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Incorporating the Impact of Climate and Weather Variables in Impact Assessments: An Application to an IFAD Climate Change Adaptation Project in Viet Nam

by
Nancy McCarthy
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Abstract

The authors integrate climate variables into an IFAD project impact assessment, discussing in detail the steps taken to determine which climate variables to collect, and from which sources. The impact assessment is based on cross-section data collected ex post, and the impact assessment team carefully selected control areas to implement a propensity score matching procedure to isolate the causal impacts of the project on household-level production and livelihood outcomes. The authors show that incorporating climate variables provides important relevant information in its own right; in particular, findings show that severe saline intrusion – caused by both climate change and land and water use taking place up- and downstream – had significant effects on crop choices, as well as significant negative impacts on a wide range of production and livelihood outcomes. Thus, not including climate variables would lead to a downward bias in the impact assessment estimates, particularly for crop production. Additionally, results show that rice yields for treated households are lower than those for control households, when there is no severe saline intrusion, but are actually significantly higher under severe saline intrusion. This reveals that the project was able to increase "resilience" in the face of an extreme weather-related shock; however, previous research suggests that practices are often disadopted if yields are not also higher in "normal" years, with implications for future programme design. Finally, the paper notes that a very high proportion of the project budget was spent on supra-household-level activities to increase the performance of women's credit cooperatives and to invest in community-level infrastructure designed to build resilience to climate change. However, the authors were unable to assess resilience benefits at those levels, as relevant data were not collected. Collecting those data will be particularly important to inform future projects that explicitly attempt to scale promising pilot projects.

1. Introduction

While Viet Nam has seen rapid economic growth in the past two decades accompanied by major shifts from agriculture to the industrial and service sectors, agriculture still accounts for just over 40 per cent of the labour force (World Bank, 2019). At the same time, the fertile Mekong delta still produces 50 per cent of Viet Nam's rice and contributes nearly 30 per cent to agricultural GDP (Thanh et al., 2021). The Mekong delta is also highly vulnerable to impacts of climate change, including increased frequency and severity of saline intrusion, rising sea levels, higher temperatures, drought spells, delayed onset of growing seasons, and greater frequency of extreme climate events (Smajgl et al., 2015; Vu, Yamada and Ishidaira, 2018; Dang, Kumar and Reid, 2020). Non-climate factors often exacerbate negative impacts of climate change on agricultural and aquaculture productivity, including reduced river flow due to greater water diversion upstream and mangrove deforestation (Dang et al., 2018; Duc Tran et al., 2018). Saline intrusion and rising sea levels are particular threats in the two provinces of the Mekong delta where the IFAD project operated, Ben Tre and Tra Vinh (Tan, Tran and Loc, 2020; Febriamansyah and Tran, 2020). Indeed, in 2020, saline intrusion affected nearly the entire province of Ben Tre, compared to about 20 per cent of the province being affected during "normal" years (Hoang-Phi, 2020).

Due to these climate impacts, the government and donors have promoted a shift from rice cultivation to alternative agriculture and acquaculture products such as shrimp, coconuts and various vegetables (Hoang and Tran, 2019; Febriamansyah and Tran, 2020; Thanh et al., 2021). There has also been an emphasis on diversifying income sources and generating more non-farm-based income (Liu et al., 2020). IFAD's Adaptation to Climate Change in the Mekong Delta in Ben Tre and Tra Vinh Provinces (AMD) project sought to foster adaptation to climate change in these two provinces, primarily by helping households shift from rice production practices that are sensitive to salinity levels, towards more saline-resilient rice production practices, as well as diversifying production and increasing market participation.

In this study, we complement an existing impact assessment of the project found in Afonina et al. (2022). This paper is one of four in a series of papers incorporating climate variables into IFAD impact assessments, and builds on lessons learned in those papers (McCarthy et al., 2022a; 2022b; McCarthy, Cavatassi and Maggio, 2023). In this study, we focus on the explanatory performance of different estimates of rainfall across different seasons, as well as on the extent of saline intrusion. We do not include temperature data, as the geographic coverage of the two provinces is too small to observe sufficient variation in temperature across the area. After a brief overview of the project in section 2, in section 3 we discuss the empirical strategy for evaluating the performance of alternative rainfall variables in explaining household-level outputs and outcomes, and present two sets of climate variables to be used in the remainder of the analysis. In section 4 we evaluate the impact of climate variables on household outputs and outcomes, and in section 5 we evaluate whether not including climate variables leads to biased estimates of project impact. In section 6 we summarize results and conclude with observations on how project proposers can use climate variables in developing the theory of change and in designing monitoring and evaluation (M&E) systems, and how those implementing impact assessments can use climate variables to select control sites, and draw implications for project design from results.

2. Project overview

According to the project's proposal document, the main goal of the project was to promote sustainable livelihoods for rural smallholders by building resilience to impacts of climate change. This was to be achieved by building adaptive capacity of communities and institutions, developing robust adaptive and applied research, improving knowledge management and monitoring systems as well as expanding and diversifying climate-resilient agricultural and other livelihood options. In addition, the project introduced more flexible land-use zoning and planning, instituting rural microfinance institutions/services, including credit and matching grants, as well as adopting government co-financing of adaptive investments at household, community and enterprise levels.

The project operated in 60 communes in two provinces – Ben Tre and Tra Vinh – with 30 communes located in each province. The project builds on previous projects implemented in the two provinces that focused on increasing incomes and the participation of poor households in sustainable value chains, and investing in community infrastructure. Unfortunately, the extent to which earlier project activities overlap with the 60 communes included in the AMD project is unclear (Afonina et al., 2022).

Afonina et al. (2022) lay out the project's theory of change and impact assessment plan, on which we draw considerably here. First, the project focused on helping poor and near-poor households largely dependent on agriculture or aquaculture, and also prioritized female-headed and Khmer[1] households. The project had two main components: (i) building adaptive capacity; and (ii) investing in sustainable livelihoods. The first component focused on generating empirical evidence on sustainable and resilient value chains and establishing saline monitoring stations, and integrating evidence and saline data into development planning at the village, commune and province levels. As such, the outputs of this component have no direct impact on beneficiary households, but rather contribute to the implementation of the design and implementation of the second component.[2] While salinity station monitoring could have an impact on farmers' knowledge of current salinity levels, few salinity monitoring stations were actually built, so this potential impact could not be measured. Thus, our focus will be on the second main component, where (some) activities had direct impacts on household beneficiaries.

Under subcomponent 2.1, the first set of activities focused on rural finance, and included activities to increase access to credit for women and Khmer households, and increase financial literacy. The second set of activities focused on value chain financing, by facilitating the establishment of value chains and convening agro-financial workshops, among other information dissemination strategies. Under subcomponent 2.2, the project operated a climate change adaptation co-finance fund that distributed funds to community investment groups and cooperative groups. To receive funds, the group proposal had to indicate the climate-smart nature of the agriculture/aquaculture investments they were proposing. The project also invested in small-scale community infrastructure to build resilience (e.g. upgraded roads, water tanks), and distributed matching grants to enterprises and cooperatives that could demonstrate that the additional finance would increase jobs for the poor rural population.

