A Multi-Objective Framework for the Integrated Planning of Water–Energy–Food Systems*

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***Abstract*—Growing pressure on water, energy, and food systems underscores the need for integrated planning approaches. This paper presents a novel framework for the design and optimization of agro-energy systems within the Water–Energy–Food (WEF) nexus. The methodology combines system modeling and multi-objective optimization to jointly allocate land and size energy infrastructure while considering the availability of local water and energy resources. Implemented through the weighted-sum method, the model simultaneously minimizes total annualized cost and water use while maximizing employment generation. Results show that the framework effectively integrates resource availability with infrastructure planning, achieving balanced configurations that enhance sustainability and support replicable WEF-based development in rural contexts.**

***Index Terms*—Water-energy-food nexus, multi-objective optimization, agro-energy systems, availability resources and infrastructure.**

NOMENCLATURE

Symbol	**Description [Unit]**
A_c	Area allocated to crop c [ha]
$A_{\max}$	Maximum available agricultural area [ha]
C_{batt}	Battery nominal capacity [Ah]
$C_{\text{PV}}^{\text{Inv}}$	PV investment cost [USD/kW]
$C_{\text{DG}}^{\text{Inv}}$	Diesel investment cost [USD/kW]
C_{fuel}	Diesel fuel annual consumption cost[USD/year]
CRF_j	Capital recovery factor for tech. j [–]
$DoD_{\max}$	Max. depth of discharge [–]
$E_{\text{batt}}(t)$	Battery energy at time t [kWh]
$E_c(t)$	Energy demand per hectare [kW/ha]
$E_{\text{R}}(t)$	Residential energy demand [kW]
$G_{\text{PS}}(t)$	Pumped water at time t [m^3/h]
GHI(t)	Global horizontal irradiance [W/m^2]
h, g	Pumping head [m], gravity [m/s^2]
L_c	Employment factor of crop c [jobs/ha]
N_{batt}	Number of batteries [units]
$P_{\text{batt}}^{\pm}(t)$	Charge/discharge battery power [kW]
$P_{\text{PV}}(t)$, $P_{\text{DG}}(t)$	PV and diesel generation [kW]
P_c, P_{fuel}	Market price of crop c [USD/ton] & Fuel price [USD/L]
S_{PV}, S_{DG}	Installed PV and diesel capacity [kW]
S_{batt}	Installed battery capacity [kWh]
T	Number of intra-day time steps (24) [–]
$W_{\text{PS}}(t)$	Pumping power [kW]
$W_c(t)$	Crop water demand [m^3/ha/h]
$W_{\text{R}}(t)$	Residential water demand [m^3/h]
$W_{\max}$	Max. annual available water [m^3/yr]
Y_c	Crop yield [ton/ha]
$\eta_{\text{batt}}, \eta_{\text{PS}}, \eta_{\text{PV}}$	Efficiencies of battery, pump, and PV [–]
β	Diesel fuel consumption [L/kWh]

I. INTRODUCTION

Global demand for water, energy, and food is expected to rise sharply in the coming decades, intensifying pressures on resource security under climate change and population growth [1], [2]. These challenges are particularly evident in irrigated agriculture, where water and energy mismanagement directly affect food production and rural livelihoods [3], and where sector-wise planning is often insufficient due to strong cross-sector linkages and shared infrastructures. The Water-Energy-Food (WEF) nexus framework, introduced by the World Economic Forum in 2008 [4], advocates for the integrated analysis of interdependencies among these critical sectors to enhance long-term sustainability [5]. It helps identify synergies and trade-offs across economic, environmental, and social dimensions; however, the social dimension remains underrepresented in most studies [6]. WEF assessments can be performed at different spatial scales, yet most works emphasize macro-scale analyses, often overlooking local complexities [7]. Because agricultural regions face distinct but interconnected challenges, local-scale analysis is essential for developing effective and equitable resource management strategies [8]. Despite progress in modeling interdependencies, many studies still focus on one or two components of the nexus, limiting full integration. To overcome these limitations, recent studies have increasingly adopted multi-objective optimization (MOO) techniques to quantify trade-offs among conflicting goals [9]. Common approaches include the weighted-sum [10], ϵ-constraint [11], and heuristic-based formulations [12]. However, the integration of economic, environmental, and social objectives within a unified optimization framework remains an open challenge [13].

