

Article

Crop and Water Allocation in Andean Community Irrigation Systems: An Optimization Framework for Sustainable Irrigation Planning from a Social-Ecological Perspective

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Featured Application

This model can support irrigation boards, local governments, and territorial planners in comparing crop-allocation rules under limited hydrological data, clarifying trade-offs among gross output value, modeled supplemental irrigation, and crop diversification before community or institutional decisions are made.

Abstract

Community-managed irrigation systems in Andean mountain catchments often operate with limited hydrometric information, complicating crop- and water-allocation planning. This study developed a reproducible annual linear-programming framework for the Santul Irrigation System, Ecuador, combining census data from all 46 registered irrigators with documented agronomic, climatic, economic, phenological, and irrigation-efficiency parameters. Three allocation configurations were compared: an economic-only benchmark, a maximum-share diversification model, and a hypothetical crop-specific four-crop diversification scenario. Survey-informed proxy annual water budgets were derived from the reported nominal flow and self-reported irrigation intensity. Under the reference specification, all nine baseline cases used the complete 15,945 ha modeled-crop domain; the land constraint was binding, whereas the water constraint was non-binding. Annual gross output values were USD 129,634, USD 79,845, and USD 76,412, while annual modeled supplemental irrigation requirements were 9007, 8445, and 7740 m³/year, respectively. Under maximum planting-month demand, water became binding and modeled land use declined to 69.6%, 81.5%, and 80.0%. Of 328 baseline and robustness runs, 324 were feasible. The framework is a diagnostic decision-support tool whose outputs are interpreted from a social-ecological perspective; it does not directly optimize social-ecological outcomes or prescribe a crop plan.



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1. Introduction

Crop and water allocation in mountain catchments requires translating limited hydrological information, seasonal variability, and local distribution rules into operational

decisions. Irrigation can sustain crop yields, reduce exposure to rainfall variability, and support rural livelihoods, but allocation choices may also increase pressure on water sources, associated ecosystems, and the institutions responsible for distributing scarce resources [1,2]. These tensions are particularly important in mountain territories, where water availability depends on elevational gradients, seasonal rainfall, conveyance infrastructure, irrigation turns, crop calendars, and local agreements. In such settings, the analytical challenge is to compare feasible crop-allocation rules under explicit land and water constraints rather than assume that improved hydraulic performance alone ensures sustainable irrigation planning.

This allocation problem is further complicated by the irrigation-efficiency paradox. Improvements in conveyance or application efficiency do not necessarily reduce total water consumption when they stimulate agricultural expansion, intensification or changes in return flows and downstream uses [3–6]. In an optimization model, efficiency parameters therefore affect estimated crop-water requirements, but they should not be interpreted as direct indicators of system-level sustainability. Allocation results must be read in relation to the hydrological assumptions, crop portfolio, land constraints and local distribution rules under which each scenario is defined.

Social-ecological systems theory provides a useful basis for interpreting crop and water allocation as more than a hydraulic or economic problem. Ostrom's framework for common-pool resources emphasizes the interactions among resource systems, resource units, actors and governance arrangements [7]. Subsequent work on resilience and adaptive governance has shown that diversity, learning capacity, participation and cross-level coordination shape the capacity of resource systems to respond to change [8,9]. For community-managed irrigation systems, this perspective helps situate optimization outputs within a broader set of interdependent conditions: water availability, infrastructure, crop choices, local rules, collective decision making and environmental limits.

In the Andean region, community irrigation systems have developed historically as arrangements that combine hydraulic infrastructure, collective norms, productive practices, access rights, and territorial organization. Research on Andean water governance has shown that these systems cannot be understood simply as technical devices for conveying water because their functioning depends on reciprocity, negotiated distribution, collective labor, local authority, and relationships among communities, markets, and the state [10–13]. From this perspective, community irrigation constitutes both a social-ecological and a hydrosocial arrangement: it mobilizes water, land, crops, local knowledge, and collective organization while also reflecting disputes over control, autonomy, recognition, and territorial sustainability. In Ecuador and other Andean countries, rural communities have recreated water territories through self-governance practices, collective work practices (*mingas*), reciprocal rules, and relationships with external actors, confirming that irrigation sustainability depends on both biophysical conditions and social-institutional arrangements [14].

Optimization models have become increasingly relevant for agricultural water management because they allow alternative allocations of water, land and crops to be compared under explicit constraints. Hydroeconomic and mathematical programming approaches have been used to estimate economic returns, identify binding resource constraints and explore trade-offs between productivity, water availability and environmental sustainability [15–17]. Simulation–optimization models have further incorporated spatial, temporal and hydrological detail into irrigation planning, particularly in large irrigation districts, arid regions and watershed-scale allocation problems [18,19]. More recent studies have extended this literature by integrating uncertainty, scenario analysis and adaptive regulation. For example, Cao et al. [20] developed a hydro-agro-economic optimization framework for irrigated farming, while Yang et al. [21] proposed an uncertainty-informed optimization

and dynamic regulation framework that combines fractional programming, Dinkelbach's algorithm and Monte Carlo simulation to support robust irrigation water allocation under uncertain conditions.

These advances demonstrate the value of optimization for water allocation and decision support, but they also reveal an important gap. Much of the recent irrigation-optimization literature has focused on regional irrigation districts, watershed-scale allocation problems, or data-intensive simulation frameworks supported by relatively detailed hydrological, spatial, and operational information [18–21]. The application of these approaches to small community-managed systems in mountain catchments remains limited. Such systems are not merely hydraulic or economic units; they are hydrosocial territories in which water, infrastructure, local rules, reciprocity, and community governance jointly shape productive decisions. Consequently, optimization in this context is better suited to scenario comparison than to prescribing an automatic allocation rule.

The Sustainable Development Goals (SDGs) reinforce the need for such an integrated perspective. Irrigation is directly related to food production and rural income, but also to sustainable water management, inequality reduction, climate adaptation, mountain ecosystems and participatory governance. The literature on SDG interactions has shown that progress toward one target may reinforce other targets, generate trade-offs or produce context-dependent effects shaped by institutional, territorial and environmental conditions [22–24]. In Andean contexts, nexus approaches have similarly shown that water decisions cannot be evaluated from a single-sector perspective, particularly in territories affected by climate pressure, urbanization, productive change and competition among water users [25,26]. For this reason, optimization results should be interpreted not only in terms of gross output value, but also in relation to modeled supplemental irrigation, crop diversity, and the territorial implications of alternative allocation rules.

This study addresses this gap by examining the Santul Irrigation System, located in Tomebamba Parish, Paute Canton, Azuay Province, Ecuador, as a case of a small community-managed irrigation system in an Andean mountain catchment. The study integrates primary information from irrigators and farm units with external agronomic, climatic, and economic parameters, including crop prices, yields, crop-cycle duration, crop coefficients, reference evapotranspiration, effective precipitation, irrigation efficiency, and survey-informed proxy annual water budgets. On this basis, a linear-programming model is used to compare three allocation configurations: an economic-only benchmark without crop-diversification constraints, a maximum-share diversification model, and a hypothetical crop-specific four-crop diversification scenario designed to test explicit crop-presence and anti-concentration rules.

The objective of this study is to implement an optimization model for irrigation systems in Andean mountain catchments by evaluating how different land, proxy water-budget, and crop-share rules modify annual gross output value, modeled supplemental irrigation, and crop diversification. The contribution is twofold. First, the study adapts a linear-programming approach to a small-scale community-managed irrigation system, where data availability and operational conditions differ from those of large irrigation districts and spatially explicit allocation models. Second, it interprets model outputs through a social-ecological and SDG-oriented framework, showing how scenario comparison can support deliberation on gross output performance, irrigation requirements, and productive diversity without replacing community decision making. In doing so, the article presents an agricultural crop- and water-allocation model whose results are interpreted through a social-ecological framework for Andean irrigation planning.

2. Materials and Methods

2.1. Study Area, Census Design, and Modeled Land Domain

The analysis focused on the Santul Irrigation System, located in Tomebamba Parish, Paute Canton, Azuay Province, Ecuador, at approximately 2642 m a.s.l. (Figure 1). A structured census survey was administered between September 2023 and February 2024 to the complete registry of 46 irrigators associated with the system. The database therefore represents the full eligible registered population rather than a sample, with one record corresponding to each participating irrigator and associated farm unit. The instrument collected information on socioeconomic conditions, irrigation infrastructure and practices, irrigated area, crop presence, production, governance, institutional cooperation, costs, and adaptation.

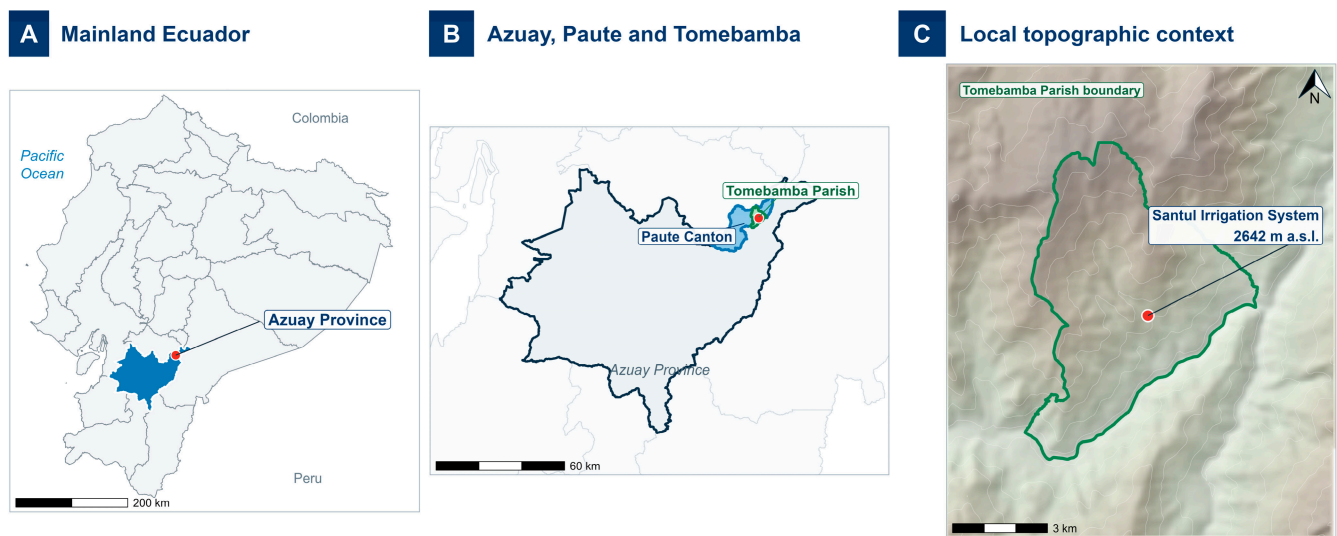


Figure 1. Location of the Santul Irrigation System in Tomebamba Parish, Paute Canton, Azuay Province, Ecuador. Panel (A) locates Azuay Province within mainland Ecuador. Panel (B) identifies Paute Canton and Tomebamba Parish within Azuay Province. Panel (C) shows the local topographic context. The green outline in Panel (C) represents the Tomebamba Parish boundary, and the red point indicates the Santul Irrigation System at 2642 m above sea level (a.s.l.) (2.7238° S, 78.6758° W). Source: authors' elaboration based on field coordinates, official territorial-organization boundaries from the Comité Nacional de Límites Internos, accessed through the public ArcGIS REST Feature Services provided by the Secretaría Nacional de Gestión de Riesgos [27], and the hole-filled Shuttle Radar Topography Mission (SRTM) 90 m digital elevation model [28].

Item-level valid sample sizes vary because some questions were unanswered or were not applicable. Entries designated in the database as non-response or not applicable were recoded as missing and excluded only from the corresponding item-level calculation. Zero was not recoded as missing; the data audit confirmed that no valid zero values were present in the final variables for irrigation days per week or daily irrigation hours. Weekly irrigation intensity was calculated for the 36 records containing both variables as the respondent-level product $D_j \times H_j$, where D_j is irrigation days per week and H_j is daily irrigation hours. The mean weekly intensity was therefore obtained by averaging the individual products, rather than by multiplying the two marginal means.

Among the 46 census records, 27 had a valid positive irrigated-area value, totaling 35.493 ha. The primary optimization domain was restricted to farm units that reported both a positive irrigated area and the presence of at least one of the four crops represented in the model. This restriction yielded a modeled land domain of 15.945 ha across 20 farm units, thereby preventing the aggregate optimization from reallocating land reported by units that did not identify any modeled crop. Two alternative domain definitions were

retained for sensitivity analysis: a strict modeled-crop complete-efficiency domain of 13.885 ha across 18 farm units and a broader complete-efficiency domain of 33.033 ha across 24 farm units. The area variable represents the total irrigated land associated with each eligible farm unit; observed crop-specific area shares were unavailable. Accordingly, the optimized allocations represent analytical scenario solutions rather than reconstructions of current crop areas. The census, irrigation, and modeled-land-domain characteristics of the Santul Irrigation System are summarized in Table 1.

Table 1. Census, irrigation, and modeled-land-domain characteristics of the Santul Irrigation System.

