñez-López et al. 2022
A two-way coupled agent-based model (ABM-SWAT)	Calculating the water availability for irrigated crop production, hydropower generation, and riverine ecosystem health	Meteorological data, DEM, land use type, soil characteristics, agent preference, agent priority, and historical irrigated area	Watershed	Daily	Yang et al. 2018
GCAM	Simulation of interactions among various systems between society-earth-climate	Energy resources, technologies and users, agriculture and land use information, greenhouse gas emissions, climate feedback parameters, socioeconomics, policies information	Global	5-year	Giuliani et al. 2022

Table 3 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 28) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
Integrated Model to Assess the Global Environment (IMAGE)	Simulating the environmental consequences of human activities worldwide	Population, economy, policies, technology, lifestyle, resources, agriculture and land use, energy supply and demand	Global	Annual	de Vos et al. 2021
Hydrology					**9 studies (32%)**
SWAT	Simulation of the quality and quantity of surface and ground water	Meteorological data, DEM, land use type and soil characteristics	Small watershed to river basin-scale	Daily	Schull et al. 2020; Sedighkia and Abdoli 2022
VIC	Simulation of land–atmosphere fluxes, and the land surface process	Meteorological data, elevation band data, land cover information	Global to regional	Daily	Sridhar et al. 2021; Tariku et al. 2021
LPJmL	Simulation of the global terrestrial carbon and water cycle	Spatially explicit time series of climate, human land use, soil properties, and river flow directions	Global	Daily	Siderius et al. 2021; de Vos et al. 2021
HBV	Streamflow simulation	Meteorological data, DEM, land use/cover data	Watershed	Hourly	Giuliani et al. 2022; Teutschbein et al. 2023
Hydro-BID	Streamflow simulation	Climate, land cover and soil properties	Watershed	Daily	Wade et al. 2022
Water management					**8 studies (29%)**

Table 3 (continued)

a. Physical modelling methods. Models are classified into two groups: based on a single discipline (e.g., Hydrology, Energy, and Agriculture) and interdisciplinary. The number of physics-based modelling studies for each discipline and the percentage of total physics-based modelling studies (n = 28) is summarized in bold headings. Many studies used more than one model and there are studies that do not use models; thus, percentages listed by category do not add to 100%

Model name	Main purpose	Data required	Spatial scale	Minimum temporal scale	Reference studies
WEAP	Water resources planning	DEM, demand data, supply data, hydrology, groundwater and reservoirs	Watershed	Monthly	Momblanch et al. 2019; Sridharan et al. 2019; Nasrollahi et al. 2021; Siderius et al. 2021; Bhave et al. 2022; Ghimire et al. 2022; Golfam and Ashofteh 2022; Jander et al. 2023
Agriculture					**2 studies (7%)**
DSSAT	Simulation of crops growth, development and yield	Meteorological data, soil surface and profile information, and detailed crop management	Site	Daily	Lee et al. 2020; Phetheet et al. 2021
Energy					**1 study (4%)**
LEAP	Energy policy analysis and climate change mitigation assessment	Energy data, climate data, social and economic data	National to regional	Annual	Nasrollahi et al. 2021

b. Statistical methods

Method	Main purpose	Data required	Reference studies
Penman–Monteith equation and crop coefficient approach recommended by the FAO/Cropwat	Calculation of crop water requirements and irrigation requirements	Site location, air temperature, humidity, radiation, wind speed, and crop coefficient	Lee et al. 2020; Li et al. 2021; Bhave et al. 2022; Golfam and Ashofteh 2022

Table 3 (continued)

b. Statistical methods

Method	Main purpose	Data required	Reference studies
Water, land and energy footprint analysis	Calculating the volume of water, land and energy required for producing one ton of crops	Irrigation water requirement, the area of fields, the production, energy use for using agricultural machinery in fields, energy use for supplying 1 m^3 of irrigation water, and irrigation water use	Lee et al. 2020
Life Cycle Assessment (LCA)	Assessing the inputs and outputs of raw materials and energy linked to environmental consequences throughout the stages of production, utilization, and disposal	Unit process data, and environmental input–output data	Yuan et al. 2018
Pearson's correlation test	Identifying synergies and trade-offs, here for disentangle the synergies and trade-offs between nexus component indicators	A correlation matrix which shows the level of consistency between pairs of nexus indicators under each global change scenario	Momblanch et al. 2019
Multi-criteria decision analysis (MCDA) approach	Evaluating multiple conflicting criteria in decision making	Policy scenarios, criteria and indicators	Nasrollahi et al. 2021

c. Supervised learning

Algorithm	Purpose in related research	Description	Reference studies
Feedforward Neural Network	Rainfall-runoff process simulation	Each neuron is arranged in layers, and only connected to the neuron in the previous layer. Outputs are received and sent to the next layer, without feedback between layers	Giuliani et al. 2022; Golfam and Ashofteh 2022