The project's theory of change suggests that the above activities would lead to a very wide range of outcomes and impacts at the household level, including increased (average) income, food security and diversification of income-generating activities, increased "resilience", increased asset ownership, reduced poverty and malnutrition, and empowerment of women and marginalized groups such as indigenous peoples. We modify the theory of change found in Afonina et al. (2022) by focusing on the second component and making climate-related assumptions more explicit. This modified theory of change is captured in figure 1.

[1] Within Viet Nam, the Khmer are Indigenous Peoples who are considered an ethnic minority group and are mainly found in Tra Vinh province.

[2] As discussed further below, the first component did have activities directly engaging villages in incorporating climate change resilience into socio-economic development plans, and to disseminate relevant information to farm households. Unfortunately, no corresponding data were collected at the community level, so we do not pursue this further.

Figure 1. Theory of change, with climate-related assumptions

Activities

- Finance for rural women/marginalized groups to invest in adaptation of agriculture/aquaculture
- Facilitating value chains
- Finance for collectives to invest in adaptation of agriculture/aquaculture
- Investment in small-scale rural infrastructure
- Finance for private and collective rural job creation (PPPs)

Outputs

- 1,040 groups with 19,000 members access credit
- Workshops on value chains
- 15,000 people receive collective funding
- Rural infrastructure constructed
- US$1.8 million invested in PPP for rural job creation

Outcomes

- Households improved productivity through adaptation investment
- Value chains established
- 15,000 people receive collective funding
- Improved investment in adaptation at community level
- Increased rural employment

Climate-related assumptions

- Households' knowledge on climate change and weather shocks is sufficient to invest in resilient agriculture/aquaculture
- Value chains for climate-resilient products are promoted
- Collectives' knowledge on climate change and weather shocks is sufficient to invest in resilient agriculture/aquaculture
- Investment in climate-resilient small-scale rural infrastructure
- Rural job creation (PPPs) in climate-resilient sectors

- Households invest in resilient agriculture/aquaculture
- Value chains for climate-resilient products are established
- Collectives invest in resilient agriculture/aquaculture
- Resilient small-scale rural infrastructure are operational
- Number of jobs created in climate-resilient sectors

- Households' agriculture/aquaculture resilient to climate shocks
- Value chains operational under climate shocks
- Collective-financed production resilient to climate shocks
- Small-scale rural infrastructure not damaged by shocks
- Number of jobs created stable in the face of climate shocks

The primary climate-related assumptions are that: (i) Households, collectives and communities are aware of climate change and weather shocks and have the capacity to invest in production systems that are resilient to the climate shocks;

(ii) That value chains are developed for products that are resilient to climate change and that infrastructure investments incorporate climate change-related concerns into their design and construction;

(iii) That jobs are created in sectors that are resilient to climate change and investments in resilient production, value chains, infrastructure, and job creation lead to outcomes that are also resilient to climatic shocks and stressors.

To get from outputs to outcomes requires that these investments actually increase resilience sufficiently so that outcomes – which are a function of more than the outputs captured in the theory of change – are also made more resilient. This includes more stable agricultural production outcomes and the operation of value chains in the face of climate shocks and stressors; infrastructure that is not damaged by (or suffers less damage from) climate shocks; and a more stable demand for jobs in the face of climate shocks.

Because we only have outputs and outcomes at the household and household-plot levels – with no data on community infrastructure or other value chain metrics – our analysis focuses on the following outputs and outcomes:

Outputs

Ag Loan[3]:	Dummy, whether the household took a loan specifically for agricultural/aquaculture production
Wage Job:	Dummy, whether any household member held a wage job
Self Emp.:	Dummy, whether any household member was self-employed
Coconut:	Dummy, whether the household grew coconuts
Shrimp:	Dummy, whether the household cropped shrimp

Intermediate and final outcomes:

# Crops&Live[4]:	Number of different livestock species held and crops cultivated
# Inc. Sources:	Number of income sources household members engaged in during the past year
Rice:	Quantity of rice produced, per capita, in natural logs, during the past year
Coconut:	Quantity of coconut produced, per capita, in natural logs, during the past year

[3] We have information on whether households obtained any loans, and whether they secured loans through savings and loan groups, but because the explanatory variables have similar impacts across all loan equations, we only report results for obtaining a loan specifically for agriculture.
[4] We also analysed the number of crops and the number of livestock separately, but since results are similar to the combined number of crops and livestock variable, we report results only for that variable.

Val. Harvest: Value of total rice, coconut and shrimp harvested per capita, in natural logs, during the past year

Resilience-related outcomes:

Low Harvest: Dummy, whether the value of total harvest, per capita, in natural logs, fell into the bottom 20th percentile of value of harvest per capita

Food Secure: Dummy, whether the household reported being very food-secure.

Crop, livestock and income diversification are generally associated with less variable production and consumption outcomes, and therefore are often used as proxies for resilience. We consider these to be intermediate outcomes. In the dataset, only a sufficient number of observations were available to separately estimate rice and coconut at the plot-cycle level. The plot-cycle level has observations for each cycle within the year that was cropped on a specific plot. For the estimations, we generate the output per capita instead of output per unit of land area (crop yields) for two reasons. The pragmatic reason is that crop yields were much noisier than per capita production, which is consistent with the observation that measurement bias can be particularly severe on very small plots (Carletto et al., 2017; Desiere and Jolliffe, 2018). In this dataset, the median plot size is just 0.3 hectares. Second, it can also be argued that the per capita measure of crop production also better captures household resilience. We also aggregate the value of production for rice, coconut and shrimp and express it on a per capita basis. Most households grew at least one of those crops; however, many also grew a number of other crops. Unfortunately, the very large variety of crops grown and the limited (and very noisy) unit value data for many crops precluded us from using total value of crop production per capita.

To better probe whether the project and climate variables affected downside risk, we also estimate the impacts of these variables on the probability of realizing low value of production per capita at the household level. Reduced exposure to downside risk captures increased resilience. Finally, we estimate whether the household reported being very food-secure. In this area, over 90 per cent of respondents felt food-secure, so we use the stricter category of very food-secure. Here, 74 per cent of respondents felt that they were very food-secure.[5]

Table 1 provides descriptive statistics for the output and outcome variables for treatment and control households. In general, treatment households have higher outputs and outcomes when looking at these unweighted statistics, while our empirical strategy aims to determine whether these differences are indeed related to treatment.

[5] In general, food security is relatively high in the Mekong Delta region and these estimates reveal that our data are consistent with food security estimates in the region (see Kim et al., 2021).