Characteristic	Summary
Census and farm-unit characteristics	
Registered irrigator universe	46 registered irrigators
Survey participants and registry coverage	46/46; 100.0% registry coverage
Survey period	September 2023–February 2024
Age of irrigators, years	$n = 46$; mean = 55.78; SD = 12.21; median = 57.00 [47.25–62.75]
Sex of irrigators	$n = 46$; female: 24 (52.2%); male: 22 (47.8%)
Education level	$n = 46$; primary: 29 (63.0%); secondary or higher: 12 (26.1%); none: 5 (10.9%)
Household size, persons	$n = 46$; mean = 3.67; SD = 1.92; median = 3.00 [2.00–5.00]
Main irrigation method	$n = 46$; sprinkler: 25 (54.3%); gravity: 7 (15.2%); hose: 4 (8.7%); drip: 2 (4.3%); none reported: 8 (17.4%)
Monthly water tariff, USD/month	$n = 37$; mean = 4.11; SD = 4.42; median = 2.50 [2.50–3.00]
Internal irrigation regulations	$n = 44$; yes: 37 (84.1%); no: 7 (15.9%)
Paired irrigation descriptors	
Irrigation days per week	$n = 36$; mean = 4.03; SD = 2.42; median = 4.00 [2.00–7.00]; range = 1–7
Daily irrigation hours	$n = 36$; mean = 4.64; SD = 3.83; median = 3.00 [2.00–7.25]; range = 1–15
Weekly irrigation intensity, hours/week	$n = 36$; mean = 19.89; SD = 22.27; median = 9.00 [4.00–32.50]; range = 1–98
Modeled land domains and system efficiency	
All valid reported irrigated area	$n = 27$ farm units; 35.493 ha
Primary modeled-crop domain	$n = 20$ farm units; 15.945 ha; main optimization domain
Strict modeled-crop complete-efficiency domain	$n = 18$ farm units; 13.885 ha; sensitivity analysis
Broad complete-efficiency domain	$n = 24$ farm units; 33.033 ha; broad-domain sensitivity
Area-weighted irrigation efficiencies	$n = 24$ farm units; weighting area = 33.033 ha; application = 0.759; conveyance = 0.919; overall = 0.706

Note: Continuous variables are summarized as mean, standard deviation (SD), and median [Q1–Q3], with ranges additionally reported for the paired irrigation descriptors. Categorical variables are summarized as n (%). Irrigation days, daily hours, and weekly intensity are based on the same 36 paired observations. Weekly irrigation intensity was calculated for each irrigator as irrigation days per week multiplied by daily irrigation hours and was then summarized across irrigators. The 15.945 ha modeled-crop domain is the primary optimization domain; the 13.885 and 33.033 ha domains are used only in area-domain sensitivity analyses. Irrigation efficiencies are area-weighted estimates based on 24 farm units and 33.033 ha.

Among the 44 irrigators with valid crop-presence information, the four modeled crops were soft dry maize (27 irrigators; 61.4%), fresh bean (19; 43.2%), Superchola potato (16;

36.4%), and fresh pea (11; 25.0%). These are non-exclusive crop-presence frequencies and do not represent shares of irrigated land. The traditional Chacra, particularly the maize–bean association, is practiced in Santul but was not modeled as a separate production alternative because local joint parameters for yield, modeled supplemental irrigation requirement, and gross output value were unavailable. The model therefore treats the four crops as separate activities; the exclusion of associated cropping may underrepresent a locally important form of agricultural diversification and is considered when interpreting the results.

2.2. External Parameters, Climatic Inputs, and Annualized Crop-Water Coefficients

The census database was complemented with a non-confidential external-parameter matrix containing the agronomic, climatic, economic, phenological, and irrigation-efficiency inputs required by the model (Supplementary File S3). Model prices were expressed in USD/kg and corresponded to the September 2023–February 2024 fieldwork period. Producer prices were used for Superchola potato, fresh pea, and fresh bean. For soft dry maize, the wholesale price of white soft dry maize marketed for mote was retained because the producer-price bulletins did not report an equivalent dry-maize category; the available producer categories referred to hard dry maize or fresh soft maize [29]. Only one producer-price observation for fresh bean was available during the period examined. The use of a different market level for maize and the limited producer-price coverage for fresh bean were therefore treated as sources of uncertainty and evaluated through crop-specific price perturbations and an alternative scenario based on median prices reported by Santul producers.

Reference yields were obtained from the 2023 agricultural statistics for Azuay and from the Continuous Agricultural Surface and Production Survey (ESPAC 2023) [30,31]. Crop coefficients were taken from the Food and Agriculture Organization's *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*, FAO Irrigation and Drainage Paper No. 56 (FAO-56) [32]. Crop-cycle durations were based on INIAP technical documentation for Superchola potato, soft dry maize, fresh pea, and fresh bean [33–36]. The adopted cycle durations were 250 days for soft dry maize, 160 days for Superchola potato, 120 days for fresh pea, and 140 days for fresh bean. The cited sources support the total duration of each crop cycle; however, the division into initial, development, mid-season, and late-season stages was an operational adaptation for irrigation modeling rather than locally observed phenology. The complete stage durations, coefficients, parameter sources, and operational decisions are documented in Supplementary File S3.

Monthly climatic inputs were obtained from the National Aeronautics and Space Administration Prediction Of Worldwide Energy Resources (NASA POWER) Point Climatology product, using local solar time, for 2014–2023 at 2.7238° S and 78.6758° W, corresponding to the Santul Irrigation System [37]. The variables used to calculate reference evapotranspiration were surface solar radiation (ALLSKY_SFC_SW_DWN), atmospheric pressure (PS), relative humidity at 2 m (RH2M), maximum and minimum air temperature at 2 m (T2M_MAX and T2M_MIN), and wind speed at 2 m (WS2M). Monthly total precipitation was represented by PRECTOTCORR_SUM. NASA POWER was used because a complete local meteorological-station record was unavailable; previous studies support its use for estimating reference evapotranspiration while also documenting potential biases related to spatial resolution and local climatic conditions [38,39]. The associated Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), grid-cell elevation was 2843.93 m, compared with the reported study-site elevation of 2642 m above sea level. This difference was treated as a source of climatic uncertainty rather than as a local elevation measurement. Reference evapotranspiration (ET_0) was estimated using the FAO-56 Penman–Monteith method [32]. The calculations used monthly mean climatic

inputs, mid-month day-of-year values, a soil heat flux of zero, an albedo of 0.23, and actual vapor pressure derived from relative humidity.

Effective precipitation was derived from monthly total precipitation using the United States Department of Agriculture Soil Conservation Service (USDA-SCS) procedure documented in the CROPWAT methodology [40]. For monthly precipitation $P_m \leq 250$ mm, effective precipitation was calculated as $P_{\text{eff},m} = P_m(125 - 0.2P_m)/125$; for $P_m > 250$ mm, it was calculated as $P_{\text{eff},m} = 125 + 0.1P_m$. The monthly effective-precipitation total was divided by the corresponding number of days to obtain a representative daily value. For the crop-cycle simulations, monthly ET_0 and effective-precipitation totals were distributed uniformly across the days of each month. The resulting daily series therefore represents a repeated monthly climatology rather than an observed daily meteorological record.

The climatic derivation was independently reconstructed in the reproducibility script. The maximum absolute difference between stored and reconstructed ET_0 was 0.002493 mm/day, and the corresponding maximum difference for effective precipitation was 0.004601 mm/month. Both were within the predefined rounding tolerances. This audit verifies the internal reproducibility of the climatic calculations but does not constitute validation against a local meteorological station.

For each crop i , production cycles beginning in each of the twelve calendar months m were simulated. When a crop cycle extended beyond December, the 365-day climatological sequence was repeated cyclically. The crop coefficient remained constant during the initial stage, increased linearly from Kc_{ini} to Kc_{mid} during the development stage, remained constant during the mid-season stage, and changed linearly from Kc_{mid} to Kc_{end} during the late-season stage. Daily crop evapotranspiration was calculated as:

$$ET_{c,i,m,d} = ET_{0,m,d} \times Kc_{i,d} \quad (1)$$

where $ET_{c,i,m,d}$ is crop evapotranspiration for crop i , planted in month m , on day d of its production cycle, expressed in mm/day; $ET_{0,m,d}$ is daily reference evapotranspiration; and $Kc_{i,d}$ is the crop coefficient corresponding to the phenological stage of crop i .

The net irrigation requirement was calculated by accumulating only positive daily differences between crop evapotranspiration and effective precipitation:

$$NIR_{i,m} = \sum_{d=1}^{D_i} \max(ET_{c,i,m,d} - P_{m,d}^{\text{eff}}, 0) \quad (2)$$

where $NIR_{i,m}$ is the net irrigation requirement of crop i planted in month m , expressed in mm/cycle; D_i is crop-cycle duration in days; and $P_{m,d}^{\text{eff}}$ is daily effective precipitation. The maximum operator prevents negative irrigation requirements when effective precipitation exceeds crop evapotranspiration.

The net requirement was adjusted by the area-weighted overall irrigation efficiency and converted from millimeters to cubic meters per hectare:

$$MSIR_{i,m} = \frac{NIR_{i,m}}{E_g} \times 10 \quad (3)$$

where $MSIR_{i,m}$ is the modeled supplemental irrigation requirement for crop i planted in month m , expressed in m³/ha/cycle; E_g is the area-weighted overall irrigation efficiency; and the factor 10 converts a water depth of 1 mm over 1 ha into 10 m³. The term “modeled supplemental irrigation requirement” is used throughout this manuscript because actual plot-level water abstraction, delivery, and application volumes were not measured.

Overall irrigation efficiency was first calculated for each farm unit and then aggregated using irrigated-area weights:

$$E_{g,j} = E_{a,j} \times E_{c,j}, \quad E_g = \frac{\sum_{j=1}^J A_j E_{g,j}}{\sum_{j=1}^J A_j} \quad (4)$$

where $E_{g,j}$, $E_{a,j}$, and $E_{c,j}$ are the overall, application, and conveyance efficiencies of farm unit j , respectively; A_j is its reported irrigated area; and J is the number of farm units with complete area and efficiency information. Application-efficiency coefficients were assigned according to irrigation method using values reported for the Ecuadorian highlands, while conveyance-efficiency coefficients were assigned according to reported canal characteristics using FAO indicative values [34,41]. The calculation included 24 farm units representing 33.033 ha and produced area-weighted application, conveyance, and overall efficiencies of 0.758831, 0.919061, and 0.706345, respectively. The model used the area-weighted mean of the farm-level overall efficiencies, reported as $E_g = 0.706$, rather than the product of the separately rounded application- and conveyance-efficiency averages.

For each crop, the mean, median, 75th-percentile, and maximum modeled supplemental irrigation requirements were calculated across the twelve simulated planting months. The mean requirement was used in the principal optimization model. The median was retained as a descriptive statistic, whereas the 75th-percentile and maximum requirements were used as higher-demand assumptions in the robustness and water-stress analyses. Values below 1 m³/ha/cycle indicate that modeled supplemental irrigation was negligible under the corresponding planting-month simulation; they do not imply that crop evapotranspiration was zero.

To place the economic and irrigation coefficients on the same annual basis as the water-budget constraint, per-cycle values were annualized using the crop-specific median number of harvests per year among producers who reported a positive value. The adopted medians were one cycle per year for soft dry maize, two for Superchola potato, two for fresh pea, and one for fresh bean. These medians were based on 26, 16, 10, and 16 valid positive responses, respectively.

The annual gross output value coefficient was calculated as:

$$v_i = p_i \times Y_i \times C_i \quad (5)$$

where v_i is annual gross output value in USD/ha/year; p_i is the model price in USD/kg; Y_i is reference yield in kg/ha per modeled crop cycle; and C_i is the median number of reported cycles per year for crop i .

The corresponding annual modeled supplemental irrigation coefficient was calculated as:

$$w_i^{(b)} = MSIR_i^{(b)} \times C_i \quad (6)$$

where $w_i^{(b)}$ is the annual modeled supplemental irrigation requirement in m³/ha/year and $MSIR_i^{(b)}$ is the per-cycle requirement under demand basis b . The principal model used the mean planting-month requirement, while the 75th-percentile and maximum bases were used in the robustness analysis.

Gross economic water productivity was calculated as $GEWP_i = v_i / w_i^{(\text{mean})}$ and expressed in USD/m³. It represents annual gross output value per cubic meter of modeled supplemental irrigation and does not represent net economic return, profitability, or household income because fertilizer, labor, machinery, land, irrigation, transport, and post-harvest costs were not consistently available by crop, hectare, and production cycle. Annualization

assumes that the same reference yield, model price, and crop-specific water coefficient apply to each repeated cycle; uncertainty in crop frequency, prices, and yields was therefore evaluated in the sensitivity analysis. Table 2 summarizes the crop-level agronomic inputs and annualized coefficients used in the optimization model.

Table 2. Crop-level agronomic inputs and annualized coefficients used in the optimization model.