Table 3 (continued)

d. Operation optimisation methods

Method	Purpose in related research	Description	Reference studies
Compromise programming (CP)	Optimising allocation of surface water, groundwater and planting structure for crops	CP uses a distance measure to identify the optimal solution	Li et al. 2021
Particle swarm optimisation (PSO)	Optimising energy, irrigation and yield of production	PSO is inspired by social behaviour of birds and fish. PSO introduces a number of variables called particles that are scattered in search space	Sedighkia and Abdoli 2022
Multi-objective programming (MOP)	Optimising the trade-off between water, food, energy, climate change, and land subsystems	MOP is widely used to deal with sustainable management in a coordinated manner	Yue et al. 2021
Stochastic Dual Dynamic Programming (SDDP) algorithm	Optimising the operation of reservoir systems	SDDP is an approximate stochastic optimisation algorithm to analyse multistage, stochastic, decision-making problems	Tariku et al. 2021
Dynamic Bayesian network	Optimising the management of food, energy, and water systems under the effect of climate variability	Dynamic Bayesian network is a specific family of model-based reinforcement learning	Memarzadeh et al. 2019
Linear programming (LP)	Optimising the trade-off between water, food and energy	LP is done with a mathematical model where all the functions in the model are linear functions	Yuan et al. 2018
Evolutionary multiobjective direct policy search method	Solving multi-objective policy design problems for large-scale water systems	It is a reinforcement learning method that combines direct policy search, nonlinear approximation network and multi-objective evolutionary algorithms	Giuliani et al. 2022
Multi-attribute decision-making (MADM) framework	Addressing the water-energy-food security problems	MADM can conduct planning and management under changing circumstances such as climate change	Enayati et al. 2021

Table 4 Summary of research objectives and typical models of selected studies categorised by research scales and themes. The number of each type of study in different scales, total number of each type of study and the percentage is summarised in the column of 'Themes'

Research scale	Themes	Research objectives related to climate change impacts	Typical models used
Global scale	Water-Food (6 of 45, 13%)	• Evaluating possible food and water deficits • Evaluating the effects of climate change on crop and irrigation water requirements • Identifying regions and crops that are most dependent on snowmelt water resources • Assessing future global crop production under a changing climate and expanded surface water irrigation • Optimizing the allocation of future cropland and water withdrawals	GFWS GCWM LPJmL
	Water-Energy (2 of 64, 3%)	• Projecting future global hydropower production under climate change	WaterGAP
	Water-Energy-Food (2 of 36, 6%)	• Quantifying competing water demands between food production, freshwater ecosystems and utilities (energy, industries and households) • Analysing potential trade-offs and related impacts of climate change scenarios • Projecting future water scarcity under climate change	IMAGE GCAM LPJmL
National scale	Water-Food (13 of 45, 29%)	• Assessing climate change impact on water linked parameters (soil moisture, water availability) and crop yields • Evaluating the effects of climate change on crop and irrigation water requirements • Analysing primary driver of future yields under climate change	SWAT IGSM
	Water-Energy (5 of 64, 8%)	• Evaluating climate change impacts on water resources availability and energy parameters (hydropower generation and thermoelectric plants) • Providing optimal schemes for energy system management under climate change • Simulating hydropower availability during drought period and estimating the indirect impacts of a drought in neighboring nations	HBV WBM TIMES
	Water-Energy-Food (5 of 36, 14%)	• Projecting food parameters (e.g., crop production, farm incomes) based on climate and human factors (e.g., crop selection, irrigation practices, water availability, energy input) • Quantifying increased agricultural challenges under climate change • Investigating energy implications of implementing the irrigation master plan • Assessing the present status and historical changing pattern of Water-Energy-Food nexus • Assessing future drought conditions from the aspect of water-energy-food	DSSAT WEAP
Watershed scale Regional scale City scale Reservoir systems scale	Water-Food (23 of 45, 51%)	• Simulating watershed hydrology and crop parameters (crop yield, crop growing period) • Evaluating the effects of climate change on crop and irrigation water requirements • Assessing how the sources of irrigation water supply may shift • Determining optimal crop production strategies	SWAT DSSAT LPJmL VIC-CropSyst

