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Representing farmer irrigated crop area adaptation in a large-scale hydrological model

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Supplement

Matching crop categories between datasets

For the model, we use 10 general crop categories that closely follow those used in the Global Change Assessment Model (GCAM), which include: corn, fiber, fodder, grain, miscellaneous, oil, rice, root tuber, sugar, and wheat. Each of the datasets used to calibrate the farmer agents (USDA Farm and Ranch Irrigation Survey, USDA Cropland Data Layer, and USDA Economic Research Service's Commodity Costs and Return datasets) reports on crop statistics using different (typically more detailed) crop categorizations compared to GCAM. We accordingly assign crop types from the various datasets to one of the general GCAM crop categories using the crop category mapping provided in Table S2.

The utilization of the 10 general crop categories for the model introduces simplifications in modeled crop representations with potential implications for model results. For example, over 50 crops from the CDL dataset are assigned to the miscellaneous crop category, with the model only tracking irrigated areas for all these crops combined into a single category. Similarly, each general crop category is characterized by a representative economic price/cost (e.g., the miscellaneous crop category is characterized by a single representative price, though this price can vary between regions/agents). Such an aggregation of economic prices/costs could introduce significant bias in the calibration procedure, specifically as cost data from the USDA ERS dataset is limited to a select group of crops. For miscellaneous crops for example, the economic data for peanuts is utilized as the representative crop for all other miscellaneous crops due to limitations in the USDA ERS dataset.

While such aggregation and mapping of crops introduces limitations and potential inaccuracies in the model calibration and outcomes, we argue that such aggregation is necessary and reasonable given the large-scale nature of the modeling endeavor and limited data at more detailed levels of crop categories at CONUS-scale. The introduction of additional or more detailed crop categories would also result in excessive computational burden (each new crop is an additional decision variable in the farmer's optimization problem) for such a large-scale effort. For future research, we recommend evaluating the sensitivity of model results to these crop categories and the underlying data inputs used for each crop category during model calibration.

GCAM Category	USDA FRIS Crops	USDA ERS	CDL Crops
Corn	Corn for grain or seed, Alfalfa, Corn for Silage or Greenchop	Corn	Corn, Sweet Corn, Por or Orn Corn, Dbl Crop Barley/Corn, Dbl Crop Corn/Soybeans
Fiber	All cotton	Cotton	Cotton
Fodder	All other hay,	Grain Sorghum*	Alfalfa, Other Hay/Non Alfalfa
Grain	Other small grains, Sorghum for grain or seed	Barley, Oats, Sorghum	Sorghum, Barley, Other Small Grains, Rye, Oats, Millet, Speltz, Buckwheat, Triticale, Dbl Crop Oats/Corn, Dbl Crop Lettuce/Barley, Dbl Crop Durum Wht/Sorghum, Dbl Crop Barley/Sorghum, Dbl Crop WinWht/Sorghum, Dbl Crop Soybeans/Oats, Dbl Crop Barley/Soybeans
Miscellaneous	Beans, Tomato, Berries, Orchards, Vegetable, Lettuce, Peanuts, Sweet Corn, Tomatoes	Peanut	Tobacco, Mint, Mustard, Dry Beans, Other Crops, Misc Vegs & Fruits, Watermelons, Onions, Cucumbers, Chick Peas, Lentils, Peas, Tomatoes, Caneberries, Hops, Herbs, Clover/Wildflowers, Sod/Grass Seed, Cherries, Peaches, Apples, Grapes, Christmas Trees, Other Tree Crops, Citrus, Pecans, Almonds, Walnuts, Pears, Pistachios, Asparagus, Garlic, Cantaloupes, Prunes, Oranges, Honeydew Melons, Broccoli, Peppers, Pomegranates, Nectarines, Greens, Plums, Strawberries, Squash, Apricots, Vetch, Lettuce, Pumpkins, Dbl Crop Lettuce/Cantaloupe, Dbl Crop Lettuce/Cotton, Blueberries, Cabbage, Cauliflower, Celery, Eggplants, Gourds, Cranberries
Oil	Soybeans for beans	Soybean	Soybeans, Sunflower, Peanuts, Canola, Flaxseed, Safflower, Rape Seed, Camelina, Olives, Dbl Crop Soybeans/Cotton
Rice	Rice	Rice	Rice
Root Tuber	Potatoes	Potatoes*	Potatoes, Sweet Potatoes, Carrots, Radishes, Turnips
Sugar	Sugarbeets*	Beets	Sugarbeets, Sugarcane
Wheat	Wheat for grain or seed	Wheat	Durum Wheat, Spring Wheat, Winter Wheat, Dbl Crop WinWht/Soybeans, Dbl Crop Lettuce/Durum Wht, Dbl Crop WinWht/Cotton

Table S1. Crop category mappings between datasets.

USDA Economic Research Service's (ERS) Commodity Costs and Return Datasets

Economic data on agricultural crop prices and productions costs for calibration of the farmer agent model is obtained from the USDA ERS Commodity Costs and Return Datasets. The USDA has estimated annual agricultural production costs and returns since 1975, with the annual estimates based upon producer surveys that are conducted every 4-8 years depending upon the commodity. As reported in the USDA ERS documentation, "The theoretical basis and accounting methods used for the most recent estimates of commodity costs and returns conform with standards recommended by the American Agricultural Economics Association (AAEA) Task Force on Commodity Costs and Returns." While some previous studies deploy similar economic costs and returns, these are typically focused on specific locales or regions. While datasets collected for specific locales might provide a more accurate economic farm information, such local studies likely adopt different data collection methods and estimates potentially leading to regional biases in model results if consolidated for use in our analysis. As such the, USDA ERS commodity costs and returns dataset is adopted for the current analysis, given its national coverage and consistent data collection and estimation approach across all regions.

Agent Memory Parameterization

The agent memory parameter controls how agents weigh the relative importance of recent versus distant experience in their expectations of future water availability. Based on the memory decay formulation, a chart indicating the relative weight for preceding years on agents' expectations of water availability is shown on Figure S1.

