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Climate change mitigation and adaptation for rice-based farming systems in the Red River Delta, Vietnam

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Abstract

Background Rice is a major contributor to anthropogenic greenhouse gas (GHG) emissions, primarily methane, and at the same time will be negatively impacted by regional climate changes. Identifying rice management interventions to reduce methane emissions while improving productivity is, therefore, critical for climate change mitigation, adaptation, and food security. However, it can be challenging to conduct multivariate assessments of rice interventions in the field owing to the intensiveness of data collection and/or the challenges in testing long-term changes in meteorological and climate conditions. Process-based modeling, evaluated against site-based data, provides an entry point for evaluating the impacts of climate change on rice systems and assessing the impacts, co-benefits, and trade-offs of interventions under historical and future climate conditions.

Methods We leverage existing site-based management data to model combined rice yields, methane emissions, and water productivity using a suite of process-based coupled crop-soil model experiments for 83 growing sites across the Red River Delta, Vietnam. We test three rice management interventions with our coupled crop-soil model, characterized by Alternate Wetting and Drying (AWD) water management and other principles representing the System of Rice Intensification (SRI). Our simulations are forced with historical as well as future climate conditions, represented by five Earth System Models for a high-emission climate scenario centered on the year 2050. We evaluate the efficacy of these interventions for combined climate change mitigation and adaptation under historical and future climate change.

Results Two SRI interventions significantly increased yields (one by over 50%) under historical climate conditions while also reducing (or not increasing) methane emissions. These interventions also increase yields under future climate conditions relative to baseline management practices, although climate change decreases absolute yields across all management practices. Generally, where yield improved, so did crop water-use efficiency. However, impacts on methane emissions were mixed across the sites under future climate conditions. Two of the interventions resulted in increased methane emissions, depending on the baseline management point of comparison. Nevertheless, one intervention reduced (or did not significantly increase) methane under both historical and future climate conditions and relative to all baseline management systems, although there was considerable variation across five selected climate models.

Conclusions SRI management principles combined with high-yielding varieties, implemented for site-specific conditions, can serve climate change adaptation and mitigation goals, although the magnitude of future climate

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changes, particularly warming, may reduce the efficacy of these interventions with respect to methane reductions. Future work should better bracket important sensitivities of coupled crop-soil models and disentangle which management and climate factors drive the responses shown. Furthermore, future analyses that integrate these findings into socio-economic assessment can better inform if and how SRI/AWD can potentially benefit farmer livelihoods now and in the future, which will be critical to the adoption and scaling of these management principles.

Keywords Climate mitigation, Climate adaptation, Rice, Vietnam, Trade-offs, Water, Greenhouse gasses, Soil carbon

Background

Rice directly feeds ~ 3 billion people and is critical to global food security, farmer livelihoods, and national agricultural economies (Fukagawa and Ziska 2019; Muthayya et al. 2014). Climate change is expected to reduce rice yields globally, by some estimates 10% or more (Peng et al. 2004; Hasegawa et al. 2021), primarily through increases in temperature, reduced and/or highly variable water availability, and via a host of other climate change-mediated changes (e.g. pests and diseases) to agroecosystems (Yuen et al. 2021). While some of these losses may be partly offset by CO_2 fertilization effects (Fukagawa and Ziska 2019; Muthayya et al. 2014; Hasegawa et al. 2018; Jägermeyr et al. 2021; Toreti et al. 2020; Deryng et al. 2016), emerging evidence suggests that higher CO_2 concentrations may also reduce the concentrations of important nutrients, such as zinc and iron, in consumed rice (Zhu et al. 2018). There is thus a need to identify regional, context-specific interventions that can facilitate rice-based farming systems' adaptation to climate change.

At the same time, rice is also a major contributor to climate (and environmental) change, primarily by way of methane emissions that result from the anaerobic conditions created by paddy flood irrigation (Carlson et al. 2016; McDermid et al. 2020), practiced in part to reduce weed pressure. Rice contributes about 10% and 2% of agricultural and total anthropogenic global greenhouse gas (GHG) emissions, respectively, and 8-12% of global methane emissions (Saunois et al. 2020; Crippa et al. 2021; Tubiello et al. 2021). Methane is ~ 21 × more powerful than CO_2 on a 100-year timescale, and it is critical to reduce methane emissions to meet urgent, high-ambition global climate change mitigation targets (IPCC 2018; Masson-Delmotte et al. 2021). Therefore, alongside climate change adaptation, rice farming practices and interventions that also mitigate methane (as well as other GHG) emissions are in increasing demand (Yuan et al. 2021).

Among the range of interventions currently being explored, alternative water management—such as Alternate Wetting and Drying (AWD) in which the rice paddy is irrigated and then allowed to dry to a certain depth before irrigating again (Kosmowski et al. 2023)—has been identified as a means of mitigating methane (CH_4 herein) emissions from rice production (LaHue et al. 2016; Lampayan et al. 2015; Nelson et al. 2015; Carrijo et al. 2017; Setyanto et al. 2018). Furthermore, AWD and similar irrigation practices may help conserve precious freshwater resources in water-scarce regions for future use as warming trends continue (Silalertruksa et al. 2017). Many countries now list water management in rice systems, including AWD, as part of the Nationally Determined Contributions (2020–2022) for either climate change mitigation, adaptation, or both. The government of Vietnam, in particular, has emphasized AWD as part of their climate change mitigation strategy, with the intent of converting up to 0.5 million hectares of rice cultivation to AWD by 2030 (Kosmowski et al. 2023), and an overall goal of reducing GHG emissions by 8–10% (Narayan et al. 2020). As of 2012, rice cultivation contributed ~ 48% of Vietnam's CO2-equivalent emissions (Narayan et al. 2020; FAO 2018), and between 2010 and 2019, rice fields in Vietnam were estimated to have produced 2634 Gg CH_4 yr^{-1} (Butterbach-Bahl et al. 2022).

AWD, and conservation water management more generally, can be further coupled with early rice transplanting or direct seeding (LaHue et al. 2016; Jat et al. 2022), wider plant spacing, and weed control that promotes root stimulation and plant growth. In particular, several of these management principles practiced together constitute the System of Rice Intensification (SRI) (Thakur et al. 2016, 2010) which has been reported to improve rice productivity and yields and facilitate improved plant growth that displays less sensitivity to changing environmental conditions (Thakur et al. 2016). Moving beyond AWD alone, SRI principles [described in full elsewhere, e.g. (Thakur et al. 2016; Uphoff 2023)] also broadly include all or a combination of the following: early transplanting (or direct-seeding) and reduced plant density to allow for optimal plant growth, as well as organic nutrient additions, compost, and minimal reliance on chemical fertilizers. It is possible that the interactive effects of combined principles may contribute to productivity and environmental gains beyond changes to one management factor alone, highlighting the importance of systems approaches to crop (rice) management (Thakur et al. 2016; Uphoff 2023, 2003). Additionally, the importance of high yielding varieties and overall resource-use efficiency via improved agronomic techniques may be critical determinants of rice system sustainability (Yuan et al. 2021; Tseng et al. 2020).

However, despite reported and potential benefits of these alternative production practices, there remain outstanding uncertainties and challenges to their widespread adoption across space and time. Some studies suggest that the biggest benefits accrue when multiple management practices and principles are coupled together such as in SRI (Gathorne-Hardy et al. 2016). However, simultaneously implementing many practices can be difficult, leading to high variation in practices and possible rice system environmental or social externalities beyond methane emissions (Gathorne-Hardy et al. 2016; Deb 2020; Graf and Oya 2021). SRI has yet to be widely adopted across major production zones, the reasons for which remain under active exploration (Thakur et al. 2016; Glover 2011a, b; Berkhout et al. 2015). Some farmers cycle through SRI adoption and "dis-adoption", perhaps related partly to labor considerations in some regions (Gathorne-Hardy et al. 2016; Graf and Oya 2021). The combination of multiple practices also presents challenges to understanding interactions between techniques and/or identifying which dominates the observed rice system responses. And while evidence exists to show that AWD (and SRI more generally) reduces methane emissions in many domains (Thakur et al. 2016; Uphoff 2023), there exists more variability and uncertainty regarding impacts on nitrous oxide emissions and soil carbon sequestration between alternative and conventional rice production, which may complicate assessments towards mitigation goals (Cheng et al. 2022; Kritee et al. 2018).

Process-based crop, soil, and agroecosystem models are important tools for climate change impact assessment (Rosenzweig et al. 2013), which can help to better explore some of the processes discussed above. However, it can be challenging to comprehensively represent all principles of alternative rice management practices, like SRI, in such models. This contributes to some uncertainty on how SRI or other alternative rice production practices can contribute to climate change adaptation and mitigation goals under continued climate change trends (i.e. both now and in the future). Nevertheless, developing and improving modeling tools to these ends is essential because testing the full range of changing climate conditions across multiple related variables and scenarios can be extremely challenging (if not impossible for future climate conditions) in field-based research, owing to physical and/or economic limitations in collecting a full suite of agronomic and agroeconomic data. Nevertheless, agricultural stakeholders require more comprehensive assessments of alternative rice production practices such as SRI, particularly their efficacy in achieving combined climate change mitigation and adaptation goals. Such assessments should also consider a range of regionally relevant co-benefits and trade-offs, e.g. food security, water conservation, household livelihoods, and gender and labor equity. Additionally, these assessments must be conducted for both historical and future climate (and socio-economic) conditions to better ascertain the sustainability of alternative management practices like SRI.