Table 4 (continued)

Research scale	Themes	Research objectives related to climate change impacts	Typical models used
	Water-Energy (55 of 64, 86%)	• Simulating future streamflow/water availability/flood and hydropower generation/electricity parameters • Calculating hydropower system operation scheduling under climate change • Evaluating the impacts of climate change on evaporative water losses of power generation • Assessing the sensitivity of reservoir operation to water resource uncertainty driven by a combination of climate change and upstream cascade dam development • Evaluating impact of energy policies on water resources management under climate change • Identifying power shortfall risk under compound climate change impacts on hydropower	ANN VIC SWAT HBV WEAP LEAP HEC-Ressim HEC-HMS Xinanjiang model
	Water-Energy-Food (28 of 36, 78%)	• Simulating changes in water, energy, food (e.g., yield change and irrigation requirements) under climate change scenarios • Ensuring water, energy, and food security • Analysing the supply–demand scenarios and trade-offs between water, food and energy • Addressing issues of water management through a nexus lens • Assessing the impacts of proposed lake restoration measures and climate change to lake level • Obtaining optimal allocation schemes of Water-Energy-Food (planting structure, irrigation water, hydropower production, energy use) under climate change • Understanding the main source of climate risk to development plans across the water, energy, and food sectors • Evaluating how the system failures caused by hurricanes, low-temperature events, and droughts affect the supply of water, energy and food • Investigating potential plausible cross-nexus implications and synergies on Water-Energy-Food due to policy interventions • Calculating the water availability for irrigated crop production, hydropower generation, and riverine ecosystem health • Analysing appropriate bioenergy production rates under climate change • Evaluating impacts of hydrologic extremes on the reservoir operations during flood and low flow events • Assessing the impact of seasonal variability on water, energy and food	SWAT VIC HBV ANN WEAP LEAP TIMES LPJmL ABM SD model WEF Nexus Tool 2.0
Site scale Reservoir/Dam/Plant scale Household scale	Water-Food (3 of 45, 7%)	• Investigating crop yield, irrigation water requirement and other parameters linked to irrigation in response to future climate change	ORYAZ
	Water-Energy (2 of 64, 3%)	• Simulating future streamflow/water availability and hydropower generation • optimizing hydropower multi-reservoir systems • Quantifying the effect of changes in price and water seasonality on future revenue distribution and its related uncertainty in run-of-the-river plant	ANN
	Water-Energy-Food (1 of 36, 3%)	• Assessing the impact of seasonal variability on water, energy and food	SD model

Water-Energy-Food studies at the global scale focused on the competition for water between energy and food. The interlinkages between water, energy and food sectors were explored more in small to middle scale studies. Meanwhile, there were many more optimisations and policy scenarios in research at the regional scale. The Water-Energy research at large scale mainly focused on the impacts of river flow on potential hydropower production, while the optimisation of hydropower system operation is also concerned at small-middle scale research. The focuses of Water-Food research at large and small-middle scale were similar, mainly investigating the water management and crop production strategies. Local water, energy and food management strategies may not be applicable to other regions, so the trade-off between water, energy and food under climate change and the strategies for sustainable development at a larger scale still require continuous efforts from the academic community.

