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Climate change impacts on crop yields: A review of empirical findings, statistical crop models, and machine learning methods

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ABSTRACT

Understanding crop responses to climate change is crucial for ensuring food security. Here, we reviewed ∼230 statistical crop modeling studies for major crops and summarized recent progress in estimating climate change impacts on crop yields. Evidence was strong that increasing temperatures reduce crop yields. A 1 °C warming decreased the yields by 7.5 ± 5.3% (maize), 6.0 ± 3.3% (wheat), 6.8 ± 5.9% (soybean), and 1.2 ±5.2% (rice) across the world, but spatial heterogeneity was noticeable, due partly to asymmetric nonlinear crop responses to temperature (e.g., warming-induced gains in cold regions). Yield responses to precipitation were not consistent across the studies or geographical areas. On average, climate explained 37% of yield variability. We also observed a methodological shift from linear regression to machine learning (e.g., explainable AI and interpretable machine learning), which on average reduced predictve errors by 44%. Furthermore, we discussed the opportunities and challenges facing statistical crop modeling, such as ensemble modeling, physics-informed machine learning, spatiotemporal heterogeneity in crop responses, climate extremes, extrapolation under novel climates, and the confounding from technology, management, CO_2, and O_3.

1. Introduction

Global demand for food has been on the rise, driven by a growing population, rapid urbanization, and changing diet preferences. To keep pace with the future demand, global agricultural productivity needs to grow at an annual rate of at least 1.75% (Global Harvest Initiative, 2017). However, attaining this rate faces challenges from future climate conditions, which are expected to be warmer with more frequent extreme weather events. The novel climate increases variability and vulnerability in crop yields, threatening food security (Ray et al., 2015; Najafi Ehsan et al., 2018). To mitigate and adapt to future climate, extensive research efforts have been conducted to enhance our understanding of how climate changes affect crop yields and to improve characterizing yield-climate relationships.

Scientific methods for investigating crop yield responses to climate change fall roughly into three categories: field experiments, process-based modeling, and statistical modeling. Field experiments directly observe the effects of interest. Process-based modeling leverages the first principles from multiple disciplines such as biophysics, plant sciences, and agronomy to build computer models and simulate crop growth. Statistical modeling explores historical observations to find correlative relationships between crop yield and climate. Of the three, field experiments are limited in spatial footprints and often constrained by logistic costs; process-based modeling has fewer constraints, finding wide use under both real and hypothetical climate scenarios across scales (Challinor et al., 2009). There are several reviews focused on progress and challenges in using process-based models to estimate climate change impacts on crop yields (Kang et al., 2009; White et al., 2011; Hansen

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et al., 2006; Challinor et al., 2009). The focus of this review is on statistical modeling.

Statistical models have long been applied to infer crop-climate relationships, dating back to more than a century ago (Blair, 1919). Their applications recently have seen a rapid surge, driven primarily by the rising concerns over climate change and the concomitant need to assess climate impacts on agriculture. The popularity was also fueled by the growing availability of data analyticsand statistical tools. On one hand, historical climate and agricultural records have been made more accessible via the internet; on the other hand, new data are being constantly generated with the accelerated use of sensor networks and commercial technologies. The past decades also witnessed substantive advances in data analytics. Earlier studies relied mostly on linear regression to relate crop yields to climate. Now, the trend is shifting to favor machine learning or artificial intelligence (AI), such as support vector machines, neural networks, random forests, XGBoost, and deep learning (Crane-Droesch, 2018; Lobell, 2017; Roberts et al., 2017; Ciscar et al., 2018; Hu et al., 2023). Machine learning models are capable of unraveling complex and nonlinear crop-climate relationships. Compared to classical regression, they demonstrated superior predictive performances but had lower interpretability—a drawback being addressed by new waves of machine learning research on explainable AI (Hu et al., 2023). The body of recent literature on statistical or AI-based crop modeling for climate change assessments has been increasing exponentially, but a comprehensive review of recent progress is lacking.

Here, we reviewed recent studies and advances in statistical crop modeling, with attention to both empirical findings and modeling techniques used. We summarized common practices, strengths, limitations, and issues in applying classical regression models or machine learning for insights into crop yield responses to climate changes. We also identified ~230 case studies conducted across the globe in the past two decades (details in Section 3) and synthesized the empirical findings for four major staple crops—maize, soybean, wheat, and rice—concerning their responses to temperature and precipitation (Section 4). In what follows, we first provided an overview of statistical modeling as contrasted to field experiments and process-based modeling. We then synthesized the results from the case studies in terms of study regions, crop types, model techniques, and empirical findings. As a path forward, we identified the existing challenges and future opportunities in the use of statistical modeling to understand complex relationships between climate factors and crop yields.

2. Overview

Statistical models come in a myriad of forms. The nomenclature pertinent to statistical crop modeling is not consistent in the literature. To clarify, here we consider the many terms–statistical models, empirical models, regression models, machine learning, artificial intelligence models (AI), data-driven models, data analytics, and data mining–roughly synonymous, although machine learning is not always statistical models. One reason for the inconsistent terminology is the sheer diversity of data analysis tools available. These models, for example, can be inferential or heuristic, probabilistic or deterministic, parametric or non-parametric, linear or nonlinear, frequentist-based or Bayesian, and black-box or explainable. Another reason is that the endeavors to characterize crop-climate relationships have been pursued by researchers with different domain backgrounds (e.g., geography, environmental sciences, agronomy, biological engineering, ecology, economics, and climate sciences). Irrespective of their technical specifics, these models are broadly understood as any analytical or numerical procedures to uncover an empirical relationship between crop yield and climate variables from observations, which is in stark contrast to the other two research paradigms—field experiments and process-based modeling.

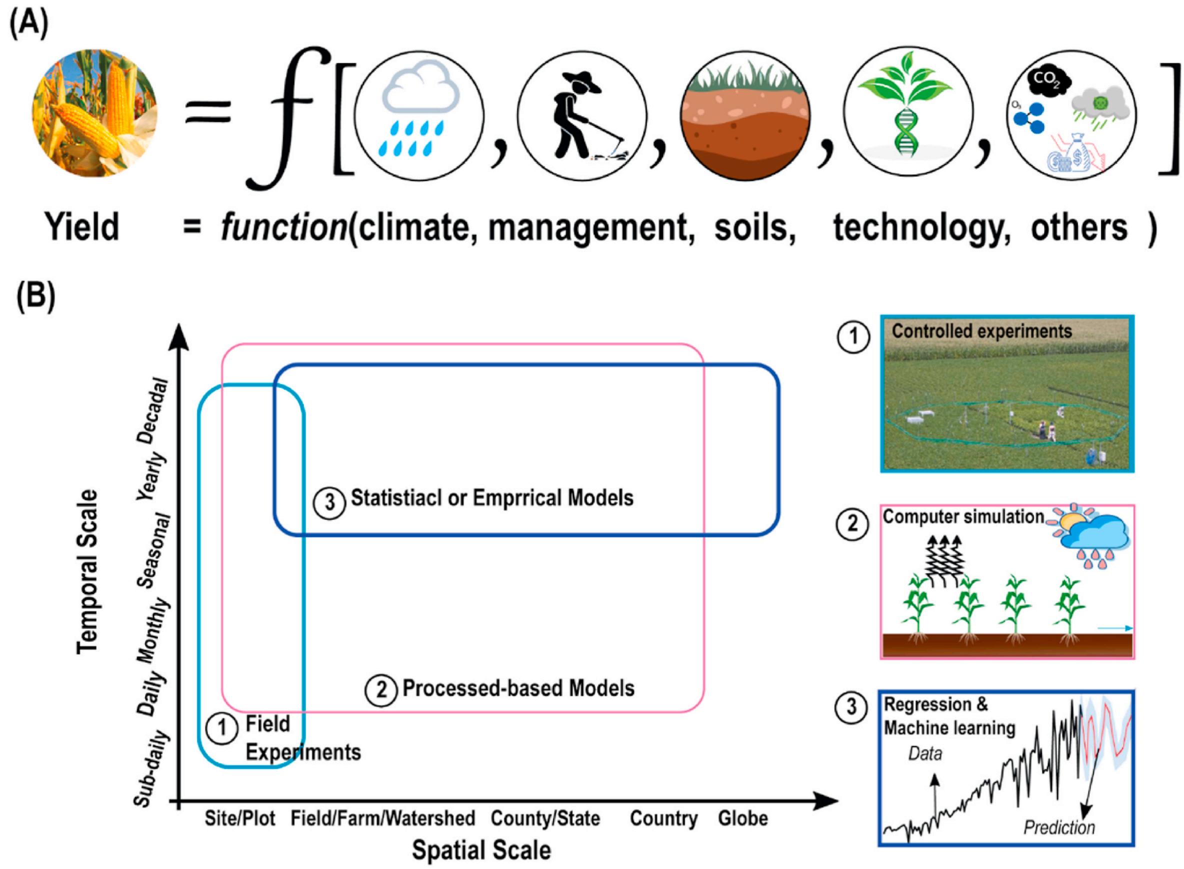
2.1. Field experiments, process-based models, and statistical models: Not rivals but allies

Of the three major approaches —field experiments, process-based modeling, and statistical modeling, field experiments provide direct observations and generate the most realistic insights into the impacts of climate change (Ainsworth et al., 2008). Field-based methods involve manipulating climate and environmental variables, such as elevated CO_2, increased temperature, enhanced precipitation, and augmented nitrogen deposition, within controlled systems or sites. The experiments can focus on one or multiple climate factors (e.g., the Giessence Free-Air Carbon Dioxide Enrichment Study and the Jasper Ridge Global Change Experiment) (Obermeier et al., 2017). Despite their self-evident strengths, they are laborious, time-consuming, and resource intensive. Additionally, their physical footprints (e.g., number of sites) are often limited, making it difficult to generalize findings to other geographic regions.