Table 1. Descriptive statistics, output and outcome variables

	Treated			Control		
Variables	**# Obs.**	**Mean**	**Std. Dev.**	**# Obs.**	**Mean**	**Std. Dev.**
Ag Loan	1,055	0.604	0.489	1,070	0.439	0.496
Wage Job	1,055	0.710	0.454	1,070	0.681	0.466
Self Emp.	1,055	0.263	0.441	1,070	0.191	0.394
Coconut	1,055	0.261	0.440	1,070	0.257	0.437
Shrimp	1,055	0.055	0.229	1,070	0.033	0.177
# Crops&Live	1,055	1.541	1.159	1,070	1.020	1.008
# Income Sources	1,055	1.943	0.949	1,070	1.583	0.953
Rice Production	435	5.531	1.911	285	5.514	1.856
Coco. Production	335	5.632	1.428	306	5.532	1.394
Value of Harvest	897	15.221	2.609	674	14.747	3.132
Low Harvest	463	0.270	0.444	401	0.289	0.454
Food Secure	1,055	0.756	0.429	1,070	0.651	0.477

3. Empirical strategy

3.1 Conceptual framework guiding estimations

As noted in the introduction, this paper is one of four papers that incorporate climate variables into a project impact evaluation. In the first two papers (McCarthy et al., 2022a; 2022b), we develop a theoretical model to draw hypotheses on the relevant variables to include. Here, we summarize those hypotheses and refer interested readers to those papers for a more rigorous treatment. Assuming that farmers are risk-averse, maximizing expected utility given risky crop production leads to the following hypotheses: (ii) input choices at the beginning of the season will be a function of expected (average) weather conditions and the variance of those weather conditions; and (ii) actual outcomes at the end of the season will be a function of deviations of actual weather from expected weather. It is very important to control for expected weather and variance of weather in cross-sectional surveys because their inclusion means that the current period deviations will be conditionally exogenous.

To further restrict our evaluation of alternative climate variables, we turn to the agronomic literature. In the provinces studied here, the cropping system is very complex, with many different types of seasonal, annual and perennial crops grown, up to five growing seasons per year, and both irrigated and rainfed crop production (Van Kien et al., 2020). However, there is a "primary" rice-growing season when a greater proportion of crops rely on rainfall, which occurs from June to October, and the critical water requirement period for rice is from August to mid-September (ibid.). Given year-round production and the primary rice growing season, we consider variables constructed over the whole year, the entire primary rice-growing period and the critical water requirement period for rice. In addition to the agronomic evidence, we also reviewed information from agencies and organizations that track weather conditions, to determine reported conditions during the survey year. For instance, the Food and Agriculture Organization's Global Information

Early Warning System (GIEWS) reported that rainfall was fairly normal across rice-growing regions of Viet Nam during the summer and autumn of 2019, though it also noted that rainfall was somewhat lower than average in the Mekong delta specifically.[6] However, reliefweb, operated by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), noted the severe saline intrusion that occurred in both 2019 and 2020.[7] In summary, we use theory, agronomic evidence and real-time weather assessments to guide our choice of climate variables.

3.2 Estimation strategy

Our empirical strategy relies on first matching treatment and control households on time-invariant variables, as well as household variables measured at the start of the project (e.g. assets and livestock holdings). We recover the inverse probability weights from a logit regression with standard errors clustered at the village level, since the village level is the unit of treatment. We then run the output and outcome regressions using the inverse probability weights.[8] The output and outcome variables are dichotomous, count and continuous; for dichotomous variables we run probit regressions, for count variables we run Poisson regressions, and for the continuous variables we run OLS regressions. All variables are run using household-level data, except for the rice and coconut production per capita, and the value of harvest per capita, which use plot-level data.

3.3 Climate variables

In the study area, households grow many different crops throughout the year, with some farmers sowing up to five different times in the previous 12 months. Survey data were collected in June and July 2020, including information on all crops grown during the period between June 2019 and May 2020.

For the climate variables, we used data from two different rainfall estimate sources, NASA's Integrated Multi-satellite Retrievals for GPM (IMERG) and UC Santa Barbara's Climate Hazards Group InfraRed Precipitation with Station (CHIRPS). We did not use temperature data because the study area is not large, and temperature data exhibited very high correlations across the small study space. We ran a number of exploratory regressions to determine which rainfall variables best captured relevant weather conditions throughout the period. As noted above, we calculated total rainfall throughout the 12 months, total rainfall during the primary rice-growing season (June to October), and total rainfall during the critical rice flowering period (August to mid-September). We then created percentage differences across those three periods, as well as threshold dummy variables, since thresholds have predicted crop outcomes in other studies (McCarthy et al., 2021; Arslan et al., 2014; Asfaw et al., 2016). In addition to rainfall variables, we also included a dummy variable that indicates whether severe saline intrusion (>4 g/L) occurred in 2019 and 2020

[6] The GIEWS Country Brief: Vietnam, 18 October 2019 can be accessed at https://reliefweb.int/report/viet-nam/giews-country-briefs-viet-nam-18-october-2019.
[7] A situation report can be accessed at https://reliefweb.int/report/viet-nam/vietnam-drought-and-saltwater-intrusion-emergency-plan-action-epoa-dref-operation-2.
[8] We run the inverse probability regressions manually in STATA 17, instead of using the "teffects" command to directly evaluate the impact of interaction between treatment and saline shocks on outputs and outcomes. The benefit of using the teffects command is that it accounts for the fact that the weights themselves are estimated in the regressions. Manually implementing the command does not do so, and may underestimate standard errors. However, the teffects command is akin to forcing all variables to be interacted with treatment, which itself could be costly when coefficients on interaction terms with many of the regressors are not significant. In many cases, there is also no theoretical reason to believe impacts of various regressors – outside saline shocks – should differ across treatment and controls. We have run all regressions using teffects, which provides similar results, but here we report on the manual implementation results for which it was more convenient to evaluate the treatment*saline shock interaction coefficients.

(Hoang-Phi, 2020).[9] In the early spring of 2020, it is estimated that 62 per cent of plots suffered severe saline intrusion, while 32 per cent were affected in 2019 (ibid.). We note that nearly all households affected in 2019 were also affected in 2020, and due to collinearity (and in the case of probit regressions, perfect predictions), it was not possible to include both the 2019 and 2020 severe saline intrusion dummies in the same equation. Below, we report results from separate regressions for the two dummies.

We also include variables that capture the underlying climate conditions to ensure that current period weather-related variables are conditionally exogenous. We include the expected (historical average) rainfall, as well as the coefficient of variation for above-average rainfall and the coefficient of variation for below-average rainfall. Separating the coefficients of variation allows for impacts on input choices under greater variability in dry/drought conditions to differ from impacts of greater variability in wet/flood conditions. Finally, to control for saline intrusion, we include distance from the coast. Distance from the coast is highly correlated with saline intrusions experienced in 2015, 2016, 2019 and 2020, and is thus a good conditioning variable to control for expected saline intrusion.