The goal of this study is to investigate how differing rice management systems, inclusive of AWD and SRI principles and multiple interacting components, can serve both climate mitigation and adaptation goals under present-day and future climate change by providing meaningful environmental (e.g. methane emissions) and biophysical (e.g. crop yields) co-benefits and trade-offs. We specifically ask and answer the following research questions: (1) How do alternative management interventions (defined as systems of multiple management components/principles) compare to current rice management practices regarding yield, water use efficiency, and methane emissions? (2) How do these interventions perform under future climate change conditions? (3) How "climate-smart" are these interventions to increase productivity while reducing methane emissions? We answer these questions by adapting a set of climate-crop modeling protocols developed by the Agricultural Model Intercomparison and Improvement Project, described below. We leverage existing data compiled by the AgResults project (AgResults) (Narayan et al. 2020; Mainville et al. 2023) in the Red River Delta, Vietnam to implement in a newly-coupled rice growth-soil process based modeling system, also developed and deployed by AgResults to assess yields alongside methane emissions in this region. Our methodological approach, findings, and implications are nevertheless relevant to other major rice production regions around the globe.

Methods

Description of rice production systems in the Red River *Delta*, Vietnam

We leverage data and information for rice farming sites participating in the AgResults Project (https://agresults.org/) (Narayan et al. 2020; Mainville et al. 2023) across the Thai Binh province, Red River Delta, Vietnam (Fig. 1) (Mainville et al. 2023). Vietnam is an important national producer and leading rice exporter globally. Depending on the year, the Red River Delta comprises ~ 1 million hectares of rice cultivation (or < 20% of the national total area) (Yuen et al. 2021; Butterbach-Bahl et al. 2022), of which ~ 77,000 hectares are situated in Thai Binh province (Narayan et al. 2020; Mainville et al. 2023). The AgResults project was conducted over a four-year

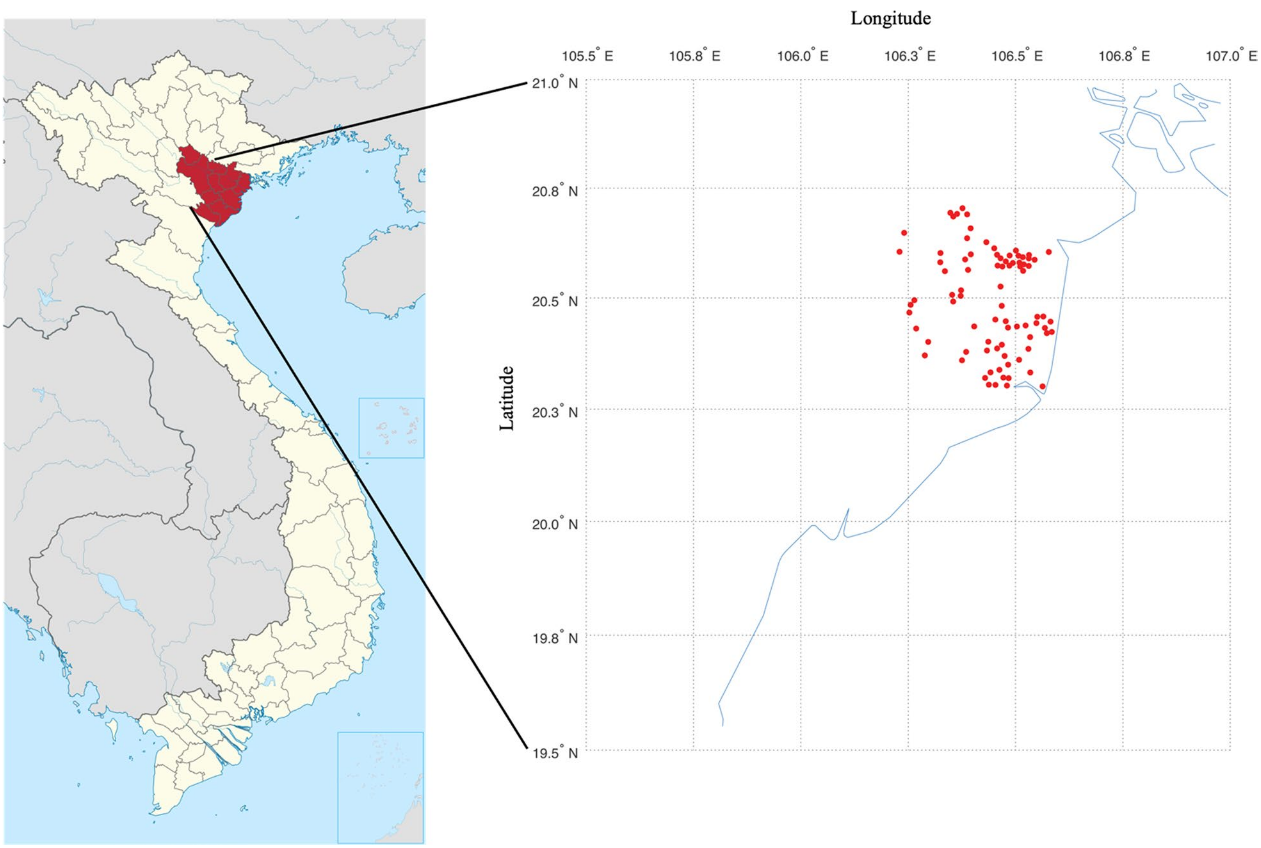

Fig. 1 Map shows the Red River Delta, Vietnam (red) and (right) the locations of the selected rice fields

(2017–2020) period to assess rice system interventions that maintained or boosted productivity while reducing greenhouse gas (GHG) emissions using field trials and experimental data collection along with new modeling approaches (detailed below) (Narayan et al. 2020; Mainville et al. 2023). The data collected during this project was used in a process-based model framework (described below) to evaluate climate change mitigation and adaptation in rice farming systems in response to management interventions, including AWD and implementation of critical elements of SRI, under historical and future climate conditions. We used 83 field trial sites from the available data that sampled the regional soil variability, shown in Fig. 1.

Model assessment framework and a coupled crop growth and soil biogeochemical model for mitigation and adaptation assessment

This work builds off the Regional Integrated Assessment methodology and model framework developed by the Agricultural Model Intercomparison and Improvement Project (Fig. 2) (Rosenzweig et al. 2013, Antle 2021). In summary, this model framework links climate information (historical and future projection time series) with process-based crop models and a socioeconomic trade-off analysis model to understand the impacts of climate change on agricultural production and socioeconomic household conditions, such as livelihood and food security. AgMIP methods also closely integrate stakeholder engagement to design adaptation options for climate change impacts and test them within the model framework for ex-ante adoption and trade-off analysis. This framework constitutes a highly systematic means to globally standardize the regional evaluation of climate mitigation and adaptation benefits and tradeoffs of agroecosystem interventions (Rosenzweig et al. 2013).

This model assessment framework has been applied in numerous studies focused on diverse locations (Rosenzweig et al. 2013; Antle 2021), and much of the emphasis of this prior work has been on climate change adaptation. However, the AgMIP framework has only recently been applied to one previous study to evaluate the combined climate adaptation and mitigation potential of agroecosystem management (Homann-Kee Tui et al. 2023). Therefore, we leverage this framework to add a coupled, process-based rice-soil model that can dynamically and simultaneously simulate rice yields and water use alongside methane emissions. We focus here in on

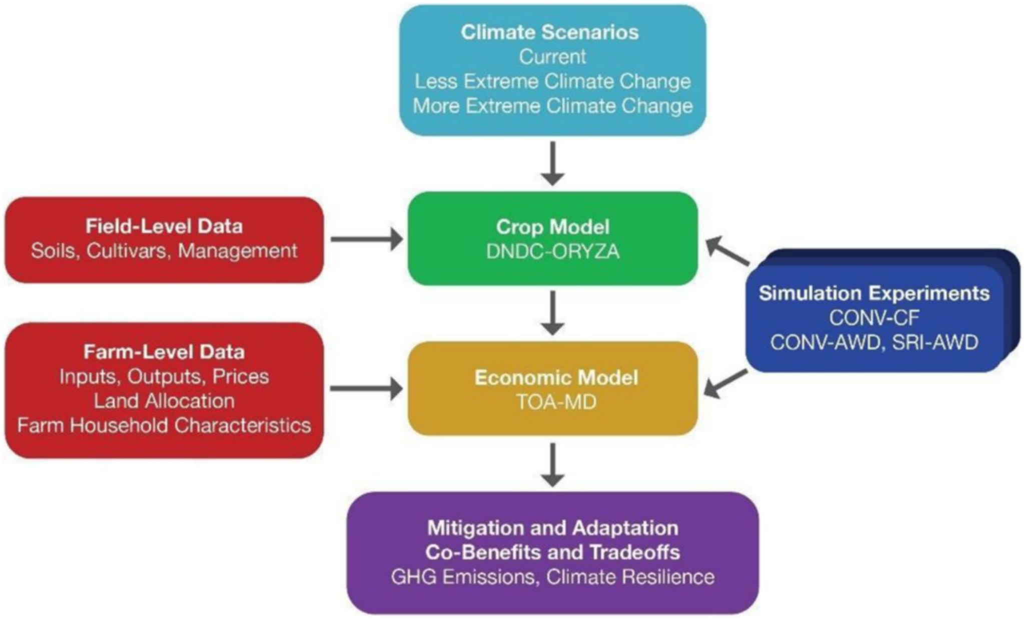

Fig. 2 AgMIP model intercomparison protocol used in Regional Integrated Assessment framework, adapted from (Rosenzweig et al. 2013; Antle 2021) to also include combined mitigation and adaptation outcomes. We note that our present study focuses on integrated climate information (light blue box) with process-based rice crop soil biogeochemistry model simulations (green box), specifically using DNDC-ORYZA, described below. Generally, this framework is intended to be multi-model, whereby multiple models are run in a harmonized way and intercompared for each framework component

those framework elements associated with biophysical system components—climate, crop growth, water use and methane production. Nevertheless, this same framework may also be used to eventually consider socioeconomic impacts of both climate change and changes in management systems, (Rosenzweig et al. 2013; Antle 2021), which we note in our Discussion. In the current study, we use just one, previously calibrated crop-soil model, given the low availability of point-based models that can simulate processes pertinent to both climate change mitigation and adaptation.