In contrast, models—either process-based or statistical—treat crop yields as a function of various drivers (Fig. 1a), including climate, agricultural management, soil properties (e.g., soil quality and water content), and technological innovations (e.g., new cultivars). The two types of models operate differently. By statistical models, we mean those purely data-driven or empirical models with no explicit representation of physical processes. Statistical models prioritize the impacts of climate and strive to isolate its effects from other influencing factors. They often rely on historical data to capture the empirical relationship between climate variables and crop yields. By process-based models, we mean those involving first-principled equations to describe biophysical or biogeochemical processes for crop growth. Process-based models are characterized by complex functional forms, involving numerous equations and parameterizations borrowed from multiple disciplines (e.g., soil science, plant physiology, and hydrology). They are developed based on mechanistic biophysical and biochemical processes that govern crop growth, such as soil water transport and photosynthesis. Statistical models take simpler forms, often without explicitly representing physical processes. Regardless of their differences, both process-based and statistical crop models have important roles to play in the latest iteration of farming and agricultural practices known collectievely as Agriculture 5.0, with its hallmark being the adoption of modern digitial technologies such as AI and big data analytics.

Of the two modeling approaches, process-based models require extensive data inputs and parameters, such as soil properties and management practices, which may not be readily available. Statistical models are less resource-intensive and easier to apply, typically providing rapid estimates of the yield-climate relationships. Given the relative ease with statistical models and the wide availability of historical climate and crop yield data, statistical modeling has been applied to a wide range of crops across many parts of the world, even for those crops (e.g., millet) that lack explicit physiological or mechanistic models (Knox et al., 2012; Lobell, 2017). Comparative studies have demonstrated that results from statistical and process-based models are generally consistent (Blanc, 2017; Liu et al., 2016; Lobell, 2017) if done carefully. In addition, given the complexity of process-based models, realistic uncertainty analysis remains challenging, but uncertainties in model parameters and structures are often straightforward to estimate using standard statistical techniques (Lobell, 2013).

The distinction among the three approaches is not always dichotomous. Rather, they complement each other (Shahhosseini et al., 2021; Eini et al., 2023). For example, process-based crop growth models are sometimes considered as a core part of a digital twin of physical systems (NASEM, 2024). When phenomena are unobservable or direct measurements are impractical, models come to the rescue. The models in the digital twin enable scientists and decision-makers to replicate real-world agroecosystems, simulate complex processes, address numerous factors simultaneously, and gain insights for large-scale applications. Development of such process-based models relies heavily on knowledge



Approach	Field Experiment	Process-based Models	Statistical & Empirical Models
Strength	Direct observation of causual effects for true mechanstic understanding	Inclusion of mechanstic insights; simulation for many real or hypothetical scenarios	Easy implementation; statistical inference; levaraging diverse datasets; global analysis possible
Weakness	Expensive to conduct; Limited in sample size and spatial extent; Less useful for projecting future yields' Not straightforward to scale up findings;	Hard to implement, calibrate, & validate; in-depth skills required of users; tedious data preparation; lack of quality data; Complicated structure with numerous parameters; oversimpifed parameterization	Correlative in nature; trickly to seek mechanstic insights; garbage in, garbage out; results sensitive to model choices; Large uncertainty in extrapolation; violaton of model assumptions

Fig. 1. (a) Crop yield as a function of multiple drivers. (b) Characteristics of three common approaches–field experiments, process-based, and empirical modeling–for evaluating climatic impacts on crop yield. These approaches are applied typically at contrasting spatial and temporal scales (i.e., colored boxes in the temporal-spatial scale plot).

gained from field experiments, with many equations directly parameterized from field data: If not informed collectively by field experiments of all kinds, the implementation of process-based models for the digital twin is unlikely successful.

Speaking differently, the three approaches are not rivals but allies (Zhang et al., 2023). Their niches of applications differ in temporal and spatial scales. Their combined use leverages independent data and knowledge to provide a more comprehensive understanding of crop growth processes. The independent insights from the alternative approaches can inform each other. When there is a lack of mechanistic understanding, empirical relationships from field data or historical data are often incorporated into process-based models (Zhang et al., 2008). These empirical components greatly enhance the applicability of process-based models beyond the geographic areas or scenarios wherein the original empirical relationships were fitted (Schlenker and Roberts, 2009). As another example, with the latest development of machine learning and statistical modeling, a hybrid modeling paradigm arises to explicitly combine the relative strengths of process-based and statistical modeling—a class of approaches sometimes called physics-informed machine learning or explainable artificial intelligence (Hu et al., 2023).

2.2. The nature of statistical crop modeling: To predict or to explain?

The use of statistical/empirical models is ubiquitous in all scientific disciplines, but their purposes differ subtly. The primary goal of statistical crop modeling is not hypothesis testing (Long et al., 2006; Lobell et al., 2011). We know from first-principled knowledge that climate matters to crops; therefore, the modeling purpose here is not to test a contrived scientific hypothesis about whether a climate factor affects crop growth or whether there are statistically significant correlation between crop yield and climate. (No statistically significant correlation between rainfall and yields doesn't mean that rainfall doesn't matter to crops.) Rather, the purpose is to derive empirical relationships between climate and crop yields and apply them to quantify to what degree climate affects crop yields.

More formally, there are two major roles of statistical crop models: To explain or to predict (Fig. 2). The two roles are subtly different. To predict, the interest lies in leveraging a fitted statistical model to estimate crop yields under certain climate conditions, especially under novel climates in the future (Blanc, 2017; Liu et al., 2016; Lobell, 2017). To explain, the interest is in deriving a statistical model that is close to the theoretically unknown true relationship. Predictive power doesn't equal explanatory power(Zhao et al., 2013). A deep neural network model can incorporate thousands of covariates to predict crop yields with impressive accuracies, but the fitted relationships often remain opaque and even wrong (van Klompenburg et al., 2020; Hu et al., 2023). In the crop modeling literature, the distinction between predictive and explanatory models are not always articulated, but the difference is apparent (Lobell and Burney, 2021; Shook et al., 2021): When using machine learning to estimate crop yields in the future, modelers emphasize predictive power; when using linear models to examine the temperature effect on crop yields, modelers emphasize explainability. Ignoring the distinction or confusing one with another is detrimental (Molnar et al., 2020; Zhang et al., 2022).

The differences between explaining and predicting can also be understood in terms of the correlative nature of statistical models. Statistical crop models seek to fit relationships to correlate variabilities in crop yields with those in climate covariates. Given that both crop yields and climate data exhibit temporal and spatial variations, the variability may arise from one year to another at the same location, as well as from heterogeneity among different sites within the same time period, or even from both temporal and spatial sources, which often determines whether time-series regression model or panel regression model are used (Lobell and Burke, 2010). When predicting, the goal is to maximize the percentage of observed spatial and/or temporal variabilities in crop yields that can be explained away by the variability in climate. Therefore, the larger the percentage of variability explained, the better the predictive power. When explaining, the goal is not purely about higher correlation or lower mean squared errors but more about understanding the origin and mechanisms driving the observed variability in crop yields, which is more of a model selection problem. Often enough, machine learning-based crop models (e.g., black-box models) have better predictive accuracies but for wrong reasons: Their derived functional relationships are not always mechanically correct.

A dilemma related to extrapolation is inevitable when using

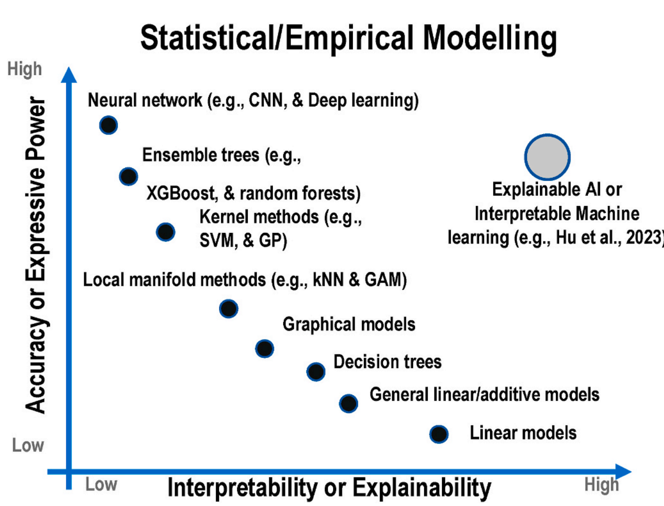


Fig. 2. Tradeoff between predictive and explaining power for common statistical and machine learning techniques: Black-box models such as neural networks and random forests tend to have better predictive accuracies but with less model interpretability, thus urging for new generations of data-driven models such as explainable AI and interpretable machine learning that have both good predictive and explaining power.

statistical crop models as predictive tools. Statistical models are calibrated using historical climate data but often applied to estimate future outcomes under novel climate scenarios (Challinor et al., 2014; Zampieri et al., 2019)—an extrapolation problem. Extrapolating beyond the range of observed data is cautioned against (Hawkins, 2004). It can lead to unreliable projections, particularly when the overlap between historical and future climate is narrow. Irrespective of the application scenarios, the farther the extrapolation extends from the historical climate regime, the greater the errors and biases of predictions. This extrapolation issue essentially defeats the original forecasting purpose when novel climates see a large shift from the current climate (Hawkins, 2004; Hu et al., 2023). Equally important, the extrapolation issue cannot be resolved solely by refining the statistical model itself because the root cause lies with the data used to fit the model: Extrapolation is not a problem about models but about data.