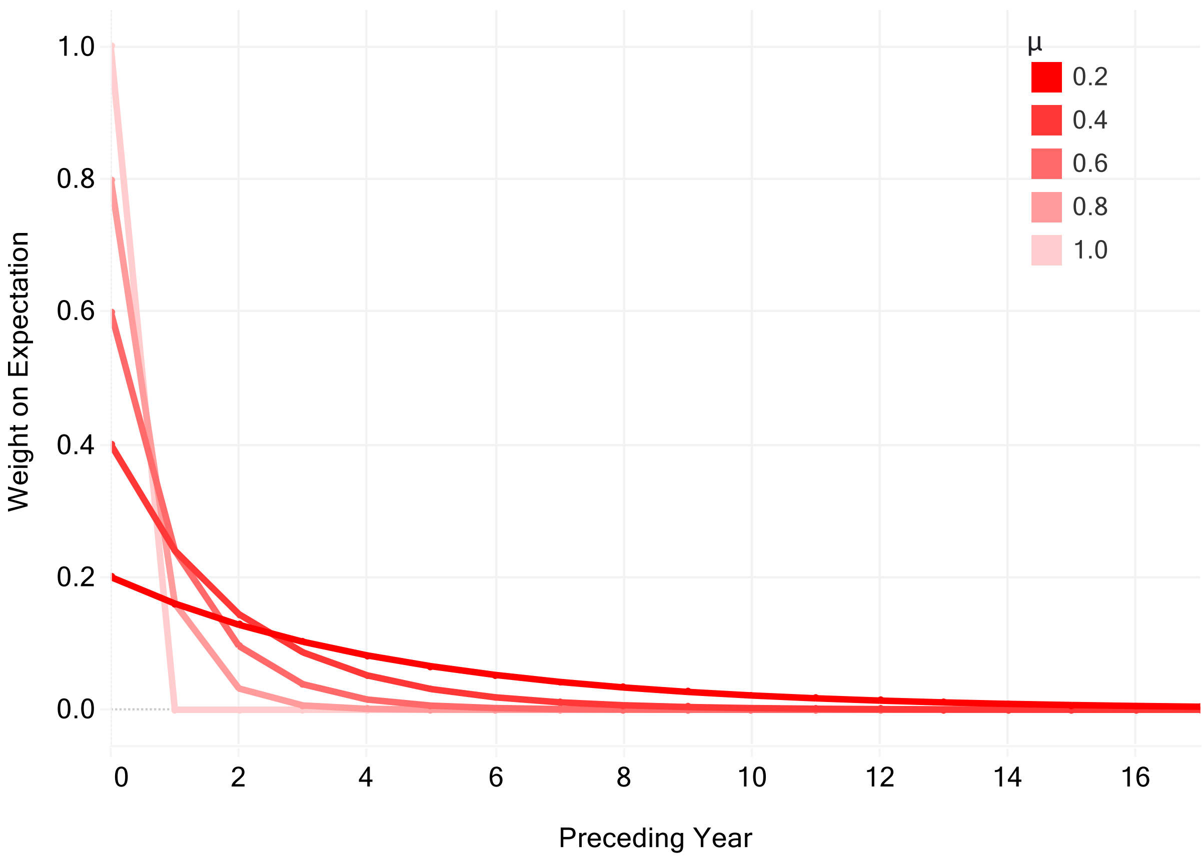

Figure S1 - The relative weight of previous years experience (with 0 being the most recent year of experience and 17 being the most distant) on influence farmer's future expectation of water availability based on various values of agent's memory decay factor, μ

Additional Monthly Model Results

Monthly water shortage changes with adaptation are presented on Fig. S2, supplementing the annual results provided in the main manuscript text.

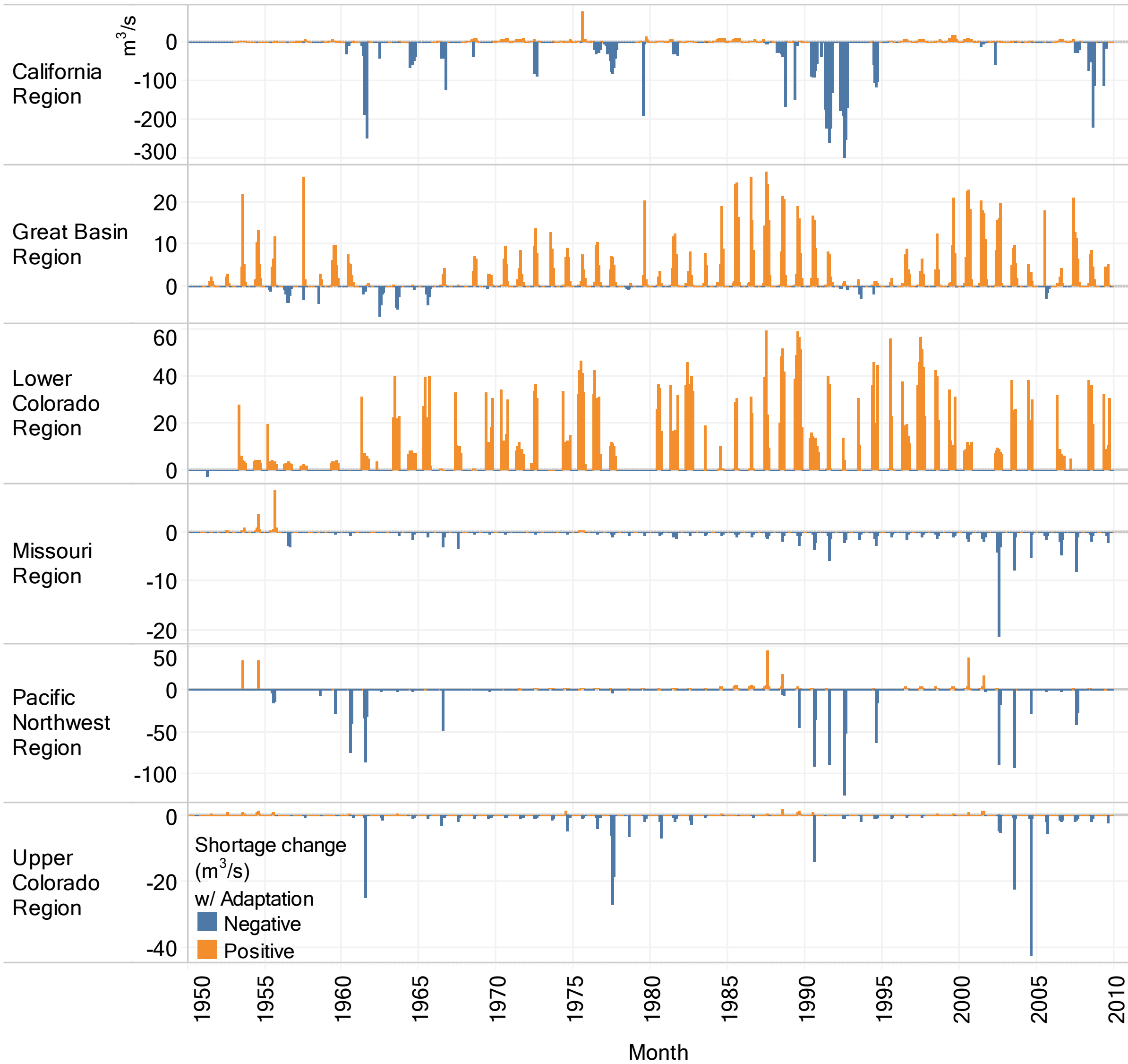

Figure S2 – Monthly water shortage change (m^3/s) with adaptation when comparing the adaptive to the baseline run (i.e., monthly water shortage in the adaptive run subtracted by monthly water shortage in the baseline run), aggregated over six HUC 2 regions of interest.. Blue colors (negative values) indicate reduced shortages when accounting for adaptation, while orange colors (positive values) indicate higher shortages when accounting for adaptation. These results provide monthly detail on the annual results presented in **Fig. 1** of the main manuscript.