We used the plot-level rice production and value of rice and coconut production per capita to explore which sets of climate variables were significant predictors of crop outcomes. Results from the analysis show that few current period rainfall variables were significant in predicting crop production outcomes using either IMERG or CHIRPS datasets. We would expect current period variables to not be significant in relatively normal years – since expected rainfall would match actual rainfall – so these results are consistent with a relatively normal rainfall year. However, saline intrusion generally has a significant negative impact on crop production outcomes. For historical variables, we find that average and coefficient of variation variables constructed using yearly observations were more likely to be significant using both CHIRPS and IMERG data sources versus using either the growing season for the primary rice cycle or the associated critical flowering period.

Our final specification of climate variables used in the following analyses thus includes a dummy variable capturing severe saline intrusion, average yearly rainfall, the coefficient of variation for high yearly rainfall, the coefficient of variation for low yearly rainfall, and the distance to the coast. We ran regressions using variables created from both IMERG and CHIRPS data sources, and full results for both specifications can be found in appendix 1. Both specifications performed similarly in many equations, so we only present results for the IMERG-based variables in the body of this paper.

3.4 Household- and community-level data

The household questionnaire captured a wide range of household-level characteristics that can be included as covariates, including rich demographic information and detailed wealth data. A community survey was also implemented and included information on basic community infrastructure and the number of other externally funded projects operating in the community.

For the matching, we included the following household-level variables: the age of the household head; the maximum years of education of adults in the household; a dummy that captures whether the household head is from the dominant ethnic group (Kinh); a dummy that captures whether the household was registered as poor in 2015; an index of consumer durables and housing quality in 2015; an index of agricultural implements held by the household in 2015; and the number of tropical livestock units (TLUs) held by the household in 2015. We also included the

[9] Specifically, we digitized the map provided in Hoang-Phi, 2020, Figure 9, p.13.

following community-level variables: an index of community isolation, the number of post-harvest facilities in the community, and dummies for whether the community had a fertilizer seller, water control structures and erosion control structures in 2015. Finally, we include underlying climate conditions, captured by average rainfall, the coefficients of variation for high and low rainfall, and distance to the coast.

Variables used in the matching are also included as covariates in the impact assessment analysis. We also include current values of certain variables that are arguably not correlated with project impact, such as the gender of the household head and current size of the household. For the crop production outcomes at the plot-cycle level we also include size of the plot, whether the plot is owned (as opposed to rented), whether the household holds title documents for the plot, and dummies that capture the month in which the plot-cycle crop was sown. For household-level outcome regressions, we include size of all plots cultivated, the proportion of plots that are owned and the proportion of plots with title.

Table 2 gives the descriptive statistics for our matching and additional covariates. In general, treatment and controls have similar means even before matching. However, treated households are further from the coast, own more parcels and had more TLUs in 2015.

Table 2. Descriptive statistics, exogenous variables

	Treated			Control		
Variables	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Climate						
Saline, 2019	1,067	0.416	0.493	1,076	0.401	0.490
Saline, 2020	1,067	0.767	0.423	1,076	0.698	0.459
Avg. Rainfall	1,067	1730.8	44.452	1,076	1725.1	40.980
CoV, High	1,067	0.119	0.041	1,076	0.111	0.034
CoV, Low	1,067	0.179	0.023	1,076	0.181	0.026
Distance, Coast	1,067	2.645	1.548	1,076	2.453	1.392
Agricultural production						
ln(Total Land)	1,067	-2.092	2.264	1,076	-2.773	2.122
# Parcels	1,067	1.978	3.252	1,076	1.179	2.260
% Parc. Owned	1,067	0.435	0.483	1,076	0.349	0.471
No Docs.	1,067	0.089	0.276	1,076	0.051	0.215
Irrigation	1,067	0.175	0.357	1,076	0.126	0.321
Demographics and wealth						
Male HH Head	1,067	1.262	0.440	1,076	1.327	0.469
HH Size	1,067	3.992	1.473	1,076	3.658	1.531
HH Max. Educ.	1,067	4.548	1.604	1,076	4.179	1.752
Ethnicity, Kinh	1,067	0.771	0.420	1,076	0.818	0.386
Head Age	1,067	51.468	12.453	1,076	55.944	13.596
Poor, ‘15	1,067	0.462	0.499	1,076	0.627	0.484
Cons.Index, ‘15	1,067	0.058	-1.026	1,076	-0.058	-0.974
Ag. Assets, ‘15	1,067	0.017	-0.956	1,076	-0.013	-1.047
TLU, ‘15	1,067	0.963	2.499	1,076	0.649	2.133
Location						
Isolation Index	1,055	0.064	-1.048	1,070	-0.062	-0.943
# Post-Harv. ‘15	1,055	1.045	0.939	1,070	1.109	1.126
Fert. Seller ‘15	1,055	0.490	0.481	1,070	0.452	0.467
Water Infra. ‘15	1,055	0.728	0.437	1,070	0.679	0.461
Erosion Infra. ‘15	1,055	0.842	0.365	1,070	0.861	0.346

4. Results and discussion

4.1 Propensity score matching

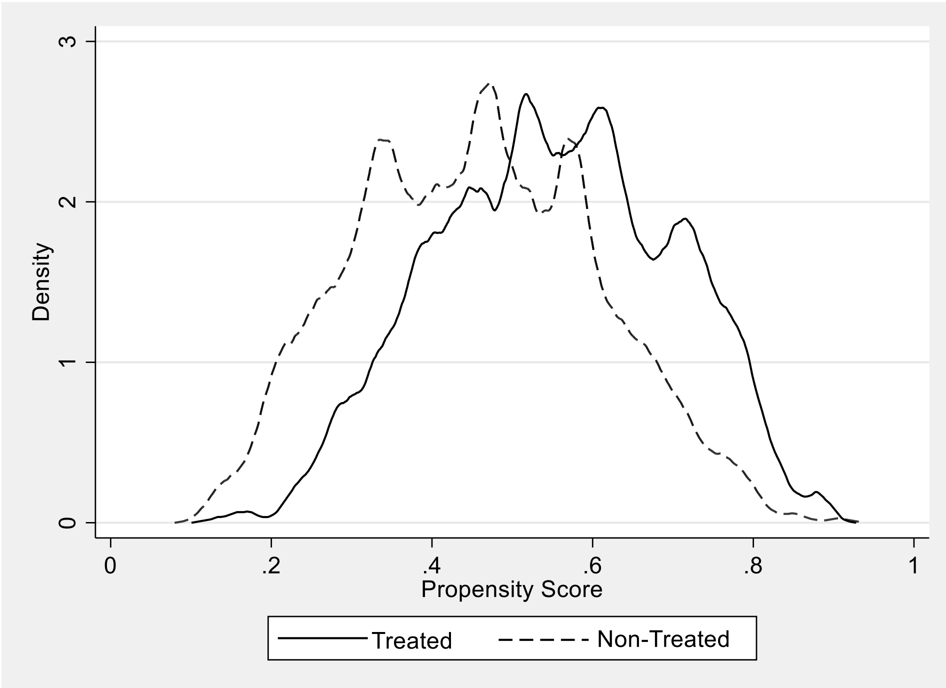
Table 3 presents the raw, or unweighted, standardized difference in matching variables in the second column, weighted differences in the third column, the raw variance ratio in the fourth column, and the weighted variance ratio in the fifth column.[10] Matching results in weighted differences that are much smaller than raw differences, and the variance ratio is close to 1 for all variables except for TLUs held in 2015. Propensity scores for all observations fall within common support for both samples. Figure 2 provides additional evidence that the propensity scores achieve balance, given the overlap between the distributions of scores across treated and control households.