Another dilemma related to model selection is inevitable when using statistical crop models as explanatory tools to infer true climate-crop relationships. The problem is related to which models to trust and how to validate the truthfulness of the inferred empirical relationships. Practical applications of statistical models are knowingly subjective. At least, multiple models could be built for the same datasets, based on alternative statistical techniques and assumptions. More often than not, the different models can give inconsistent or contradictory findings, which represents both a challenge and a promise. On one hand, there is no consensus on how to reconcile the inconsistency or determine the "best" model; on the other hand, inconsistency often highlights fundamental weaknesses and paves an avenue for further model scrutiny and new studies (Hu et al., 2021; Zhao et al., 2019a,b). Instead of finding the "best" model, an alternative strategy is to embrace all the models altogether in the inference–a class of methods known as ensemble modeling (Hossard et al., 2017; Zhao et al., 2013).

3. Literature survey

To summarize the most recent progress and findings in modeling climate impacts on crop yield using both classical and advanced statistical techniques, we conducted a literature search in the Web of Science (https://apps.webofknowledge.com) using terms "crop yield", "climate change", "statistical models", and "machine learning" as article topics. Initial filtering was based on the titles, then the abstracts. A total of 423 papers published between 2000 and 2020 were identified and screened based on their relevance to our research topic. Subsequently, 189 of these papers were selected for further review, and their full texts were carefully analyzed with criteria in Table S1. Additionally, 37 more papers were found by cross-referencing citations from the original articles using Google Scholar. Hence, the total sample size of our review comprises 226 publications. The complete list of articles can be found in Supplementary Material 2.

The reviewed studies vary greatly in terms of data preparation, study area, crop types, model development, and research objectives. Some studies aim to determine the overall impacts of global warming (e.g., a 1.5 °C warming) on future crop yields (Challinor et al., 2014; Lobell et al., 2011; Tebaldi and Lobell, 2018a,b). Others focus on yield variability caused by mean climate changes or extreme events (Roberts et al., 2013; Zhu et al., 2019; Zipper et al., 2016). There are also many studies investigating interactions between climate factors or examining spatiotemporal variations in yield responses to climate (Leng et al., 2016; Li et al., 2019). In this section, we summarized these studies based on study regions and crop types, data sources, and model techniques. The empirical findings are synthesized in Section 4.

3.1. Study regions and crop types

Our literature review showed that empirical studies on crop yields were conducted across various geographical regions but with a strong disparity in their geographic distribution. About 50% of the research focused on the United States (U.S.) and Europe (Fig. 3 and Table S2). China and India–the highest populations in the world–accounted for only 10% and 8% of the studies, respectively. Africa and South America were studied in 9% and 4% of them, respectively. The majority of research efforts were concentrated on developed countries where food security is of lesser concern. Unfortunately, much less attention was given to food-insecure regions or densely populated areas in Africa, Asia, and South America. This finding aligns with a recent text-mining study of 16000 abstracts from the food security literature (Cooper et al., 2020). We therefor call for the research community to pay more attention to crop yields in food-insecure countries with high population or low incomes, given that these areas are particularly vulnerable to food supply disruptions under climate change (Müller et al., 2011).

The reviewed empirical studies have focused primarily on four major crops—maize, wheat, rice, and soybean. The four crops were the subject of 199 out of 226 publications. Maize was the most studied crop and was examined in about 59% of the surveyed literature (Table S2), followed by wheat (∼42%), soybean (∼24%), and rice (∼6%). Many studies focused on maize production because it is the world's most grown and heavily traded cereal crop in international markets (Tigchelaar et al., 2018; Xiong et al., 2016). The four crops also feature prominently in studies employing process-based models (Kang et al., 2009). The need for more future research on other crops (e.g., nonfood crops such as cotton) are apparent. Statistical models have the potential to expand this scope and examine more crop types, particularly for those where established process-based models are lacking due to a scarcity of crop-specific parameters (e.g., millet). Going beyond the four major crops to include more will provide a better picture of future global food availability under climate change.

3.2. Climate datasets and predictors

The reviewed studies also differ greatly in the choices of data sources, data processing, and forms of predictors. Climate data are obtained from either meteorological stations or gridded data products. Meteorological stations provide the most accurate measurements and have been used primarily for local studies at site or field levels (Franz et al., 2020; Ramankutty et al., 2013). A freely available station-based dataset is the World Meteorological Organization's archive (WMO) that provides daily weather data from stations across the globe. Despite the global extent of the WMO dataset, its spatial footprints are sparse, additionally with large temporal gaps; therefore, it is not always possible to access station-based data for a particular research area.

Gridded climate datasets are the dominant sources for statistical crop modeling over large geographic areas. A common way to generate gridded climate variables is to interpolate station-based observations to fill the spatial and temporal gaps. Spatial regression is also used to combine station-based weather measurement and auxiliary spatial data (e.g., elevation and remote sensing data) for estimating climate variables continuously across space. In the United States, one well-known example is the Parameter-elevation Regressions on Independent Slop Model (PRISM, 2016), offering daily and monthly climate estimates at a spatial resolution of 4 × 4 or 0.8 × 0.8 km for the contiguous US. On the global scale, a widely used dataset is from the Climatic Research Unit (CRU), providing monthly gridded datasets at multiple spatial resolutions (e.g., 0.5 × 0.5°) (Harris et al., 2014). The PRISM and CRU datasets have been frequently used for statistical crop modeling to represent historical climate due to their extensive spatial coverage and long-term temporal data spanning (usually more than 30 years).

Another common method for generating gridded climate data are model-based reanalysis, which combines observational data and weather models (e.g., global circulation models). Compared to interpolation-based methods, reanalysis methods can provide climate variables for regions where observational data are poor or unavailable; more importantly, they generate not only historical data but also future climate projections. Reanalysis climate data have been used for statistical crop modeling (Ortiz-Bobea et al., 2019; Schlenker and Lobell, 2010), but their adoption is not yet widespread, partly because reanalysis data are sensitive to the climate models of choice and are considered less accurate than station-based observations or

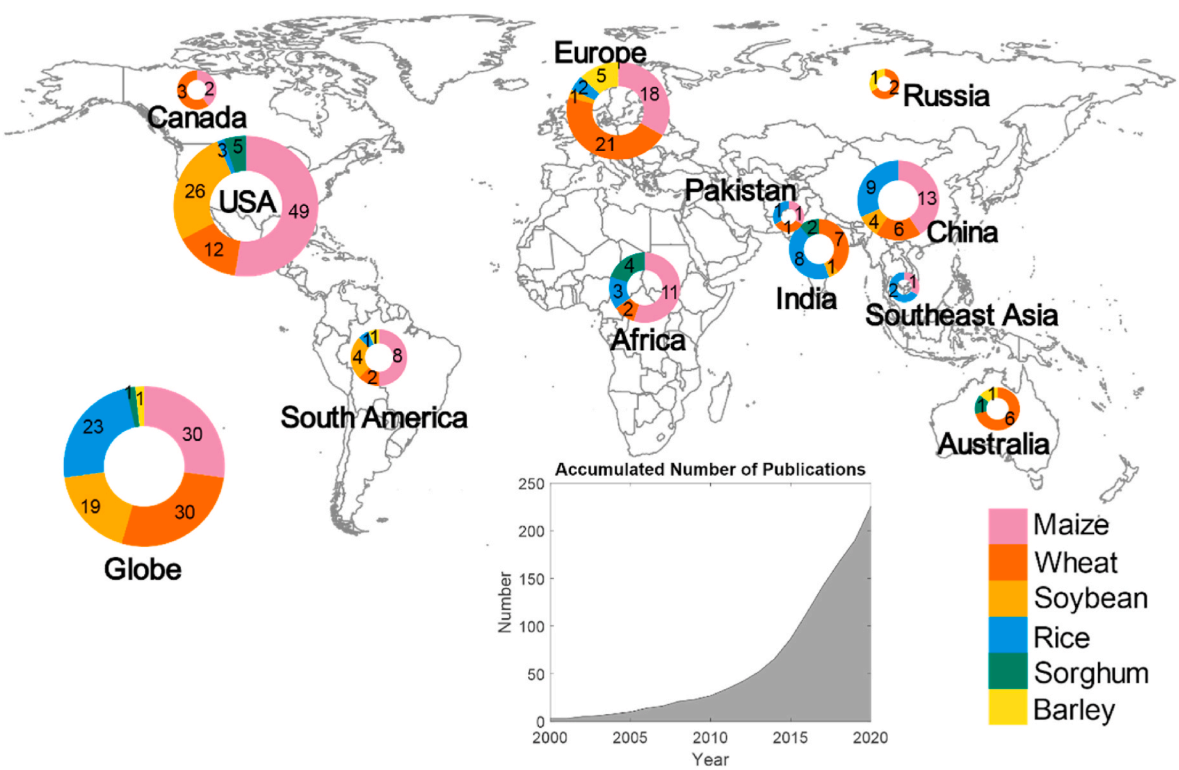


Fig. 3. Numbers of studies employing empirical models conducted in different geographical areas and for different crops.

interpolation-based gridded products.