To quantify rice growth and productivity, as well as soil biogeochemistry and resulting methane emissions, we use the newly-coupled DNDC-ORYZA process-based model (Narayan et al. 2020; Mainville et al. 2023). In summary, DNDC-ORYZA integrates two process-based models (see Additional file 1: Fig. SI-1): the DNDC soil biogeochemisty model (DNDC 2017; Giltrap et al. 2010; Gilhespy et al. 2014) and the ORYZA rice ecophysiological model (Li et al. 2017). The DNDC model was developed for quantifying soil carbon and nitrogen biochemical dynamics (DNDC 2017; Li et al. 1992), particularly for soil carbon changes and greenhouse gas (GHG) emissions (Gilhespy et al. 2014). It has been evaluated and applied in many ecosystems (Giltrap et al. 2010; Haas et al. 2013; Dias de Oliveira and Moraes 2017; Dutta et al. 2016). ORYZA is an ecophysiological model for rice (Li et al. 2017, 2015; Bouman et al. 2002). It has also been evaluated and applied to the study rice ecosystem production in many domains across the globe (Ribas et al. 2021; Gao et al. 2021; Yuan et al. 2017; Ling et al. 2021; Tan et al. 2022).

To simulate crop growth and soil biogeochemistry, DNDC-ORYZA requires the soil physical, chemical, and hydraulic properties, information on rice management, and driving weather/climate datasets. To represent AWD in the DNDC-ORYZA irrigation scheme, we manually set the wet period in the wet and dry irrigation cycling scheme, rather than using a threshold value. Therefore, the "dryness" achieved in the drying cycle is site-specific, and dependent on the local soil hydraulic properties, crop growth, and the weather. The wet and dry cycling periods are the same for all sites and given management systems (Table 1). The soil physics and chemical information, including texture, bulk density, organic carbon and nitrogen, and pH, were extracted for each of the 83 sites used in this study from the global gridded soil information of the International Soil Reference and Information Centre (ISRIC) (Bai et al. 1981). The soil hydraulic properties, including saturated hydraulic conductivity, total porosity, and water content at field capacity and wilting point, were derived from the soil texture, bulk density, and organic matter contents using pedotransfer functions (Nemes et al. 2003).

Table 1 Description of summarized, representative rice management systems evaluated

Rice management system	Base1	Base2	Base3	Intervention 1 (INV1)	Intervention 2 (INV2)	Intervention 3 (INV3)
Cultivar	DS1	T10	BT7	DS1	LTH31	BC15
Establishment						
Seedling age	11	11	11	11	11	11
Transplanting density (#/m^2)	135	123	145	60	110	109
Tillage[1]	2 (4) + 1(3)	2(3)	2(4, 3)	2 (4) + 1(3)	1(3)	1(3)
Fertilizing (kg/ha)						
Urea N[2]	54.0(3)	54.0(3)	81.0 (2 + 2 s)[b]		25.6(1)	
Ammonium N[2]	63.0(2)	63.0(2)	63.0(2)	82.8(4)	83.3(1)	81.1(1 + 2 s)
P[2]	60.0(2)	60.0(2)	60.0(2)	103.6(4)		90.9(3)
S[2]				0.6(1)		
Organic[2]	43.5(46)	4.6(70)		47.8(46)	45.7(46)	27.9(86)
Irrigation[4]	A(2, 5)	A(2, 5)	A(2, 5)	A(5, 6)	A(5, 6)	A(4, 5)
Pest and disease	Complete pest and disease-free					

[1] Tillage management was described as tilling numbers (tilling method) before planting + tilling numbers (tilling method) after harvest, for method, 2: ploughing slightly, 3: ploughing with disk or chisel (10 cm), and 4: ploughing with moldboard (20 cm)

[2] Fertilizer application described as total N, P, or S amount (splits). The "s" was followed for the slow-release fertilizer type

[3] Organic fertilizer application in N amount (C:N ratio)

[4] Irrigation management: "C" for continuous flooded; "A" for alternative wet and dry management, which includes the wet and dry cycles and drying days in brackets such as (4, 5)

[a] There was no irrigation during the vegetation period, but the field was flooded during the reproductive stage

[b] The total 81 kg/ha urea N was applied in four splits, where the last two applications were slow-release urea. The similar meanings in urea and ammonium fertilizer management in scenario Innovative 3

DNDC-ORYZA had been previously calibrated and validated as part of the AgResults work using experimental field data (Additional file 1: Fig. SI-2) (Mainville et al. 2023; AgResults. 2021; Salas 2018). The model calibration was undertaken with randomly selected data from the AgResults dataset, representing high-quality, standardized data collection procedures covering the 2017 to 2020 cropping seasons (Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018). The calibration exercise resulted in a (Additional file 1: Fig. SI-2, top row) root mean square error (between simulated and measured values and normalized by the average of measurements) around 15% for rice grain yield and less than 30% for GHG emissions. Methane was underpredicted by the coupled model (Additional file 1: Fig. SI-2, bottom row) for higher methane values. We note that the data quality for model validation was lower since it was obtained through farmer household information, and there is likely more variation between farmers and between their reported management and what was actually undertaken on the field. Furthermore, DNDC-ORYZA was not evaluated on its prediction power on CO_2 and N_2O emissions, soil carbon, and water use efficiency because of a lack of direct field or experimental site measurements. As a result, the predictions on CO_2 and N_2O emissions, soil carbon contents, and water productivity contain uncertainties with different cropping management practices and climate conditions. Given this, we assume that the biases in these values are consistent across forcing conditions, and we present most of our results in terms of relative (percent or fractional) changes.

Rice management scenarios and simulations

Due to intellectual property policies and restrictions on AgResults data access, we summarized the farm management information collected via AgResults (Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018) into six rice management scenarios for the Spring season (January-June) and adopted the calibrated and validated cultivars for all simulations shown herein (Table 1). The six management scenarios included three baseline scenarios (hereafter "Base") that are representative of the current regional rice management systems, and include several management components/principles (e.g. variety, water management, nutrient management, etc.) that display variation across the region. We also test three scenarios of rice management interventions (hereafter "INV") suggested to aid mitigation and adaptation of climate change per the AgResults project and prior work (Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018) (Table 1). Similar to the Base scenarios, the INV scenarios include changes to multiple components/principles of the rice management system. Again, we note that our primary goal is to evaluate how these whole management systems—which were found to be the most impactful in the AgResults project—performed under long term simulation for both current and future climate conditions, which was not attempted in the AgResults project.

Each of the six management systems was simulated at each of the 83 sites (hereafter, the combination of management systems simulated across these sites will be referred to as "management-sites") using our modeling framework (Fig. 1). Data collection from the AgResults project indicate that across the Red River Delta, many farmers have adopted a practice of multiple drainage or AWD during the major Spring growing season, which is of focus for the present work (Kosmowski et al. 2023; Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018). Furthermore, the AgResults project adopted multiple drainage as their baseline against which to conservatively measure the combined yield, water, and GHG benefits of further interventions (AgResults. 2021). Therefore, for relevance to this regional context, the baseline scenarios use different AWD management systems while our INV scenarios (Table 1) include additional SRI practices such as: earlier transplanting, greater plant spacing, and altered nutrient applications (Table 1). In our Discussion section below, we raise implications of this decision to treat AWD as part of baseline conditions.

Our INV scenarios may therefore be considered "variations of SRI" (Table 1) (Bouman et al. 2002) and differ in several major ways from Base management. First, INV transplanting densities were substantially reduced, with INV1 testing the greatest reduction in transplanting density at less than half of most baseline management systems. Second, for INV2 and INV3, the number of tills was reduced during the spring season. Third, the INV systems tested enhanced the application of organic fertilizer and/or increased the proportion of slow-release nitrogen fertilizer. Fourth, while the Base systems also use AWD, the INV systems increased the number of cycles and/or the length of the AWD drying period, leading to overall changes in water use (discussed in the results section below).

We acknowledge that changes across multiple management principles can lead to challenges in identifying those with the strongest effects. To this end, we undertake some simple factorial model assessments (Additional file 1: SI Fig. SI-3) to provide a sense of model sensitivity to key management parameters, including cultivar choice. In doing so, we find that the choice of cultivar based on the management system could potentially impact the results (Additional file 1: SI Fig. SI-4), particularly yields and related measures (e.g. water-use efficiency). While the variety selection also appears to impact methane emissions, the differences between the varieties and sites are relatively small. Nevertheless, a high-yielding variety appears more efficient when looking at GHG intensity (i.e., GHG emissions per unit of output). Future work will determine the importance of individual management practices, particularly for interventions resulting in substantive co-benefits with minimal tradeoffs.

