Supplementary Materials to "Representing Farmer Irrigated Crop Area Adaptation in a Large-Scale Hydrological Model"

Authors: Jim Yoon[1], Nathalie Voisin[1], Christian Klassert[2], Travis Thurber[1], Wenwei Xu[1]

[1]Pacific Northwest National Laboratory

[2]Helmholtz Centre for Environmental Research – UFZ

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.

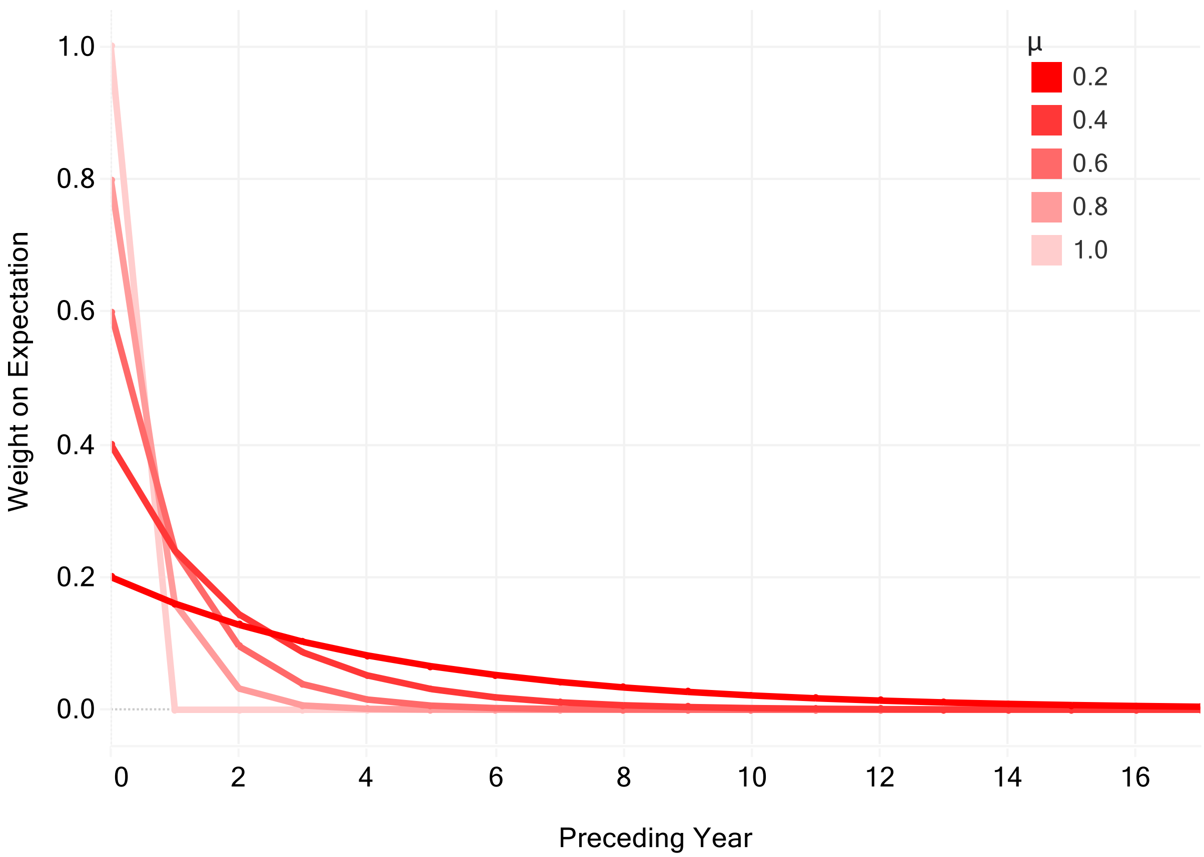

Figure S1 - The relative weight of previous years experience (with 0 being the most recent year of experience and 17 being the most distant) on influence farmer's future expectation of water availability based on various values of agent's memory decay factor, μ

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.