Given a climate dataset, there was no consensus on what climate metrics or variable should be included into statical crop models. Myriads of choices are possible. Examples include but are not limited to raw climate variables (e.g., daily or monthly temperature), climate statistics (e.g., mean temperature, and 90-th percentiles of rainfall), detrended climate variables (e.g., temperature anomaly), physics informed metrics (e.g., growing degree days), and model-based variable selection (e.g., optimal predictors via stepwise regression). Even for the same climate metrics, the fashions in computing them varied a lot. For instance, a metric of mean temperature can be calculated as average daily values, average monthly values, average daily minimum, average daily maximum, average anomaly temperature, averages over a fixed period, averages over growing seasons, spatial average of temporally averaged values, or temporal average of spatially averaged values, to name a few. Aside from temperature and precipitation, other climate variables such as soil moisture and vapor pressure deficit have also been considered in some empirical studies (Table 1). In the reviewed studies, we found that the authors rarely justified their choices of climate predictors. And how to reduce the subjectivity in constructing climate predictors remains a challenge to address.

3.3. Crop yield datasets

Yield data used for statistical crop modeling are predominantly from historical observations and occasionally from synthetic data generated by process-based crop model. Historical data are typically collected through field surveys or agricultural census, reported on an annual basis for a given region. The majority of the studies considered coarse-scale yield data at the levels of political units (e.g., county, state, and country). Field-level crop yield data were also examined but their availability to the research community is limited, partially because such data are often commercial or proprietary. In contrast to historical observations, synthetic data were used not to infer the true climate effects but mostly to test and evaluate alternative statistical modeling techniques. Regardless of the data sources, one of the most important practices is to log-transform crop yields for mitigating potential heteroskedasticity: The use of log-transformed yield as the response variable can homogenize the model errors to better meet the assumption of Gaussian errors in regression models (Urban et al., 2015).

Historical crop yields as time-series data were driven by both climatic and non-climatic factors (e.g., soil, management, and technology advances). To isolate the climate effects, the majority of the reviewed studies pre-processed yield data before feeding them into statistical models. A simple but popular method used is to detrend the crop yield time series in the hopes to remove the contributions from technological innovations. The trends were often fitted as linear, quadratic, polynomial, or spline-based models and sometimes were removed by first-order differences (Lobell and Field, 2007; Verón et al., 2015). Because of the subjectivity and imperfection in estimating the technological trends, the detrending in the first stage inevitably introduces some incorrigible biases that will be populated into the regression models in the second stage. As recently argued and exemplified, an alternative approach is to estimate the technological trends and climate effects jointly and simultaneously in a single stage (Hu et al., 2023), thus circumventing the needs of pre-processing crop yield data.

Table 1
Common variables used as a proxy for the climate in the reviewed literture

Climate proxy	Description
Tmin	Minimum temperature
Tmax	Maximum temperature
Tmean	Average temperature
TP	Total precipitation
AP	Average precipitation
GDD	Growing degree days are an accumulation of heat during a period
VPD	Vapor pressure deficit
SM	Soil moisture
SR	Solar radiation
CO_2	Carbon dioxide concentration in the atmosphere
ET	Evapotranspiration

3.4. Statistical modeling techniques

Common statistical techniques for crop modeling can be divided into two major categories: classical regression and machine learning. Their strengths and weaknesses are summarized in Table 2. The most commonly used classical technique is general linear models, which include but are not limited to simple linear regression, multiple linear regression (MLR), and quadratic regression (Das et al., 2018). For example, MLR was used in 133 of the 226 reviewed publications (~60%). Other variants of classical regression (e.g., mixed models, and ANCOVA) were used in 66 of the reviewed studies (Sexton et al., 2016). The popularity of MLR is attributed largely to the ease with its implementation and interpretability.

MLR allows accounting for non-linear relationships between climate factors and yields by incorporating quadratic or higher-order terms (Lobell and Field, 2007; Liu et al., 2016; Tebaldi and Lobell, 2018). Despite this potential for nonlinear regression, their analytical forms may be too restrictive to adequately capture complex climate-yield relationships. For example, MLR commonly incorporates a quadratic term to represent non-linear yield responses to climate variables, which results in a symmetrical concave relationship. Such symmetric responses are unlikely true because in most cases, crops respond to temperature or rainfall asymmetrically around the optimum (Blanc, 2017). As another example, interactive effects of climate variables on crop yields are 2D or multi-dimensional response surfaces that are difficult to model by a MLR model unless enough prior knowledge about the interaction is available to inform the model parametrization (Li and Troy, 2018).

In recent years, machine learning (ML) models, such as Random Forest and Neural Networks, have been increasingly used to model climate-yield relationships (Crane-Droesch, 2018; Arrieta et al., 2020). Thirty-four of our reviewed studies (~15%) employed ML models, and 17 of them considered both ML and classical regression methods. A significant distinction between ML and classical regression models lies in their focus and inference approach. ML models emphasize prediction and pattern extraction from data without explicit parametric forms whereas classical regression models stress statistical inference with parametric equations based on certain assumptions (Bzdok et al., 2018). Because of the less constraints on model forms, ML methods generally fit a better predictive relationship with lower root mean square errors (RMSE) than classical regression models.

The better predictive accuracies of ML are exemplified in the 17 studies that evaluated both ML and classical regression models (Fig. 4). On average, the RMSEs of the ML models were 44% lower than those of classical regression models. Some studies reported comparable performance between the two, especially when fitted to data aggregated at coarse spatial or temporal resolutions (Matsumura et al., 2015). This scale dependence is expected because the spatial aggregation can smooth out local nonlinearity and make the climate-yield relationships more linear (Lobell and Asner, 2003; Zhao et al., 2009): The coarser the scales, the more likely the climate-yield relationships will be linear. ML methods generally work better when data are more fine-grained and there is a larger set of predictors or when climate-yield relationships are complex.

Despite their stronger predictive power, ML methods are known to be black-box models with poor model interpretability; therefore, their use has been criticized for the opaque representation of causal links between crop yields and climate variables. This drawback provides a plausible explanation on why classical regression models still remain popular (199 out of 226 reviewed studies). To help unwrap the black box, new data analytics tools such as partial dependence plots (PDP) have been

Table 2
Commonly used modeling techniques in the reviewed publications focused on climatic impacts on crop yield.

Common Techniques		Yield Detrending	Strengths	Weaknesses
Classical Regression	Simple Linear Regression	Yes	Simplicity: Easy to implement	Limited complexity: Assumes a linear relationship between a climate variable and yield, which may not always hold true
			Interpretability: Highly interpretable	Limited applicability: Suitable for investigating impacts of a single variable
	Multiple Linear Regression	Yes/No	Flexibility: Allows for complex relationships between multiple climate variables and crop yield.	Assumptions: Assumes linear relationships between multiple climate variables (or terms) and yield, as well as no multicollinearity which may not be true.
			Interpretability: Provides insights into impacts of each climate variable on crop yield	Overfitting: Risks of overfitting to the training data
	Non-linear Regression	No	Flexibility: Allows for more flexible modeling compared to linear regression	Complexity: Can be complex and difficult to interpret
			Non-linearity: Captures complex and non-linear relationships between climate variables and yields	Overfitting: Risks of overfitting if a model is too flexible or not properly regularized
Machine Learning	Neural Network	No	High flexibility: Models a wide range of problems with large amounts of data.	Complexity: Requires large amounts of data and computational resources to train models.
			Non-linearity: Captures complex non-linear relationships between climate variables and yield.	Interpretability: Difficult to interpret and understand because of complex structures.
	Random Forest	No	High accuracy: Provides accurate predictions due to ensample nature in general	Interpretability: Difficult to interpret
			Robustness: Handles large amounts of data and less sensitive to outliers	Overfitting: Less prone to overfitting but still could overfit noisy data
	Support Vector Machine	No	Effective in high-dimensional data: Works well with large number of data with various dimensions	Choice of kernel: Can be challenging to select an appropriate kernel
			Robustness: Less sensitive to nosiy data points	Computation requirement: Computationally expensive, especially for large datasets, for training SVMs can be
	Boosted Trees	No	High accuracy: Hands complex relationships with strong predictive power	Interpretability: Difficult to interpret because of black-box nature
			Robustness: Less prone to overfitting	Computation requirement: Computationally expensive and time-consuming for training and evaluating boosted trees
	Multivariate Adaptive Regression Splines	No	Flexibility: Captures complex, non-linear relationships without relying on a predefined function form	Complexity: Can become complex and difficult to interpret with high-dimensional data or interactions
			Interpretability: Provides interpretable relationships between variables	Robustness: Can be sensitive to outliers and noisy data

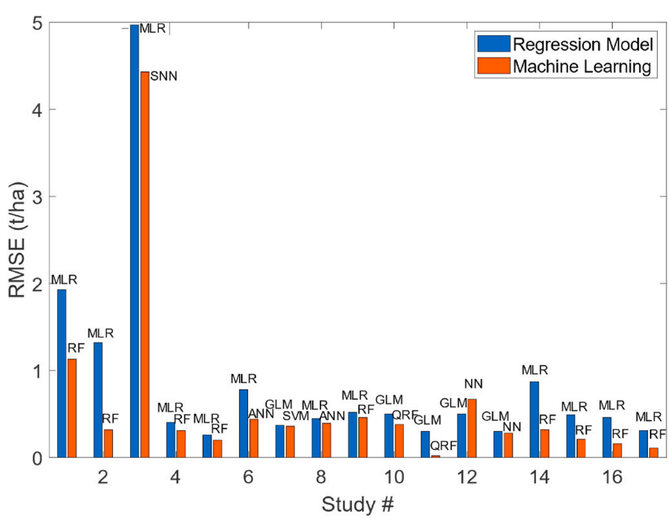


Fig. 4. Comparison of classical regression techniques and machine learning based on 17 reviewed studies. Machine learning improved over classical regression with an average reduction error by 44%. Detailed information including crops and references is provided in Table S3. (RF: random forests; SNN: semiparametric neural network; ANN: artificial neural network; GLM: generalized linear model; SVM: support vector machines).

introduced and used to improve the interpretability of ML models (Fig. 5). But such tools treat the symptoms but not the root cause because they do not change the black-box nature of the model itself. As exemplified in Fig. 5, the inferred PDP relationships from a ML model may be useless or wrong.