CONUS-wide results for Water Shortage Differences

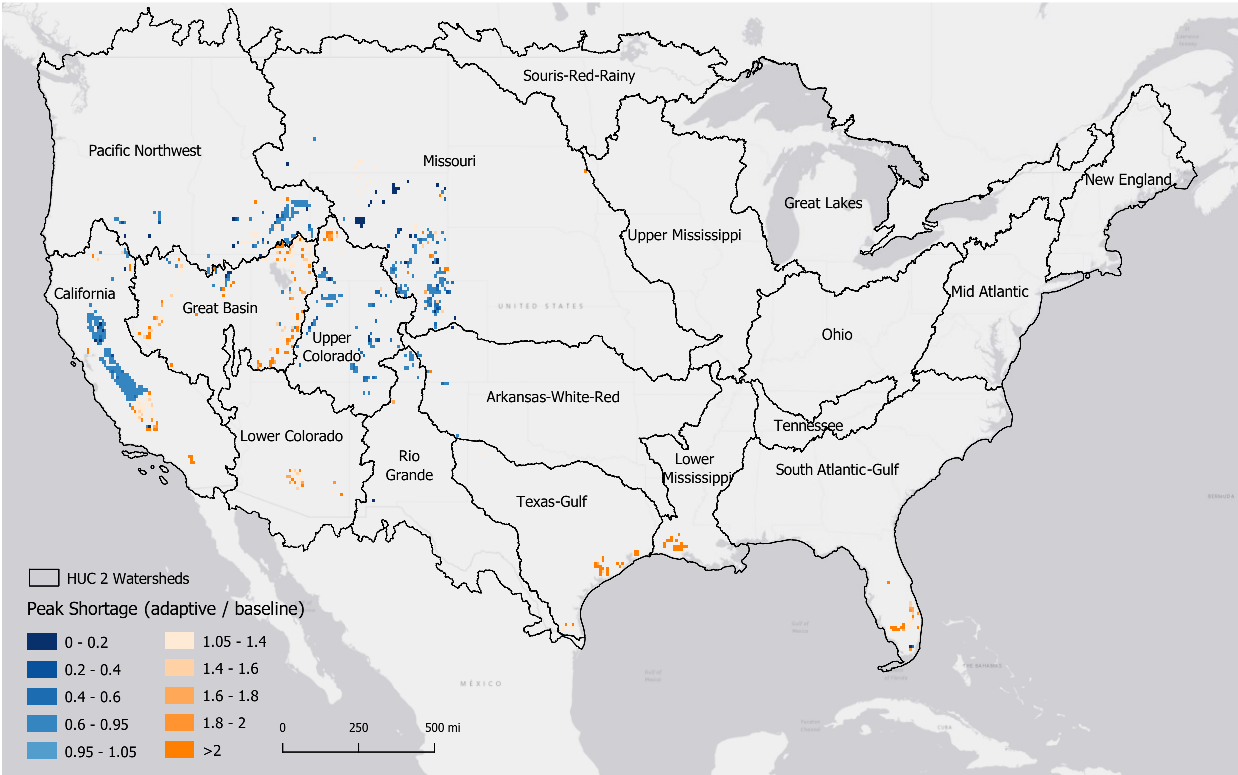

Figure S3 - Comparative water shortage results from a hypothetical comparative model experiment mimicking 1950-2009 hydrology. The figure identifies the peak annual water shortage (across all model years) for farm agents across the western United States for both the adaptive and baseline runs. The ratio of peak annual water shortage of the adaptive and baseline runs (i.e., peak annual water shortage of the adaptive divided by that of the baseline) is shown on the figure.

CONUS-wide results for Farm Cropping Adaptation

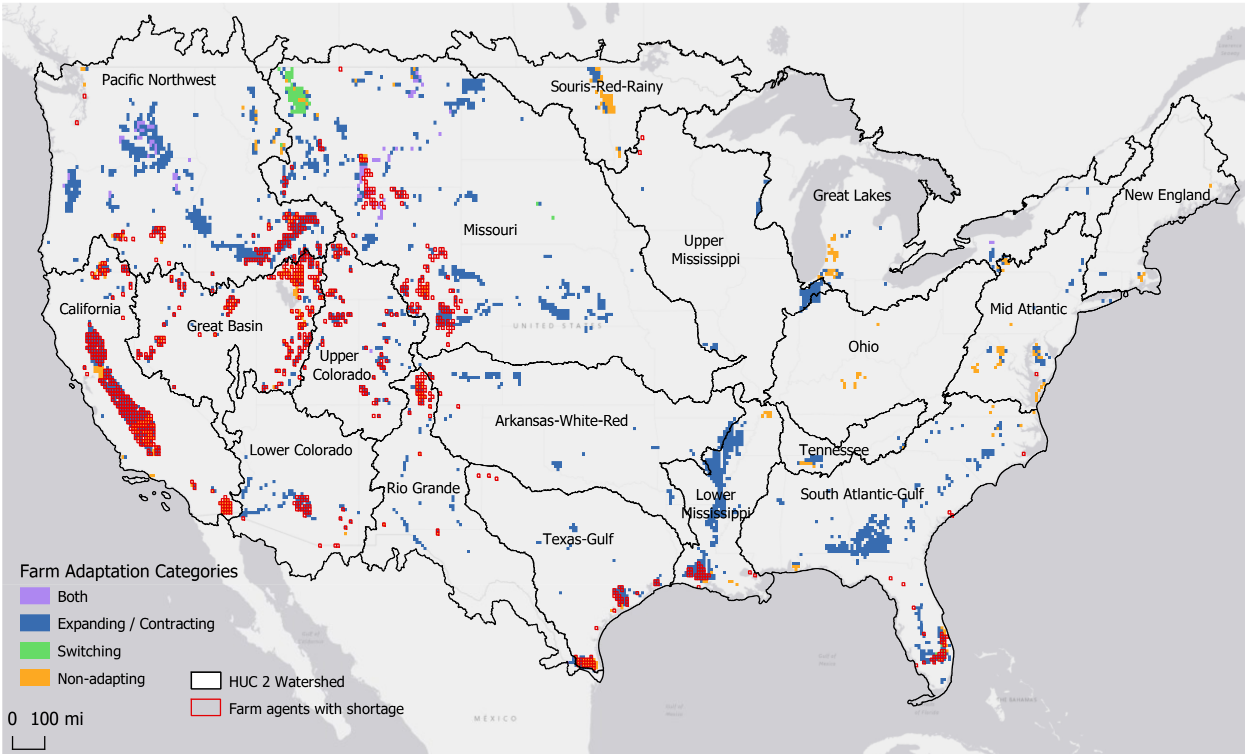

Figure S4 - Farmer cropping results from a hypothetical comparative model experiment mimicking 1950-2009 hydrology. The figure classifies individual farm agents in the adaptive model run with significant irrigation into one of four categories based upon their level of cropping adaptation (looking over the entire model period): 1) “crop expansion/contraction” (in blue) if the ratio of an agent’s annual minimum surface-water irrigated crop area is less than 80 percent of the annual maximum surface-water irrigated crop area, 2) “ crop switching” (in green) if the predominant crop’s share of the total crop makeup for any given agent (measured in terms of crop area) changes by at least 5 percent between any two years of the model run (which do not need to be consecutive), 3) “both” (in purple) if the agent satisfies both criteria 1 and 2 above, and 4) “none” (in orange) if the agent satisfies none of these criteria. Farm agents that experience significant water shortage, likewise evaluated over the entire model run, are indicated with a red outline. Expansions and contractions in irrigated cropped areas are simulated in response to major hydrological events (a-d). Farmer agents in the model largely adapt (e-h) to drought through crop contraction (blue cells with red outline), whereas crop switching (green cells) plays a less prominent role and is more prevalent in non-shortage areas. Some agents do not adapt in spite of shortage (orange cells w/ red outline).