Table 3. Standardized differences and variance ratios

	Standardized differences		Variance ratio	
	Raw	**Weighted**	**Raw**	**Weighted**
Demographics and wealth				
HH Max. Education	0.228	-0.012	0.850	0.763
Dummy, HH Kinh Ethnicity	-0.105	0.009	1.168	0.989
Head Age	-0.337	0.001	0.844	1.041
Dummy, Poor in 2015	-0.347	0.005	1.065	1.001
Cons. Dur. Index, 2015	0.123	0.024	1.116	0.987
Ag. Assets Index, 2015	0.028	0.003	0.835	0.861
TLU, 2015	0.137	-0.013	1.379	0.715
Location characteristics				
Isolation Index	0.126	0.012	1.234	1.111
# Post-Harvest Facilities	-0.063	0.020	0.696	0.797
Dummy, Inorg. Fert. Seller	0.080	0.043	1.062	1.059
Dummy, Water Control	0.109	0.027	0.900	0.980
Dummy, Erosion Control	-0.054	-0.044	1.112	1.091
Climate conditions				
Average Yearly Rainfall	0.129	0.004	1.162	1.071
Coef. of Var. Rainfall, High	0.246	0.016	1.378	1.148
Coef. of Var. Rainfall, Low	-0.104	-0.010	0.790	0.805
Distance to Coast	0.129	0.083	1.252	1.261

[10] The results in table 3 include observations for the household-level outcome variables; results for the subset of households that cultivated rice, coconut and/or shrimp give similar results, and both show good balance after weighting.

Figure 2. Propensity score densities



4.2 Results for outputs

The outputs are all dichotomous variables, and table 4 presents results for marginal effects of regressors at evaluated variable means. We first note that treatment has a positive impact on agricultural loans, self-employment and the adoption of shrimp cultivation, suggesting that the programme had positive impacts on outputs targeted by project activities. With respect to saline intrusion, we see that there are negative marginal impacts only on self-employment, suggesting saline intrusion reduced opportunities to offset negative impacts from these shocks. Securing wage employment and receiving transfers were less likely in areas with higher yearly rainfall, indicating that both of these mechanisms may help households cope with recurring rainfall deficits. Those closer to the coast, and thus facing higher risk of saline shocks, were more likely to take an agricultural loan and to adopt shrimp, while those farther from the coast were more likely to adopt coconut trees. While coconut trees are more resilient to saline intrusion than rice, results suggest that shrimp rather than coconuts are preferred in high saline risk areas.

Table 4. Output results, probits, marginal effects

Variables	Ag. Loan	Ag. Loan	Wage Job	Wage Job	Self Empl.	Self Empl.	Coconut	Coconut	Shrimp	Shrimp
Treated	0.160***	0.153***	0.015	0.010	0.057**	0.064***	-0.014	-0.022	0.034***	0.033***
	(0.024)	(0.024)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.012)	(0.012)
Saline intrusion										
Saline 2019	-0.005		0.010		-0.070***		-0.013		0.014	
	(0.033)		(0.030)		(0.025)		(0.024)		(0.013)	
Saline 2020		0.022		0.031		-0.065**		0.044		-0.001
		(0.031)		(0.030)		(0.031)		(0.028)		(0.019)
Climate conditions										
Avg. Yearly Rainfall	-0.000	-0.000	-0.001***	-0.001***	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CoV, High	-0.613*	-0.704*	-0.734**	-0.664*	-0.360	-0.507	0.143	0.154	0.335	0.302
	(0.361)	(0.365)	(0.351)	(0.365)	(0.308)	(0.315)	(0.233)	(0.245)	(0.217)	(0.213)
CoV, Low	0.241	0.054	0.577	0.427	-0.934*	-0.527	0.119	-0.097	-0.374	-0.361
	(0.564)	(0.549)	(0.479)	(0.498)	(0.495)	(0.495)	(0.484)	(0.470)	(0.330)	(0.336)
Distance to Coast	-0.022**	-0.018**	0.005	0.006	0.003	0.012	0.133***	0.140***	-0.119***	-0.121***
	(0.011)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.011)	(0.010)	(0.011)	(0.011)
Observations	2,125	2,125	2,125	2,125	2,125	2,125	854	854	854	854

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.3 Results for intermediate outcomes

Table 5a presents results for the Poisson regressions of two measures of diversification: the number of crops and livestock species held, and the number of income sources. Here we can explicitly evaluate the impact of the treatment and saline intrusion interaction terms. The project had significant direct impacts on diversification. For crop and livestock diversification, neither saline shock had a significant impact, nor the interaction terms. For income sources, saline intrusion has a significant negative impact, consistent with the negative impact of saline intrusion on self-employment. The impacts of climate conditions are generally similar across both on-farm and income diversification. In particular, those located in low rainfall areas with greater exposure to both dry conditions and saline intrusion were more likely to have diversified on-farm and income portfolios. Taken together, results suggest that households located in riskier agricultural production environments attempt to manage these risks through diversification; however, they were not able to maintain more diverse income streams in response to the saline shocks in 2019 and 2020.

Table 5b presents results for OLS regressions of rice and coconut production per capita, as well as gross revenue per capita for households that produced rice, coconut and shrimp. Starting with rice, we note that treatment actually had direct negative impacts on rice production, as did the saline shocks in both years. However, the interaction term is positive, indicating that treated households that experienced a saline shock achieved higher rice production per capita than did non-treated households also subject to saline shocks. This can even be seen in the simple descriptive statistics, which show that for households not exposed to saline intrusion, the average value of rice production per capita (in natural logs) is 7.26 for treated households and 7.02 for non-treated households. For households that were exposed to saline intrusion, the average value of rice production per capita was 6.94 for treated households, but just 5.82 for non-treated households. This is both good news and bad news for the project, since a number of other researchers have shown that households tend to disadopt technologies and practices that only provide benefits under shocks but do not necessarily increase average production (Baudron et al., 2015; Arslan et al., 2014). While we cannot be sure exactly what measures the project itself took to increase rice production in the face of saline intrusion, a number of other studies have documented specific measures that can be taken, such as planting earlier if intrusion is forecast, adopting salt-tolerant varieties and constructing saline barriers (Paik et al., 2020). While Paik et al. (2020) do not find negative impacts of adopting salt-tolerant varieties for those facing low/no saline intrusion, our results do find significant negative impacts for those who did not suffer severe saline intrusion. Overall, this mixed evidence suggests that further research into specific saline-tolerant varieties and other practices is warranted to inform future project designs.