4. Synthesis of empirical findings

4.1. Climate-driven yield variability

What percentage of observed variability in crop yields is explained by climate variations? This is an important question but has not been directly answered in most of the studies we reviewed. Some of the studies reported only error metrics such as RMSE. Many studies reported R^2-like statistics, but their models comprised non-climatic predictors or their customized data pre-processing precludes a meaningful interpretation consistent with other studies. As a result, we were able to find only 25 publications that have explicitly reported yield variability explained by climate factors (Fig. 6).

Crop yield variability explained directly by climate factors is highly variable across regions. On the global scale, climate factors explained approximately 34% of inter-annual yield variability for all four crops. In the US, the percent of explained inter-annual yield variability averaged 29.8% whereas Europe, China, and Africa had higher percentages at 40.5%, 45.0%, and 50.0%, respectively. In Fig. 6, both Russia and Canada showed a relatively high climate-explained variability. However, it is cautioned that only one publication explicitly reported such results for these two regions (Zampieri et al., 2017). Overall, climate factors (primarily temperature and precipitation) explained approximately 38% of yield variability when averaged across all crops and regions. Future research is needed to provide more detailed examination of yield variability in other regions such as Europe, Central and South

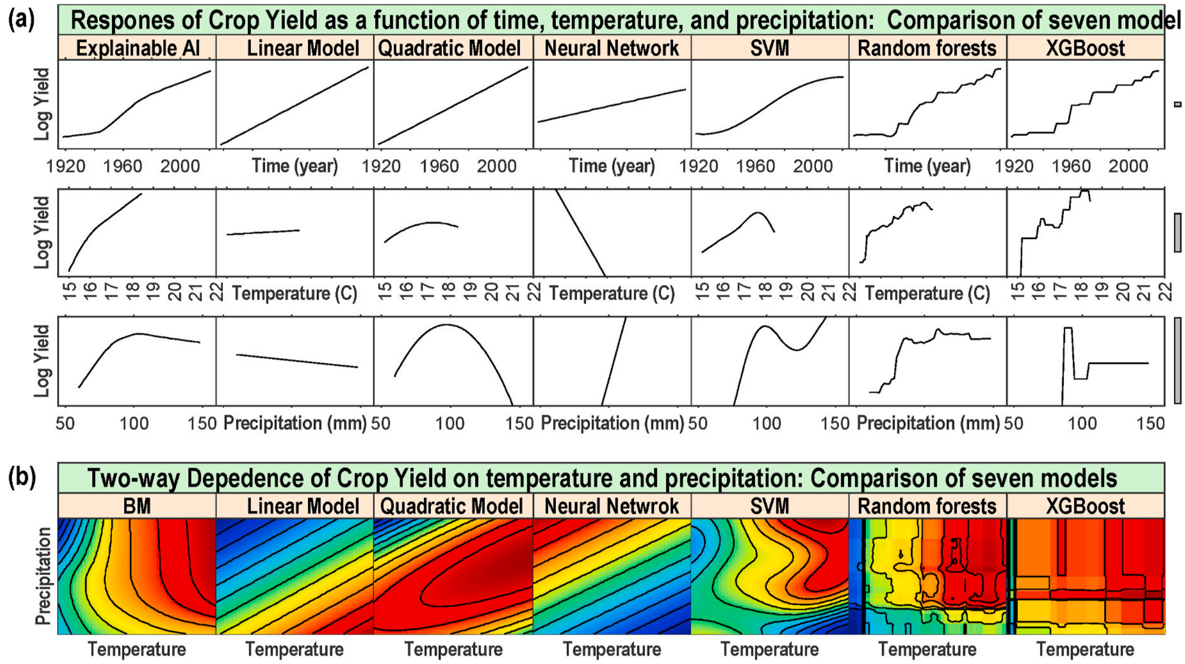


Fig. 5. An example to illustrate the diverging results of classical regression, machine learning, and explainable AI models fitted on a sample climate-yield time series dataset over Ohio, USA for inferring the functional relationship $Log\,(Yield) = f\,(Year, Temperature, Precipitation)$. Depicted here are one-way and 2D partial dependecne plots for (a) yield responses to individual predictors (i.e., time, temperature, and precipitation) and (b) yield responses to interactions between temperature and precipitation.

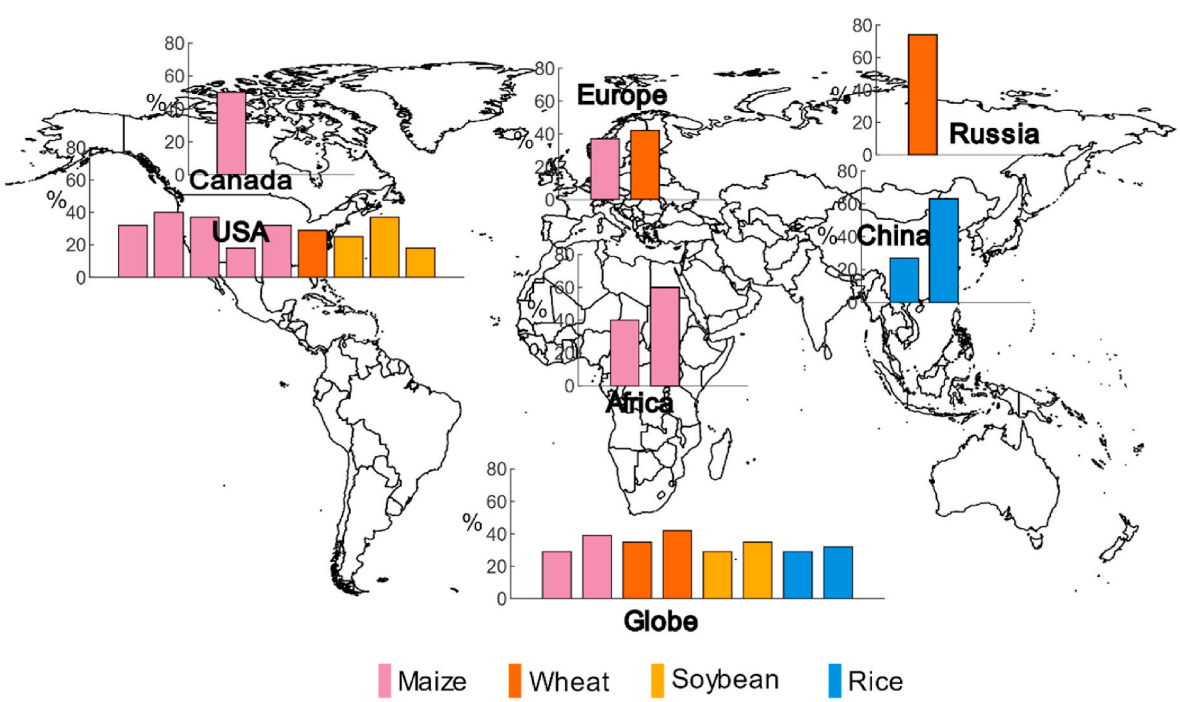


Fig. 6. Yield variability explained by changes in climate factors (mainly temperature and precipitation) for different crops and geolocations as reported in 25 publications (see Supplementary Materials).

America, Asia, and Africa in order to gain a more comprehensive understanding of regional-specific climate impacts on yield variability.

4.2. Marginal effects of temperature and precipitation on yields

Most of the reviewed studies showed that crop yields decrease with temperature, and a fraction of the studies in cold regions showed the opposite relationship. More specifically, a total of 170 studies we reviewed explored marginal effects of temperature, and 133 of them (75%) found negative relationships between yields and temperature: Increasing temperatures will reduce yields. There exist optimal growth temperatures for crops (Fig. 5a), explaining why crops respond to warming positively at some locations but negatively at other locations. Extremely high or low temperatures from the normal climatic conditions to which crops have been adapted to will increase the risks of yield loss. For example, maize is at higher risk of yield loss at temperatures of 35 °C or above (Ortiz-Bobea et al., 2019), and wheat faces increased vulnerability at temperatures of 34 °C or above (Lobell et al., 2012).