Crop	Model Price, USD/kg (Market Level)	Reference Yield, kg/ha/Cycle	Crop Duration, Days	$Kc_{ini}/Kc_{mid}/Kc_{end}$	Median Cycles/Year	Annual Gross Output Value, USD/ha/Year	Annual MSIR: Mean/P75/Maximum, m ³ /ha/Year	Gross Economic Water Productivity, USD/m ³
Soft dry maize	1.820 (wholesale)	680	250	0.30/1.20/0.35	1	1237.60	379.36/714.59/1136.56	3.262
Superchola potato	0.558 (producer)	7285	160	0.50/1.15/0.75	2	8130.06	564.86/1211.42/1827.44	14.393
Fresh pea	0.725 (producer)	1300	120	0.50/1.15/1.10	2	1885.00	494.39/808.07/1803.65	3.813
Fresh bean	0.584 (producer)	650	140	0.50/1.05/0.90	1	379.60	167.21/346.90/645.86	2.270

Note: MSIR = modeled supplemental irrigation requirement; P75 = 75th percentile. Mean, P75, and maximum MSIR coefficients were derived from twelve planting-month simulations and annualized using the crop-specific median number of reported cycles per year. The principal optimization uses the mean annual MSIR; P75 and maximum values are used in robustness analyses. Gross economic water productivity is calculated using annual gross output value and mean annual MSIR. Prices are reported to three decimal places so that the gross output coefficients can be reproduced. Complete phenological-stage durations, source information, alternative survey-price summaries, and unrounded model coefficients are provided in Supplementary Files S2 and S3.

Because no local lysimeter measurements, soil-moisture records, continuous hydrometric observations, or measured plot-level irrigation deliveries were available, the crop-water calculations could not be directly validated against local observations. External plausibility was instead assessed by comparing the modeled crop-cycle ranges with broad FAO indicative seasonal crop-water ranges [42]. Superchola potato was additionally compared with a recent drainage-lysimeter study conducted under high-Andean conditions in Tungurahua, Ecuador [43]. These comparisons were intended only as order-of-magnitude plausibility checks. The FAO values are generic and climate dependent, whereas the Superchola study reports irrigation depth applied under experimental conditions rather than the modeled metric used here. The external values were not used to recalibrate the model, and these comparisons should not be interpreted as direct empirical validation.

The annualization procedure makes the objective-function and water-constraint coefficients temporally consistent in USD/ha/year and m³/ha/year. Nevertheless, it does not reconstruct observed parcel-level planting dates, overlapping monthly demands, within-year crop switching, rotations, or irrigation schedules. The model therefore evaluates annual volumetric feasibility and the sensitivity of alternative allocation rules under explicitly stated assumptions. Higher-demand planting-month scenarios and synthetic water-budget stress tests are used to probe sensitivity to adverse crop-demand and water-budget assumptions; they do not establish seasonal or monthly irrigation feasibility.

2.3. Survey-Informed Proxy Water Budgets and Annual Allocation Model

The annual allocation model combined the census-derived irrigation and land-domain information described in Section 2.1 with the annualized crop-specific economic and irrigation coefficients defined in Section 2.2. The analysis was conducted at the aggregate irrigation-system level rather than at the level of individual irrigators or parcels. Figure 2 summarizes the complete sequence from census characterization and external-parameter integration to crop-water simulation, annualization, linear programming, robustness analysis, and scenario interpretation.

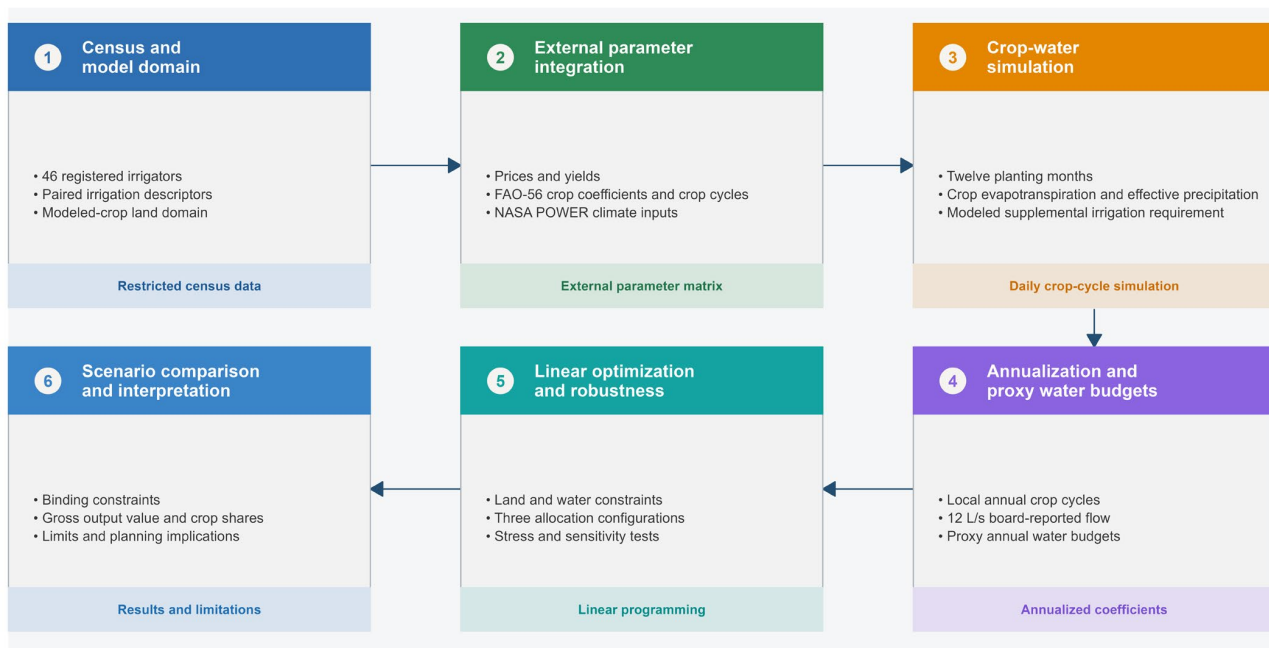


Figure 2. Methodological workflow of the annual crop- and water-allocation analysis. The workflow comprises: (1) census characterization and definition of the modeled-crop land domain; (2) integration of agronomic, economic, phenological, climatic, and irrigation-efficiency parameters; (3) daily crop-water simulation for twelve alternative planting months; (4) annualization of crop-specific coefficients and construction of survey-informed proxy annual water budgets; (5) linear optimization and robustness analyses; and (6) comparison and cautious interpretation of the allocation scenarios.

2.3.1. Survey-Informed Proxy Annual Water Budgets

The nominal flow rate of 12 L/s was reported to the research team by the Santul Irrigation Board during fieldwork. It was not obtained from continuous or periodic hydrometric gauging, nor were system-level operating records, turn-by-turn discharge measurements, or volumetric delivery records available. The reported flow was therefore treated as a nominal local reference and not as continuously available or directly measured annual water supply.

For each irrigator j with paired information, weekly irrigation intensity was calculated as $I_j = D_j H_j$, where D_j is irrigation days per week and H_j is daily irrigation hours. Three statistics from the distribution of the 36 respondent-level intensities were used to construct standardized annual proxy budgets: the median, the mean, and the third quartile. For scenario s , the corresponding annual proxy water budget was calculated as:

$$W_s = Q \times I_s \times 3600 \times \frac{365}{7} \times 10^{-3} \quad (7)$$

where W_s is the survey-informed proxy annual water budget for scenario s , expressed in m^3/year ; Q is the nominal flow reported by the irrigation board, expressed in L/s; I_s is the selected statistic of respondent-level weekly irrigation intensity, expressed in hours/week; 3600 converts hours to seconds; $365/7$ converts weekly duration to an annual basis; and 10^{-3} converts liters to cubic meters.

This transformation treats I_s as an equivalent weekly duration during which the nominal reported flow is applied to the modeled system domain. It is an analytical scaling assumption rather than a measurement of aggregate system operating time. Individual irrigation durations may overlap and may reflect differences in plot area, application method, discharge, pressure, conveyance conditions, and irrigation practices. Consequently, the resulting values are referred to throughout the manuscript as survey-informed proxy

annual water budgets, not as measured water availability, actual withdrawals, delivered volumes, or water use.

The median weekly intensity generated the conservative proxy budget; the mean generated the mean proxy; and the third quartile generated the upper proxy. A continuous-flow volume based on 168 h/week was calculated only as a hydraulic reference. It was not included among the water-budget scenarios used in the optimization. The resulting proxy budgets and their analytical status are summarized in Table 3.

Table 3. Survey-informed proxy annual water budgets derived from the nominal flow reported by the Santul Irrigation Board.

Water-Budget Case	Statistical or Hydraulic Basis	Equivalent Weekly Duration (h/Week)	Equivalent Fraction of Continuous Operation (%)	Annual Water Volume (m ³ /Year)	Status in the Analysis
Conservative survey-informed proxy	Median respondent-level weekly irrigation intensity	9.000	5.357	20,273	Main optimization and robustness analyses
Mean survey-informed proxy	Mean respondent-level weekly irrigation intensity	19.889	11.839	44,801	Main optimization
Upper survey-informed proxy	Third quartile of respondent-level weekly irrigation intensity	32.500	19.345	73,209	Main optimization
Nominal continuous-flow reference	24 h/day × 7 days/week × 365 days/year	168.000	100.000	378,432	Hydraulic reference only; not used as an optimization scenario

Note: Annual volumes were calculated with the unrounded respondent-level statistics and Equation (7); displayed weekly durations and percentages are rounded. The three proxy cases are alternative analytical scalings of the nominal 12 L/s flow and do not represent measured dry-, normal-, or wet-year water supplies. The nominal continuous-flow reference assumes uninterrupted operation and is included only to show the theoretical volume corresponding to the reported flow.

2.3.2. Annual Linear-Programming Model

Let $i = 1, \dots, 4$ index the four modeled crops: soft dry maize, Superchola potato, fresh pea, and fresh bean. The continuous decision variable x_i represents the number of hectares assigned to the annual production program of crop i . Fractional hectare values were permitted; no integer or binary decision variables were used.

Each hectare could be assigned to only one crop-specific annual program. When the locally reported median frequency exceeded one crop cycle per year, the annual gross output and irrigation coefficients incorporated the repeated cycles on that same hectare. The land constraint nevertheless counted the hectare only once. The model therefore does not represent within-year switching between crops, crop rotations, intercropping sequences, or separate parcel-level assignments. The annualized coefficients should be interpreted as standardized annual crop programs rather than as observed crop calendars or recommendations for continuous monocropping.

For water-budget scenario s and crop-water-demand basis b , the objective was to maximize annual gross output value:

$$\max_x Z_{s,b} = \sum_{i=1}^4 v_i x_i \quad (8)$$

where $Z_{s,b}$ is total annual gross output value in USD/year; v_i is the annual gross output coefficient of crop i , expressed in USD/ha/year; and x_i is the modeled area assigned to crop i ,

expressed in hectares. Because the objective uses gross output rather than net returns, it does not deduct labor, fertilizer, machinery, transport, land, irrigation, or post-harvest costs.

The modeled-land constraint was:

$$\sum_{i=1}^4 x_i \leq A \quad (9)$$

where $A = 15.945$ ha is the primary modeled-crop land domain defined in Section 2.1. The constraint was specified as an upper bound rather than an equality, allowing part of the modeled domain to remain unallocated when the water budget was insufficient.

The annual proxy water-budget constraint was:

$$\sum_{i=1}^4 w_i^{(b)} x_i \leq W_s \quad (10)$$

where $w_i^{(b)}$ is the annual modeled supplemental irrigation coefficient of crop i , expressed in $\text{m}^3/\text{ha}/\text{year}$, under crop-water-demand basis b ; and W_s is the survey-informed proxy annual water budget defined in Equation (7). The principal optimization used the mean requirement across the twelve planting-month simulations. The 75th-percentile and maximum planting-month requirements were used in the robustness analyses described in Section 2.4.

All decision variables satisfied:

$$x_i \geq 0 \quad i = 1, \dots, 4 \quad (11)$$

The three allocation configurations were evaluated under the same annual objective function, modeled-land constraint, proxy water-budget constraint, and non-negativity conditions.

Economic-Only Benchmark

The economic-only benchmark imposed no crop-share restrictions beyond Equations (9)–(11). It identifies the allocation with the highest annual gross output value under the specified land domain, annualized crop coefficients, and proxy water budget. It is an analytical economic reference and not an agronomic, social, or territorial recommendation.

Maximum-Share Diversification Model

The maximum-share diversification model imposed a uniform anti-concentration ceiling:

$$x_i \leq 0.50A \quad i = 1, \dots, 4 \quad (12)$$

This rule prevents any single crop from occupying more than half of the complete modeled-crop land domain. The 50% threshold was selected as a simple and transparent analytical benchmark distinguishing an unrestricted solution from one in which no crop may constitute an absolute majority of modeled land. It was not derived from an existing irrigation-board rule or empirically estimated farmer preference.

Crop-Specific Four-Crop Diversification Scenario

The crop-specific four-crop diversification scenario imposed the following crop-specific bounds:

$$\begin{aligned} x_{\text{potato}} &\leq 0.50A, \\ 0.10A &\leq x_{\text{maize}} \leq 0.30A, \\ x_{\text{pea}} &\geq 0.10A, \\ x_{\text{bean}} &\geq 0.10A. \end{aligned} \quad (13)$$

The potato ceiling limits concentration in the crop with the highest annual gross output coefficient. The 10% minimum for maize ensures its representation, while the 10% minimum for each legume reserves at least 20% of the full modeled domain for fresh pea and fresh bean. The 30% maize ceiling, combined with the 50% potato ceiling, prevents a two-crop potato–maize allocation from occupying the entire modeled domain. No minimum was imposed on potato because the scenario was designed to limit concentration in the economically dominant crop rather than mandate its cultivation.