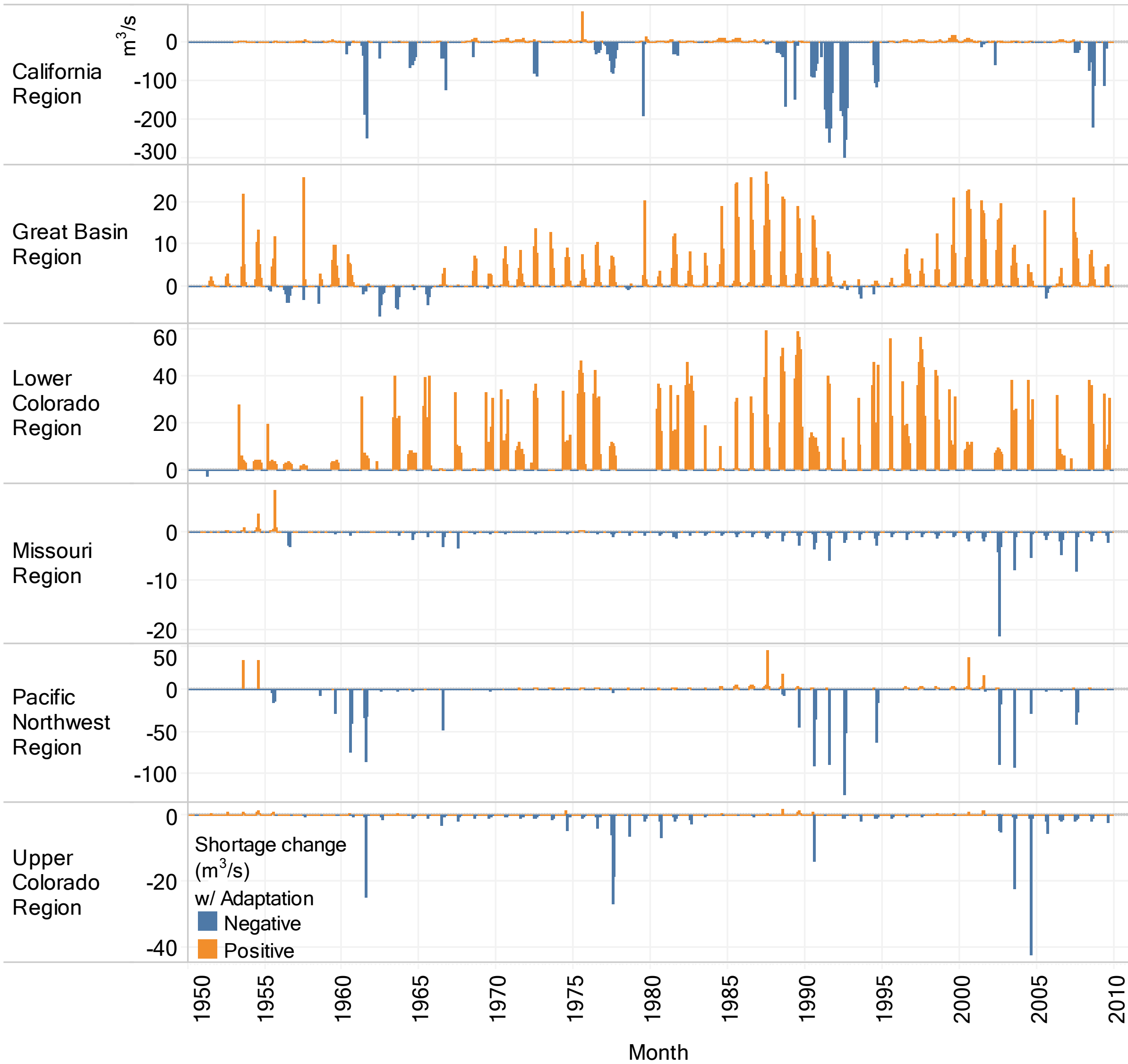

Figure S2 – Monthly water shortage change (m^3/s) with adaptation when comparing the adaptive to the baseline run (i.e., monthly water shortage in the adaptive run subtracted by monthly water shortage in the baseline run), aggregated over six HUC 2 regions of interest.. Blue colors (negative values) 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.