In particular, increasing temperatures have adverse impacts on crop productivity through soil water deficits or heat stress. Guo et al. (2017), for example, demonstrated that the global warming intensified drought conditions with longer drought periods and number of consecutive drought days, thereby harming maize yield in China. Leng and Hall (2019) highlighted substantial risks of yield losses for wheat, maize, rice, and soybean in the presence of warming-induced drought events. Zipper et al. (2016) found that drought explained 13% of overall crop yield variability. Implementing irrigation practices to alleviate soil water deficits was shown to mitigate negative impacts of drought on maize and soybean in the central United States (Zhang et al., 2015).

The reported relationships between yields and precipitation on crop yields are location-specific, showing strong regional heterogeneity. Some studies estimated a concave relationship between precipitation and crop yields, suggesting there was a precipitation level for optimal crop growth (Gammans et al., 2017; Schlenker and Roberts, 2009). In particular, a few studies concluded that current precipitation levels were optimal for most crops (Challinor et al., 2014) and future increases in the frequency and intensity of rainfall will be harmful to crops. For example, in the central US, extreme wetness during planting may lead up to a 10% reduction in maize and soybean yields (Urban et al., 2015). Several other studies found precipitation did not have a significant relationship with crop yields (Ortiz-Bobea et al., 2019; Parkes et al., 2019).

The reviewed studies often attributed the complicated relationships between yield and precipitation to three factors. The first one is great uncertainty and geographical heterogeneity in precipitation. Often enough, the spatial scales at which models are fitted are too coarse to resolve strong local heterogeneity (Fishman, 2016). The second factor concerns the use of monthly average precipitation or growing-season total precipitation in the statistical models. These precipitation indices might not accurately represent actual soil water moisture conditions of soils, thus being a poor proxy of total water available for crop usage. Precipitation can be a poor predictor of crop yields where irrigation is practiced. A third factor is the complicated indirect effects of precipitation. For example, increased precipitation may heighten the risks of pests and diseases, cause delays in planting, or damage crops at early stages (Ierna and Mauromicale, 2020). These indirect impacts are challenging to represent in statistical models.

4.3. Interactive effects of climate factors on yields

Effects of temperature and precipitation on crop yields are unlikely independent and additive (Fig. 5b), but previous studies focused primarily on assessing marginal impacts of individual climate factors, with limited attention given to exploring interactive impacts of climate variables. Only 5 out of the 226 reviewed publications examined the interactive effects. Although all the machine learning-based studies also implicitly considered interactive effects in the overall climate-yield relationships, these models were black boxes and none of the ML-based studies attempted to decompose the overall relationships for isolating main and interactive effects.

Evidence is strong and consistent that the interactive effects of temperature and precipitation were non-negligible (Fig. 5b) and any failure to incorporate these impacts may cause biases or lead to systemic errors. Although the addition of interaction terms increases model complexity and may not always fit a model with lower predictive RMSEs, the inferred relationships proved more realistic (Challinor et al., 2014; Schlenker and Roberts, 2009). Carter et al. (2018), for example, showed that the yield responses to high temperature and low precipitation conditions are consistent with physiological responses of maize only when interaction terms were included. In some empirical models, incorporating interactive terms could exacerbate projected damages of climate on yields, with the results significantly different from those models without the interaction terms (Ortiz-Bobea et al., 2019). Increasingly, the community has urged for more emphasis on quantifying interactions within models. One line of evidence is that high precipitation could buffer the impacts of high temperatures on crops (Carter et al., 2016; Kukal and Irmak, 2018; Troy et al., 2015). Additionally, the negative impacts of warming can be exacerbated under dry conditions. Matiu et al. (2017) projected that increasing temperature could decrease the global maize yield by an average of −7.8% but the decrease could reach −11.6% under drier conditions. As suggested by Lobell (2017), more work is needed to include interactions between climate variables in models, especially under extreme conditions such as drought (Feng and Hao, 2020).

4.4. Projected yields under a 1 °C warming

On average, global warming was reported to have negative impacts on agricultural production. We synthesized the projections of yield change for maize, wheat, soybean, and rice under a 1 °C warming scenario from the reviewed studies. The estimated yield changes were either explicitly reported in the publications or derived from the reported model coefficients (Fig. 7). Averaged across all the chosen studies, crop yields are expected to decrease 7.5 ± 5.3% for maize (n = 54), 6.0 ± 3.3% for wheat (n = 23), 6.8 ± 5.9% for soybean (n = 12), and 1.2 ± 5.2% for rice (n = 12). These findings align with tie results obtained from field experiments and gridded global crop process-based models (Wang et al., 2020). In general, warming shows negative impacts on maize, wheat, and soybean whereas the impact on rice yields remains highly uncertain.

4.5. Impacts of elevated CO_2 and O_3

The rising atmospheric CO_2 level is known to benefit crop growth to some degree, especially for C3 crops, but we found many empirical studies did not represent the impacts of CO_2 on crop yields. Only 19 of the 266 reviewed studies incorporated the impacts of elevated CO_2. We identified two main reasons from the reviewed literature for the limited inclusion of CO_2 impacts. One is that atmospheric CO_2 concentrations exhibit a gradual upward trend over time with minimal year-to-year variability, making it challenging to disentangle the CO_2 impacts from technology advancements (Liu et al., 2016; Lobell et al., 2011; Schlenker and Roberts, 2009). Another one is that for C4 crops such as maize, the effect of CO_2 is expected to be negligible because the photosynthetic pathway for C4 crops is independent of ambient CO_2 in well-moisturized conditions (Lobell et al., 2011). Of the 19 studies that included the CO_2 effects, 14 of the studies didn't identify any conclusive findings about the CO_2 effects; only 5 of them reported explicit relationships between CO_2 and yields (Sakurai et al., 2014; Tebaldi and Lobell, 2018a,b; Shindell et al., 2019). For example, Blanc and Sultan (2015) found a concave relationship between CO_2 and yields based on synthetic data from process-based models; Luo and Wen (2015) used site-based observations to show a positive, non-linear relationship between CO_2 and

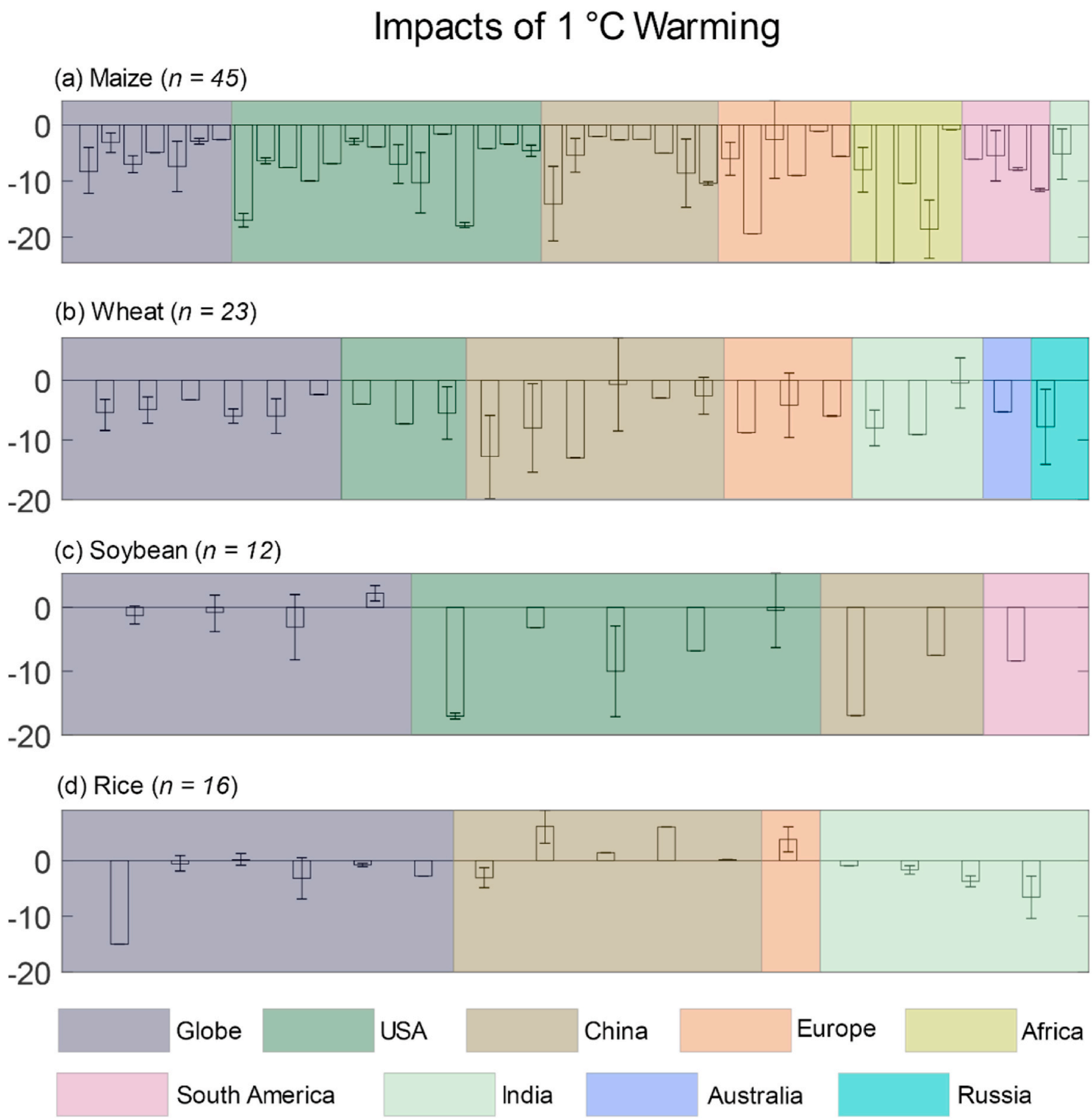


Fig. 7. Impacts of 1 °C warming on crop yields (%) for each of those studies with reported values. Uncertainty is presented as error bars (one standard deviation of the values reported in each of the reviewed studies). Some error bars are not available because in those studies the changes in yield were derived based on coefficients of a regression model and uncertainty of the coefficients was not reported. *n* is the number of publications.

yields for wheat, barley, and oat.