However, this study was intended to test those management interventions identified as promising for climate mitigation and adaptation, moving beyond AWD in this region (AgResults 2021; Final evaluation report: Vietnam emissions reduction challenge project final report 2022). We therefore focus on an overall assessment of these more comprehensive management interventions relevant to decision-making at multiple levels. Lastly, we assumed no pest/disease or weed pressure in these experiments.

Description of climate data: historical and future climate scenarios

Daily climate data for key variables, including maximum and minimum temperatures, precipitation, and solar radiation, is required for crop and soil model simulations (described below). Furthermore, we performed all simulations for 30 continuous rice cropping years to account for climate and consequent yield variation. However, continuous station data that best represented the geographic distribution of sites was sparse. We, therefore, leveraged the spatially explicit 0.25° latitude × longitude AgMERRA climate dataset, which has been widely used for crop model applications (Ruane et al. 2015a, b).

Before forcing the crop model simulations with AgMERRA climate data, we evaluated and removed monthly biases using an observational product for one co-located (i.e. within the Red River Delta) station. Specifically, we obtained maximum and minimum temperatures and precipitation, ranging from 1980 to 2010 for Phu Lien, Vietnam (20.8°N, 106.63°E) from the National Oceanic and Atmospheric Administration's Global Summary of the Day. Months with the most continuous available data were used to evaluate monthly biases in the AgMERRA dataset extracted for the exact latitude and longitude. These biases were then removed for five AgMERRA sites extracted to best represent the distribution of climate conditions that characterize the 83 rice field sites (Additional file 1: Fig. SI-5). These climate data represent our "historical" climate forcing for the crop-soil model, as discussed in the Results section below.

Future climate scenarios were then constructed using established AgMIP procedures (Ruane et al. 2015a, b; Ruane and McDermid 2017), which have also been evaluated in independent studies (Qian et al. 2021). Figure 3 shows the distribution of CMIP5 climate models' surface temperature anomaly vs precipitation anomaly (%

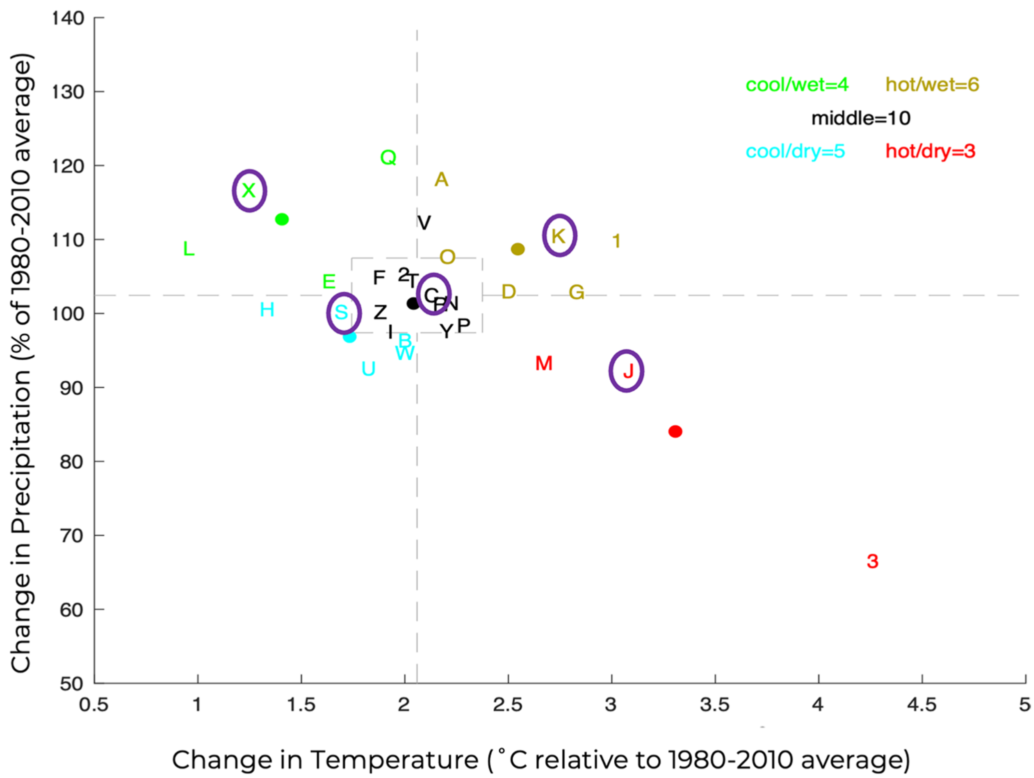

Fig. 3 Temperature and precipitation anomalies for 29 different climate models (represented by alphanumeric characters) under RCP8.5 averaged for 2040–2069 (i.e. mid-century) conditions. Colors represent "quadrants" that break the distribution of climate changes into cool/wet (green), hot/wet (yellow), cool/dry (blue), and hot/dry (red) conditions relative to the model distribution mean (black dot). The "middle" area is defined by ± one standard deviation of change on each axis. Models close to this median value were circled in purple for the crop model simulations

change) for the model grid cells overlapping the weather station site used for bias correction (described above), averaged over the relevant growing season months. From this distribution, four "quadrants" of change may be defined relative to the distribution's mean (black dot on graph): hotter/wetter, hotter/drier, cooler/wetter, and cooler/drier relative to the median value. One model was selected for each of these "quadrants" (closest to the quadrant mean, colored dots), and in addition the model closest to the mean value of the distribution resulting in five selected models. Per this method, the five-model subset obtained represents the wider distribution of modeled climate changes (Ruane et al. 2015a, b; Ruane and McDermid 2017).

The monthly mean anomalies and changes to daily variation in the relevant climate variables from five climate models: "X" (CNRM-CM5), "K" (HadGEM2-ES), "J" (HadGEM2-CC), "S" (MRI-CGCM3), and "C" (BNU-ESM) (Fig. 3) were then applied to the baseline, bias-corrected AgMERRA datasets described above. These climate models were selected from the Fifth Coupled Model Intercomparison Project (Taylor et al. 2012) to represent the distribution of temperature and precipitation changes for Representative Concentration Pathway 8.5 averaged over 2040–2069 (Fig. 3). The mean temperature changes for this period relative to the baseline climate were 2.09 °C ("C"), 3.19 °C ("J"), 2.80 °C ("K"), 1.56 °C ("S"), and 1.21 °C ("X"). While this work was undertaken before the completion of the new Sixth Coupled Model Intercomparison Project, future work will employ the most updated climate scenarios and models. Nevertheless, for the present study, this sample of climate models represents a reasonably broad range of possible future climate conditions that are still within the envelope of projections for updated climate projections and allows us to bracket sensitivities and uncertainties in the crop and biophysical responses. We also employ different atmospheric CO_2 concentrations that the historical climate experiments is 365.5 ppm for base weather, and the future climate experiments use 572.4 ppm.

Experimental modeling design and analysis procedures

To quantify the interactive adaptation and mitigation co-benefits and trade-offs, the model simulations were designed as complete factor interactions of baseline and intervention management systems and climate scenarios.

The six cropping management scenarios and six climate scenarios (baseline and five climate model projections) were performed at each of the 83 sites (Table 2). All management-site simulations were performed with 30-years of continuous weather data and included 60 rice cropping seasons (two per year following the regional double-cropping system described in "Rice management scenarios and simulations" section, Table 1).

In this study, the analyses of co-benefits and trade-offs were conducted for a set of model outputs during the Spring growing season, including grain yield (kg/ha), the total emissions of methane species (CH_4, kg/ha), total annual irrigated water consumption (mm), and irrigation water use efficiency, presented as the rate of grain yield to irrigation water consumption (WUE, kg grain yield/mm). The 30-year average of these simulated variables at each site were then used to produce the analyses below, including the site-specific fractional changes between baseline management and the three tested interventions.

Quantification of co-benefits and trade-offs

In general, we seek to optimize the intervention systems such that yield/production is maximized across the region, while GHG emissions, particularly CH_4, and nutrient and water use are minimized (or made more efficient per unit production). Satisfying two (at least) of these requirements are considered "co-benefits" while optimizing one at the expense of other goals is considered a "trade-off". In addition, we also use our model results to compute an adapted version of the Climate-Smart Index (CSI) (Arenas-Calle et al. 2021). The CSI is intended to aid the assessment of climate-smart agricultural interventions by identifying agroecosystem variables of key importance in this regard (e.g. yield, water use, and GHG emissions) and evaluating them in aggregate with a normalization from −1 to 1, where "1" indicates the highest level of "climate smartness". In our Results, we present the CSI per baseline management-site and mean values across the management-sites for future climate, using the modeled water productivity, (kg grain/m^3)—or herein termed water use efficiency (WUE)—and methane intensity (CH4I, kg CH_4 / kg grain) per the Eqs. 1–3:

$$\text{CH4In} = (\text{CH4Is} - \text{CH4Imin}) / (\text{CH4Imax} - \text{CH4Imin}) \tag{1}$$

$$\text{WUEn} = (\text{WUEs} - \text{WUEmin}) / (\text{WUEmax} - \text{WUEmin}) \tag{2}$$

where the subscript "s" denotes the specific management-site, CH4Imin, WUEmin, CH4Imax, and WUEmax are all obtained from our complete dataset of model simulations, including all management-sites and scenarios.