These percentages were selected as transparent, round-numbered analytical thresholds to produce a clearly differentiated crop portfolio. They were not derived from observed crop-area shares, farmer-preference elicitation, irrigation-board regulations, participatory workshops, agronomic rotation rules, food-security indicators, ecological thresholds, or statistical estimation. Accordingly, the scenario is not presented as an empirically identified social-ecological optimum. Its purpose is to evaluate the consequences of introducing explicit crop-presence and anti-concentration rules. Sensitivity to the selected percentages was assessed using alternative thresholds, as described in Section 2.4.

Because the lower bounds in Equation (13) are calculated relative to the complete modeled domain A , they remain absolute minimum-area requirements when water becomes binding. This formulation tests whether a minimum diversified portfolio remains feasible under progressively restrictive water budgets; under sufficiently low budgets, it may result in an infeasible solution. It should not be interpreted as a rule requiring the same percentages of whatever area happens to be cultivated. Table 4 summarizes the crop-share constraints, evidentiary status, and analytical purpose of the three allocation configurations.

Table 4. Annual optimization configurations and crop-share constraints.

Allocation Configuration	Additional Crop-Share Constraints	Absolute Baseline Bounds for $A=15.945$ ha	Analytical Purpose	Evidentiary Status
Economic-only benchmark	None	None beyond land, proxy water-budget, and non-negativity constraints	Identifies the allocation with the highest annual gross output value under the specified assumptions	Economic reference only; not a productive recommendation
Maximum-share diversification model	$x_i \leq 0.50 A$ for every crop	Each crop ≤ 7.9725 ha	Tests a uniform rule preventing any crop from occupying more than half of the modeled domain	Hypothetical anti-concentration benchmark
Crop-specific four-crop diversification scenario	Potato $\leq 0.50A$; maize $\geq 0.10A$ and $\leq 0.30A$; pea $\geq 0.10A$; bean $\geq 0.10A$	Potato ≤ 7.9725 ha; maize = 1.5945–4.7835 ha; pea ≥ 1.5945 ha; bean ≥ 1.5945 ha	Tests the implications of limiting potato concentration while retaining maize and minimum areas of both legumes	Hypothetical analytical scenario; not an observed community rule or an empirically estimated social-ecological optimum

Note: A denotes the complete primary modeled-crop land domain of 15.945 ha. Absolute limits are shown to facilitate interpretation; the optimization used the corresponding unrounded proportional expressions. All three configurations maximize annual gross output value. Crop-share minima and maxima are applied relative to the full modeled domain, not relative to the area ultimately cultivated when water is binding. The influence of alternative thresholds is evaluated in Section 2.4.

2.3.3. Baseline Model Runs and Output Indicators

The principal analysis combined the three survey-informed proxy water budgets with the three allocation configurations, producing nine baseline linear-programming cases. All principal cases used:

- The 15.945 ha modeled-crop land domain;

- Official model prices;
- Reference yields;
- Locally reported median annual crop-cycle frequencies;
- Mean planting-month modeled supplemental irrigation requirements.

The nominal continuous-flow reference was excluded from the optimization. It was retained only to contextualize the magnitude of the three proxy budgets.

For each model run, the analysis recorded feasibility status, crop-specific allocated area, total allocated and unused modeled area, annual gross output value, annual modeled supplemental irrigation requirement, proxy-budget slack, percentage of modeled land allocated, percentage of the proxy budget used, and the binding status of the land and water constraints. A land constraint was considered binding when unused modeled area was within the numerical tolerance of zero; the water constraint was considered binding when proxy-budget slack was within the corresponding numerical tolerance.

The optimization problems were solved as continuous linear programs using the lpSolve R package, version 5.6.23 [44]. The complete crop-level coefficients, right-hand-side values, coefficient matrices, constraint directions, crop-specific solutions, and aggregate model outputs are provided as non-confidential reproducibility outputs in Supplementary File S2. Supplementary File S3 documents the external agronomic, economic, climatic, phenological, and irrigation-efficiency inputs. The restricted individual-level census database is not included in the public package, whereas the aggregate outputs do not contain direct identifiers. The script exports the full constraint matrices used for all principal cases.

2.4. Robustness, Sensitivity, and Interpretive Scope

A deterministic robustness and sensitivity analysis was conducted to evaluate the extent to which the model results depended on uncertain parameters, crop-water-demand assumptions, and alternative definitions of the modeled land and water domains. Unless otherwise specified, the reference case used: (i) the primary modeled-crop land domain of 15.945 ha; (ii) the conservative survey-informed proxy annual water budget of 20,273 m³/year; (iii) the mean modeled supplemental irrigation requirement across the twelve planting-month simulations; (iv) official model prices and reference yields; (v) the locally reported median number of annual crop cycles; and (vi) the baseline crop-share constraints defined in Section 2.3. The tests were structured as scenario comparisons and one-at-a-time parameter perturbations rather than as a probabilistic uncertainty analysis.

First, sensitivity to the crop-water-demand basis was evaluated by solving the three allocation configurations with the mean, 75th-percentile, and maximum modeled supplemental irrigation requirements obtained across the twelve planting-month simulations. All three demand bases were annualized using the locally reported median crop-cycle frequencies and evaluated under the conservative proxy water budget. The mean requirement was retained as the reference case because it summarizes the complete set of simulated planting months, whereas the 75th-percentile and maximum requirements represent progressively more demanding assumptions concerning planting timing and climatic exposure.

Second, synthetic water-budget stress tests were used to determine when the annual water constraint became binding and when the full modeled land domain could no longer be allocated. Annual budgets ranging from 10% to 160% of the conservative survey-informed proxy budget were tested at five-percentage-point intervals. The stress tests were conducted for the mean and maximum planting-month demand bases and for each of the three allocation configurations. For every combination, the analysis identified the minimum tested budget yielding a feasible solution and the minimum tested budget allowing the complete 15.945 ha modeled domain to be used. These budget levels are analytical stress

conditions and do not represent observed historical droughts, measured water deliveries, or probabilistic forecasts.

Third, sensitivity to the definition of the modeled land domain was examined using three alternatives: the strict modeled-crop complete-efficiency domain of 13.885 ha, the primary modeled-crop domain of 15.945 ha, and a broader complete-efficiency domain of 33.033 ha retained as an alternative sensitivity domain. Each domain was evaluated for the three allocation configurations using the conservative proxy budget, mean crop-water requirements, official prices, and locally reported median annual cycle frequencies. This comparison was designed to determine whether the principal conclusions depended on including farm units that did not report any of the four modeled crops.

Fourth, uncertainty arising from the annualization of crop coefficients was examined using three cycle-frequency assumptions. The first assigned one annual cycle to every crop. The second used the locally reported medians adopted in the reference model: one cycle for soft dry maize, two for Superchola potato, two for fresh pea, and one for fresh bean. The third used the corresponding reported means as annualization multipliers: 1.231, 2.188, 1.900, and 1.375 cycles/year, respectively. The mean values were used only as analytical multipliers and should not be interpreted as integer crop calendars for individual farms. All three frequency assumptions were evaluated under the primary land domain and conservative proxy budget.

Fifth, crop-price and yield uncertainty was assessed through one-at-a-time perturbations. The model price of each crop was independently reduced and increased by 20%, while all other prices, yields, water coefficients, and constraints were held at their reference values. The same procedure was applied separately to the reference yield of each crop. Every crop-specific price and yield perturbation was evaluated for all three allocation configurations. An additional price-basis scenario replaced the official model prices with the median prices reported by Santul producers. This alternative was included to assess whether the allocation results depended on using a wholesale price for soft dry maize while producer prices were used for the other crops.

Sixth, sensitivity to climatic and irrigation-efficiency inputs was evaluated by independently varying reference evapotranspiration, effective precipitation, and area-weighted overall irrigation efficiency by -10% and $+10\%$. For each perturbation, the daily crop-water balance was recalculated and new crop-level modeled supplemental irrigation coefficients were generated before solving the optimization model. Thus, each perturbation was propagated through the crop-water calculations rather than applied only to post-optimization outputs. These tests were conducted under both the conservative survey-informed proxy budget and a synthetic restrictive budget defined as 75% of the baseline annual water requirement for assigning the complete primary land domain to Superchola potato. The latter was included solely to reveal parameter influence under a water-limited condition and does not represent measured system availability.

Seventh, the crop-specific four-crop diversification scenario was evaluated under alternative crop-share thresholds. The potato maximum was tested at 40%, 50%, and 60% of the complete modeled domain. The maize minimum was tested at 5%, 10%, and 15%, and the maize maximum at 20%, 30%, and 40%. The minimum shares for fresh pea and fresh bean were each tested at 5%, 10%, and 15%. Except for the combined cases described below, one threshold was modified at a time while the remaining baseline thresholds were retained.

Two combined threshold configurations were also evaluated. The less restrictive configuration imposed a maximum potato share of 60%, a maize share of 5–40%, and minimum shares of 5% for both fresh pea and fresh bean. The more restrictive configuration imposed a maximum potato share of 40%, a maize share of 15–25%, and minimum shares

of 15% for both legumes. All threshold tests used the primary modeled-crop domain, conservative proxy water budget, official prices, locally reported median annual crop frequencies, and mean planting-month water requirements. These tests evaluate the model's dependence on the selected analytical assumptions; they do not identify or validate any threshold as a socially, agronomically, or ecologically optimal crop share.

For every robustness and sensitivity case, the analysis recorded model feasibility, solver status, crop-specific allocated area, total allocated and unused modeled area, annual gross output value, annual modeled supplemental irrigation requirement, proxy-budget slack, percentage of the modeled land domain used, percentage of the annual proxy budget used, and the binding status of the land and water constraints. The complete scenario definitions, crop-level coefficients, constraint matrices, allocations, and aggregate summaries were exported as non-confidential reproducibility outputs in Supplementary File S2. The underlying agronomic, climatic, economic, phenological, and irrigation-efficiency parameters are documented in Supplementary File S3. Supplementary File S2 comprises the principal R script, the independent Figure 1 cartographic script, README, analysis manifest, and non-confidential aggregate outputs required to inspect and reconstruct the principal model inputs and results; Supplementary File S3 provides the external parameter workbook required by the principal script.

The robustness analyses assess the internal behavior and conditional stability of the model but do not substitute for empirical validation against continuous hydrometric measurements, measured volumetric deliveries, soil-moisture observations, parcel-level crop-area records, or complete planting calendars. The results therefore indicate annual volumetric feasibility under explicit assumptions. They do not demonstrate that the resulting allocations would be feasible in every month, irrigation turn, or farm unit, nor do they predict the crop choices that irrigators would necessarily adopt.

The model did not include equity, household food security, livelihood resilience, labor availability, governance quality, adaptive capacity, ecosystem condition, or formal SDG indicators as objective functions, mathematical constraints, or model coefficients. Accordingly, no quantitative SDG impact scores or empirically estimated positive or negative SDG effects were assigned to the allocation solutions. Potential social-ecological and SDG-related implications are addressed only as cautious conceptual interpretations in the Discussion and are distinguished from the directly modeled results.

2.5. Software, Reproducibility, and Use of Generative Artificial Intelligence

Data preparation, census-data auditing, crop-parameter processing, crop-water requirement estimation, annualization of model coefficients, linear programming, robustness analyses, and figure generation were conducted in R version 4.6.0 (R Foundation for Statistical Computing, Vienna, Austria) within RStudio 2026.07.1 Build 147 (Posit Software, PBC, Boston, MA, USA). Linear-programming problems were solved using the lpSolve R package, version 5.6.23. Data import, restructuring, transformation, and export were performed primarily with haven, dplyr, tidyr, readxl, readr, and stringr. Statistical graphics and multi-panel figures were produced using ggplot2, patchwork, and ragg.

The final cartographic Figure 1 was generated using a separate reproducible R script. Official provincial, cantonal, and parish boundaries were accessed from the public ArcGIS REST services of the Secretaría Nacional de Gestión de Riesgos and the Comité Nacional de Límites Internos, while local topography was derived from SRTM elevation data. Spatial-data retrieval, processing, relief construction, cartographic annotation, and export used primarily the R packages sf, terra, geodata, ggspatial, ggnewscale, httr2, ggplot2, patchwork, and ragg. The map script records the administrative-boundary service used during execution and does not represent the Tomebamba Parish boundary as the physical bound-

ary of the Santul Irrigation System. All final raster figures were exported in PNG and TIFF formats at 600 dpi; TIFF files used lossless LZW compression. Exact R-package versions, the operating system, locale, and computational environment are documented through `sessionInfo()` in Supplementary File S4.

The non-confidential reproducibility package provided as Supplementary File S2 contains: (i) the principal R script used to generate the aggregate census audits, annualized crop and irrigation coefficients, linear-programming solutions, robustness analyses, model-input tables, constraint matrices, and publication-quality figures; (ii) the independent R script used to generate Figure 1; (iii) a README describing the required inputs, folder structure, execution procedure, analytical scope, and data restrictions; (iv) an analysis manifest; and (v) the aggregate tabular outputs required to inspect and reconstruct the principal model inputs and results. Supplementary File S3 contains the external agronomic, economic, climatic, phenological, and irrigation-efficiency parameter matrix required by the principal script. Supplementary File S4 documents the computational environment generated through `sessionInfo()`.

The original individual-level field-survey database is not included in the public reproducibility materials because it remains subject to the confidentiality, institutional, and ethical access restrictions described in the Data Availability Statement. The publicly supplied outputs contain aggregate census descriptors, crop-level parameters, complete optimization constraint matrices, scenario definitions, crop-specific model solutions, sensitivity results, and figure-ready data, but no directly identifying participant information.