The findings on the global scale may inform future research at different scales. For Water-Energy research, roughly 65% of the world's current hydropower capacity will face vulnerabilities due to alterations in the 1-in-100-year river flow pattern (Paltán et al. 2021), the most prominent encompassing Europe, northern Africa, the Middle East, and North America (Turner et al. 2017; Paltán et al. 2021). Pursuing a 1.5 °C warming target would mitigate these risks when contrasted with a 2.0 °C scenario (Paltán et al. 2021). For Water-Food research, a projected food deficit might occur prior to 2050 in the scenario of the worst-case climate change, significant water shortages stemming from irrigation in major food-producing nations will hinder these countries from satisfying their domestic food needs (Grafton et al. 2017). An expansion of irrigated land by 100 Mha would be necessary to double food production to meet the projected global food demands by 2050, and an additional 10% to 20% of trade flow will be required, directing water-abundant regions toward water-scarce regions, to maintain environmental flow requirements (Pastor et al. 2019). Expanding irrigation will lead to increased maize production in Europe, but the same cannot be said for rice production in East Asia (Okada et al. 2018). In a scenario of 3 °C warming, a "soft-path" approach with small water storage and deficit irrigation can extend irrigated land by 70 Mha and feed additional 300 million people worldwide, a "hard-path" with substantial annual water storage has the potential to expand irrigation up to 350 Mha and feed 1.4 billion more people (Rosa et al. 2020). The regions that heavily rely on snowmelt as an agricultural water resource are high-mountain regions like the Tibetan Plateau, Central Asia, western Russia, the western United States, and the southern Andes (Qin et al. 2020b). For Water-Energy-Food research, water scarcity reductions driven by human is likely to result in 44% of land area in the world by the end of twenty-first century in certain socioeconomic scenarios (Graham et al. 2020). An additional 1.7 billion people could potentially experience severe water shortages for electricity, industrial use, and household needs if priority becomes for food production and maintaining environmental flow (de Vos et al. 2021).

4.1 Models for Medium to Small Spatial Scale

Watershed hydrological models can be categorised into three types: (1) conceptual models, (2) physics-based models, and (3) data driven models. Conceptual hydrological models are based on physical basis but are in highly simplified forms, they also have the characteristics of statistical regression models (e.g., HBV and Xinanjiang model). The biggest limitation is that they treat the watershed as a whole, ignoring the heterogeneity of spatially distributed watershed characteristic parameters (Devia et al. 2015). Physics-based models adopt spatially varied parameters to reflect the physical mechanism of hydrological process influenced by multiple factors (e.g., SWAT and HEC-HMS). The data-driven models establish statistical relationships between input and output. They work well at the data range, but the simulation performance degrades when applied to epitaxial projection because of the lack of physical basis. Over the past decade, a cutting-edge machine learning methodology, named deep learning, has evolved from the traditional neural network and has outperformed traditional models with considerable improvement in performance (Yuan et al. 2020). However, deep learning cannot completely replace the physics-based models, and the combination of physics-based models and deep learning may open a promising door (Yuan et al. 2020).

Water management models aim to optimise water allocation to fulfil the demands from multiple sectors. Many selected studies established optimisation frameworks for planning and management of water resources. There were some studies employing existing water management models directly, among which WEAP and HEC-ResSim were most used. Crop models are used to simulate crop growth, DSSAT and CropSyst are typical and most common used crop models in selected studies. TIMES and LEAP were relatively frequently employed in investigating climate change impacts on water and energy. Interdisciplinary models like ABM, SD model and WEF Nexus Tool 2.0 were utilised in the Water-Energy-Food nexus studies.

4.2 Models for Large Spatial Scale

Global hydrological models consider more land surface processes like recycling of evapotranspiration. The approach integrates knowledge from multiple disciplines encompassing atmospheric sciences, geography, ecology, oceanography, soil science, global change science, etc. All global hydrological models run in a grid format (Sood and Smakhtin 2015). Typical global-scale hydrological models used in selected studies include WBM, VIC, WaterGAP and LPJmL. Different models have different emphases and characteristics. For example, WaterGAP model is more detailed in water demand simulation including water use for domestic, industry, thermal power production, livestock and irrigation (Döll et al. 2003). LPJmL model puts more emphasis on vegetation and crop simulations (Bondeau et al. 2007). High degree of uncertainty and rough resolution are main limitations of global hydrological models (Sood and Smakhtin 2015).

In selected global-scale studies investigating climate change impacts on Water-Food, GCWM and GFWS were utilised. GCWM mainly focuses on blue and green consumptive water use as well as virtual water of 23 specific crops (Siebert and Döll 2010). GFWS puts more attention on global food and irrigated water availability risks through simulation of food generation and demand, water supply and agricultural water requirement (Grafton et al. 2015).

Integrated Assessment Models (IAMs) are important tools to evaluate human feedback and impacts on climate change and mitigation of greenhouse gases (Schwanitz 2013). The IGSM framework consists primarily of two interacting components (Sokolov et al. 2018): the Economic Projection and Policy Analysis model and the Earth System model. GCAM links water, energy, landuse, earth systems and economics to analyse consequences of policy strategies and interdependencies. IMAGE simulates interactions between biosphere, society and the climate system to assess environmental and sustainable development issues. Delimitation of the system, explanatory power of models, as well as linkage of model evaluation and usefulness are the main challenges for IAMs (Schwanitz 2013).