The CSI score is then calculated per Eq. 3, and ranges from "1" (highest climate-smartness) to "−1" (lowest climate smartness)

$$\text{CSI} = \text{WUEn} - \text{CH4In} \tag{3}$$

Table 2 Climate-crop-soil experimental design and description

Climate scenario (no. of scenarios)	Management SYSTEMS	No. of simulations (climate × management × site)	Simulation purpose
Historical (1)	Base1	83	Baseline results will serve as a comparison population for the experiment sets below
Historical (1)	Base2	83	Baseline results will serve as a comparison population for the experiment sets below
Historical (1)	Base3	83	Baseline results will serve as a comparison population for the experiment sets below
Historical (1)	INV1	83	Assess impacts of SRI interventions relative to Base under historical climate
Historical (1)	INV2	83	Assess impacts of SRI interventions relative to Base under historical climate
Historical (1)	INV3	83	Assess impacts of SRI interventions relative to Base under historical climate
Future (5)	Base1	415	Impacts of climate change on Base rice systems
Future (5)	Base2	415	Impacts of climate change on Base rice systems
Future (5)	Base3	415	Impacts of climate change on Base rice systems
Future (5)	INV1	415	Interactions between climate change and management interventions for key variables
Future (5)	INV2	415	Interactions between climate change and management interventions for key variables
Future (5)	INV3	415	Interactions between climate change and management interventions for key variables

* Each simulation was performed with 30-years of continuous weather data and one (Spring) cropping season

Results

Impact of rice management interventions under historical and future climate conditions

Returning to our research questions, we first evaluate how the three rice system interventions compared to baseline management under historical climate conditions for key variables shown in Fig. 4.

All three SRI interventions produce absolute yield values comparable to or higher than the baseline management systems, with INV2 showing the most substantial yield improvements relative to all other management systems (Fig. 4a). The methane responses are decidedly more mixed: Base1 has the highest methane emissions, followed by INV1 (Fig. 4b). While resulting in the highest yields, INV2 incurs the least methane emissions, on par with the lowest yield system Base2, indicating a significant gain in methane intensity for this management system. Similarly, INV2 also results in the highest WUE relative to all other management systems (which follows largely from the substantially higher yields used in the WUE calculation) (Fig. 4c).

All three interventions generally increase yields under historical climate conditions (Fig. 5a), except for INV1 relative to Base1. However, there are differences in the magnitude and spread of these yield changes, with INV2 showing substantially and significantly larger fractional yield changes than the other interventions. The fractional changes resulting from the interventions are comparable for both Base2 and Base3, while overall lower in Base1. Relative to the other SRI interventions, INV2 also results in overall lower fractional methane changes relative to each baseline management (Fig. 5b). In the case of Base1 and Base3, shows reduced methane emissions relative to the baseline. Relative to Base1, we note that all three interventions appear to reduce methane, and the most substantial decreases result from INV2. This suggests that INV2 presents a possible optimum of enhancing yields while not significantly increasing methane. This is also true of INV2's fractional change in water use efficiency (a function of yield), which again displays a higher increase compared to the other interventions (Fig. 5c). Improvements in WUE are also shown for INV3 compared to all baselines, while INV1 shows reduced WUE (again relating partly to the yield responses).

We next evaluate the fractional changes between the interventions and baseline management under future climate change (as described in the Methods) (Figs. 4 and 5, bottom row). We note here again that each boxplot shown reflects the distributions of simulated fractional changes across the management sites for all five

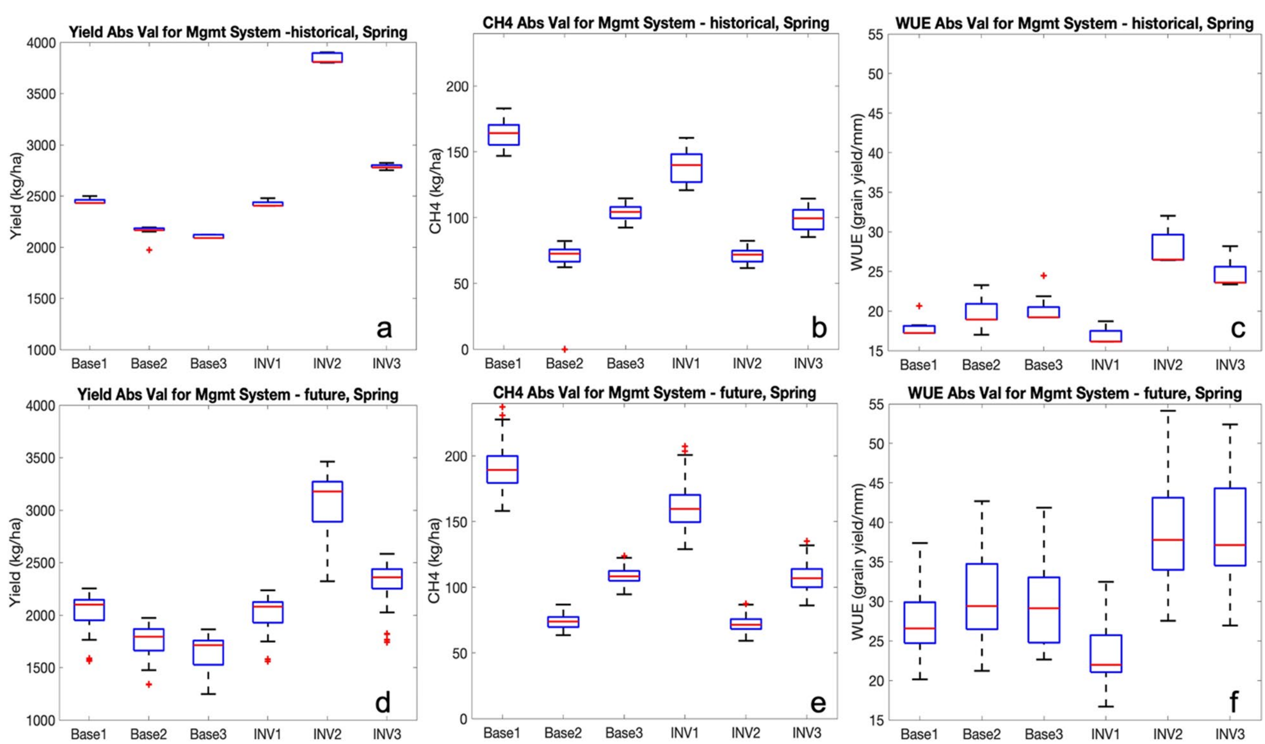

Fig. 4 Boxplots show the absolute value of **a** yields (kg/ha), **b** methane emissions (kg/ha), and **c** WUE (grain yield/mm) across the management-sites, inclusive of the three baselines and three SRI interventions during the Spring season. **d**–**f** same as (**a**–**c**) but for future climate, where distributions include the management-sites run for all five climate modeled futures

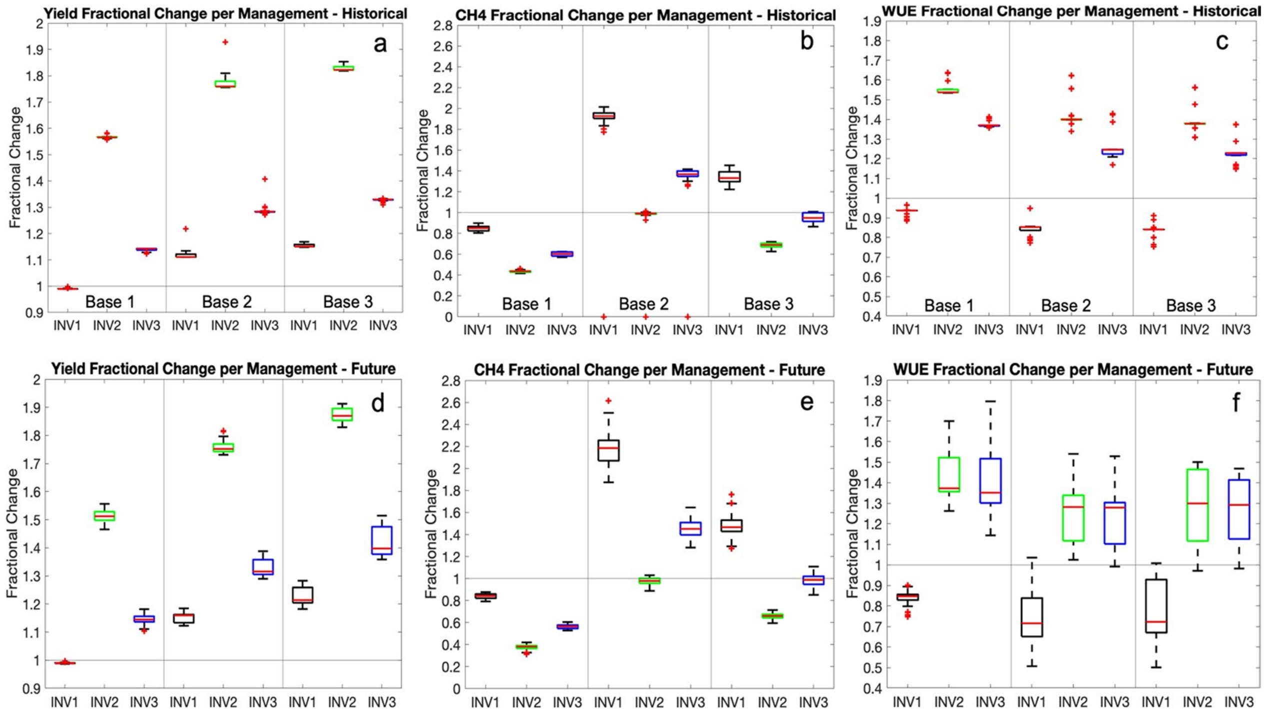

Fig. 5 Boxplots of fractional anomalies between the SRI interventions and baseline management across sites for key variables under historical (top row) and future (bottom row) climate conditions. Variables shown are yield (**a**), CH4 (**b**), and WUE (**c**). Black boxplots denote the INV1 response (relative to the respective baseline column), green boxplots denote the INV2 response and blue boxplots denote the INV3 response. The bottom row variables showing the fractional changes under future climate conditions are ordered the same as the top row, and the boxplot distributions also include the management-site responses for each of the five climate models used. A fractional change greater than 1, indicates that the variable in question increases and values less than 1, indicate a decrease relative to the respective

climate models for each management system (Fig. 4), and for each of the three interventions compared to each of the baseline management systems (that is, the fractional changes shown are not computed with respect to historical conditions but rather the base management system indicated simulated for the same climate) (Fig. 5).

