Behavioral feedbacks reshape blue–green water scarcity and sustainability trade-offs in irrigated agriculture: A sociohydrological perspective

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Introduction

This Supporting Information summarizes the coupled SWAT–agent-based modeling framework, detailing the farmer decision module (rolling-horizon MIP optimization), the SWAT setup and coupling interface (HRU–agent mapping, irrigation scheduling, and calibration/validation), and the associated supplementary materials (Tables S1–S4 and Figure S1).

Text S1. Optimization Model for Multi-Year Production Planning

Optimization Logic (Rolling Horizon Strategy): Agents employ a Rolling Horizon Optimization Strategy with a planning window of n years. At the beginning of each simulation year, agents utilize updated forecasts to formulate a comprehensive production plan (crop type, irrigation technology, and irrigation depth) that maximizes the cumulative expected net present value(NPV)(Duan et al., 2024) over the next years. The underlying mathematical problem is formulated as a Mixed-Integer Programming (MIP) model and solved using the Gurobi Optimizer. Reflecting the prevalent double-cropping system in the study area, Winter Wheat is treated as the fixed, mandatory crop for the winter season. Consequently, the agent's active decision-making—regarding crop selection, water allocation—is exclusively restricted to the spring season. Although the optimization yields a trajectory for the entire horizon), only the decision corresponding to the immediate planning year (t=1) is implemented as the actual farming practice.

(1) Sets and Indices:

$t \in \{1,2,\ldots,n\}$: Index for planning years, where t=1 represents the current decision year.

$c \in C$: Set of spring crops {Maize, Soybean, Peanut}.

$k \in K$: Set of irrigation technologies {Conventional, Sprinkler, Drip}.

(2) Decision Variables:

$\delta_{c,k.t}$: Binary variable, equal to 1 if spring crop c is cultivated using technology k in year t, 0 otherwise.

$I_{c,t}$: Continuous variable, representing the gross irrigation depth (mm) applied to the crop in year t.

(3) Objective Function: Maximize the discounted cumulative profit:

$$MAX(B) = \sum_{t=1}^{n} \frac{1}{(1+r)^{t-1}} \left(\sum_{c \in C} \sum_{k \in K} \delta_{c,k,t} \cdot profit_{c,k,t}\right) \quad (1)$$

$$profit_{c,k,t} = Y_c(W_{root,t}) \cdot P_c - (C_{fix,c} + C_{tech,k} + C_{water} \cdot I_{c,t}/\eta_k) \quad (2)$$

Crop Water Production Function: To accurately quantify the impact of water stress on crop productivity, we adopt a quadratic crop water production function:

$$\begin{cases} Y_c = \theta_c \times Y_{c,max} \\ \theta_c = a_c \cdot W_{root,c}^2 + b_c \cdot W_{root,c} + C_c \\ W_{root,c} = (W_{per,c} + I_c)/W_{root,max} \end{cases} \quad (3)$$

Where $Y_{\mathrm{c,max}}$ is the potential maximum yield of crop c under optimal water conditions (kg/ha); θ_c is the relative yield coefficient (0 to 1), representing the reduction factor due to water stress(Nozari et al., 2024); Empirical coefficients a_c, b_c, c_c are crop-specific parameters derived by fitting water–yield response curves using data from(Mialyk et al., 2024); the calibrated values are provided in Table S1. $W_{root,max}$ maximum total water availability in the root zone; $W_{per,c}$ perceived effective precipitation (mm); I_c irrigation depth (Decision Variable, mm). η_k is irrigation efficiency.

(4) Constraints:

Mutually Exclusive Choice (Spring Season): In each year, exactly one spring crop-technology combination must be selected:

$$\sum_{c \in C} \sum_{k \in K} \delta_{c,k,t} = 1 \ \forall t \in \{1,2,\ldots,n\} \quad (4)$$

Crop-Specific Irrigation Quota Constraint: The irrigation depth applied to the spring crop must not exceed its specific allocated quota:

$$0 \leq I_t \leq \sum_{c \in C} \sum_{k \in K} \left(\delta_{c,k,t} \cdot Q_{max,\,c}\right) \forall t \in \{1,2,\ldots,n\} \quad (5)$$

Text S2. SWAT model setup

Spatial Discretization and Drainage Network: Given the flat topography of the study area, a "stream burning" technique was employed to improve the accuracy of watershed segmentation. The drainage canal network, manually digitized from Google Earth high-resolution imagery, was superimposed onto the DEM to define the hydrological flow paths. Consequently, the watershed was discretized into 814 Hydrologic Response Units (HRUs).

Coupling Interface: HRU-Agent Mapping: A critical one-to-one mapping strategy was established to link the SWAT model with the ABM module. Specifically, the 664 agricultural HRUs were conceptualized as 664 individual farming agents. Through this interface, static attributes (e.g., area, soil type) and dynamic environmental variables (e.g., historical precipitation) of each HRU were directly projected onto the corresponding agents in the ABM.

Management Operations and Irrigation Scheduling: Agro-management practices, including crop phenology and fertilization, were parameterized based on records from the local irrigation authority. For simulation simplicity, we assumed static annual schedules for planting and fertilization, with uniform fertilizer application rates across all agricultural HRUs. The Yahekou Reservoir serves as the primary irrigation source. Daily observed outflow data were input into the model to define water availability. To accurately simulate the district's rotational and continuous irrigation schemes, the 664 agents were stratified into four temporal batches based on their hydraulic distance from the canal intake. This setup allows for the spatial-temporal staggering of irrigation events, mirroring actual water allocation protocols. Table S2 presents specific management operations.