Unlike most existing WEF optimization approaches, which typically adopt centralized perspectives and overlook decentralized interactions and technical coupling among resources [7], this study proposes a novel integrated framework that simultaneously optimizes land allocation, energy infrastructure sizing, and resource flows within the WEF nexus. The proposed methodology combines system modeling with MOO to jointly balance water and energy demands while capturing key interdependencies among WEF subsystems. Implemented through the weighted-sum approach, the framework explicitly evaluates trade-offs across technical, economic, and environmental objectives under realistic operational constraints. Applied to a rural agro-energy system, it demonstrates the potential of MOO-based WEF integration to guide sustainable and data-driven decision-making in community-scale agricultural contexts.

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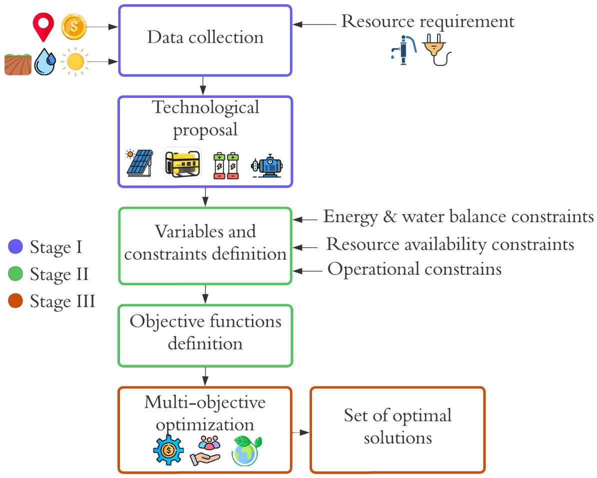
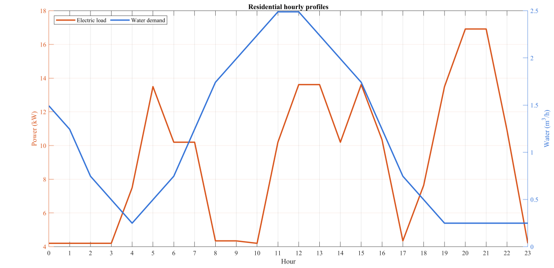
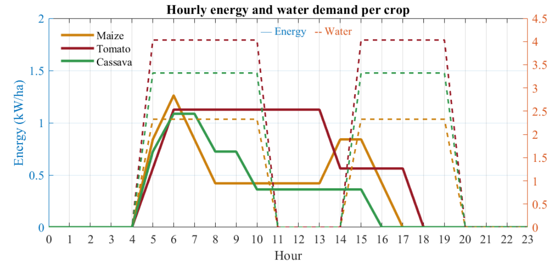


Fig. 1: Methodological framework for the WEF-based agro-energy system design: Stage I (preliminary assessment and data collection) in purple; Stage II (model formulation) in green; and Stage III (optimization) in orange.



(a) Residential electricity and water demand.



(b) Crop-specific energy and water requirements per hectare.

Fig. 2: Characterization of hourly and crop-specific demand in the study area.

II. Methodology

The proposed methodological framework, illustrated in Fig. 1, consists of three main stages. Stage I, *preliminary assessment and data collection*, compiles data on resource availability, crop characteristics, and technological parameters relevant to the study area. Stage II, *model formulation*, establishes the decision variables, constraints, and objective functions representing the economic, environmental, and social dimensions of the problem. Finally, Stage III *Optimization* solves the multi-objective problem using the weighted-sum method, evaluating eight representative scenarios to explore trade-offs among objectives and identify balanced configurations of land allocation and system sizing, complemented by a sensitivity analysis of key technical and resource parameters.