Relative to historical climate conditions, future climate change (as represented by the five chosen climate models) results in yield declines across all management systems (Fig. 4d). INV2, in particular, displays the largest percentage losses of all the management systems—a reduction of ~ 30% averaged across sites and climate models. The distributions of methane emissions under future climate are broadly similar to those of the historical climate simulations, although for some management systems such as Base1 and INV1, the median values are significantly higher, though these increases are not substantial (Fig. 4e). However, WUE does display more substantial changes and overall increases across most management systems while also displaying larger distributions (i.e. higher variation between management site-climate model combinations) (Fig. 4f).

Under future climate conditions, the fractional changes of the three interventions are broadly similar to those under historical climate conditions, primarily in that INV2 results in the largest yield increases across all baselines (Fig. 5d) while also mostly reducing methane emissions (Fig. 5e) and improving WUE (Fig. 5f). This demonstrates that relative to baseline management, INV2 still has the potential to meet mitigation and adaptation needs under future climate conditions. INV3 also results in higher yields and more modest reductions in methane relative to baseline management, although methane emissions do increase in comparison to Base2. Similar to INV2, INV3 also improves WUE relative to all baselines, although more substantial variation exists across the sites. Results for INV1 are more mixed, and yields are actually relative to Base1 (Fig. 5d), while methane increases relative to Base2 and Base3 (Fig. 5e). INV1 WUE (Fig. 5f) is lower across nearly all sites than all baselines. The inclusion of results for each climate model partly contributes to a larger spread in each distribution relative to those shown in the top row under historical climate conditions.

Assessing co-benefits and trade-offs of rice interventions under historical and future climate conditions

Figure 6 shows a multivariate evaluation of the SRI interventions' biophysical trade-offs and co-benefits using fractional changes from all the baseline management systems for methane vs yield (Fig. 6a, b), fractional changes in methane vs WUE (Fig. 6c, d), and methane intensity vs absolute yield (Fig. 6e, f). Under historical climate conditions, INV2 shows that ~ 83–100% of sites fall in the "win–win" quadrant (Fig. 6a, yellow-highlighted plot area), depending on the baseline management comparison (Table 3), indicating a multi-optimum for increasing yields while reducing methane. Likewise, INV2 also shows that most sites display relative methane reductions from baseline management while increasing WUE under historical climate conditions (Fig. 6c). When compared to Base1 or Base3, INV3 also produces win-wins at 100% and ~ 80% of sites, respectively (Table 3). In contrast, INV1 shows that almost no sites fall into the win–win methane vs. yield quadrant, with the exception of ~ 2% when compared with Base2.

While overall reductions in methane are needed to meet climate targets, it can also be useful to consider methane intensity (unit methane/unit yield) in tandem with fractional changes in methane. In other words, what interventions produce less methane for a given yield? Figure 6e shows that INV2 has the lowest methane intensity while producing the highest yields, thereby further supporting INV2 as among the more optimal combined adaptation and mitigation strategies. INV3 similarly produces higher yields for methane intensities that are on par with Base2, although Base2 yields are considerably lower. The other two baselines and INV1 display higher methane intensities and low-to-moderate yields compared to the other management systems.

Under future climate conditions, ~ 7–100% of the INV2 management-sites, depending on the climate model and baseline management system (Table 3), still fall within the win–win quadrant for methane vs yield (Fig. 6b). When considering methane vs WUE (Fig. 6d), all the management-systems, including INV2, display a substantial spread across the sites resulting in part from the varied responses to the climate models projected futures. Nevertheless, INV2 still shows the most robust win–win responses (Table 3) relative to all baseline management systems. Results for INV1 and INV3 are more mixed. INV1 does not produce any win-wins across Fig. 6b and d, while INV3 shows that ~ 33–100%

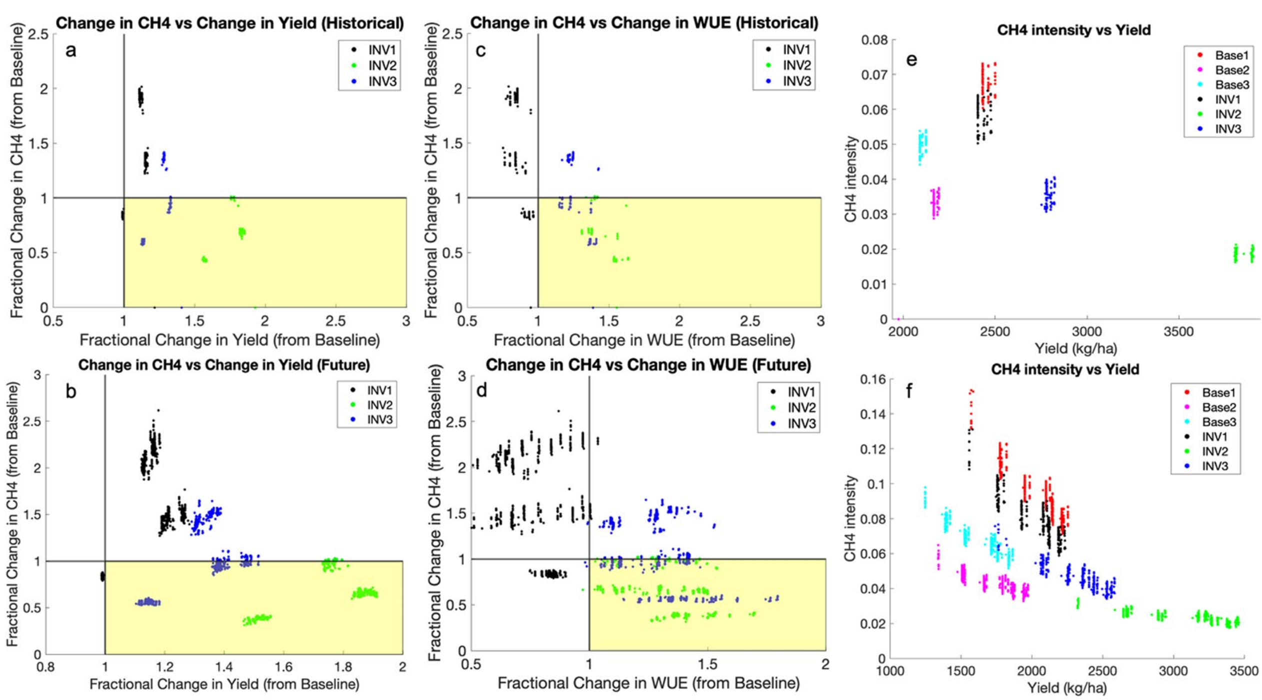

Fig. 6 Trade-offs and co-benefits of SRI interventions. Top row: fractional changes from all the baseline management systems under historical climate conditions for methane vs yield (**a**), fractional changes in methane vs WUE (**b**), and methane intensity vs absolute yield (**c**). Bottom row is the same as top row but for future climate conditions, where the increased number of points denote results from five (undifferentiated) climate models. The yellow areas on each plot show those management-sites that display co-benefits—or "win-wins"—for adaptation and mitigation. The values in the legend are the proportion of management-sites that fall in the green, co-benefit area, and ranges for the future climate show the maximum and minimum proportion across the five climate models

Table 3 Percent (%) of management-sites that fall into the "win–win" quadrant in Fig. 6

Win–win quadrant	Climate scenario	Base1			Base2			Base3		
		INV1	INV2	INV3	INV1	INV2	INV3	INV1	INV2	INV3
CH4 and yield	Historical	0	100	100	34	83	24	0	100	81
CH4 and yield	ICXF	0	100	100	0	7	0	0	100	55
CH4 and yield	IJXF	0	100	100	0	94	0	0	100	33
CH4 and yield	IKXF	0	100	100	0	82	0	0	100	54
CH4 and yield	ISXF	0	100	100	0	83	0	0	100	65
CH4 and yield	IXXF	0	100	100	0	100	0	0	100	92
CH4 and WUE	Historical	0	100	100	0	83	0	0	100	81
CH4 and WUE	ICXF	0	100	100	0	7	0	0	100	55
CH4 and WUE	IJXF	0	100	100	0	94	0	0	100	33
CH4 and WUE	IKXF	0	100	100	0	82	0	0	100	54
CH4 and WUE	ISXF	0	100	100	0	83	0	0	100	65
CH4 and WUE	IXXF	0	100	100	0	100	0	0	99	89

of management-sites (again depending on the climate model and baseline management) (Table 3) fall in the methane vs yield win–win quadrant (Fig. 6b), and 0–100% of management sites fall in the methane vs WUE win–win quadrant (Fig. 6d).