Generative artificial intelligence was not used to collect, generate, or alter the source data; define the analytical strategy; select crops, variables, parameters, allocation scenarios, or model constraints; execute the statistical or optimization analyses; generate numerical results; or make methodological or interpretive decisions. During manuscript preparation and revision, ChatGPT (OpenAI, San Francisco, CA, USA, GPT-5.6) was used only as a supporting tool for manuscript organization, figure-layout refinement, troubleshooting and refinement of author-directed R code, and preparation of reproducibility documentation. All analyses and final figures were generated by the authors in their local R environment. All AI-assisted organizational and technical suggestions were critically reviewed, corrected where necessary, and independently verified by the authors, who retained full responsibility for all methodological, analytical, interpretive, and editorial decisions.

2.6. Ethical Considerations

The field-survey data used in this study were collected within the institutional project “Manejo integral comunitario del agua en sistemas de riego y agua potable andinos para la consecución de los Objetivos de Desarrollo Sostenible” [“Integral community management of water in Andean irrigation and drinking water systems for the achievement of the Sustainable Development Goals”]. Before fieldwork, the project proposal was submitted to the then Committee on Bioethics in Health Research (COBIAS) of the University of Cuenca. Following its analysis of the proposal, COBIAS notified the project team on 9 November 2021 that the proposal did not need to undergo formal evaluation by the Committee. This determination applied to the broader institutional project under which the Santul census survey was conducted, rather than to the present manuscript as a separate study.

The census survey was administered in Spanish through the KoboToolbox web-based data-collection platform (Kobo, Inc., Cambridge, MA, USA) between September 2023 and February 2024 to the complete registry of 46 irrigators associated with the Santul Irrigation System. Informed consent was obtained through a statement placed at the beginning of the questionnaire, before the substantive survey sections, with “Sí” and “No” response options. The statement explained that the survey sought information for a general

characterization of the irrigation system, that participation was voluntary and anonymous, and that the information would be used for academic purposes and handled with complete confidentiality. The blank questionnaire, including the original Spanish-language informed-consent statement, is provided as Supplementary File S1.

The present study uses selected variables from this broader census survey, together with external agronomic, climatic, economic, phenological, and irrigation-efficiency parameters, to construct the annual crop- and water-allocation model. No participants were recruited or re-contacted, no intervention was undertaken, and no additional personal information was collected for the present analysis. Individual-level survey records were used to derive aggregate census descriptors and model inputs, whereas the optimization and scenario results are reported at the irrigation-system and crop levels. The original individual-level field-survey database remains restricted and is not included in the public Supplementary Materials; the publicly shared reproducibility outputs contain no directly identifying participant information.

3. Results

3.1. Irrigation Intensity and Survey-Informed Proxy Annual Water Budgets

Paired information on irrigation frequency and daily duration was available for 36 of the 46 census records. Within this common subset, the mean irrigation frequency was 4.03 days/week and the mean daily duration was 4.64 h/day. Weekly irrigation intensity, calculated separately for each irrigator as the product of these two variables, had a mean of 19.89 h/week and a standard deviation of 22.27 h/week. The median was 9.00 h/week, the interquartile range was 4.00–32.50 h/week, and reported values ranged from 1 to 98 h/week. The difference between the mean and median reflected a right-skewed distribution containing a small number of high-intensity observations (Figure 3).

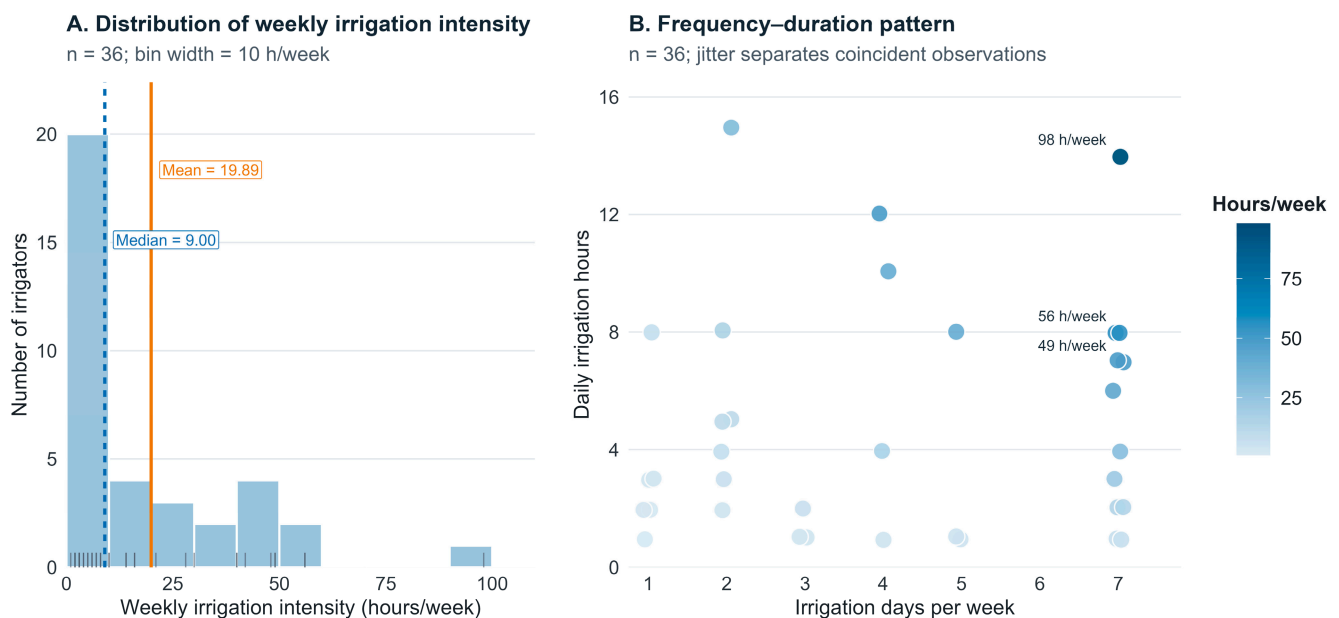


Figure 3. Distribution and frequency–duration structure of reported weekly irrigation intensity. Panel (A) presents the distribution of respondent-level weekly irrigation intensity for the 36 paired observations; the solid vertical line indicates the mean, the dashed vertical line indicates the median, and the histogram bin width is 10 h/week. Short tick marks along the x-axis in Panel (A) represent individual observations. Panel (B) presents the relationship between irrigation days per week and daily irrigation hours for the same 36 observations. Color intensity represents weekly irrigation intensity, jitter separates coincident observations, and labels identify the three highest distinct intensity combinations.

Panel A of Figure 3 shows that most reported weekly intensities were concentrated in the lower part of the distribution. Panel B indicates that the upper values resulted from combinations of comparatively frequent irrigation and long daily durations. The three highest distinct intensity combinations were 98, 56, and 49 h/week.

Application of Equation (7) to the median, mean, and third quartile of the respondent-level intensity distribution produced annual proxy budgets of 20,273, 44,801, and 73,209 m³/year, respectively. These values corresponded to 5.357%, 11.839%, and 19.345% of the nominal continuous-flow reference of 378,432 m³/year. The continuous-flow value was not included as an optimization case. The three proxy budgets were retained as alternative analytical scalings of the reported 12 L/s nominal flow.

3.2. Planting-Month Crop-Water Requirements and Hydroeconomic Profiles

Modeled supplemental irrigation requirements varied across crops and planting months. Across the twelve planting-month simulations, soft dry maize had the highest mean per-cycle requirement, at 379.36 m³/ha/cycle, followed by Superchola potato at 282.43 m³/ha/cycle, fresh pea at 247.19 m³/ha/cycle, and fresh bean at 167.21 m³/ha/cycle. The corresponding 75th-percentile requirements were 714.59, 605.71, 404.03, and 346.90 m³/ha/cycle. Maximum requirements reached 1136.56 m³/ha/cycle for maize, 913.72 for potato, 901.82 for pea, and 645.86 for bean.

Peak requirements occurred for planting in May for soft dry maize, June for Superchola potato and fresh bean, and July for fresh pea. The number of simulated planting months with less than 1 m³/ha/cycle of modeled supplemental irrigation was four for maize, five for potato, five for pea, and six for bean. Figure 4 shows that the highest requirements were generally concentrated between April and August, although the timing and magnitude differed among crops.

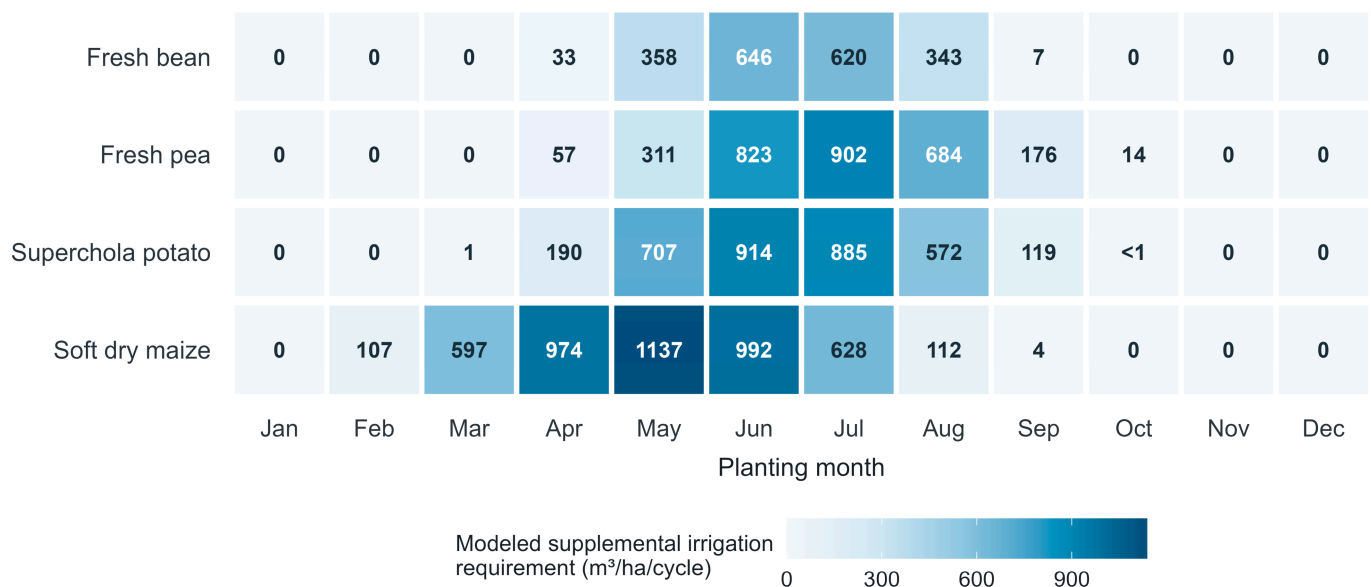


Figure 4. Planting-month variation in modeled supplemental irrigation requirements. Each cell reports the modeled supplemental irrigation requirement, expressed in m³/ha/cycle, for a crop cycle beginning in the indicated month. A value of 0 indicates that the accumulated positive daily irrigation deficit was zero under the simulated climatology, whereas “<1” indicates a positive requirement below 1 m³/ha/cycle. Values displayed in the cells are rounded; the calculations used unrounded results.

The external plausibility comparison was based on modeled crop evapotranspiration rather than modeled supplemental irrigation. Modeled crop-cycle *ET_c* ranged from

445.0 to 510.2 mm for soft dry maize, 318.0 to 383.8 mm for Superchola potato, 243.4 to 302.7 mm for fresh pea, and 264.9 to 322.2 mm for fresh bean. The maize and bean ranges partially overlapped the lower limits of the broad FAO indicative seasonal ranges, whereas the potato and pea ranges remained below their corresponding generic ranges [42]. For Superchola potato, the maximum modeled ET_c of 383.8 mm was 6.0% below the 408.3 mm full-irrigation depth reported in the contextual high-Andean lysimeter study [43]. Because that study reports experimentally applied irrigation depth rather than the modeled ET_c metric used here, the comparison provides an order-of-magnitude plausibility check rather than direct empirical validation.

Annualization using the locally reported median crop-cycle frequencies produced the hydroeconomic profile shown in Figure 5. Superchola potato had an annual gross output value coefficient of USD 8130.06/ha/year, an annual mean modeled supplemental irrigation coefficient of 564.86 m³/ha/year, and gross economic water productivity of 14.393 USD/m³. The corresponding values were USD 1885.00/ha/year, 494.39 m³/ha/year, and 3.813 USD/m³ for fresh pea; USD 1237.60/ha/year, 379.36 m³/ha/year, and 3.262 USD/m³ for soft dry maize; and USD 379.60/ha/year, 167.21 m³/ha/year, and 2.270 USD/m³ for fresh bean. Superchola potato also retained the highest gross economic water productivity when the 75th-percentile and maximum planting-month requirements were used, at 6.711 and 4.449 USD/m³, respectively.