With respect to coconut production per capita, we note that the project did not have significant impacts on production, either directly or indirectly through the interaction with saline shocks. The saline shocks also both had significant negative impacts on coconut production. Finally, the project had no direct impact on revenues per capita, whereas both saline shocks had significant negative impacts. However, similar to rice production, revenues per capita were higher for treated households subject to saline shocks.

Finally, with respect to climate conditions, we note that rice production per capita is higher in areas with higher average rainfall, while coconut production per capita is higher for those closer to the coast. Measures of rainfall variability, however, have no impacts on production outcomes.

Table 5a. Intermediate outcomes, Poisson

Variables	# Crop & Livestock	# Crop & Livestock	# Income Sources	# Income Sources
Treated	0.254***	0.251***	0.126***	0.117***
	(0.041)	(0.056)	(0.028)	(0.045)
Saline intrusion, interaction				
Saline Intrusion, 2019	-0.086		-0.171***	
	(0.064)		(0.043)	
Saline 2019*Treated	-0.064		0.029	
	(0.076)		(0.050)	
Saline Intrusion, 2020		-0.001		-0.136***
		(0.059)		(0.041)
Saline 2020*Treated		-0.035		0.043
		(0.070)		(0.053)
Climate conditions				
Average Yearly Rainfall	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Coef. of Var. Rainfall, High	0.222	0.193	-0.890**	-1.144***
	(0.433)	(0.456)	(0.365)	(0.373)
Coef. of Var. Rainfall, Low	2.634***	2.985***	1.070**	1.912***
	(0.734)	(0.727)	(0.506)	(0.483)
Distance to Coast	-0.042**	-0.020	-0.039***	-0.018**
	(0.016)	(0.014)	(0.011)	(0.009)
Constant	3.052***	3.069***	2.955***	2.941***
	(0.853)	(0.844)	(0.547)	(0.548)
Observations	2,125	2,125	2,125	2,125
Chi^2 p Value	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5b. Intermediate outcomes, rice and coconut production per capita, and value of harvest per capita; OLS

Variables	Rice	Rice	Coconut	Coconut	Val. Harvest	Val. Harvest
Treated	-0.615***	-0.609***	-0.157	-0.348	-0.358	-0.441
	(0.204)	(0.216)	(0.123)	(0.236)	(0.236)	(0.306)
Saline intrusion, interaction						
Saline Intrusion, 2019	-0.942*		-0.476*		-1.869***	
	(0.477)		(0.245)		(0.517)	
Saline 2019*Treated	1.111**		0.276		1.131*	
	(0.558)		(0.314)		(0.665)	
Saline Intrusion, 2020		-0.489		-0.710***		-1.426***
		(0.393)		(0.210)		(0.397)
Saline 2020*Treated		0.709		0.450		1.068**
		(0.449)		(0.278)		(0.460)
Climate conditions						
Avg. Yearly Rainfall	0.008***	0.008**	-0.000	-0.001	0.007	0.006
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
CoV, High	0.710	0.930	1.342	-0.043	4.970	2.946
	(1.833)	(1.874)	(1.609)	(1.733)	(3.179)	(3.136)
CoV, Low	-7.481	-6.658	0.661	2.885	-3.207	2.740
	(4.678)	(4.448)	(2.644)	(2.648)	(4.864)	(4.329)
Distance to Coast	0.390***	0.415***	-0.219***	-0.215***	0.162	0.256*
	(0.133)	(0.148)	(0.072)	(0.071)	(0.139)	(0.145)
Constant	-3.174	-3.324	8.947**	11.293***	6.817	8.215
	(5.834)	(6.049)	(3.647)	(3.668)	(8.264)	(8.545)
Observations	707	707	638	638	1,543	1,543
Adjusted R-squared	0.383	0.377	0.304	0.313	0.192	0.185

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4 Results for outcomes

We have two direct measures of resilience: whether the household received very low production per capita, and whether the household considers itself to be very food-secure. Table 6a presents results of marginal effects from the probit specifications. The impact of treatment on the probability of receiving very low yields is unfortunately positive and significant. The impact of a saline shock in 2019 is also positive and significant. On the other hand, the impact of treatment on whether the household considers itself to be very food-secure is positive and significant, with no impacts of the saline shocks. In table 6b, we present results for the coefficients in the probit specifications, which capture impacts on the linear arguments of the estimated probabilities and therefore allow us to look at the interaction terms explicitly. Consistent with the results on rice production and revenue per capita, the direct impact of treatment is positive, as is saline shock in both years. However, the treatment*saline shock interaction terms are both negative and significant. Thus, households in treated areas were less likely than control households to realize very low revenue per capita under a saline shock, but treated households that did not receive a shock were more likely to fall below the 20th percentile of realized revenue per capita.

Table 6a. Outcomes, probit, marginal effects

Variables	Low Production	Low Production	Food Secure	Food Secure
Treated	-0.001	-0.015	0.069***	0.066***
	(0.031)	(0.032)	(0.023)	(0.023)
Saline intrusion				
Saline 2019	0.121***		-0.043	
	(0.037)		(0.028)	
Saline 2020		0.061		0.013
		(0.039)		(0.029)
Climate conditions				
Avg. Yearly Rainfall	-0.001**	-0.001*	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
CoV, High	0.226	0.356	0.174	0.180
	(0.503)	(0.507)	(0.313)	(0.340)
CoV, Low	0.928	0.355	1.217**	1.257**
	(0.714)	(0.779)	(0.539)	(0.550)
Distance to Coast	0.002	-0.017	-0.016*	-0.007
	(0.017)	(0.016)	(0.010)	(0.008)
Observations	864	864	2,125	2,125

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6b. Outcomes, probits, coefficients for the linear argument

Variables	Low Production	Low Production	Food Secure	Food Secure
Treated	0.167	0.365*	0.262***	0.254*
	(0.140)	(0.207)	(0.100)	(0.150)
Saline intrusion, interaction				
Saline Intrusion, 2019	0.623***		-0.099	
	(0.181)		(0.118)	
Saline 2019*Treated	-0.434*		-0.090	
	(0.231)		(0.154)	
Saline Intrusion, 2020		0.500**		0.065
		(0.198)		(0.117)
Saline 2020*Treated		-0.543**		-0.050
		(0.247)		(0.172)
Climate conditions				
Avg. Yearly Rainfall	-0.004**	-0.003*	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
CoV, High	0.764	1.181	0.574	0.593
	(1.699)	(1.682)	(1.030)	(1.118)
CoV, Low	3.131	1.178	4.011**	4.139**
	(2.411)	(2.583)	(1.793)	(1.831)
Distance to Coast	0.005	-0.055	-0.053*	-0.024
	(0.057)	(0.052)	(0.032)	(0.027)
Constant	3.885	3.749	2.583	2.104
	(3.142)	(3.232)	(1.658)	(1.665)
Observations	854	854	2,125	2,125
Psuedo R^2	0.112	0.105	0.120	0.119