5 Future Climate Scenarios Setting Methods

Most selected research assessed and projected future water, energy and food systems based on future climate change models. The emission scenarios, climate models, downscaling methods and global warming scenarios in selected articles are summarised and introduced below.

5.1 Emissions Scenarios

For climate change impacts assessment, the Intergovernmental Panel on Climate Change (IPCC) has published Assessment Reports (AR) on climate change based on greenhouse gas emissions scenarios. Future climate projections in the IPCC Fourth Assessment Report (AR4, IPCC 2007) were based on Special Report on Emissions Scenarios (SRES, IPCC 2000) and simulations of the third phase of the Coupled Model Intercomparison Project (CMIP3, Meehl et al. 2005). SRES was superseded by Representative Concentration Pathways (RCPs) in the IPCC fifth assessment report (AR5, IPCC 2014) based on the CMIP5 (Taylor et al. 2012).

The IPCC Sixth Assessment Report (AR6, IPCC 2021) assessed the future climate outcomes based on the combination of socio-economic (SSP1-SSP5) and future radiative forcing scenarios (1.9 to 8.5 W/m^2), which called Shared Socioeconomic Pathways (SSPs). The latest SSPs can quantitatively describe the relationship between socioeconomic development and global climate change to reflect the climate change challenges that society will face in the future (Eyring et al. 2016). Basically, some older studies (generally in 2017 and 2018) used SRES of CIMIP3 models. Most selected studies utilised RCPs of CMIP5 models. Some post-2020 studies were starting to use SSPs from CMIP6.

5.2 Climate Models and Downscaling Methods

Global climate model (GCM) is capable and useful for projecting future climate (Overland et al. 2011). Many research institutions have developed GCMs based on their own experiment assumptions and mathematical representations of physical climate system.

Studies at global scale in this review inputted GCMs directly into global models to project climate change impacts (Turner et al. 2017; Pastor et al. 2019). However, GCMs are generally insufficient to provide useful climate predictions on the local to regional scales because of relatively coarse resolution and significant uncertainties in the modelling process (Allen and Ingram 2002; Dibike and Coulibaly 2005). When the climate change impacts studies are carried out at local and regional scales, downscaling methods have been developed to overcome the mismatch of spatial resolution between GCMs and models (Hwang and Graham 2013).

Downscaling techniques are categorised by two approaches (Hwang and Graham 2013):

1. Statistical downscaling using the empirical relationship between GCMs simulated features at the grid scale and surface observations at the sub-grid scale. For example, Bias-Correction Spatial Disaggregation (BCSD, e.g., Zhao et al. 2022) and the Statistical Downscaling Model (SDSM, e.g., Goodarzi et al. 2020) were employed to downscale GCMs in the selected studies.
2. Dynamic downscaling using regional climate models (RCMs) based on physical relations between the climate parameters at large and smaller scale.

Most selected articles using dynamic downscaling method generally applied results from the Coordinated Regional Climate Downscaling Experiment (CORDEX). CORDEX was to create an enhanced modelling framework for generating climate projections at regional scales, enabling impact assessments and adaptation studies globally within the IPCC AR5 (Giorgi et al. 2022).

5.3 Global Warming Scenarios

The Paris Agreement (UNFCCC 2015) aims to keep global mean surface air temperature increasing below 2℃ relatives to pre-industrial levels and targets to limit it to 1.5℃. Some articles simulated future Water-Food or Water-Energy under global warming 1.5℃, 2℃, 3℃ or 4℃ (Donk et al. 2018; Sylla et al. 2018; Meng et al. 2020; Qin et al. 2020b; Rosa et al. 2020; Zhao et al. 2021b). These studies utilised two approaches (James et al. 2017) to assess the regional implications of different degrees of warming: (1) time sampling; (2) pattern scaling.

In time sampling approach, the global warming scenarios are derived by extracting a period of time (usually 30 years) when the driving climate model projects an increase of specified degrees (e.g., 1.5℃ and 2℃) of warming compared to the pre-industrial level (Sylla et al. 2018).

Pattern scaling assumes the relationship between global mean temperature and local change is linear (Huntingford and Cox 2000; Mitchell 2003; James et al. 2017). These patterns can scale changes in global mean annual temperature to local and seasonal changes for climate variables by linear regressions (Qin et al. 2020b).