A. Preliminary assessment

The study focuses on an isolated rural community in Colombia comprising 60 households. Residential electricity demand is characterized using data reported in [14]. As shown in Fig. 2a, the resulting hourly profile exhibits a peak of 17 kW between 20:00 and 21:00, with an average daily consumption of 217.08 kWh. Similarly, residential water consumption is modeled through a fixed hourly profile derived from standardized per capita rates. Agricultural activities in the study area include tomato, cassava, and maize, selected based on regional production and harvested area data[1]. The corresponding agricultural water demand is modeled dynamically as a function of the cultivated area and each crop's specific water requirements (m^3/ha/day) [15], [16], while the crop-specific electricity demand, derived from empirical data [17], [18], represents the total agricultural energy use, including irrigation, processing, and auxiliary operations. The hourly profiles of energy and water requirements per hectare for each crop are presented in Fig. 2b.

Once the resource requirements are identified, the technological configuration is defined. The proposed system integrates solar photovoltaic (PV) generation, diesel backup, battery storage, and water pumping infrastructure to meet both residential and agricultural demands. The pumping subsystem is explicitly linked to energy consumption through the hydraulic head and friction losses. After establishing this architecture, the key economic, technical, and operational parameters[2] are compiled from secondary sources and summarized in Table I.

B. Stage II: Model Formulation

The system is formulated as a nonlinear programming (NLP) model that integrates the coupled dynamics of energy generation, water use, and land allocation. The decision variables correspond to the installed capacities of the technologies and the land area assigned to each crop. The NLP model is constrained by a set of technical and operational conditions, organized into five categories: electricity balance, water balance, resource availability, technical limitations, and boundary conditions. At each time step $t \in \mathcal{T}$, the total electricity supplied by PV generation $P_{\text{PV}}(t)$, diesel generators $P_{\text{DG}}(t)$, and battery discharge $P^{-}_{\text{batt}}(t)$ must be equal to the combined electricity demands of the residential sector $E_{\text{R}}(t)$, water pumping systems $W_{\text{PS}}(t)$, and agricultural activities $\sum_{c \in \mathcal{C}} A_c E_c(t)$, in addition to the

[1]Data obtained from the *Evaluaciones Agropecuarias Municipales* (EVA) for 2023–2024.

[2]Solar PV investment cost: Renewable Power Generation Costs in 2021, International Renewable Energy Agency (IRENA); Technologies O&M costs & investment cost: Informe de Costos Tecnologías de Generación, Comisión Nacional de Energía (CNE), 2022; AGM batteries investment cost: Batería Plomo-Acido AGM 12V 255 Ah, Autosolar, 2023. Available at: https://www.autosolar.co

979-8-3315-8138-1

power required for battery charging $P^+_{\text{batt}}(t)$, that is, $P_{\text{PV}}(t) + P_{\text{DG}}(t) + P^-_{\text{batt}}(t) = E_{\text{R}}(t) + W_{\text{PS}}(t) + \sum_{c\in\mathcal{C}} A_c E_c(t) + P^+_{\text{batt}}(t)$. The water balance at each time step t is defined such that the total volume of water extracted $G_{\text{PS}}(t)$ equals the residential demand $W_{\text{R}}(t)$ plus the sum of the irrigation requirements of each crop $c \in \mathcal{C}$, weighted by the cultivated area, that is, $G_{\text{PS}}(t) = W_{\text{R}}(t) + \sum_{c\in\mathcal{C}} A_c W_c(t)$.

Regarding resource availability, water extraction is limited by the source capacity, ensuring that total withdrawal does not exceed $W_{\max}$. Likewise, the cumulative cultivated area is restricted to the maximum agricultural land $A_{\max}$, and to avoid monocropping, the area assigned to any single crop cannot exceed 50% of the total ($A_c \leq 0.5\, A_{\max}$). In addition, the system's technical behavior is defined through the physical relations. PV generation is expressed as $P_{\text{PV}}(t) = S_{\text{PV}} \dfrac{\text{GHI}(t)}{\text{GHI}_{\text{STC}}} \eta_{\text{PV}} \eta_{\text{inv}}$, where S_{PV} is the PV system size, $\text{GHI}(t)$ is the global horizontal irradiance at time t, GHI_{STC} is the standard irradiance, η_{PV} is the module efficiency, and η_{inv} is the inverter efficiency.