Calibration and Validation: Model hydrological parameters were calibrated using the SWAT-CUP software. Figure S1 illustrates the comparison between simulated and observed monthly streamflow during both calibration and validation periods, demonstrating satisfactory model performance. Table S3 displays the calibrated parameter values.

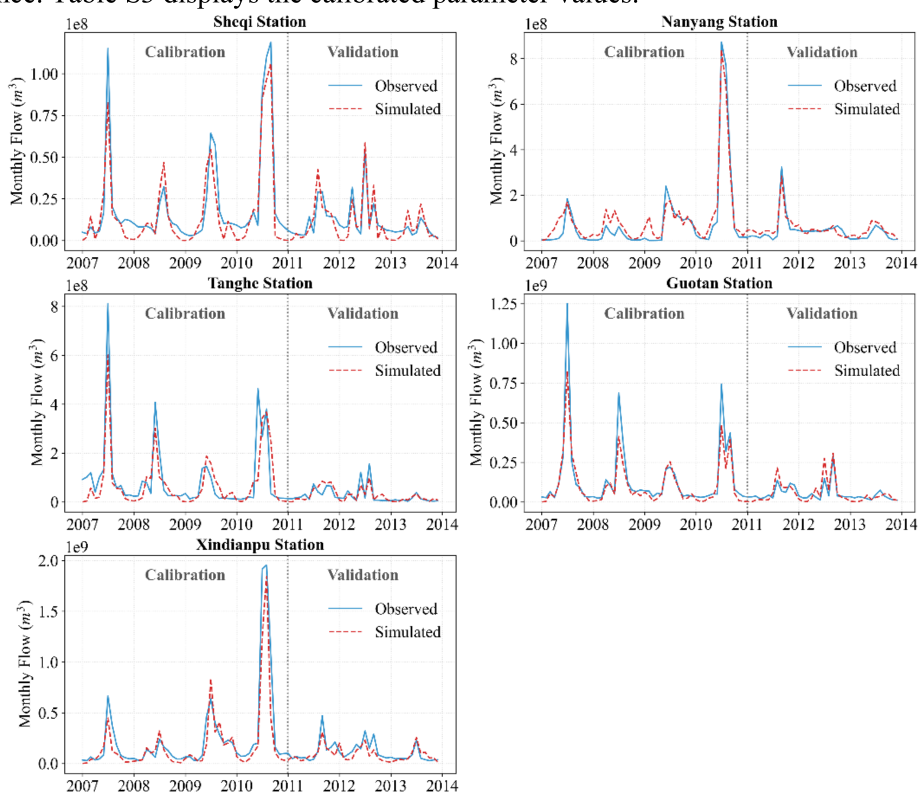

Figure S1. Comparison of Observed and Simulated Monthly Streamflow for Model Calibration and Validation (2007–2013).

Table S1. Crop-specific water–yield response parameters and variables used in this study.

Variable/parameter	corn	soybean	peanut

$Y_{\mathrm{c,max}}$ t/ha	5.409	2.0543	3.427
$W_{root,max}$ mm	403.933	518.35	516.925
a_c	-6.81	-5.98	-8.929
b_c	12.35	11.412	16.51
c_c	-4.59	-4.44	-6.63

Table S2. Management operations

Management operation	Data	Crop	Irrigation Depth(mm)	Fertilizer ratio (N-P2O5-K2O)
Plangting	June 10	Peanut		28-10-10 600kg/ha
	June 15	Corn		28-10-10 450kg/ha
	June 15	Soybean		10/20/20 225kg/ha
	Oct. 20	Wheat		28-10-10 450kg/ha
Irrigation	July 4-15	Peanut	60	
	Aug. 6-15		60	
	July 4-15	Corn	55	
	Aug. 1-10		55	
	July 4-15	Soybean	50	
	Aug. 11-20		50	
	Sept. 8-12		50	
	Dec. 1-15	Wheat	50	
	Mar. 16-25		50	
	Apr. 26- May5		50	
Harvest	Oct. 10	Peanut		
	Sept. 15	Corn		
	Oct. 20	Soybean		
	May 31	Wheat		

Table S3. Calibrated parameters

Parameters	Description	Values/relative change
CN2	Initial SCS CN II value	+0.1908
ALPHA_BF	Baseflow alpha factor	0.915
GW_DELAY	Groundwater delay time	295.02
SURLAG	Surface runoff lag coefficient	2.995
OV_N	Manning's "n" value for overland flow	0.357
ESCO	Soil evaporation compensation factor	0.739
GW_REVAP	Groundwater "Revap" coefficient	0.178
CH_N2	Manning's "n" value for main channel	0.010
CH_K2	Effective hydraulic conductivity in main channel	225.505
ALPHA_BNK	Baseflow alpha factor for bank storage	0.385
SOL_K	Saturated hydraulic conductivity	+0.443
SOL_AWC	Available water capacity of the soil layer	-0.1086
SOL_BD	Moist bulk density	+0.091

Table S4. Data sources

Data type	Input data	Data source

Meteorological	Precipitation, temperature, Relative humidity, solar radiation, wind speed	National meteorological science data sharing service platform (https://data.cma.cn/site/index. html)
Streamflow data	Daily runoff	Hydrological Yearbook of the People's Republic of China
Spatial	Land use (30m resolution)	Resource and Environment Science and Data Center (https://www.resdc.cn)
	Soil	Harmonized World soil Database
	Digital Elevation Model	Geospatial Data cloud (https://www.gscloud.cn/)
Socioeconomic	Crop benefits and costs, technology costs, water prices	Compilation of Cost Benefit of Major Agricultural Products Nationwide https://www.ndrc.gov.cn/fgsj/

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