6 Directions of Future Research and Prospects

Future challenges in climate change and nexus research are identified from five aspects: (1) scale and resolution of study area; (2) internal physical mechanism; (3) extreme climate events; (4) potential competition between sectors; (5) data and model uncertainty.

6.1 Scale and Resolution of Study Area

Most selected studies related to climate change impacts on Water-Food generally focused on watershed, regional and national scale, the analyses not only focused on temporal differences but also spatial difference according to different geographical resolution. In contrast, studies investigating climate change impacts on Water-Energy mainly analysed hydropower, therefore, results were generally shown within hydropower plants, dams and reservoirs without spatial difference. Evaluation studies of climate change impacts on Water-Energy-Food nexus mainly focused on basin and regional scale, the analysis put water, energy, and food into a whole system, but the spatial resolution was often ignored.

It is of great significance for local sustainability management and decision-making to study climate change impacts on Water-Energy-Food on basin and regional scale, but the results may be limited by the boundaries of the study area. For example, the simulated streamflow at the outlet of the study basin is not necessarily the amount of water available in the basin because the water demands in the downstream regions should be considered. The absence of water, energy and food scheduling with other regions may have effects on inaccurate supply and demand simulations, further resulting in inaccurate management strategies. The water transport routes of water resources are sometimes cross-watershed. For example, reservoirs or weirs provide for agriculture, industry, or domestic use through their own pipeline systems. With the impact of climate change, economic globalization and other strong human activities, local Water-Energy-Food nexus is bound to be influenced by global hydrological cycle and non-local human activities. It requires scholars to understand local nexus relationships from a large-scale perspective.

Meanwhile, considering climate change has obvious spatial differences, and the response speed of different regions to climate change is also different, the climate change impacts study on Water-Energy-Food nexus with geographical resolution can show spatial difference of water, energy, food change due to climate change and provide a better reference for sustainability management.

6.2 Internal Physical Mechanisms in Modelling

Most of the studies about evaluating climate change impacts on Water-Food and Water-Energy considered hydrological processes based on physical mechanisms. Research on Water-Energy-Food and climate change impacts consisted of interdisciplinary and transdisciplinary analysis, while the complexity of the system leads to the simplification of many physical mechanisms. Many mathematical or data-driven models were used for investigating climate change impacts on Water-Energy-Food, but the lack of internal physical mechanisms cannot well explain the interactive process between water, energy and food to climate change.

Future research needs to understand the interlinkages and internal physical mechanisms of the nexus sectors and climate change. Meanwhile, science and policy should be integrated to reveal the dynamics of natural processes along with social processes.

6.3 Novel Artificial Intelligence Models

Many selected studies employed Artificial Intelligence (AI) in simulation and operation optimisation. Feedforward and feedback neural networks were used for simulation. Most selected studies used programming and meta-heuristic algorithms, and a small number used reinforcement learning for operation optimisation. In recent years, with the rapid development of AI, many novel AI models have been proposed repeatedly. These AI models will provide a feasible direction for these complex interdisciplinary sciences. For example, deep reinforcement learning (DRL) was developed by combining traditional reinforcement learning with deep learning, and it is capable of handling high-dimensional states and actions (Mnih et al. 2015). DRL has been applied for optimal hydropower reservoir operation (Xu et al. 2020), irrigation optimisation (Alibabaei et al. 2022) and water-energy-food nexus security assessment (Raya-Tapia et al. 2023). The application of DRL on complex water-energy-food system under climate change is still to be investigated.

6.4 Extreme Climate Events

Most projections of future nexus were generally based on temporal continuous climate change scenarios, only few reviewed studies have considered extreme weather events.

Climate change will increase the intensity, frequency and spatial extent of extreme climate events (Hasegawa et al. 2021) and compound hazards (Zscheischler et al. 2018). More frequent and extreme events will cause disruptions in the management of water, energy, and food (Núñez-López et al. 2022). For example, relative to moderate-level climate change, an additional 20–36% population may face hunger under a 1-in-100 yr extreme climate event under RCP8.5 (Hasegawa et al. 2021). Compound hazards will cause devastating impacts at a scale far beyond any single disaster in isolation (Zscheischler et al. 2018). For example, increasing compound drought–heatwave risks may affect 90% of the global population and gross domestic product in the future (Yin et al. 2023). Considering the water, energy and food relationship under extreme climate events in any future studies has an important role in developing strategies to ensure water, energy and food security.