Elevated O_3 concentrations can harm crop yields, as reported in both field experiments (Mills et al., 2011) and simulations (Avnery et al., 2011). The significance of O_3 impacts is increasingly recognized and considered comparable to those of climate variables. Thus, many studies started to consider O_3 concentrations in process-based models (Emberson et al., 2018). But due to a lack of high-quality data, we did not identify any statistical models that have explicitly included O_3 impacts. Previous reviews and inter-method comparisons on climate impacts on crop yields have also emphasized the need to incorporate impacts of elevated O_3 into statistical models (Challinor et al., 2009).

5. Challenges and perspectives

Although statistical models have gained popularity over the last two decades, they face several challenges in unraveling the complex mechanistic yield-climate relationships. Here, we discussed the many challenges and perspectives for future research to consider. In essence, we recommend leveraging multi-source data, high-resolution observations, interpretable machine learning, ensemble algorithms, and spatial statistics, fusing statistical and process-based models (e.g., physics-informed machine learning), and considering indirect effects of climate change.

5.1. Integrating multiple sources of data

Current empirical studies relied mainly on gridded weather datasets to investigate the crop yield responses to climate change. Consideration of only climate-based predictors is insufficient for disentangling the complex yield-climate relationships or fully explaining inter-annual yield variability (Fig. 6). For example, about 38% of yield variability was explained by climate factors across regions and crops at a global scale. Thus, we recommend future research, on one hand, to incorporate multi-source/type data to improve model performance, and on the other hand to balance the predictive and explanatory power of models to inform policies for agriculture under climate change. By incorporating multi-source data, we mean to fuse different types of data that are related to crop growth, such as data related to soil conditions, water availability, or plant physiology from various sources. Examples of such sources include but are not limited to remote sensing, reanalysis, and economic datasets (Ribeiro et al., 2019).

Remote sensing data could provide unique information regarding crop growth and yields with varied spatial, temporal, and spectral dimensions. They have been successfully combined with artificial intelligence (AI) algorithms to improve field yield prediction in the agronomy community (Trevisan et al., 2019). Evidence has shown that including remote sensing data (e.g., Enhanced Vegetation Index) could improve prediction over those models with only climate variables (Peng et al., 2018). The potential is vast in leveraging the rich set of remotely sensed data, such as solar radiation, soil moisture, and Spectral Induced Fluorescence (SIF).

Model-based reanalysis data provide a full set of biophysical characteristics rather than just temperature and precipitation; therefore, they sometimes are more suitable as model inputs than commonly used station- or grid-based climate variables. Precipitation does not fully capture the water availability in soils. Soil moisture is a good replacement for precipitation in empirical modeling because it could reflect how much water is available to crops during growth and represent water stress to crops. But soil moisture is highly variable across space and large networks of soil moisture observations are not always available. In such cases, reanalysis soil moisture data can serve as a viable alternative.

Economic data provide an alternative and valuable angle to look at the climate impacts on crop yields (Bakker et al., 2005; Perry et al., 2020). Increases in historical crop yield have been primarily driven by non-climate technological factors such as applications of fertilizer, improved genetics, and agricultural practices (Sadras and Calderini, 2014). These non-climate factors are closely related to farmers' financial investments, which could vary significantly across different regions, especially between developed and developing countries. In this regard, economic indicators such as variables reflecting economic conditions (e.g., GDP) can serve as useful proxies to capture the non-climatic contributions to yields. Instead of simply modeling the historical yield increase as a linear or quadratic temporal trend, incorporating economic variables can provide a more comprehensive representation of the factors driving the changes of crop yields across space and over time, especially for studies across large scales.

5.2. Leveraging explainable AI and interpretable machine learning

To model yield-climate relationships, we need a model to have good predictive power in projecting yield changes as well as good explanatory power in capturing direct linkages between yield responses and climate variables so that we can make adaptations according to these responses. Our review showed that the current methods for tackling the yield-climate relationships could either have high predictive power or high interpretability/explainability but seldom have achieved both (Fig. 2). The tradeoff between predictive power and explanatory power—predictive accuracies vs model interpretability—is long known and has been an active topic for decades (Hu et al., 2023; Shmueli, 2010). But for crop modeling, modelers probably have an implicit purpose in mind without articulating the distinctions (Lobell and Asner, 2003; Shook et al., 2021): emphasize interpretability when using linear models to test the directional temperature effect on crop yield; emphasize predictive accuracies when using machine learning to predict future crop yields.

An avenue worth exploring is the integration of multiple alternative models via ensemble algorithms such as Bayesian model averaging (Hu et al., 2023). Another more exciting avenue is the development of explainable or interpretable AI models for crop yield modeling. Although there has been a growing interest in developing explainable AI techniques to shed light on the decision-making process of machine learning models in various fields such as health care and criminal justice, these new AI approaches have remained largely unexplored for crop yield modeling. By focusing on explainable AI for crop yield models, we strive to uncover the relationships and mechanisms that contribute to the model's predictions. This would enable us to better understand the factors driving crop yield outcomes and provide actionable insights to inform stakeholders and policymakers. Advancements in explainable AI techniques specific to crop yield modeling can enhance transparency, accountability, and trust in the models, leading to more informed and responsible decision-making in the agricultural context. Overall, AI and machine learning have been recogized as a key for precision agriculture in the era of Agriculture 5.0 or beyond.

5.3. Integrating statistical and process-based models

Both statistical and process-based models have weaknesses in exploring the impacts of climate change on crop yields. However, there is great potential in combining these two types of models to overcome their respective limitations (Pylianidis et al., 2022). One simple example is developing emulators based on simulated yields from process-based models. Many more sophisticated techniques have been successfully used in Earth System Models. Examples include physics-guided machine learning (Tsai et al., 2021) and digital twin methodologies (Bauer et al., 2021), with their potential to be tapped for crop modeling.

Integration of statistical and process-based models can help fill important gaps difficult to tackle by using either alone. One area is assessing the effects of CO_2 or O_3 effects on crop yields. To account for elevated CO_2 and O_3 in statistical models, one promising approach is to introduce multiplication factors (e.g., a fertilization factor for CO_2) to adjust the estimated yields. Crop-specific fertilization factor can be derived separately by process-based models. Fig. 8a shows examples of process-based model derived fertilization factors using CO_2 at 330 ppm as a reference. This approach allows for the differentiation of CO_2 impacts on C3 and C4 crops without increasing the complexity of statistical models. Likewise, a penalty factor for O_3 impacts could be derived and applied to reflect the extent of yield reduction associated with varied levels of O_3 exposure (Fig. 8b). Another area where model integration helps is concerning climate extremes, as discussed next.

5.4. Climate extremes

Most of the current studies have focused on the impacts of climate factors under normal conditions. The interest has been increasing in addressing the effects of extreme weather events (Ewert et al., 2015; Troy et al., 2015; Waldhoff et al., 2020). The shift in focus is driven by the anticipated rise in the frequency of extreme weather events, such as heatwaves, drought, and heavy precipitation in future. Despite the interest, the inference for extreme climates is inherently challenging, if not impossible, because extreme events are rare and not well represented in the training sample—a data problem not curable by statistical techniques themselves. One strategy to overcome this is to integrate process -based and statistical models because process-based models enable generating sufficient synthetic data under any climate conditions. Another strategy is to expand the scope of climate predictors from mean statistics to extreme metrics (e.g., percentiles); strictly speaking, the use of extreme metrics as model predictors cures only the symptoms not the root cause models (Tebaldi et al., 2020, 2021). For example, extreme metrics may enter the models as useful predictors merely because of their inter-correlation with other mean climate statistics.