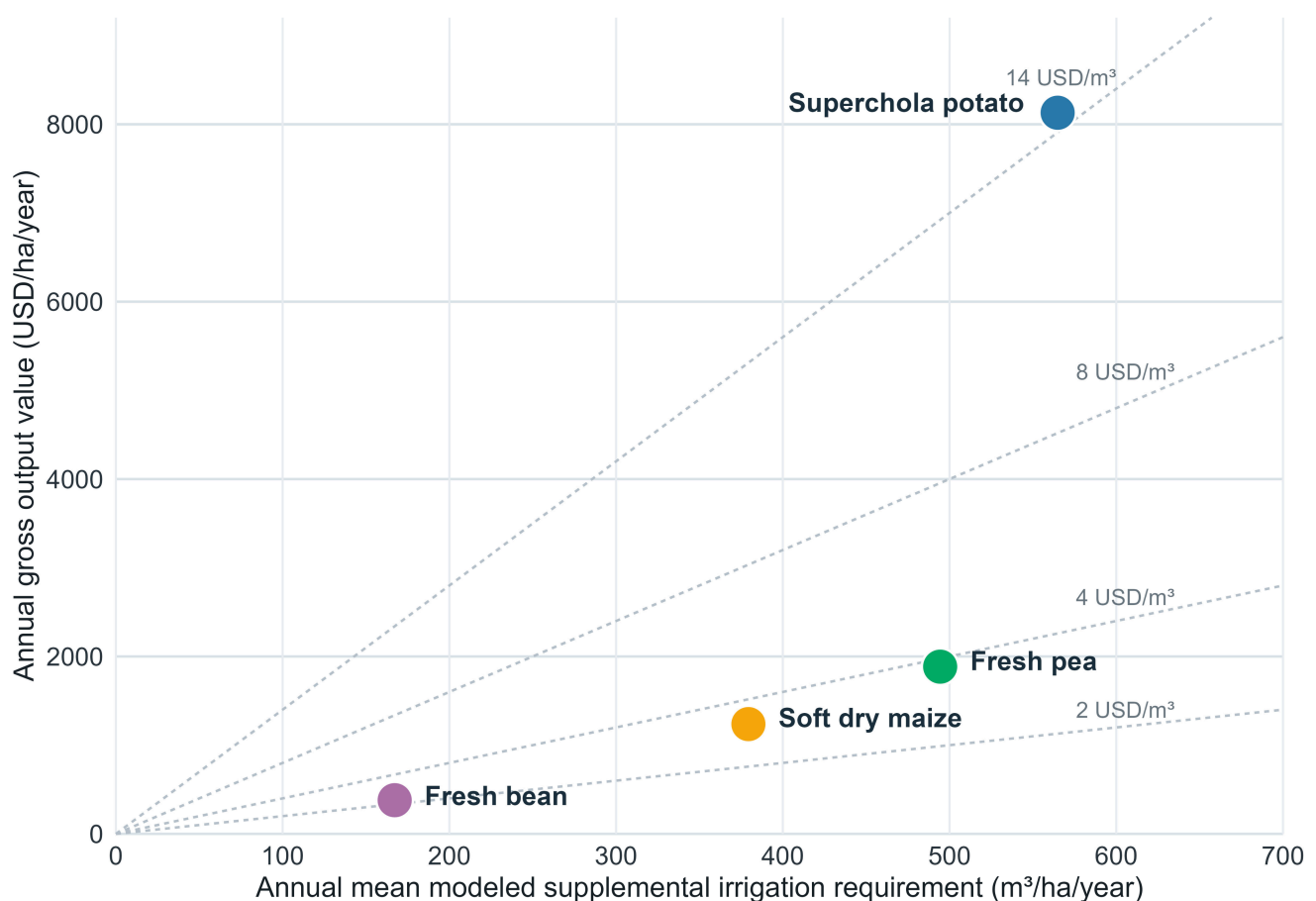


Figure 5. Annual crop-level hydroeconomic profile under the reference coefficients. The horizontal axis represents the annual mean modeled supplemental irrigation requirement and the vertical axis represents annual gross output value. Dashed rays indicate constant gross economic water productivity levels of 2, 4, 8, and 14 USD/m³. Annual coefficients were calculated using official model prices, reference yields, and the crop-specific median number of annual cycles reported by producers. Gross output value excludes production and marketing costs.

3.3. Baseline Annual Allocation Results

All nine baseline optimization cases were feasible. Each configuration allocated the complete 15.945 ha primary modeled-crop domain, and the land constraint was binding in every case. By contrast, the annual proxy water-budget constraint was non-binding under the conservative, mean, and upper proxy budgets. Consequently, changing the proxy budget altered the percentage of the budget used and the remaining slack, but did not change crop allocation, annual modeled supplemental irrigation, or annual gross output value.

The economic-only benchmark allocated the complete domain to Superchola potato and generated an annual gross output value of USD 129,634. The maximum-share diversification model allocated 7.9725 ha to Superchola potato and 7.9725 ha to fresh pea, generating USD 79,845/year. The crop-specific four-crop diversification scenario allocated 7.9725 ha to potato, 4.7835 ha to fresh pea, and 1.5945 ha each to soft dry maize and fresh bean, generating USD 76,412/year.

Relative to the economic-only benchmark, annual gross output value was 38.4% lower under the maximum-share model and 41.1% lower under the four-crop scenario. Annual modeled supplemental irrigation declined from 9007 m³/year in the economic-only benchmark to 8445 m³/year in the maximum-share model and 7740 m³/year in the four-crop scenario, corresponding to reductions of 6.2% and 14.1%, respectively. The complete baseline allocation results across the three proxy budgets are reported in Table 5.

Table 5. Baseline annual allocation results across the three survey-informed proxy water budgets.

Allocation Configuration	Crop Allocation Within the 15.945 ha Domain	Annual Gross Output Value (USD/Year)	Annual MSIR (m ³ /Year)	Proxy-Budget Use: Conservative/Mean/Upper (%)	Binding Constraints
Economic-only benchmark	Superchola potato: 15.9450 ha (100%)	129,634	9007	44.4/20.1/12.3	Land only
Maximum-share diversification model	Superchola potato: 7.9725 ha (50%); fresh pea: 7.9725 ha (50%)	79,845	8445	41.7/18.8/11.5	Land only
Crop-specific four-crop diversification scenario	Soft dry maize: 1.5945 ha (10%); Superchola potato: 7.9725 ha (50%); fresh pea: 4.7835 ha (30%); fresh bean: 1.5945 ha (10%)	76,412	7740	38.2/17.3/10.6	Land only

Note: MSIR = modeled supplemental irrigation requirement. All cases use the mean requirement across the twelve planting-month simulations, official model prices, reference yields, locally reported median annual crop-cycle frequencies, and the primary modeled-crop domain of 15.945 ha. The three percentages correspond to the conservative, mean, and upper survey-informed proxy budgets of 20,273, 44,801, and 73,209 m³/year. Crop allocations, annual gross output values, and annual MSIR were identical across the three budgets because the water constraint remained non-binding. Monetary values represent gross output rather than profit or net income. Displayed values are rounded; the optimization used unrounded coefficients.

3.4. Robustness and Sensitivity Results

The complete set of baseline and robustness analyses comprised 328 model runs. Of these, 324 were feasible. The four infeasible cases occurred only in the crop-specific four-crop scenario when maximum planting-month requirements were combined with synthetic budgets equal to 10%, 15%, 20%, or 25% of the conservative proxy. In those cases, the budget was insufficient to satisfy the absolute minimum-area requirements imposed for maize, pea, and bean.

Changing the crop-water-demand basis produced the clearest shift in the binding constraint. Under the 75th-percentile requirements, all three configurations continued

to allocate the complete 15.945 ha domain and retained their baseline crop composition. The conservative proxy-budget use increased to 95.3% for the economic-only benchmark, 79.4% for the maximum-share model, and 75.1% for the four-crop scenario, but the water constraint remained non-binding.

Under the maximum planting-month requirements, the water constraint became binding in all three configurations. The economic-only benchmark allocated 11.094 ha to potato, equivalent to 69.6% of the modeled domain, and generated USD 90,193/year. The maximum-share model allocated 7.9725 ha to potato and 5.0186 ha to maize, used 81.5% of the modeled domain, and generated USD 71,028/year. The four-crop scenario allocated the required minimum of 1.5945 ha to maize, pea, and bean, together with 7.9648 ha of potato; total modeled land use was 12.748 ha, or 80.0%, and annual gross output value was USD 70,338.

The synthetic water-budget stress tests identified the minimum tested budgets at which the complete modeled domain could be allocated. With mean planting-month requirements, full land use was first obtained at 45% of the conservative proxy for the economic-only and maximum-share configurations and at 40% for the four-crop scenario. With maximum planting-month requirements, the corresponding thresholds increased to 145% for the economic-only benchmark and 120% for both diversification configurations. These are discrete tested thresholds at five-percentage-point intervals rather than estimated exact breakpoints. Figure 6 shows the corresponding response of modeled land use to the synthetic budget series under the mean and maximum planting-month demand bases.

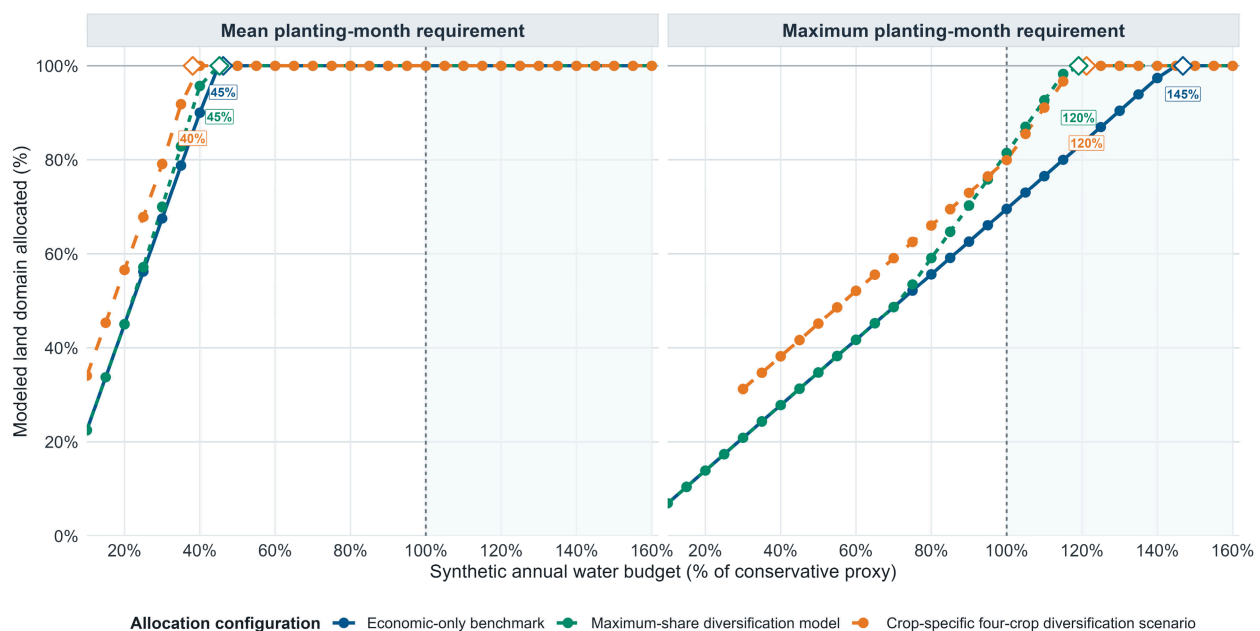


Figure 6. Modeled land allocation under synthetic annual water-budget stress tests using mean and maximum planting-month requirements. The horizontal axis expresses each synthetic budget as a percentage of the conservative survey-informed proxy budget. The dashed vertical line marks the conservative proxy budget. Diamonds identify the first tested budget at which the complete modeled land domain was allocated. Coincident diamonds are offset slightly for legibility, and labels report the exact tested thresholds.

The remaining robustness analyses showed that the main allocation hierarchy was stable under several tested assumptions, although some model specifications changed the solution. Changes in the modeled land domain affected absolute areas and gross output values without altering proportional crop composition. Crop-cycle assumptions affected which non-potato crop entered the diversified solutions. Price and yield perturbations

changed gross output values but did not alter crop composition within the $\pm 20\%$ range. Climatic and irrigation-efficiency perturbations changed the allocation only when the water budget was restrictive. Crop-specific threshold tests altered both the composition and annual gross output value of the four-crop scenario, confirming that its results depend on the imposed analytical bounds. Table 6 summarizes the main robustness and sensitivity results.

Table 6. Summary of robustness and sensitivity results.