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5. Impacts of not using climate variables to match or as regressors

We next determine the extent of bias in the estimate of treatment effects when we do not include climate variables in the matching, or saline shocks or climate variables in the regressions. We present results for the marginal effects of treatment on our outputs in table 7a. In tables 7a and 7b, we use "2019" to signify that the coefficient is from the regression where the 2019 saline shock was included, and "2020" to signify that the coefficient is from the regression where the 2020 saline shock was included. The results in table 7a suggest that coefficients on loans and income sources are generally biased slightly downward, but the differences are quite small. However, the bias is significantly lower for growing coconut. The bias is also negative for shrimp cultivation, though the coefficients in this case are not significantly different.

Table 7a. Coefficients on loans and income sources when climate variables are excluded

Variables	Ag. Loan, 2019	Ag. Loan, 2020	Wage Job, 2019	Wage Job, 2020	Self Empl. 2019	Self Empl. 2020	Coconut, 2019	Coconut, 2020	Shrimp, 2019	Shrimp, 2020
With climate variables										
Treated	0.160***	0.153***	0.015	0.01	0.057**	0.064***	-0.014	-0.022	0.034***	0.033***
	-0.024	-0.024	-0.021	-0.021	-0.022	-0.022	-0.022	-0.022	-0.012	-0.012
Without climate variables										
Treated	0.146***		-0.002		0.061***		-0.040*		0.018*	
	(0.024)		(0.020)		(0.021)		(0.023)		(0.009)	

Table 7b. Coefficients on rice production and value of harvest when climate variables are excluded

Variables	Rice, No Shock 2019	Rice, Shock 2019	Rice, No Shock 2020	Rice, Shock 2020	Val. Harv., No Shock 2019	Val. Harvest, Shock 2019	Val. Harv., No Shock 2020	Val. Harv., Shock 2020
With climate variables								
Treated	-0.615***	0.468*	-0.609***	0.119**	-0.358	0.772*	-0.441	0.623*
	(0.204)	(.453)	(0.216)	(.361)	(0.236)	(0.423)	(0.306)	(.379)
Without climate variables								
Treated	-0.213				0.151			
	(0.196)				(0.281)			

Here we also note that the bias is negative for on-farm and income diversification, but the differences are small, similar to the bias seen in the loan and income source results; thus, we chose not to display these results here.

For production outcome OLS regression results, the interaction terms are significant for both rice production per capita and value of harvest per capita. To capture potential biased coefficient estimates, we calculate the marginal effect of treatment when a shock did not occur and when a shock did occur, for the 2019 and 2020 shocks, so that there are four columns with marginal effects for rice and value of harvest, respectively. As shown in table 7b, when the saline shock is omitted, the marginal effect of treatment is not significant for either rice or value of production per capita. However, the marginal effect of treatment is negative for rice production per capita under no saline shock, but positive under a saline shock. These two impacts – when not separated out – cancel each other, leading to an insignificant treatment coefficient. Similarly, the positive impacts of the project on value of harvest when subject to a saline shock is also not captured when the shock is omitted from the estimation.

6. Concluding comments

The results suggest that the project did build resilience through increased access to credit, participation in self-employment, saline-resilient rice production practices, adoption of shrimp farming, and on-farm and income diversification. However, rice production and revenue per capita are lower for treatment households than for control households not subject to shocks, and the probability of realizing very low revenue per capita is higher for treated than control households not subject to shocks. Future projects need to assess how to improve production outcomes in relatively favourable years to discourage households from disadopting production practices that increase resilience to saline shocks but do not confer benefits in normal years. The extent of saline exposure does drive adoption of specific crops; specifically, shrimp cultivation is preferred closer to the coast, where saline intrusion is more likely, while coconuts are more likely to be adopted further from the coast. Evidence thus suggests that degree of exposure does affect crop decisions, which can inform future project designs, including crop varieties and the development of resilient value chains. Finally, not including climate variables in the analysis tends to bias treatment affects downwards for those facing saline shocks, though this bias is only pronounced for some of the agricultural production outcomes. Nonetheless, the results reinforce the need to control for climate variables, particularly in projects that are promoting adaptation to climate change, as in the present case.

The data collection did not allow us to pursue a number of other analyses that would have helped shed light on resilience-building. For instance, we know that a good deal of effort was made to increase the performance of women's credit cooperatives, but we have no data on how saline shocks affected the operations of those cooperatives. Did the cooperatives face higher rates of delayed payments or defaults? Are there any mechanisms in place within the cooperative lending programmes for debt rescheduling in the face of severe weather shocks? Second, funds were also allocated to invest in village-level infrastructure to increase resilience and for villages to develop climate resilience planning documents, but there was extremely limited evidence on these activities with which to analyse how climate conditions affect the investment choices or resilience planning. Given the amount of project resources dedicated to supra-household-level institution-building and investments, it is critical that future projects – and impact assessment teams – collect data at those levels to fully exploit the capacity to evaluate the impacts of climate conditions and weather shocks on the performance of those institutions, including in terms of resilience of service provision.

There are a number of lessons to be drawn for future project designs and implementation. First, it is critical that project activities both increase average incomes and reduce downside risk. To be able to fully achieve the Sustainable Development Goal on zero hunger (SDG 2), there is need for continued progress on increasing food security in all types of circumstances, as well as to reduce losses that arise due to weather shocks. Theories of change for adaptation projects should emphasize how project activities will help achieve both objectives – greater, and more stable, agricultural production and food security. Theories of change should also incorporate the best available data and evidence on exposure to different weather shocks and how project activities increase resilience in the face of those shocks, including risk-coping mechanisms. Project M&E systems should track major covariate shocks faced by households living in geographic locations containing both treatment and control households. While we can always determine the types of weather shocks that have occurred ex post, the ability to base the search for objective measures of shocks on sound M&E data will reduce research "transactions costs" and will enable researchers to triangulate results and therefore better support the ultimate choice of objective measures. Perhaps more importantly, in cases where an ex post impact assessment will occur, the M&E data will alert the impact assessment team that they need to gather certain types of climate data and need to design the questionnaires to specifically address weather shocks. Even without M&E data on weather shocks, the impact assessment team should search for documentation on weather shocks – for instance, FEWSNET or GIEWS, as well as local newspapers – to determine data required to capture specific weather events. This information should then also inform questionnaire design, as well as the empirical estimation strategy. Finally, both M&E instruments and impact assessment questionnaires should collect data at the level of project implementation as well as include climate-related resilience questions at that level, not only at household level. For instance, substantial resources in the AMD project in Viet Nam were dedicated to women's credit cooperatives and village-level infrastructure and climate adaptation plans. Collecting data that correspond to these levels and areas of investments is critical, especially as it would be particularly important to understand the impacts of climate variables at these higher levels when considering evidence for scaling.