6.5 Potential Competition Between Sectors

Previous studies related to climate change impacts on Water-Food and Water-Energy did not consider competition between subsystems because there was no/limited competition between two sectors in early days. When considering three sectors together, competition arises. Competition for water between food and energy sectors is an important part of the Water-Energy-Food nexus (Qin 2021). The competitive relationship is not conducive to the sustainable development. For example, the average total production water footprint in 31 provinces of the Chinese Mainland in the Industry Competition Unsustainability scenario reached 4.08 m^3/kg in 2016 (Hua et al. 2022). Considering the economic and social situation, energy production is more profitable than food, so water flows easily into the energy sector. Especially in the context of climate change, water availability is greatly affected. How to ensure food and energy security within limited water resources context should be considered in any future studies.

6.6 Data and Model Uncertainty

In the evaluation of climate change impacts on Water-Energy-Food, numerous data from multiple disciplines including meteorology, agriculture, environment, hydrology, economics, society are needed. The use of different data sets, mismatch of data resolution, the varying quality and availability of data (Perrone et al. 2011), and assumptions and simplifications introduced to deal with data scarcity could lead to very different results. High uncertainty may be caused to exert negative impacts on the nexus analysis and even misrepresent the interactions among nexus sectors (Zhang et al. 2018). What is more, models and analysis tools also introduce uncertainty. Downscaling of future meteorological data, numerous parameters in modelling, limited understanding of nexus processes, the intrinsic indeterminism of complex dynamic systems, and myriad future scenarios will bring uncertainty into final results, making it difficult to identify an optimal policy choice (Gallopín et al. 2001; Antón et al. 2013; Yung et al. 2019).

Endeavours should be made in future studies to identify, analyse and reduce uncertainty in data use and modelling for nexus research to increase the reliability of projection results and build capacity for decision-making in the context of uncertainty.

7 Conclusions

This paper provides a systematic review on the analytical approaches in the evaluation of climate change impacts on Water-Food, Water-Energy and Water-Energy-Food. The key findings are summarised as below:

1. Analytical methodologies used in selected research can be classified into four categories: Statistical methods, Physics-based modelling, Supervised learning and Operation optimisation. Catalogues of methods used in the evaluation of climate change impacts on Water-Food, Water-Energy and Water-Energy-Food are listed respectively based on the classification (see Tables 1, 2 and 3). Such catalogues are helpful to clearly show popular and promising methods in selected studies.
2. The focus of research on different topics at different scales are discussed. Large scale and medium-small scale models are introduced in terms of their characteristics, limitations, providing references for selection of models and issues to consider when using the models. Some models are applicable for different scales but there is no single model suitable for all scales. The classification and discussion of topics and models is helpful to provide guidance on appropriate model selection by considering research scales, objectives and themes (Water-Food, Water-Energy and Water-Energy-Food).
3. Future climate scenarios setting including emission scenarios, climate models, downscaling methods and global warming scenarios are summarised. Climate scenarios are important for simulating interactions between water, energy and food under various future climate change conditions, as well as exploring the effectiveness of mitigation measures or policies. The study has provided references for the setting of climate scenarios and processing of future meteorological data in future research.
4. Despite significant efforts were made in investigating climate change impacts on Water-Energy-Food, limitations of current research still exist, and the challenges for future study are discussed. Current studies do not adequately address the uncertainties generated by data and models. Research about extreme climate events and potential competition in nexus systems is not sufficient. Efforts can be made in the internal physical mechanisms analysis, application of novel artificial intelligence models and spatial differences analysis of nexus issues.

Acknowledgements The study was supported by the China Scholarship Council scholarship.

Authors Contributions Danyang Gao: Conceptualization, Methodology, Writing – original draft & revise. Albert S. Chen: Supervision – review & editing. Fayyaz Ali Memon: Supervision – review & editing.

Data Availability The data sources are listed in the 'Selected articles' in References, some articles are not cited in the manuscript but are selected for review (Carvajal et al. 2017; Solaun and Cerda 2017; Yin et al. 2017; Bieber et al. 2018; Gaudard et al. 2018; Hasan and Wyseure 2018; Gohar et al. 2019; Ortiz-Bobea 2019; Rigden et al. 2020; Beltran-Peña and D'Odorico 2022; Kumar et al. 2023).

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish The authors have approved manuscript submission.

Competing Interests The authors declare that they have no competing interests.

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