Expected Agricultural Profit Results

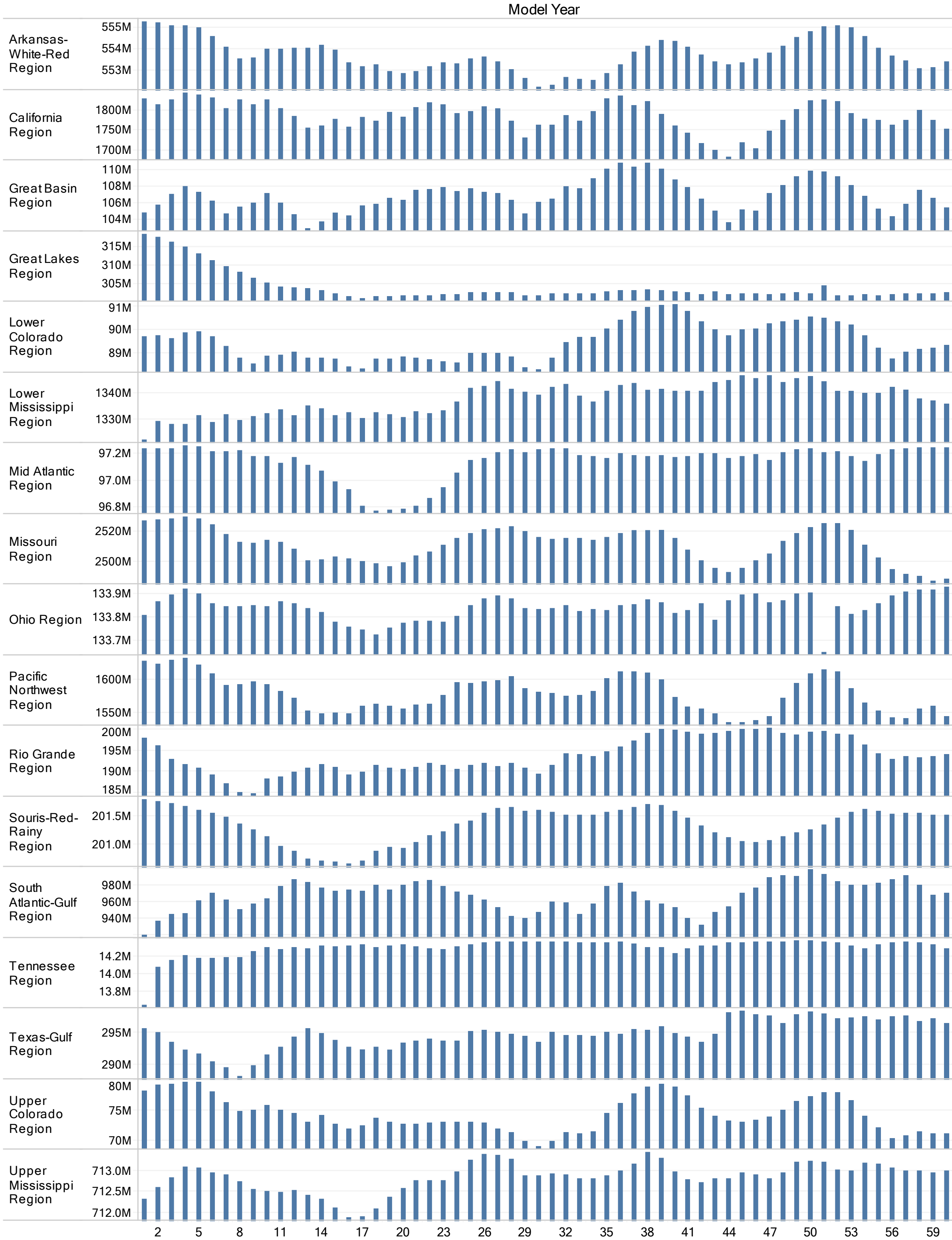

Figure S5 – Expected Agricultural Profit Results ($) from irrigated crops for all HUC 2 regions.

Evaluating the plausibility of simulated modeling results

To evaluate the plausibility of our modeling results, we compare simulated irrigated land use values via WM-ABM with observed irrigated land use values from the USDA Agricultural Census, retrieved using the USDA's National Agricultural Statistics Quick Stats tool (USDA, 2017). As non-hydrological factors (e.g., crop prices, crop production costs, equipped irrigated area, etc.) are treated statically in our simulations, a formal validation process is not possible for the model results for the hypothetical experiments. Given such, our strategy for the evaluation of model plausibility is to isolate a relatively short time window over which significant hydrological changes occurred, comparing model results against USDA surveyed data over this time period. As irrigated land use data from the USDA census is limited (available in 5-year intervals from 1997-2007), we specifically focus on the 2000-2005 time period during which much of the Western United States experienced drought conditions.

For the evaluation, we specifically compare percent changes in irrigated land use area between 2000-2005 from WM-ABM, comparing these changes with those recorded by the USDA agricultural census in 2002 and 2007. For the WM-ABM output, we report the total irrigated land use area (over all crops and including both surface water and groundwater sources). For the USDA data, we specifically report the land area of harvested cropland that is entirely irrigated. The comparison (shown in Table S2) is conducted for the 11 states in the Western United States in which irrigated land use and water shortages are most prevalent.

States	USDA Initial Area (2002)	ABM Initial Area (2000)	USDA Initial Area (2007)	ABM Final Area (2005)	USDA Percentage Change	ABM Percentage Change
Arizona	0.90	0.91	0.82	0.85	-8.9%	-6.6%
California	7.40	7.78	6.90	7.37	-6.8%	-5.3%
Colorado	1.74	2.05	1.77	1.83	1.7%	-10.7%
Idaho	2.68	3.65	2.67	3.16	-0.4%	-13.4%
Montana	1.12	1.50	1.08	1.18	-3.6%	-21.3%
Nevada	0.61	0.50	0.62	0.49	1.6%	-2.0%
New Mexico	0.64	0.61	0.61	0.60	-4.7%	-1.6%
Oregon	1.28	1.19	1.21	1.03	-5.5%	-13.4%
Utah	0.81	0.89	0.90	0.82	11.1%	-7.9%
Washington	1.40	1.40	1.31	1.22	-6.4%	-12.9%
Wyoming	1.28	1.07	1.12	0.84	-12.5%	-21.5%

Table S2. Comparing simulated versus observed irrigated land use areas (in millions of acres) for the early to mid 2000s for eleven states across the Western United States.