Robustness Dimension	Evaluated Conditions	Main Quantitative Result	Allocation and Constraint Result
Planting-month demand basis	Mean, 75th percentile, and maximum requirements under the conservative proxy	P75 proxy-budget use: 75.1–95.3%. Under maximum requirements, land use was 69.6%, 81.5%, and 80.0% for the economic-only, maximum-share, and four-crop configurations	Mean and P75 retained baseline allocations. Maximum requirements made water binding and changed the diversified allocations
Synthetic water-budget stress	10–160% of the conservative proxy at five-percentage-point intervals; mean and maximum demand bases	Full-land thresholds under mean demand: 45%, 45%, and 40%. Under maximum demand: 145%, 120%, and 120%, respectively	The four-crop scenario under maximum demand was first feasible at the 30% tested budget; the other model–demand combinations were feasible at 10%
Modeled land domain	13.885, 15.945, and 33.033 ha	All domains were fully allocated; conservative proxy-budget use ranged from 33.2% to 92.0%	Crop rankings and proportional allocation structures were unchanged; land was binding and water remained non-binding
Annual crop-cycle frequency	One cycle for every crop, local medians, and local means	Annual gross output ranges were USD 64,817–141,787 for the economic-only model, USD 42,275–85,170 for the maximum-share model, and USD 40,437–82,721 for the four-crop scenario	Economic-only allocation remained all potato. Under one cycle, maize replaced pea as the second crop in the diversified solutions; local median and mean frequencies retained pea
Crop prices and reference yields	Independent $\pm 20\%$ perturbations for every crop and parameter	Gross output ranges were USD 103,707–155,561, USD 66,882–92,808, and USD 63,449–89,376 for the three configurations, respectively	Crop composition did not change in any of the 48 one-at-a-time cases. Potato price and yield produced the largest gross output changes
Alternative local price basis	Median prices reported by Santul producers	Annual gross output was USD 128,044, USD 73,162, and USD 70,207, equivalent to changes of -1.2% , -8.4% , and -8.1% from the corresponding reference cases	Allocation composition and binding constraints were unchanged
Climate and irrigation efficiency	ET_0 , effective precipitation, and overall efficiency varied independently by $\pm 10\%$; conservative and synthetic restrictive budgets	Under the conservative proxy, budget use ranged from 21.3% to 71.0%. Under the restrictive 6755 m ³ budget, modeled land use ranged from 46.9% to 100%	Allocations were unchanged under the conservative proxy. Under the restrictive budget, water was binding in 15 of 21 cases, and allocation responded to the recalculated water coefficients

Table 6. *Cont.*

Robustness Dimension	Evaluated Conditions	Main Quantitative Result	Allocation and Constraint Result
Four-crop allocation thresholds	Thirteen one-at-a-time and combined threshold configurations	Annual gross output ranged from USD 64,738 to USD 88,086; conservative proxy-budget use ranged from 35.9% to 40.5%	All threshold cases were feasible and fully allocated. Potato ceilings, maize minima, bean minima, and combined configurations changed the solution; tested maize ceilings and pea minima were non-binding at the reference allocation

Note: Results are based on deterministic scenario comparisons and one-at-a-time perturbations; they do not represent probability distributions or confidence intervals. Values are rounded. Detailed case definitions, crop-level allocations, coefficients, constraint matrices, feasibility status, budget slack, and binding-constraint indicators are provided in Supplementary File S2.

4. Discussion

4.1. Binding Constraints and the Meaning of the Baseline Solutions

The main baseline result is that land, rather than water, governs the allocation under the reference specification. Increasing the survey-informed proxy annual water budget from 20,273 to 73,209 m³/year—a 3.61-fold difference—did not change any crop allocation. All three configurations used the complete 15.945 ha modeled-crop domain: the land constraint was binding, whereas the water constraint remained non-binding. Under the mean planting-month demand coefficients, the economic-only benchmark was therefore driven by differences in annual gross output value per hectare, while the two diversification configurations were additionally shaped by their imposed crop-share bounds. This result does not demonstrate that water is physically abundant in Santul or irrelevant to irrigation planning. It shows only that, under the specified annual coefficients, modeled land domain, and proxy budgets, modeled supplemental irrigation remained below the annual water constraint.

The composition of the three baseline solutions follows directly from this constraint structure. Superchola potato had an annual gross output value coefficient of USD 8130.06/ha/year, compared with USD 1885.00 for fresh pea, USD 1237.60 for soft dry maize, and USD 379.60 for fresh bean. Because water was non-binding, the economic-only benchmark allocated the entire modeled domain to the activity with the highest gross output value per hectare. The maximum-share model then assigned 50% of the domain to potato and the remaining 50% to fresh pea, the crop with the second-highest annual coefficient. In the crop-specific four-crop scenario, the 10% minimum areas for maize and bean ensured their inclusion, the 50% potato ceiling was reached, and the remaining 30% was assigned to pea. Representation of all four crops was therefore produced by the stipulated minimum-presence rules; it did not emerge from an unconstrained social or ecological optimum.

The economic consequences can be interpreted more precisely by separating the two diversification steps. Relative to the economic-only benchmark, the maximum-share model reduced annual gross output value by 38.4% and annual modeled supplemental irrigation by 6.2%. The four-crop scenario reduced these outcomes by 41.1% and 14.1%, respectively. However, compared directly with the maximum-share model, moving to the four-crop configuration involved only an additional 4.3% reduction in annual gross output value while reducing annual modeled supplemental irrigation by a further 8.3%. Most of the gross output difference from the benchmark therefore arose when the initial 50% anti-concentration ceiling was introduced; requiring minimum areas of maize and bean generated a substantially smaller additional monetary difference. These figures quantify

the modeled opportunity cost of the rules, but they do not demonstrate that the four-crop configuration produces greater welfare, food security, resilience, or ecological sustainability.

This finding contrasts with irrigation-optimization studies in which water scarcity, groundwater depletion, salinity, seasonal delivery, uncertainty, or multiple objectives are represented directly and frequently become active determinants of the solution [17–21,45]. Such models are often developed for large irrigation districts or regional systems supported by substantially richer hydrological and spatial information. The Santul model is deliberately more limited: it provides a transparent and reproducible comparison of annual crop programs in a small community-managed system with restricted operational data. Its contribution lies in showing how gross output coefficients, crop-water assumptions, land limits, and explicit allocation rules shape the solution; it should not be interpreted as having the predictive or prescriptive scope of a calibrated hydro-agro-economic model.

4.2. Proxy Water Budgets and the Limits of Annual Volumetric Feasibility

The survey-informed proxy budgets were introduced because the nominal 12 L/s flow reported by the Santul Irrigation Board could not be treated as continuously available throughout the year. No continuous or periodic hydrometric gauging, turn-level discharge series, or volumetric delivery records were available. Using the distribution of respondent-level irrigation frequency and duration therefore incorporated local operational information rather than simply extrapolating the nominal flow to uninterrupted annual operation. Nevertheless, this transformation remains an analytical scaling assumption. Reported irrigation durations cannot be equated with aggregate system operating time or simply summed because irrigation turns may overlap. Moreover, the irrigation events represented by those durations may differ in discharge, pressure, application method, plot size, and conveyance conditions.

Consequently, the direction of the proxy error cannot be established from the available information. The budgets could overestimate usable water if the nominal 12 L/s flow is not maintained during reported irrigation periods, if flow is interrupted, or if reported durations include low-pressure or partial-delivery conditions. Conversely, they could underestimate the annual volume associated with system operation if sequential irrigation turns keep the system active for longer than the selected respondent-level statistic implies. The median, mean, and third quartile should therefore be interpreted as standardized scenario inputs spanning alternative operational assumptions, not as estimates of observed annual abstraction, delivery, or supply. This distinction is important because the non-binding baseline result cannot itself validate the proxy from which it was derived.

The expanded analyses quantify how strongly this uncertainty can affect the conclusions. Under the 75th-percentile crop-water coefficients, the economic-only benchmark used 95.3% of the conservative proxy budget, compared with 79.4% for the maximum-share model and 75.1% for the four-crop scenario. Although the water constraint remained formally non-binding, the economic-only case was close to the modeled limit. Under the maximum planting-month coefficients, water became binding in all three configurations: modeled land use fell to 69.6% in the economic-only benchmark, 81.5% in the maximum-share model, and 80.0% in the four-crop scenario. The economic-only gross output value simultaneously decreased from USD 129,634 to USD 90,193/year. Water is therefore a latent rather than irrelevant constraint: it does not determine the baseline solution under mean demand, but it becomes decisive when crop demand is represented by more adverse planting-month conditions.

The synthetic budget tests reinforce this binding-regime shift. With mean planting-month requirements, complete use of the modeled land domain was first obtained at 45% of the conservative proxy for the economic-only and maximum-share configurations

and at 40% for the four-crop scenario. With maximum planting-month requirements, the corresponding tested thresholds increased to 145%, 120%, and 120%, respectively. These values are discrete stress-test thresholds evaluated at five-percentage-point intervals, not estimates of actual hydrological breakpoints. They show that the influence of the assumed water budget cannot be interpreted independently of the crop-demand basis.

Even after annualization, the model demonstrates annual volumetric feasibility only. The twelve planting-month simulations reveal that peak crop requirements are concentrated between May and July, but the optimization does not reconstruct simultaneous crop calendars, monthly delivery capacity, irrigation turns, or within-year changes in crop assignment. Moreover, the maximum-demand case applies each crop's highest planting-month requirement even though those maxima do not necessarily correspond to one synchronized system-wide planting calendar. It is therefore a deliberately conservative stress representation rather than a monthly scheduling model. Demonstrating seasonal feasibility would require measured or reconstructed monthly inflows, turn-specific delivery data, parcel-level planting dates, and overlapping crop calendars, as incorporated in more data-intensive spatiotemporal and uncertainty-based allocation frameworks [18,19,21].

4.3. Gross Economic Water Productivity and Potato Dominance

The role of gross economic water productivity changes when the model moves from the land-binding to the water-binding regime. Under the baseline mean-demand specification, the all-potato solution is determined by annual gross output value per hectare because the water constraint is slack. Potato dominance should not, in that case, be attributed to water productivity as though water were rationing the solution. Once water becomes binding, however, the ratio between gross output value and the annual modeled supplemental irrigation coefficient becomes operationally relevant.

Superchola potato combined an annual gross output value of USD 8130.06/ha with an annual mean modeled supplemental irrigation requirement of 564.86 m³/ha, producing gross economic water productivity of 14.393 USD/m³. This was substantially higher than fresh pea at 3.813 USD/m³, soft dry maize at 3.262 USD/m³, and fresh bean at 2.270 USD/m³. Potato did not dominate because it had the lowest irrigation coefficient—its annual mean coefficient exceeded those of all three other crops—but because its gross output numerator was disproportionately larger. Under the maximum-demand basis, potato's gross economic water productivity declined to 4.449 USD/m³, but it remained more than four times the corresponding value of the next-ranked crop. The economic-only model consequently used the complete conservative proxy budget on approximately 11.094 ha of potato. In the maximum-share model, the second crop changed from pea under mean demand to maize under maximum demand because maize's maximum-demand gross economic water productivity slightly exceeded that of pea. This change illustrates how the active constraint determines whether ranking by gross output per hectare or by gross output per unit of modeled irrigation drives the allocation.

The value of 14.393 USD/m³ should be used primarily for comparisons among the four modeled activities rather than as a directly transferable profitability benchmark. In a high-Andean potato experiment in southern Peru, Poma-Chamana et al. [46] defined economic water productivity as net income per unit of applied irrigation water and reported values ranging from −0.31 to 0.80 USD/m³ across gravity, full-drip, and deficit-irrigation treatments. Jaafar et al. [47], using an earth-observation and economic assessment in the Litani Basin, Lebanon, reported economic irrigation water productivity of up to approximately 6 USD/m³ for early-season potato. These values are not directly comparable with the Santul coefficient because the studies differ in cultivar, climate, irrigation technology, prices, yields, cost treatment, and water denominator. Most importantly, the Santul numer-

ator is gross output rather than net income, while its denominator is modeled supplemental irrigation after adjustment for effective precipitation and irrigation efficiency rather than measured total or applied irrigation water. Accordingly, the Santul indicator should be interpreted specifically as gross economic water productivity.

The all-potato result remains agronomically and institutionally incomplete. The model does not represent rotation requirements, cumulative pest or disease pressure, soil-fertility effects, labor bottlenecks, input costs, market absorption, post-harvest losses, price volatility, household consumption, or farmers' preferences. It maximizes gross output value and cannot estimate net profitability. The unchanged crop composition under independent $\pm 20\%$ price and yield perturbations reflects the large coefficient difference between potato and the remaining crops within the tested $\pm 20\%$ range; it is not evidence that potato specialization would remain desirable or financially secure under actual market variability. The alternative scenario based on median prices reported by Santul producers also preserved crop composition but reduced annual gross output value by approximately 1.2% in the economic-only benchmark and by 8.4% and 8.1% in the two diversification configurations. These results address uncertainty arising from the different market levels used for the reference prices, but they do not replace a crop-specific cost and market-risk analysis.

Annual crop-frequency assumptions were structurally more influential than the moderate price and yield perturbations. When every crop was restricted to one annual cycle, maize replaced pea as the second activity in both diversified solutions because its single-cycle gross output exceeded that of pea. Under the locally reported median frequencies, two annual pea cycles raised its annual coefficient above that of maize, producing the potato–pea maximum-share solution. The crop-frequency sensitivity therefore shows that annualization is not merely a unit conversion: it embodies assumptions about the repetition of crop programs on the same hectare and can alter the economically preferred secondary crop.

4.4. Diversification Rules, Threshold Dependence, and the Excluded Chacra

The crop-share thresholds should be interpreted as transparent counterfactual rules rather than estimates of socially or ecologically optimal land shares. The 50% maximum-share rule tests a portfolio in which no crop can occupy an absolute majority of the modeled domain. The crop-specific scenario then combines a potato ceiling with minimum-presence requirements for maize and both legumes. These values were not derived from observed crop-area shares, irrigation-board regulations, participatory preference elicitation, agronomic rotation coefficients, food-security indicators, or ecological thresholds. Accordingly, the scenario evaluates the consequences of requiring all four crops to be represented under explicit share constraints; it does not identify the crop mix that the Santul community should adopt.