Battery dynamics are modeled by the recursive expression $E_{\text{batt}}(t{+}1) = E_{\text{batt}}(t) + \Delta t \left(\eta_{\text{batt}}\, P^+_{\text{batt}}(t) - \frac{1}{\eta_{\text{batt}}}\, P^-_{\text{batt}}(t) \right)$, which updates the battery's energy content at each time step based on charging and discharging operations. Likewise, the battery energy is constrained to lie within its operational bounds, i.e., $E^{\min}_{\text{batt}} \leq E_{\text{batt}}(t) \leq E^{\max}_{\text{batt}}$, and a cyclic condition is enforced by requiring $E_{\text{batt}}(1) = E_{\text{batt}}(T)$.

In addition, to ensure that battery charging relies exclusively on surplus PV generation, the charging power is limited by PV output at each time step ($P^+_{\text{batt}}(t) \leq P_{\text{PV}}(t)$), thereby avoiding additional fuel consumption. Simultaneous charging and discharging are prevented through the nonlinear constraint $P^+_{\text{batt}}(t) P^-_{\text{batt}}(t) \leq \varepsilon$, where ε is a small tolerance for numerical stability. The power exchange is further restricted to one-third of the total battery capacity ($P^{\max}_{\text{batt}} = E^{\max}_{\text{batt}}/3$), following standard microgrid practices and manufacturer guidelines to mitigate excessive cycling, i.e., $0 \leq P^+_{\text{batt}}(t), P^-_{\text{batt}}(t) \leq P^{\max}_{\text{batt}}$.

To ensure consistency between the pumped water flow $G_{\text{PS}}(t)$ and the electrical power consumed by the pump $W_{\text{PS}}(t)$, the two quantities are linked through the hydraulic conversion factor k_{PS}, which accounts for water density ρ_w, gravitational acceleration g, pumping head h, and pump-motor efficiency η_{PS}, according to the physical relation $G_{\text{PS}}(t) = k_{\text{PS}} W_{\text{PS}}(t)$, with $k_{\text{PS}} = \dfrac{\eta_{\text{PS}} 3.6 \times 10^6}{\rho_w g h}$. Furthermore, all decision variables are constrained within physically admissible limits to ensure realistic system behavior. The installed capacities of the photovoltaic system (S_{PV}), diesel generator (S_{DG}), and number of batteries (N_{batt}), as well as the cultivated areas (A_c) and all hourly operational variables, are required to be non-negative ($S_{\text{PV}}, S_{\text{DG}}, N_{\text{batt}}, A_c \geq 0$, for all $c \in \mathcal{C}$). The optimization model addresses the WEF nexus through three interconnected objectives representing the economic, environmental, and social dimensions of sustainability.

1) Economic objective: minimize the total annual cost (TAC), including investment, operation, and maintenance (O&M), and fuel costs:

$$\begin{aligned}\text{TAC [USD/year]} = {} & C^{\text{inv}}_{\text{PV}} S_{\text{PV}} \text{CRF}_{\text{PV}} + C^{\text{O\&M}}_{\text{PV}} S_{\text{PV}} \\ & + C^{\text{inv}}_{\text{DG}} S_{\text{DG}} \text{CRF}_{\text{DG}} + C^{\text{O\&M}}_{\text{DG}} S_{\text{DG}} \\ & + C^{\text{inv}}_{\text{batt}} N_{\text{batt}} \text{CRF}_{\text{batt}} + C_{\text{fuel}},\end{aligned} \tag{1}$$

where S_{PV}, S_{DG}, and N_{batt} represent the installed capacity for each technology, and C_{fuel} is the annual cost of diesel consumption, calculated as $C_{\text{fuel}} = 365\, \beta\, P_{\text{fuel}} \sum_{t=1}^{T} P_{\text{DG}}(t)\, \Delta t$, where P_{fuel} is the diesel price, β is the specific fuel consumption, $P_{\text{DG}}(t)$ is the hourly diesel generation, and Δt is the time step length. The Capital Recovery Factor (CRF), used to annualize investment costs, is expressed as $\text{CRF}_j = \frac{r(1+r)^{\alpha_j}}{(1+r)^{\alpha_j} - 1}$, where $j \in \{\text{PV}, \text{DG}, \text{batt}\}$, r denotes the discount rate, and α_j represents the economic lifetime of each technology.