The comparison of the simulated and USDA irrigated land use areas indicate that the model performs reasonably well in capturing irrigated land use changes over the period of interest, especially for the states in which reliance on irrigation is most prominent. In California for example, the model indicates a decrease in irrigated land use of 5.3 percent (from 7.78M acres to 7.37M acres), while the USDA survey data indicates a 6.8 percent decrease (7.40M acres to 6.90 acres). The states with the largest discrepancy between modeled and observed irrigated land use changes include Colorado, Idaho, Montana, Utah, and Oregon. We note that the most arid states with the heaviest reliance on irrigation for agriculture (e.g., California, Arizona, Nevada) show reasonably close percentage changes to the USDA data, possibly pointing to the limitations of the comparison. Specifically, comparing simulated results against USDA harvested cropland that is entirely irrigated introduces an inconsistency in the comparison (in many of the less arid states, cropland might only be partially or periodically irrigated depending on climatic conditions). Such inconsistencies potentially explain the discrepancies between modeled and observed results in the less arid states included in the comparison.

We reiterate that the comparison only provides a first-order evaluation of model plausibility, providing an initial indication that the model behaves reasonably during periods of water shortage in regions of high irrigation activity. To fully evaluate the performance of the model in reproducing historical observations, a more extensive comparison exercise would need to be conducted in which non-hydrological factors (e.g., crop prices, production costs, etc.) are also input as exogenous time series to the model, matching observed conditions over the period of comparison. The comparison would also be enhanced through identification or development of observed irrigated land use datasets at higher temporal frequency and spatial resolution.

Observed versus Modeled (Baseline) Irrigated Areas

To confirm that the PMP-based calibration is behaving appropriately, we run the farm agent model in simulation mode under the same environmental and economic conditions as the baseline model used for calibration, further using the PMP coefficients identified during the calibration procedure. We expect to find an exact or near exact match between modeled and observed irrigated areas. Results from this comparison are shown on Figure S6, which includes a scatterplot comparing modeled and observed irrigated areas for each farm agent. The near exact match between modeled and observed outcomes indicates that PMP model has been calibrated successfully and is behaving as expected.

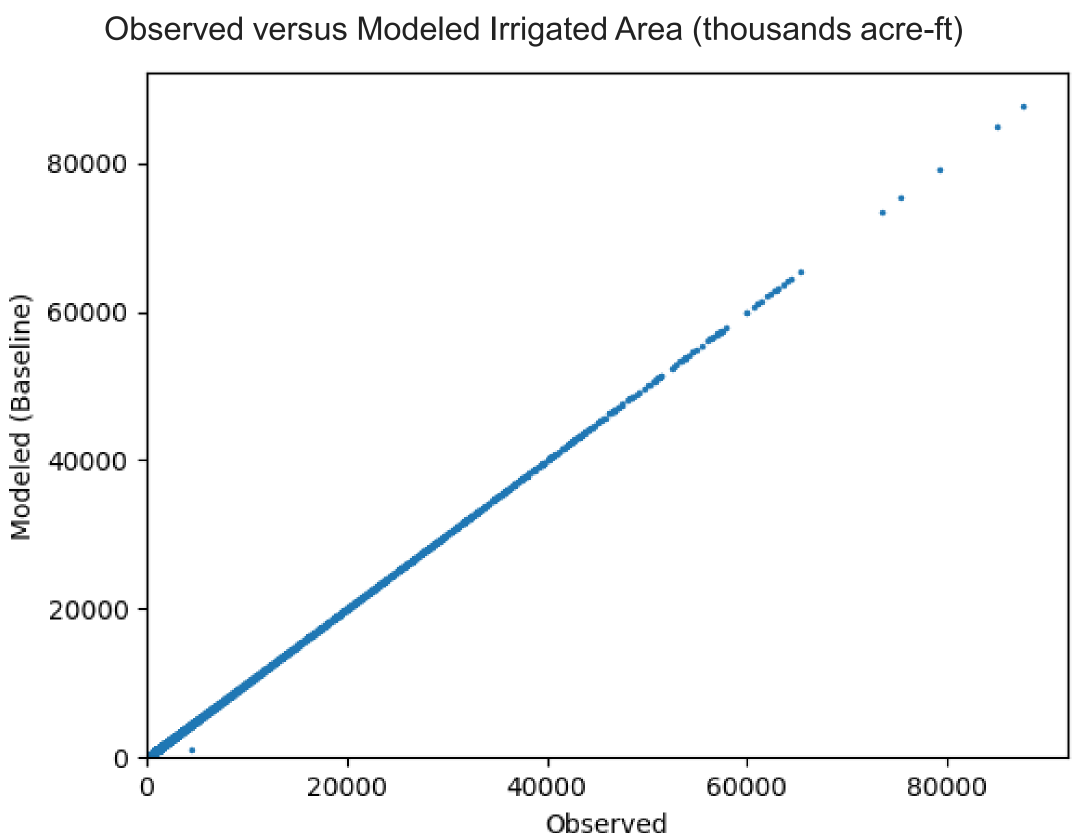

Figure S6 – Modeled versus Observed Irrigated Areas for PMP calibration.

Stress Test Results

To evaluate the plausibility and sensitivity of farm model behavior, we conduct a series of stress tests relative to the baseline model. Six different stress tests are simulated, including: 1) baseline surface water availability multiplied by 1.5, 2) baseline surface water availability multiplied by 0.5, 3) baseline crop prices multiplied by 1.5, 4) baseline crop prices multiplied by 0.5, 5) both baseline surface water availability and crop prices multiplied by 1.5 and, 6) both baseline surface water availability and crop prices multiplied by 0.5. For each stress test, we track 3 key outcomes: total irrigated area, total surface water irrigation, and total groundwater irrigation, comparing results from the stress test to the baseline scenario for each farm agent (Figures S7 – S9).

The stress tests indicate reasonable behavior and response of the farm cropping model. Total irrigated areas increase with an increase in surface water availability and decrease with a decrease in surface water availability. The relationship between crop prices and total irrigated area is less clear, which is expected as an increase in price may shift preferred crops to either those with higher or lower irrigation water needs, depending upon the specific farm.

Surface water irrigation increases with increased surface water availability, and decreases with decreased surface water availability. An increase in crop prices does not influence surface water irrigation, as limits on surface water availability constrain further increase of irrigation. However, a decrease in crop prices results in a notable decrease in surface water irrigation for most farms.

Groundwater irrigation typically shows a tradeoff effect with surface water availability. With an increase in surface water availability, groundwater irrigation is reduced. However, a decrease in surface water availability does not result in an increase in groundwater irrigation, as groundwater production capacity is constrained to the amount of groundwater irrigation observed in the baseline period. Crop price impacts on groundwater irrigation are similar to those on surface water irrigation.