The threshold analysis demonstrates why this distinction matters. Across thirteen alternative configurations, annual gross output value ranged from USD 64,738 to USD 88,086, despite all cases remaining feasible and using the complete modeled domain. Altering the potato ceiling and the minimum areas for maize or bean changed the allocation and its opportunity cost, while the tested maize ceilings and pea minima were non-binding around the reference solution. The exact composition of the four-crop portfolio is therefore threshold dependent. What remains robust is the more limited conclusion that anti-concentration and minimum-presence rules redistribute land away from the unconstrained gross output solution and that the magnitude of the resulting monetary difference depends on the selected bounds.

The fixed minimum areas also create an important tension under severe water stress. Using maximum planting-month requirements, the four-crop scenario was infeasible at budgets equal to 10%, 15%, 20%, and 25% of the conservative proxy and became feasible at

the 30% tested budget. Minimum-presence rules can therefore ensure crop representation in feasible solutions while reducing allocation flexibility as the water budget contracts. This finding does not establish that such rules are socially desirable or undesirable; rather, it identifies a condition that should be considered when participatory allocation criteria are designed.

Excluding the traditional Chacra, particularly the maize–bean association, narrows the interpretation of diversification. Treating maize and bean as separate activities assumes that each occupies independent land and has an independent yield, irrigation coefficient, and gross output value. An associated-cropping activity could exhibit different land-equivalent productivity, complementary or competing water demands, distinct labor requirements, and a different combined household or market value. Its exclusion may therefore overstate competition between maize and bean and underrepresent a locally practiced form of productive diversity. The direction and magnitude of this bias cannot be established without locally supported joint coefficients. Incorporating an explicit Chacra activity should therefore depend on measurements of associated-crop areas, joint yields, crop-specific or combined irrigation requirements, production costs, and the value of both outputs rather than on assumed parameters.

4.5. Robustness, Validation, and Decision-Support Scope

The 328 baseline and robustness runs distinguish parameter stability from structural uncertainty. Of these, 324 were feasible; the four infeasible cases occurred only under the combination of maximum crop-water requirements, severe synthetic budget reductions, and fixed minimum crop areas. Baseline composition was stable across alternative modeled land domains, independent $\pm 20\%$ price and yield perturbations, and $\pm 10\%$ climatic and efficiency perturbations under the conservative proxy. In contrast, allocation changed under maximum planting-month demand, restrictive water budgets, alternative annual crop frequencies, and modified diversification thresholds. The model is therefore more sensitive to assumptions that redefine the binding resource regime or the feasible allocation set than to moderate one-at-a-time changes around the reference economic coefficients. Because the analysis is deterministic and one-at-a-time, it does not provide probability distributions, confidence intervals, joint uncertainty propagation, or likelihoods for the scenarios.

The study provides internal computational verification and external plausibility checks, but neither constitutes direct local validation. The reconstructed ET_0 and effective-precipitation calculations matched the stored values within prespecified rounding tolerances, demonstrating internal computational reproducibility rather than empirical climatic validation. The modeled ET_c ranges for maize and bean partially overlapped the lower ends of the general FAO indicative ranges, whereas the potato and pea ranges remained below their corresponding generic intervals. For Superchola potato, the maximum modeled ET_c of 383.8 mm was approximately 6% below the 408.3 mm full-irrigation depth reported in the contextual Ecuadorian high-Andean study. Because applied irrigation depth and modeled ET_c are not identical quantities, these comparisons provide only order-of-magnitude plausibility checks [42,43]. The observed differences may reflect elevation, temperature, rainfall, crop duration, cultivar, or modeling assumptions and should be treated as sources of uncertainty rather than as evidence of local validation.

Direct validation of the optimized crop areas was not possible because observed crop-specific area shares, historical allocation records, and parcel-level planting calendars were unavailable. The questionnaire recorded crop presence, but these non-exclusive frequencies cannot be converted into hectares or used as an observed allocation vector. Because the survey was a census of all 46 registered irrigators, there was no sampling

selection within the registered population; however, item non-response remained. Weekly irrigation intensity was based on 36 paired records, and the primary modeled domain comprised 20 farm units with a positive irrigated area and at least one modeled crop. The findings are therefore representative only of the defined census-derived model domain and should not be generalized to all agricultural land in Santul, unregistered users, or other Andean irrigation systems.

The social-ecological and SDG dimensions are therefore interpretive rather than direct model outputs. The mathematical model evaluates annual gross output value, modeled supplemental irrigation, crop area, crop shares, feasibility, and binding constraints. It does not measure household welfare, food security, income stability, equity, governance quality, adaptive capacity, ecosystem condition, or formal SDG indicators. The social-ecological perspective informs the framing of the allocation problem, the recognition that community rules and crop diversity matter, and the interpretation of scenario consequences [7–14]. It does not imply that the objective function optimizes social-ecological sustainability. Potential connections with SDGs 2, 6, 8, 10, 12, 13, 15, 16, and 17 should therefore be assessed subsequently through stakeholder participation and corresponding indicators rather than interpreted as positive or negative effects demonstrated by the model [22–26]. For example, the analysis can show that a rule reduces crop concentration or modeled irrigation, but it cannot establish that this change improves food security, equity, adaptation, or ecosystem protection.

The appropriate use of the model is therefore diagnostic and deliberative. It can reveal which assumptions and constraints govern a solution, quantify the gross output implications of alternative crop-share rules, identify conditions under which water becomes binding, and expose the data required before a scenario can become a planning recommendation. A subsequent decision-support phase should incorporate measured seasonal flows and irrigation turns, parcel-level crop areas and calendars, crop-specific costs and labor, market-demand limits, rotation and pest-management requirements, local Chacra coefficients, and participatory elicitation of allocation objectives. Multi-objective or robust formulations could then evaluate net returns, water reliability, equity, food-use objectives, and ecological conditions explicitly rather than infer them from crop shares [20,21,45]. The contribution of the present model is more circumscribed but operationally relevant: it establishes a transparent, reproducible basis for comparing annual allocation rules in a data-constrained community irrigation system without presenting the mathematical solution as a substitute for agronomic evidence or collective decision making.

5. Conclusions

This study developed a reproducible annual crop- and water-allocation framework for the Santul Irrigation System by combining census-derived information from the complete registry of 46 irrigators with documented agronomic, climatic, economic, phenological, and irrigation-efficiency parameters. The reformulated model places gross output and irrigation coefficients on a common annual horizon. Its principal contribution is not to identify a universally optimal crop portfolio, but to make explicit how the objective function, the modeled land domain, crop-water-demand assumptions, and crop-share rules jointly determine feasible annual allocations in a community-managed irrigation system with limited hydrometric information.

Under the reference specification, the three survey-informed proxy annual water budgets generated identical allocations within each configuration. The complete 15.945 ha modeled-crop domain was allocated in every case; the land constraint was binding, whereas the water constraint was not. The economic-only benchmark assigned the entire domain to Superchola potato and generated an annual gross output value of USD 129,634 with an an-

nual modeled supplemental irrigation requirement of 9007 m³/year. The maximum-share model generated USD 79,845/year and required 8445 m³/year, whereas the crop-specific four-crop scenario generated USD 76,412/year and required 7740 m³/year. Relative to the benchmark, annual gross output value decreased by 38.4% and 41.1%, while annual modeled supplemental irrigation decreased by 6.2% and 14.1%, respectively. Compared directly with the maximum-share model, the four-crop scenario reduced modeled supplemental irrigation by a further 8.3% at an additional 4.3% reduction in gross output value. These differences quantify the modeled gross output opportunity costs and irrigation implications of the imposed allocation rules; they do not measure net profitability, social welfare, food security, or ecological performance.

The non-binding baseline water constraint must not be interpreted as evidence that water is physically abundant or operationally unrestricted in Santul. The annual proxy budgets were derived from the nominal 12 L/s flow reported by the irrigation board and the distribution of self-reported weekly irrigation intensity, rather than from hydrometrically measured supply, withdrawals, or deliveries. Under the 75th-percentile crop-water-demand coefficients, the economic-only benchmark used 95.3% of the conservative proxy budget. Under maximum planting-month requirements, water became binding in all three configurations and modeled land use declined to 69.6%, 81.5%, and 80.0% in the economic-only, maximum-share, and four-crop configurations, respectively. The stress tests further showed that complete land use under maximum demand was first reached at tested budgets equal to 145% of the conservative proxy for the economic-only benchmark and 120% for both diversification configurations. Water is therefore a latent constraint whose influence depends jointly on the assumed resource envelope and crop-water-demand basis. The model establishes annual volumetric feasibility under explicit assumptions; it does not establish feasibility in every month, irrigation turn, parcel, or production cycle.

The expanded robustness analysis further shows that model stability is conditional. Of 328 model runs, 324 were feasible; the four infeasible cases occurred only when maximum crop-water demand was combined with budgets equal to 10–25% of the conservative proxy and the fixed minimum areas of the four-crop scenario. Allocations remained stable under the tested $\pm 20\%$ crop-price and yield perturbations, alternative modeled land domains, and $\pm 10\%$ climatic and irrigation-efficiency perturbations under the conservative proxy. They changed, however, under maximum planting-month demand, restrictive water budgets, alternative annual crop-cycle frequencies, and modified diversification thresholds. The exact diversified portfolio is therefore assumption-dependent. Hypothetical minimum-presence and anti-concentration rules can ensure crop representation in feasible solutions, but they reduce modeled gross output value and may constrain feasibility under severe water stress; they are neither observed community rules nor empirically identified social-ecological optima.

The all-potato benchmark is consequently a mathematically coherent response to the annual gross output objective, not an agronomic or territorial recommendation. Gross economic water productivity likewise represents gross output per unit of modeled supplemental irrigation, not net economic return. The model excludes crop-specific costs, labor constraints, rotations, pest and disease pressure, soil effects, market-absorption limits, price volatility, household consumption, and farmers' preferences. It also excludes the traditional maize-bean Chacra as a separate production activity because locally supported joint coefficients were unavailable. In addition, the absence of crop-specific observed areas, parcel-level calendars, continuous hydrometric records, and measured deliveries prevented direct empirical validation of the optimized allocations. The external crop-water comparisons provide only order-of-magnitude plausibility. Numerical findings are there-

fore specific to Santul and should not be transferred to other irrigation systems without local recalibration.

Because these dimensions were neither represented by model variables nor measured using independent indicators, equity, governance, livelihood resilience, ecosystem condition, and SDG outcomes cannot be inferred as effects of the modeled allocations. The social-ecological framing concerns how the allocation problem and its constraints are interpreted; it does not mean that social-ecological sustainability was directly optimized. Potential connections with the SDGs therefore remain questions for subsequent indicator-based and participatory assessment rather than positive or negative impacts demonstrated by the allocation results.

Future applications should combine seasonal flow monitoring, turn-level deliveries, parcel-level crop areas and calendars, crop-specific costs and labor requirements, market constraints, rotation and pest-management rules, and locally measured parameters for associated cropping. Stakeholder-derived objectives and thresholds could then be incorporated into multi-objective, robust, or participatory optimization formulations and evaluated against observed decisions. Until those data are available, the framework should be used as a diagnostic and deliberative platform rather than as a prescription. Its practical value lies in identifying when land or water becomes binding, quantifying the gross output and irrigation consequences of alternative crop-share rules, and revealing which additional evidence is required before a modeled allocation can support a technically defensible and locally validated planning decision.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16189195/s1>. Supplementary File S1: Field questionnaire used in the broader characterization survey of Andean irrigation systems, including the Santul Irrigation System; Supplementary File S2: Reproducibility package containing the principal R script, the independent Figure 1 cartographic script, README, analysis manifest, aggregate model-ready inputs, optimization constraint matrices, scenario definitions, crop-specific model solutions, robustness and sensitivity outputs, and figure-ready data; Supplementary File S3: External parameter matrix documenting the agronomic, climatic, economic, phenological, and irrigation-efficiency inputs used in the analysis; Supplementary File S4: sessionInfo() report documenting the R version, platform, package versions, locale, and computational environment.

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Institutional Review Board Statement: Formal ethical review was not required for the field survey used in this study. Before fieldwork, the broader institutional project “Manejo integral comunitario del agua en sistemas de riego y agua potable andinos para la consecución de los Objetivos de Desarrollo Sostenible” [“Integral community management of water in Andean irrigation and drinking water systems for the achievement of the Sustainable Development Goals”], presented in the II University Competition of Research-Linkage Projects, was submitted to the then Committee on Bioethics in

Health Research (COBIAS) of the University of Cuenca. Following its analysis, COBIAS notified the project team on 9 November 2021 that the proposal did not need to undergo formal evaluation by the Committee.

Informed Consent Statement: Informed consent was obtained from all participants involved in the original field survey. The consent statement was presented in Spanish at the beginning of the questionnaire, before the substantive survey sections, and informed participants that participation was voluntary and anonymous and that the information would be used for academic purposes and handled with complete confidentiality.

Data Availability Statement: The public Supplementary Materials provide the field questionnaire; a non-confidential reproducibility package containing the R scripts, aggregate model-ready inputs, complete optimization constraint matrices, scenario definitions, crop-specific model solutions, robustness and sensitivity outputs, and figure-ready data; the external agronomic, climatic, economic, phenological, and irrigation-efficiency parameter matrix; and the sessionInfo() computational-environment report. The original individual-level field-survey database is not publicly available and is not included in the Supplementary Materials because it remains subject to confidentiality, institutional, and ethical access restrictions. Access to the original field-survey database may be considered only upon a duly justified request to the corresponding author and subject to those restrictions. High-resolution figure files are provided separately for editorial production.

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