References

Afonina, M., Bohn, S., Hamad, M., Marti, Mussa E., A., Pasha, A., Maggio, G., Gemessa, S. A. and Mabiso, A. 2022. *Impact assessment report: Viet Nam and Adaptation to Climate Change in the Mekong Delta in Ben Tre and Tra Vinh Provinces, Viet Nam*. Rome: IFAD.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S. and Cattaneo, A. 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, ecosystems & environment* 187: 72-86.

Asfaw, S., McCarthy, N., Lipper, L., Arslan, A. and Cattaneo, A. 2016. What determines farmers' adaptive capacity? Empirical evidence from Malawi. *Food Security* 8(3): 643-664.

Baudron, F., Sims, B., Justice, S., Kahan, D.G., Rose, R., Mkomwa, S., Kaumbutho, P., Sariah, J., Nazare, R., Moges, G. and Gérard, B. 2015. Re-examining appropriate mechanization in Eastern and Southern Africa: two-wheel tractors, conservation agriculture, and private sector involvement. *Food Security* 7(4): 889-904.

Carletto, C., Gourlay, S., Murray, S. and Zezza, A. 2017. Cheaper, faster, and more than good enough: is GPS the new gold standard in land area measurement? *Survey Research Methods* 11(3): 235-265.

Dang, A.T., Kumar, L. and Reid, M. 2020. Modelling the potential impacts of climate change on rice cultivation in Mekong Delta, Vietnam. *Sustainability* 12(22): 9608.

Dang, T.D., Cochrane, T.A. and Arias, M.E. 2018. Future hydrological alterations in the Mekong Delta under the impact of water resources development, land subsidence and sea level rise. *Journal of Hydrology: Regional Studies* 15: 119-133.

Desiere, S. and Jolliffe, D. 2018. Land productivity and plot size: Is measurement error driving the inverse relationship? *Journal of Development Economics* 130: 84-98.

Duc Tran, D., Halsema, G.V., Hellegers, P.J., Phi Hoang, L., Quang Tran, T., Kummu, M. and Ludwig, F. 2018. Assessing impacts of dike construction on the flood dynamics of the Mekong Delta. *Hydrology and Earth System Sciences* 22(3): 1875-1896.

Febriamansyah, R. and Tran, T.A. 2020. Adapting to Saline Intrusion: Empirical Insights from Two Coastal Areas in the Vietnamese Mekong Delta. *Pertanika Journal of Social Sciences & Humanities* 28(2):1553-1566.

Hoang-Phi, P., Lam-Dao, N., Pham-Van, C., Chau-Nguyen-Xuan, Q., Nguyen-Van-Anh, V., Gummadi, S. and Le-Van, T. 2020. Sentinel-1 SAR Time Series-Based Assessment of the Impact of Severe Salinity Intrusion Events on Spatiotemporal Changes in Distribution of Rice Planting Areas in Coastal Provinces of the Mekong Delta, Vietnam. *Remote Sensing* 12(19): 3196. https://doi.org/10.3390/rs12193196

Hoang, V.V. and Tran, K.T. 2019. Comparative advantages of alternative crops: A comparison study in Ben Tre, Mekong Delta, Vietnam. *AGRIS on-line Papers in Economics and Informatics* 11(665): 3993.

Kim, C., Alvarez, C., Sattar, A., Bandyopadhyay, Azzarri, C., Moltedo, A. and Haile, B. 2021. Production, consumption and food security in Viet Nam: Diagnostic Overview. Working Paper. Washington DC: IFPRI.

Liu, Y., Barrett, C.B., Pham, T. and Violette, W. 2020. The intertemporal evolution of agriculture and labor over a rapid structural transformation: Lessons from Vietnam. *Food Policy* 94: 101913.

McCarthy, N., Brubaker, J., Mabiso, A. and Cavatassi, R. 2022a. Incorporating the Impact of Climate and Weather Variables in Impact Assessments: An Application to an IFAD Coffee Production Project Implemented in Rwanda. IFAD Research Series 86. Rome: IFAD.

McCarthy, N., Brubaker, J., Mabiso, A. and Cavatassi, R. 2022b. Incorporating the Impact of Climate and Weather Variables in Impact Assessments: An Application to an IFAD Grain Storage Project Implemented in Chad. IFAD Research Series 87. Rome: IFAD.

McCarthy, N., Kilic, T., Brubaker, J., Murray, S. and de la Fuente, A. 2021. Droughts and floods in Malawi: impacts on crop production and the performance of sustainable land management practices under weather extremes. *Environment and Development Economics* 26(5-6): 432-449.

McCarthy, N., Cavatassi, R. and Maggio, G. 2023. Incorporating the Impact of Climate and Weather Variables in Impact Assessments: An Application to an IFAD Livestock Project Implemented in Mozambique. IFAD Research Series 88. Rome: IFAD.

Paik, S., Le D.T.P., Nhu, L.T. and Mills, B.F. 2020. Salt-tolerant Rice Variety Adoption in the Mekong River Delta: Farmer Adaptation to Sea-Level Rise. *PLoS One* 15(3): e0229464. https://doi.org/10.1371/journal.pone.022946

Smajgl, A. 2015. *Ecosystem Value Estimation – Technical Document*. Prepared by Mekong Region Futures Institute (MERFI) for USAID Mekong Adaption and Resilience to Climate Change (USAID Mekong ARCC).

Tan, L.V., Tran, T. and Loc, H.H. 2020. Soil and water quality indicators of diversified farming systems in a saline region of the Mekong Delta, Vietnam. *Agriculture* 10(2): 38.

Thanh, B.N., Le Van Thuy, T., Anh, M.N., Nguyen, M.N. and Hieu, T.N. 2021. Drivers of agricultural transformation in the coastal areas of the Vietnamese Mekong delta. *Environmental Science & Policy* 122: 49-58.

Van Kien N., Hoang Han N. and Cramb R. 2020. Trends in Rice-Based Farming Systems in the Mekong Delta. In *White Gold: The Commercialisation of Rice Farming in the Lower Mekong Basin*, edited by R. Cramb. Singapore: Palgrave Macmillan. https://doi.org/10.1007/978-981-15-0998-8_17

Vu, D.T., Yamada, T. and Ishidaira, H. 2018. Assessing the impact of sea level rise due to climate change on seawater intrusion in Mekong Delta, Vietnam. *Water Science and Technology* 77(6): 1632-1639.

World Bank. 2019. *Vietnam Development Report 2019: Connecting Vietnam for Growth and Shared Prosperity*. Washington, D.C.: World Bank.

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