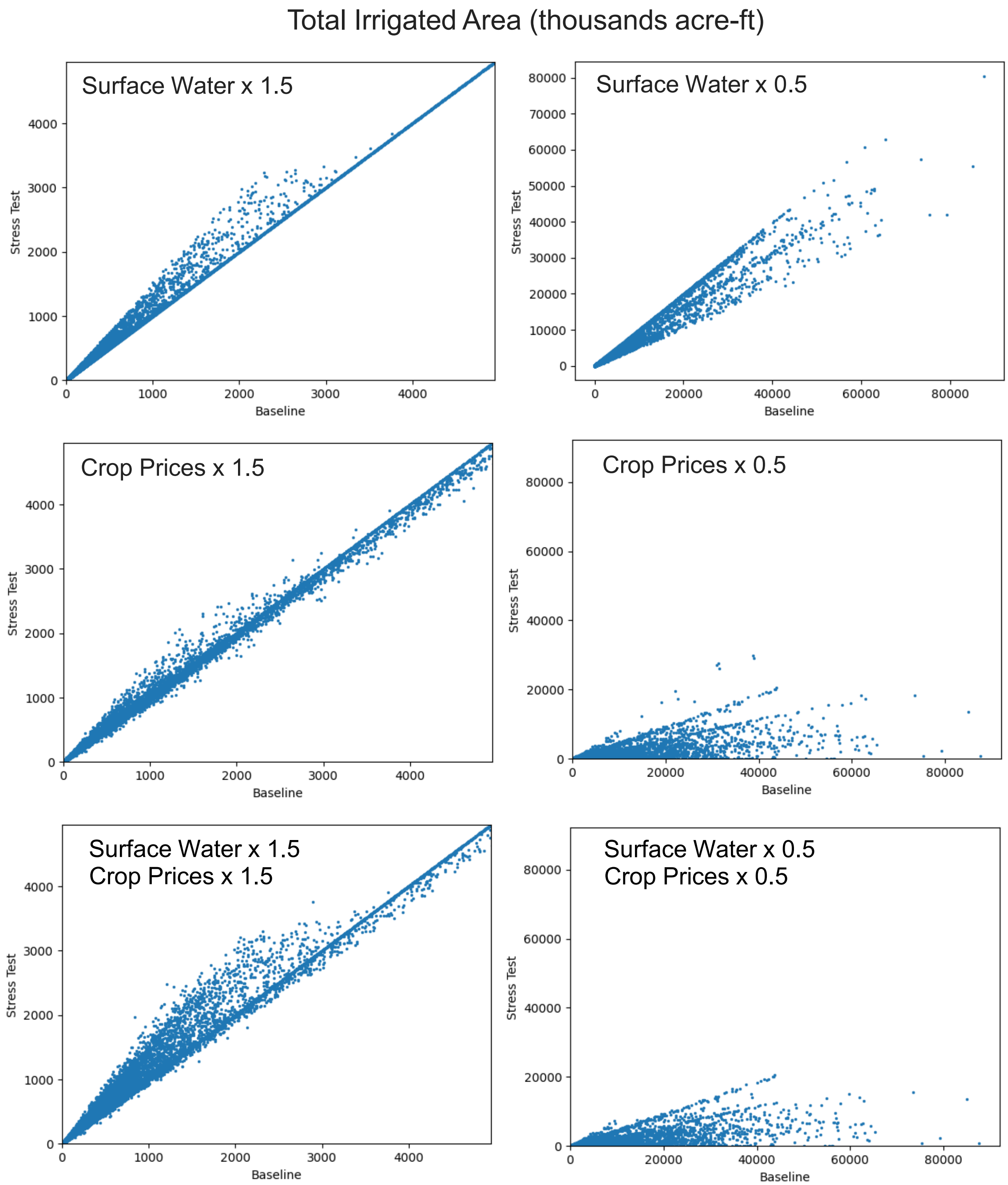

Figure S7 – Scatter plots of total irrigated area for the stress test versus baseline case (with a dot plotted for each farm). For the 3 left sub-figures, we note that only irrigated areas less than the 95th quantile (for the baseline run) are shown for visualization purposes.

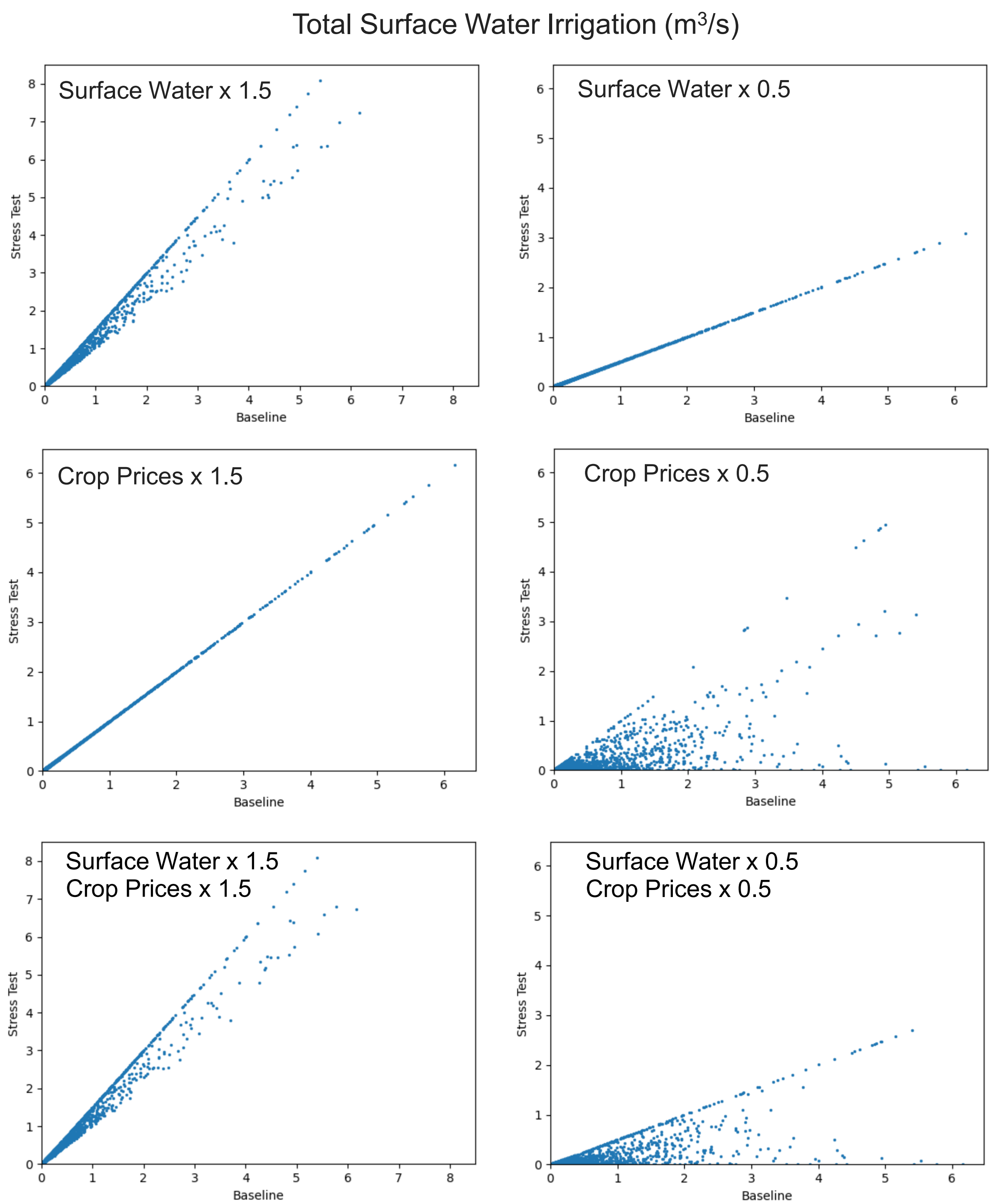

Figure S8 – Scatter plots of total surface water irrigation for the stress test versus baseline case (with a dot plotted for each farm).