The various management systems display responses in methane intensity vs yield (Fig. 6f) under future climate conditions like those under historical climate conditions: overall, INV2 shows the highest yields that are the least methane intensive. It is also notable that many INV2 climate model-site combinations in Fig. 6f show methane intensities similar to those under historical climate conditions. There is more variation owing partly to the spread in climate models. However, methane intensity across the management-sites and climate model combinations approximately doubles under future climate conditions (Fig. 6f, y-axis). Therefore, depending on the future climate conditions (model and likely scenarios), these management interventions' efficacy in producing strong adaptation and mitigation benefits are more mixed. INV3 exemplifies this: while most INV3 climate model-site combinations show higher yields than baseline systems, some combinations show lower yields and higher methane intensities relative to Base2 and Base3.

The CSI score (see Methods) in Fig. 7 displays another useful, summarized way of assessing biophysical co-benefits and trade-offs of the different management interventions. Under historical climate conditions (boxplots), INV2 and INV3 show significant and substantial increases in the CSI, increasing water productivity while reducing CH4 intensity. INV2 shows the highest CSI values of the three interventions, while INV1 shows a CSI distribution across sites akin to Base1, among the lowest CSI values, which notably both use the same rice variety. We also note that none of the baseline management systems display positive CSI scores.

The impacts of future climate conditions vary by model and by the management system. Overall, for Base1, Base2, Base3, and INV1, most climate models show improved CSI scores (or no change to minimal declines relative to the median across the sites). For INV2 and INV3, which had the highest CSI scores under historical climate conditions, future climate change depresses these scores overall. Interestingly, mean CSI scores for INV2 under future climate change are similar to those for the other management interventions and does not increase under future climate change. The primary reason for this are the yield declines between the historical and future climate conditions (shown in Fig. 4a, d), which drive changes in INV2 CH4I and WP that combine to produce lower CSI scores than those of historical climate conditions. However, the choice of climate model matters: climate models K (HadGEM2-ES) and J (HadGEM2-CC) appear to improve the CSI score substantially across most of the management systems as compared to the other three models.

Discussion

Mitigation and adaptation under historical and future climate conditions

Under historical climate conditions, at least two of the SRI-like interventions produce average (across sites) yields that are either similar to Base values or higher. Furthermore, INV2 and INV3 improve water productivity compared to the Base systems and INV1. These yield gains are the product of multiple changing factors, with

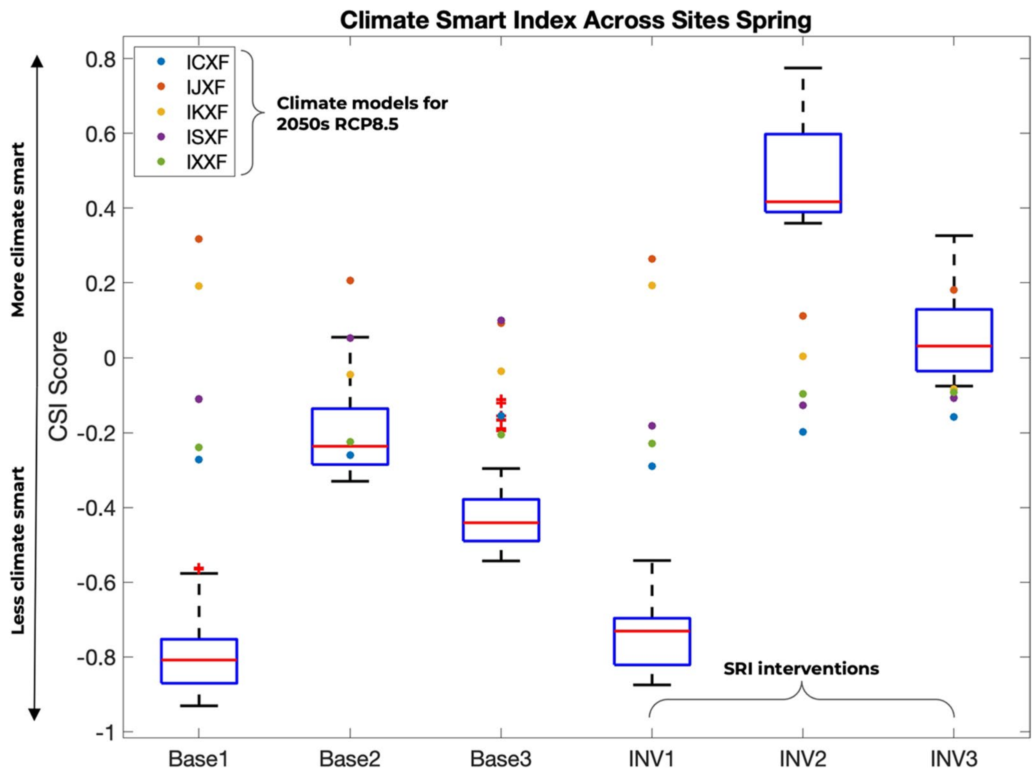

Fig. 7 Climate smart index (see Methods). Boxplots show the distribution across management-sites for baseline management and for the three interventions. Red plus signs indicate distributional outliers for the boxplots. The overplotted dots signify mean values across the management-sites for each of the five climate models (simulating RCP8.5 for 2050 conditions) identified in the Methods and also in the legend. CSI values closer to + 1 indicate higher rice water productivity and reduced CH4 intensity—or more "climate smart"—while values closer to – 1 indicate less climate smart (see Methods for more details)

important contributions from high-yield cultivars and enhanced WUE (in the case of INV2 and INV3). These modeling experiments consider the average values of key variables over a 30-year period, which embeds climate extremes and the long-term climate change trend. These results suggest that, across most management-site combinations, SRI-like interventions could serve as climate adaptation options under historical climate conditions. Furthermore, there are interventions at these management-sites that also reduce methane while increasing yields, particularly INV2 or INV3, thereby producing a "win–win" for combined climate mitigation and adaptation. The highest yielding INV2 management system also had among the lowest methane emissions across sites.

All the baseline management systems already utilized AWD (Table 1), reflecting current trends in regional rice farming practices (Kosmowski et al. 2023). Therefore, our interventions test *adaptive changes* in AWD implementation by introducing other management practices, rather than compare AWD to conventional flooding. In some cases, modifying Base AWD practices can result in more water added during AWD wetting cycles and/or fewer or shorter drying cycles. Coupled with modified nutrient management, the tested water management interventions introduce the possibility of relatively high methane emissions compared to Base management systems, which is exemplified by INV1. Although these water-saving interventions may not eliminate methane emissions across interventions, our results do suggest that taking measures to enhance WUE or increase beneficial plant water uptake can be one important measure to help facilitate climate change mitigation in rice cropping systems.

Under future climate change, the INV2 and INV3 interventions still produce yield gains from all baseline management systems, although yields are reduced overall compared to historical climate conditions. The success of INV1 is more variable, as it produces yield gains under historical and future climate only when compared to Base2 and Base3. In general, while the spatial variation across the sites was low, the different management-site combinations display more variability in WUE under climate change conditions. This larger spread relative to historical conditions may partly reflect the interaction between climate and plant growth, water uptake, the sites' soil conditions, and choice of climate model—that is, model-specific changes in temperature and precipitation interact with crop water uptake. Nevertheless, the future climate results suggest that switching from the baseline management systems to INV2 (or switching to INV3 from Base2) may still increase yields by a comparable fraction to historical climate conditions and/or serve as a methane mitigation option across most sites.

Biophysical co-benefits and trade-offs of combined mitigation and adaptation interventions

Under historical climate conditions, a fraction of modeled sites show potential for simultaneously achieving mitigation and adaptation alongside co-benefits for WUE and irrigation water use. The way SRI management principles are implemented matter greatly for this outcome. For the combination of practices comprising INV2, most sites can optimize across mitigation, adaptation, and other co-benefits (e.g. WUE) depending on which Base system is being compared. However, these gains—both in magnitude and across sites—are reduced when considering future climate change, particularly the severity of temperature change (given these are irrigated management systems) can further modulate these results. Overall, this results in a lower fraction of modeled intervention management-sites achieving both mitigation and adaptation goals simultaneously. Future climate changes across most climate models also result in lower CSI scores for INV2 and INV3.

Notably, climate change can improve the CSI score for management systems that otherwise "underperform" for yields and methane emissions compared to INV2 and INV3. This result is largely driven by increases in WUE (as opposed to reduced methane intensities) for these systems, while WUE for INV2 and INV3 displays higher variability under future climate change. For some climate models, the CSI score for INV2 and INV3 falls within the range of the CSI score for the other management systems. This makes assess assessing the optimal system challenging based on this indicator alone. As such, caution should be taken when relying on any one metric or indicator to assess how effective a particular agricultural intervention may be at achieving combined mitigation and adaptation goals.