Good metrics of weather extremes should be able to capture the temporal scales at which extreme events influence crop growth. For example, extremely high temperatures usually occur at a sub-daily level and might not last long but can cause severe crop damages. In this context, variables reflecting the duration of exposure to high temperature (e.g., numbers of days when the temperature goes above a crop-specific threshold) during the growing season hold the potential to account for heat stress. Drought is more of a creeping phenomenon that

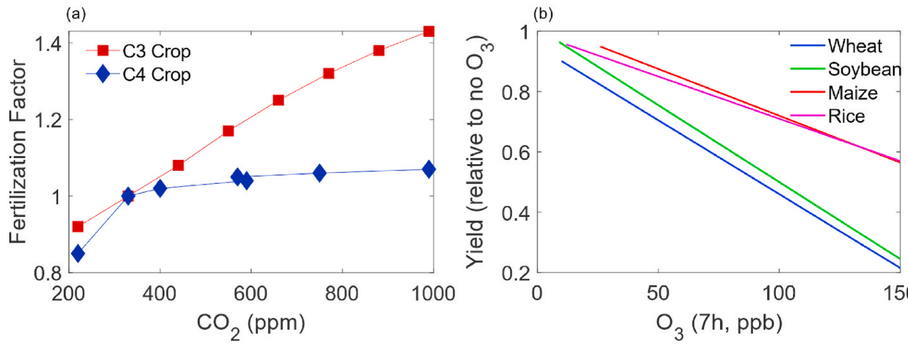


Fig. 8. (a) Fertilization factor for CO_2 concentrations for C3 and C4 crops (based on Tebaldi and Lobell, 2018b) and (b) yield responses to Ozone concentrations for wheat, soybean, maize, and rice (based on Mills and Harmens, 2011). The equations related to Ozone factor in (b) are based on dose-responses function data from field-based chamber experiments with Ozone concentration exposure at the average of the highest 7 h of each day.

slowly ramps up to affect crop growth over a prolonged period (Zang et al., 2020). Indicators of drought at a monthly resolution could be more helpful than those aggregated over the whole growing season because the monthly data could help identify when the drought begins to exert influences on crops.

Modeling the impacts of climate extremes also requires novel techniques to represent the relationships between extreme metrics and crop yields. Traditional empirical studies often relied on linear correlation to establish a deterministic model of climate factors and yields. However, these correlations assume a constant relationship throughout the distribution of the data, which may not hold true for extreme climate indices. Studies found that many climate extreme indices such as maximum five-day precipitation affect yields with a threshold behavior: Yield first increased with the maximum five-day precipitation and then started to decrease when the index exceeded a location-specific value (Troy et al., 2015; Zampieri et al., 2017). Thus, novel approaches such as probabilistic estimates of climate influence on crop yield and graphic techniques (e.g., density plots) could provide greater flexibility in assessing yield losses and describing the yield-climate relationships. No matter what techniques are used, modeling climate extremes with empirical models could be questionable when climate anomalies fall outside the range of historical data. As a possible remedy, combining both historical observations and model projections of climate anomalies to train a model could help extend the climate regimes of training data.

5.5. *Incorporating human-related factors*

Climate change and variability exert their influences on crop yields through a combination of direct biophysical and physiological processes, as well as indirect human-related processes (Fig. 9). These factors interact and shape the overall impacts on agricultural productivity. For example, farmers' management practices and decision-making depend on weather and climate (Gurgel et al., 2021), and those management choices can affect crop yield to varied degrees. At the immediate and seasonal time scales, weather conditions are a key determinant of farmers' field operation decisions (e.g., planting date, timing and rate of fertilization application, subsurface drainage control, and harvesting), all of which impact crop growth (Smit and Skinner, 2002). Although frequent rainfall events may boost crop growth biologically, they may also interfere with field operations, resulting in decreased crop yields over a certain period (Urban et al., 2015). On longer timescales, farmers' concerns about long-term weather patterns and climate risks often dictates their choices for certain management practices (e.g., new crop cultivars, unconventional tillage, diverse crop rotations, increased drainage tile, cover cropping, or irrigation) (Arbuckle et al., 2015; Chatrchyan et al., 2017; Findlater et al., 2019; Haden et al., 2012;

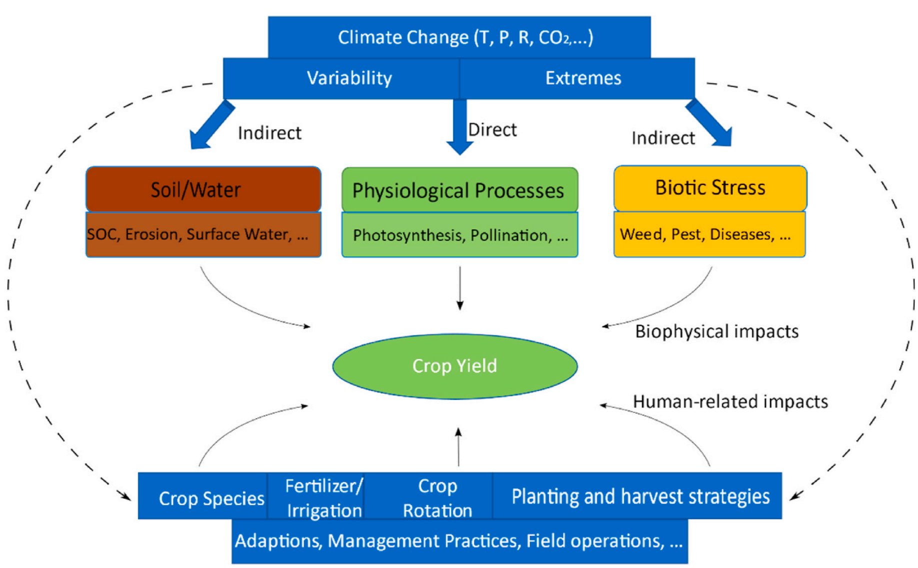


Fig. 9. A schematic representation of main pathways that climate change influences crop yields. Crop modeling including both process-based and empirical models mainly focused on the biophysical impacts (black solid lines) with less attention to how crop yields would be affected by climate change through influencing human behaviors (black dash lines), such as management decisions (e.g., choices and timing of inputs) andreduction of workable field days due to changing climatic conditions. (T: temperature, P: precipitation, R: radiation)

Roesch-McNally et al., 2017). Similarly, these management choices, as driven indirectly by climate change and variability, entangle with the direct climate-plant pathways to affect crop growth.

However, no existing statistical crop models explicitly capture these distinct pathways (e.g., biophysical vs. sociological) affecting crops. Instead, the fitted models represent an overall relationship that lumps all the climatic effects as observed in long-term crop yield data (Rötter et al., 2018). In other words, the effects of climate-induced changes in management practice are likely to be captured, but not identifiable from the direct climate-induced impacts. Without separately parameterizing the distinct processes, statistical models are bound to be biased when used to predict future crop yields, regardless of how well the models fit observed historical patterns. A useful step is to explicitly formulate the indirect and direct climate effects, perhaps by incorporating farmer behavior and management data to differentiate the biophysical impacts from the human-related pathways.

Recent advances in social and behavioral sciences point to some promising directions to disentangle indirect climate-induced changes in management and direct climatic biophysical impacts. Many theoretical and modeling frameworks, such as the theory of planned behavior and agent-based models, have been used to simulate farmers' attitudes and adaptive behaviors in response to socio-ecological and climate changes (Grilli and Notaro, 2019; Sun et al., 2017). Some of these behavioral frameworks have also been used to estimate drought risk (Schrieks et al., 2021).

Despite the potential and promise, the fusion of farmer behavior/decision models and statistical models is not straightforward, due to the incompatibility in model inputs and structures (Rötter et al., 2018). One possible initial step for improving crop modeling is to leverage the outputs from farmer behavioral models (e.g., farmers' preferences to various management options in face of climate changes) as additional predictors in empirical crop modeling (Damalas, 2021). Nevertheless, the explicit characterization of indirect climate-induced management changes is a hurdle that should be overcome in order to confidently project crop production under future climate. This task seems more feasible for process-based crop models than data-driven statistical models (Janssen and Ostrom, 2006), because the former are flexibly structured to allow inclusion of theoretical sociological and human decision processes whereas the latter is a black-box or parametric model hard to train without sufficent high-quality observations.

6. Summary

We reviewed 226 studies that used statistical models to characterize the impacts of climate change on crop yields. We elaborated on the constrating nature of statistical models in disentangling the complicated yield-climate relationships, which is used to predict or explain. We also discussed common issues related to the use of statistical models, such as strong assumptions that may not hold, inconsistencies among models, and the extrapolation dilemma associated with predicton under novel climates. Although model prediction accuracy can be improved via advanced algorithms such as machine learning, classical regression models such as multivariate linear regression are still favored in the majority of our reviewed studies due to its good model interpretability. We also summarized the reported yield responses to climate changes and found that increasing temperature would have negative impacts on crop yields in most regions, but the impacts of precipitation on crops were uncertain. Climate variability explained about one-third of the inter-annual variation in observed crop yields at the global scale for the four major crops examined here. Also, we discussed many challenges facing the applications of statistical models, such as spatiotemporal heterogeneity in crop responses, climate extremes, extrapolation under novel climate, and the confounding from technology, fertilization, CO2, and O3. As a path forward, we recommend leveraging multi-source data, high-resolution observations, interpretable machine learning, ensemble algorithms, and spatial statistics, fusing statistical and process-based models, and considering indirect effects of climate change. Unarguably, statistical crop models, including AI and machine learning, are a key pillar for climate-smart agriculture in the era of Agriculture 5.0 and beyond.

CRediT authorship contribution statement

Tongxi Hu: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Xuesong Zhang:** Conceptualization, Formal analysis, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Sami Khanal:** Funding acquisition, Writing – review & editing. **Robyn Wilson:** Funding acquisition, Writing – original draft, Writing – review & editing. **Guoyong Leng:** Writing – review & editing. **Elizabeth M. Toman:** Writing – original draft, Writing – review & editing. **Xuhui Wang:** Writing – review & editing. **Yang Li:** Writing – review & editing. **Kaiguang Zhao:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2024.106119.

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