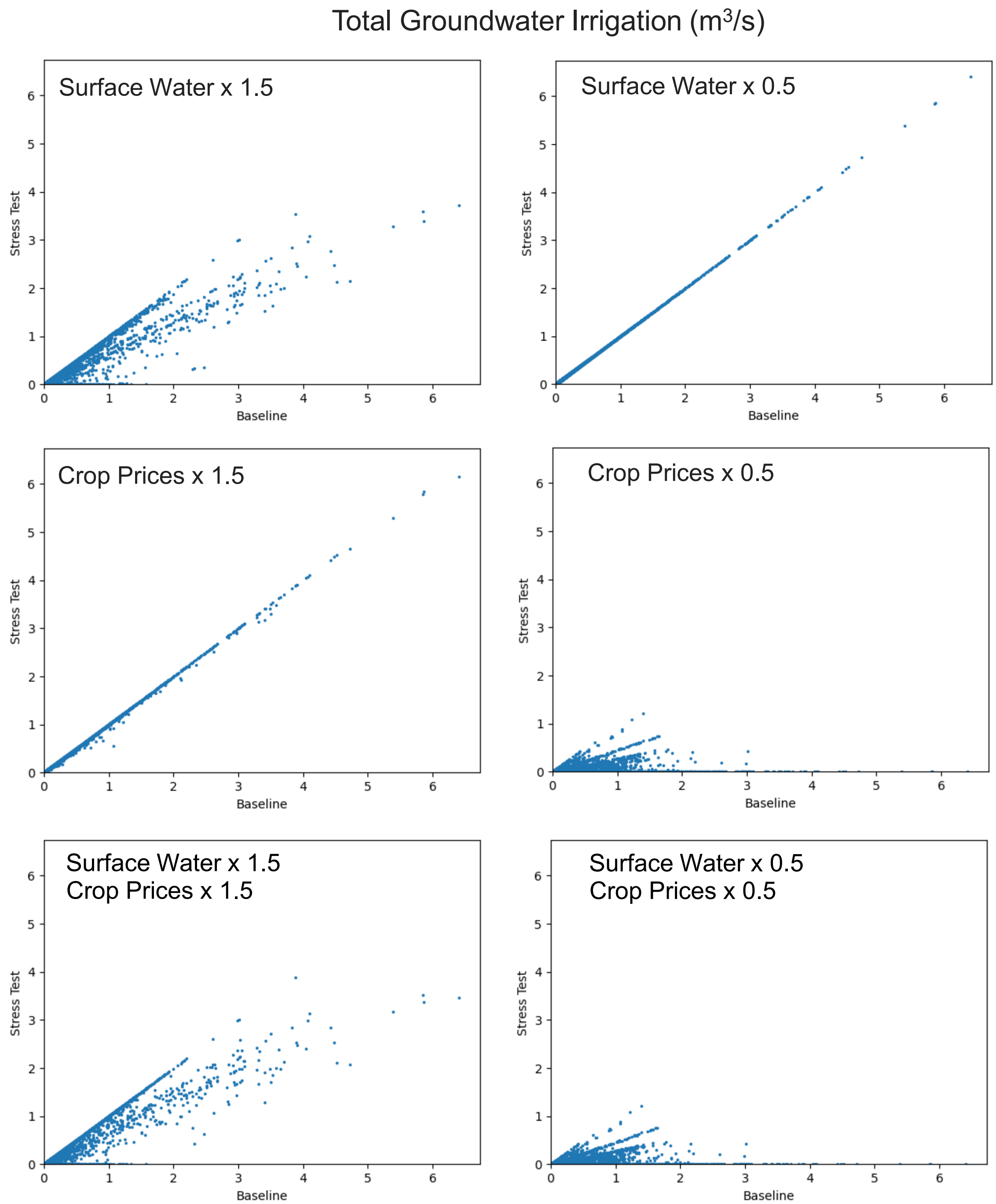

Figure S9 – Scatter plots of total groundwater irrigation for the stress test versus baseline case (with a dot plotted for each farm).

Table S3. ODD+D description for farm model.

Guiding questions			ODD+D model description
I) Overview	I.i Purpose	I.i.a What is the purpose of the study?	To evaluate the influence of farmer irrigated crop area adaptations on national-scale water shortage outcomes.
		I.ii.b For whom is the model designed?	Primarily for scientists who work with large-scale hydrological models (LHMs) and the decision makers interested in global or national scale water shortage assessments and outcomes.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	The model consists of farmer agents deciding irrigated crop areas in the context of changing water availability. The model also represents a water allocation manager, who determines how water is allocated from surface water reservoirs to various competing uses across space and sector.
		I.ii.b By what attributes (i.e., state variables and parameters) are these entities characterized?	Farmer agents decide their irrigated cropped areas (the primary state variables) across 10 representative crop categories. Farmers are characterized by their total available land area, their access to irrigation water sources (based on both cost and availability), and empirically estimated coefficients representing their unobserved costs in producing crops.
		I.ii.c What are the exogenous factors / drivers of the model?	The major exogenous driver of the model for the current experiment is changing hydrological conditions, namely precipitation forcing that drives the upstream hydrological models. Economic conditions (crop prices, production costs, water costs) also drive the model but are treated statically for the model experiment.
		I.ii.d If applicable, how is space included in the model?	Yes, space is included in the form of a grid-based spatially distributed domain. Each grid cell contains a single representative farmer agent.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	The farmer agent model runs on an annual basis, while the hydrological model runs on a daily basis. The model extends across the continental United States (CONUS), with the domain resolved by 1/8 degree grid cells following the North American Land Data Assimilation System.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	At the beginning of a model year, farm agents update their expectations of water availability and decide irrigated cropped areas. The water availability sub-model then runs on a daily basis, in which water supplies for irrigation water use are determined. At the end of a model year, water supply information from the preceding year are processed by each farmer agent for input into the