These results highlight important considerations for assessing environmental co-benefits and tradeoffs of rice management options for climate change mitigation and adaptation. Firstly, most rice GHG mitigation strategies focus on reducing methane, the most important GHG species in conventionally flooded paddy production, via alternative water management like AWD. However, changing the water management regime can also impact plant and soil nutrient cycling in ways that can in changes in N_2O and CO_2 emissions. Therefore, the choice of aggregate warming index and which GHG species are most important from a stakeholder or emissions stocktaking perspective can impact the interpretation of how well a management system performs and, thus, how these are valued in decision-making. In this vein, our CSI scores reflect high importance on WUE and overall methane intensity. Future work should seek to modify this scoring indicator by replacing or augmenting it with quantities of specific importance to regional farming systems (for example, further including SOC measures).

It is further important to note that the choice of climate future, in this case, the climate model likely also the magnitude of change in climate variables related to different scenarios, matters for these results, particularly concerning methane (or GHG) emissions and crop physiological responses (e.g. changes in WUE). These effects are mediated through the modeled interactions between plant and soil hydrological and biogeochemical processes, which are sensitive to changing temperatures and water. For example, alongside changes in water management, higher temperature anomalies from climate change contribute to more methane production in the model via more active carbon decomposition and root exudation that increases methanogenesis (Additional file 1: Fig. SI-3). However, future work would benefit from more systematic sensitivity testing and evaluation and comparison with field data where available.

Limitations and future work

While our experiments show the potential for SRI-like management interventions to achieve climate change mitigation and adaptation in rice systems both now and in the future, several limitations of our work must be addressed and/or considered by future study. First, this work was intended to evaluate different combinations of management practices as they have been previously identified, tested, and promoted as part of the AgResults project (Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018). However, considering all these management practices simultaneously complicates a rigorous scientific assessment of which management practices are most important in driving these responses and the mechanistic climate-plant-soil pathways by which they are achieved. Understanding which of the management changes—particularly water and nutrient management, plant density, and cultivar choice—are the most important levers to achieve mitigation and adaptation can be important for decision-making from the farm to the national scale. Doing so on both a seasonal and annual basis is also important given that rice may be cropped multiple times a year in Vietnam and other major rice producing countries. Evaluating management practices across both space and time (seasonal vs annual) would also add more granularity to mitigation and adaptation assessment and provide farmers and managers with more specificity on how management should be adapted to achieve multiple goals at different times of the year.

Second, the goals of this study did not include a comparison to conventional flooding nor further optimization of rice management under future climate. Conventional flooding is important to consider in modeling activities as it is the primary driver of methane from rice farming systems (Carlson et al. 2016; Zhang et al. 2020; Li et al. 2009), and many prior studies have demonstrated how switching to reduced water management, AWD or intermittent flooding, can achieve significant methane reductions (LaHue et al. 2016; Carrijo et al. 2017; Nakamura et al. 2022). A comparison to conventional flooding may have resulted in further reductions in methane under our INV scenarios, relevant for farmers who still use the practice for one or all seasons. However, as methods of evaluating rice GHG reduction and mitigation become more sophisticated (e.g. Methane Emission Reduction by adjusted Water management practice in rice cultivation—Gold Standard for the Global Goals), and practices of multiple seasonal drainage expands across regions, taking a conservative approach to estimating emissions reductions can aid more realistic estimates of AWD and/or SRI co-benefits (Narayan et al. 2020; Mainville et al. 2023; AgResults. 2021; Salas 2018; Final evaluation report: Vietnam emissions reduction challenge project final report. 2022). It is also possible, considering the responses produced by INV2, that rice management could be improved under future climate conditions to enhance WUE and target other co-benefits, such as reducing non-methane GHG emissions. For example, applying slow-release nitrogen fertilizer may help reduce N_2O emissions (and CO_2 equivalent Additional file 1: Fig. SI-3) with minimal impacts on rice yields (Tan et al. 2022). Applying organic fertilizer, with appropriate timing, could also provide co-benefits to soil organic carbon and nitrogen storage while reducing GHG emissions. Future work should seek to assess the impact of using different baselines as well as further adaptation options and management interventions under future climate conditions.

Third, systematically identifying the key factors driving change between (rice) management systems and understanding uncertainties in process representation (e.g. in the underlying parameters governing model responses) is critical to understanding the range of rice responses to environmental and management conditions. We provide a very preliminary sensitivity analysis of the influence of variety in Additional file 1: SI Fig. 4 and single factor sensitivity tests (Additional file 1: SI Fig. 3), which suggest important relationships between temperature and methane emissions and that variety selection is an important factor in yield and emissions changes between management systems. A more complete and rigorous assessment of these factors would require that each be evaluated separately for its sensitivity to environmental conditions, as well as a combined factor analyses to identify important interactions and nonlinearities. Such interactions could be explored, for example, with a Latin hypercube design randomly sampling across the entirety of the multi-factor uncertainty space similar to the Coordinated Climate-Crop Modeling Project described in Mcdermid et al. (2015); Ruane et al. 2014). Model and process sensitivity to early transplanting (or direct seeding), CO2 fertilization effects, the dependencies of nitrification and denitrification processes with changes in temperature (Liu et al. 2015; Cai et al. 2022), and any possible nonlinear interactions between rice system management decisions and changing climate conditions are also critical to assess. Therefore, future work should seek to develop more systematic sensitivity testing of key soil biogeochemical processes and overall model sensitivity to varying conditions.

Fourth, as noted in the Methods, DNDC-ORYZA was not evaluated for its prediction of CO_2 and N_2O or water use efficiency (and as such there is uncertainty in the latter's results). However, we evaluated the co-benefits and trade-offs using both absolute and relative changes in these WUE, so we do not anticipate that the existing biases would substantively change our results. Nevertheless, the growing need for evaluating combined mitigation and adaptation, as well as co-benefits and tradeoffs, in agricultural systems necessitates amassing more comprehensive and quality field and/or experimental site measurements for a larger range of quantities than conventionally recorded. We acknowledge that for some variables, like N_2O emissions, appropriate data collection can prove challenging (Kritee et al. 2018; Bouwman et al. 2013; Richards et al. 2016), although there is an emerging emphasis on higher quality measurements (Kritee et al. 2018) and so future work should seek to undertake primary data collection deploying these best practices.

Lastly, a more comprehensive identification and understanding of co-benefits and tradeoffs associated with AWD, SRI (or any other "climate-smart" management system) must include an explicit socio-economic dimension as is commonly done in previous work leveraging the AgMIP framework on which Fig. 2 is based (mostly for climate adaptation studies) (Rosenzweig et al. 2013). Even where biophysical conditions may be somewhat homogenous, as was the case of the 83 sites from AgResults used here, household socioeconomic conditions can be an important source of variability. To enable socioeconomic analyses per the framework used here

(Fig. 2), detailed information must be available concerning biophysical aspects of on-farm management, crop prices, cultivation costs, household socioeconomic information, among others. Analyses enabled by such data are important to understanding the reasons and conditions under which farmers make decisions and choose to adopt (or dis-adopt) climate-smart management systems, which may be related to costs and incomes, labor availability, access to information, norms and many other non-biophysical factors. These factors shape how effective and "scalable" a particular climate-smart management system in terms of adoption rates and must be considered alongside biophysical mitigation and adaptation indicators to identify both environmental/climate and socio-economic "win–win" outcomes.

Conclusions

We herein investigating how rice management interventions, akin to those utilized in the System of Rice Intensification, can facilitate combined climate change adaptation and mitigation goals under both historical and future climate conditions. To explore this, we adapt the AgMIP integrated process-based modeling framework that links multiple climate models to process-based crop and soil models, which have been calibrated and validated for important agronomic variables. Our case study focuses on rice farming sites in the Red River Delta, Vietnam. Overall, we find that two interventions, INV2 and INV3, produce yield gains while reducing methane emissions across most tested sites under historical climate conditions. Under future climate conditions, the SRI interventions tested still deliver benefits for yields, methane and water use efficiency, although the proportion of sites experiencing these benefits is reduced and WUE is more variable. This suggests that further modifications and optimization of SRI-like management (e.g. with improved cultivars) could help sustain co-benefits and minimize trade-offs in the future. To our knowledge, this is the first such process-based integrated assessment of combined agricultural mitigation and adaptation in the Red River Delta, and as such, several uncertainties remain regarding model/process sensitivities to changing management and climate conditions as well as limitations on the availability of comprehensive, multivariate observational datasets that can be used to constrain the models. Future work will seek to address these uncertainties and limitations through novel data collection and systematic sensitivity testing.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s43170-024-00308-0.

Additional file 1.

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Author contributions

TL performed the DNDC-Oryza model experiments and contributed analyses, figures, and manuscript writing. SM prepared the climate information and contributed analyses, figures, and manuscript writing. RV contributed to project conceptualization, obtaining data for model simulations and manuscript editing/revising.

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Availability of data and materials

Further information on the DNDC-ORYZA experiments and the simulated outputs can be found at: https://github.com/sonalimcdermid/CABI_VietnamRiceClimate. Climate data was obtained from the NASA AgMERRA data server: https://data.giss.nasa.gov/impacts/agmipcf/agmerra/. Soil information for the crop model was obtained from ISRIC: https://www.isric.org/explore/soilgrids. Calibration weather data was obtained using the NOAA Global Surface Summary of the Day: https://www.ncei.noaa.gov/metadata/geoportal/rest/metadata/item/gov.noaa.ncdc:C00516/html

Declarations

Ethics approval and consent to participate

Not applicable.

Competing interests

The authors declare no competing interests.

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