			proceeding year's water availability expectations and irrigated crop decisions.
II) Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	The modeling assumes that irrigated cropped areas are an emergent property of a coupled human-natural complex system. Namely, farmers determine their demand for irrigation water based on expectations of water availability, while the realized water availability is likewise dependent upon the total irrigation demand of farmers (e.g., increased competition for scarce water supplies generally results in lower water availability per farm). The system co-evolves according to these perpetual two-way interactions.
		II.i.b On what assumptions is/are the agents' decision model(s) based?	The farmer agents follow an economic formulation, assuming rational maximization of agricultural profits. In the positive mathematical programming approach, calibrated unobserved cost terms can account for monetary or non-monetary costs that are not explicitly accounted for otherwise in the profit maximization formulation.
		II.i.c Why is a/are certain decision model(s) chosen?	The positive mathematical programming approach is well established in the agricultural economics literature. The approach can also be readily applied at scale with the identification of appropriate data sources, which was an important consideration for a CONUS-scale study.
		II.i.d If the model / a submodel (e.g., the decision model) is based on empirical data, where does the data come from?	The farmer decision model is calibrated to historical land use and conditions based on a combination of data, primarily including observed crop land use data from USDA's Cropland Data Layer, historical irrigation information from USDA's Farm and Ranch Irrigation survey, crop prices and production costs from the USDA Economic Research Service's Commodity Costs and Returns dataset, and information on irrigated versus non-irrigated and groundwater versus surface-water irrigated areas from FAO's global map of irrigated areas.
		II.i.e At which level of aggregation were the data available?	The USDA Cropland Data Layer is available at 30-meter spatial resolution. The USDA Farm and Ranch Irrigation survey was utilized at state level. The USDA ERS Commodity Costs and Returns datasets are based on 9 ERS farm resource regions defined to cover the United States. The FAO global map of irrigated areas is available at 5 minutes resolution across the globe.

	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision-making included?	The primary subject of decision making is a representative farmer. The object of decision making is cropped areas for a 1/8 degree grid cell. The reservoir allocation mechanism embedded within the water availability sub-model may be viewed as a higher-level agent (relative to farmer agents) allocating water from surface reservoirs across individual farm agents.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	Farmer agents aim to maximize their expected agricultural profits. Their associated expectations of water availability are continuously updated based upon simulated water availability.
		II.ii.c How do agents make their decisions?	Utility function / profit maximization.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	Yes, they update their expectations of water availability (which are considered a resource input into their crop production decision) based upon continuously evolving simulated water availability.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Not explicitly, though social norms or cultural values may be embedded in the unobserved cost term that is calibrated to data.
		II.ii.f Do spatial aspects play a role in the decision process?	Yes, indirectly. Spatial heterogeneity in water availability influence farmer agent's expectation of water availability.
		II.ii.g Do temporal aspects play a role in the decision process?	Yes, farmer agent's update their expectations of water availability based upon past water availability that is continuously updated as the model progresses in time. The strength of this memory is treated as an agent parameter.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	In regards to uncertainty in environmental conditions, farmer agents do not have perfect information on how water availability conditions will unfold in an upcoming season, so they formulate expectations of water availability based upon past experience. In regards to uncertainty in agent decision making parameterization, we evaluate five different parameterizations in the

			strength of agent memory in agent formulation of expected water availability.
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	Agents update their expectations of future water availability conditions based upon past experience. Otherwise, learning is not incorporated in an agent's decision process.
		II.iii.b Is collective learning implemented in the model?	No
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	Agents sense reservoir volumes and local river flows (endogenous) as a proxy for hydrologically-driven water availability conditions. This sensing is erroneous in the sense that these states are an imperfect proxy of future water availability conditions. Agent's also sense crop prices and production costs (those these variables are exogenous and static).
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Farm agents do not sense each other's state. The reservoir allocation procedure embedded within the water availability sub-model can be said to sense farm agent's current water demand.
		II.iv.c What is the spatial scale of sensing?	Farm agent's can sense river flows in their coincident grid cell and reservoir volumes for any reservoir that can allocate them water (defined by a 50 kilometer buffer).
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Individuals are simply assumed to know these variables.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	Not explicitly, though these may be factored into the PMP unobserved cost coefficients.
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	The agent uses reservoir volumes and local river flows (assimilated through the agent memory) to predict future water availability conditions.

		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	Agents formulate expectations of future water availability based upon memory of past events. This expectation of future water availability is then input into a profit formulation of crop decision making, with agents assumed to maximize their expected agricultural profits.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Yes, formulating an expectation of future water availability based on past experience is an imperfect predictor of future conditions given stochastic hydrological conditions. This prediction can be particularly erroneous under non-stationary hydrological conditions.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Indirect. Farmer agents do not directly interact with one another, although they interact indirectly via resource demands on a shared water resource system.
		II.vi.b On what do the interactions depend?	The interactions depend on the level of water demand pressure in the system, e.g., if water shortage is severe each agent's demand can be viewed as exerting a heavier influence on another agent's water supply and ensuing water shortage.
		II.vi.c If the interactions involve communication, how are such communications represented?	Not applicable.
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	The reservoir water allocation process embedded within the water availability sub-model distributes shortage equally among farms with access to a particular reservoir. This structure is imposed.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	Yes, every farm agent that has access to a given reservoir can be viewed as an aggregation. This aggregation is imposed based upon a distance rule that links farmer agents with surface water reservoirs.
		II.vii.b How are collectives represented?	Every reservoir in the system is linked with a subset of farmer agents (which can be viewed as a collective) that has access to that reservoir.

	II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Yes, each agent has uniquely calibrated coefficients for the unobserved cost term of their profit maximization formulation.
		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	No, all agents follow a consistent PMP-based profit maximization formulation.
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	None.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	Irrigated cropped area outcomes made by the farm agents are used to evaluate the behavior and plausibility of the agent decision making process.
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	The overall water shortage in the system is the key emergent outcome of interest.
III) Details	II.i Implementation Details	III.i.a How has the model been implemented?	The ABM is developed in Python. The water availability sub-model (MOSART-WM) is originally written in FORTRAN and implemented in the Common Infrastructure for Modeling the Earth (CIME) framework.
		III.i.b Is the model accessible and if so where?	Yes, a meta-repository of all data and code required to run the model is available at: https://github.com/IMMM-SFA/yoon-etal_2023_hess
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	The initial state of the model world is based upon data used for calibration of the model, representing average conditions from 2010-2013.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	Yes, initialization is the same for our model experiments, though it can be changed.

		III.ii.c Are the initial values chosen arbitrarily or based on data?	Based on historical data.
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Yes, the agent-based model is coupled with a water availability sub-model (MOSART-WM). Communications between the two models occurs on an annual model timestep basis.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling?	There are two main sub-models. The agent-based model of farmer irrigated cropping decisions described in length in this ODD+D document. The second is the water availability sub-model, which is based on the MOSART-WM large-scale hydrological model described in detail in the following publication: https://hess.copernicus.org/articles/17/3605/2013/
		III.iv.b What are the model parameters, their dimensions and reference values?	The sub-model parameters for the agent-based model are described above. The water availability sub-model (MOSART-WM) parameters are extensive and too detailed to present here. We refer readers to the following publication: https://www.pnas.org/doi/abs/10.1073/pnas.1421675112
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The water availability sub-model (MOSART-WM) was selected as it is a common model used for large-scale hydrological modeling applications. The calibration and validation of the sub-model is described at length in the two publications provided above.