2) Environmental objective: minimizes the crop-specific water consumption (CWC), defined as the ratio between the total annual volume of water extracted for irrigation ($G_{\text{PS}}(t)$) and the total agricultural production, which depends on the cultivated area (A_c) and yield (Y_c) of each crop (one cycle per year). Hence,

$$\text{CWC [m}^3\text{/ton]} = \frac{365 \sum_{t\in\mathcal{T}} G_{\text{PS}(t)}}{\sum_{c\in\mathcal{C}} A_c Y_c}. \tag{2}$$

3) Social objective: maximizes employment generation, formulated as the total number of jobs, based on the area allocated to each crop and its corresponding labor intensity. This is given by:

$$\text{Employment [Jobs]} = \sum_{c\in\mathcal{C}} A_c L_c, \tag{3}$$

where A_c is the area allocated, and L_c is the employment factor per hectare to crop c.

C. Satge III: Optimization

The multi-objective problem is addressed using a weighted-sum formulation, selected due to its widespread application in WEF nexus studies and its compatibility with classical optimization algorithms. This approach enables the exploration of trade-offs among conflicting objectives and facilitates sensitivity analyses through the weighting of decision criteria, by integrating economic cost (f_1, Eq. 1), water use (f_2, Eq. 2), and employment (f_3, Eq. 3) into a single composite optimization function. Each is normalized with respect to its single-objective optimum $\mathbf{f}^\star = [f^\star_1, f^\star_2, f^\star_3]^\top$ as $\hat{f}_1 = (f_1 - f^\star_1)/f^\star_1$, $\hat{f}_2 = (f_2 - f^\star_2)/f^\star_2$, and $\hat{f}_3 = (f^\star_3 - f_3)/f^\star_3$. The weighted composite function is expressed as

$$\min J = \sum_{i=1}^{3} w_i \hat{f}_i \tag{4}$$

where w_i represents the relative importance assigned to each objective ($\sum_{i=1}^{3} w_i = 1$). Minimizing J yields compromise solutions according to the weight vector $\mathbf{w} = [w_1, w_2, w_3]^\top$.

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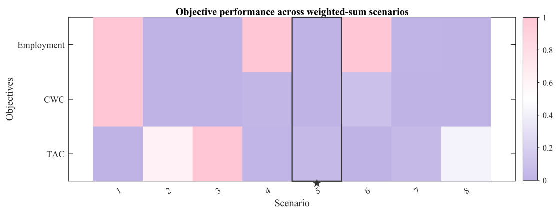
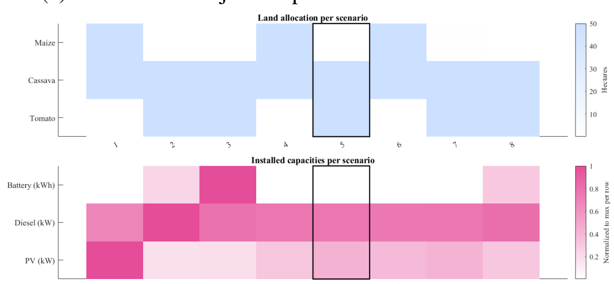
TABLE I: Key parameters of the case study

Parameter	Value	Unit	Parameter	Value	Unit
$C^{\text{inv}}_{\text{PV}}$	857	USD/kW	$C^{\text{inv}}_{\text{DG}}$	300	USD/kW
$C^{\text{inv}}_{\text{batt}}$	255	USD/unit	$C^{\text{O\&M}}_{\text{PV}}$	0.34	USD/kW·yr
$C^{\text{O\&M}}_{\text{DG}}$	20	USD/kW·yr	P_{fuel}	0.6	USD/L
β	0.3	L/kWh	r	0.12	–
η_{PV}	0.18	–	η_{batt}	0.85	–
η_{inv}	0.96	–	η_{PS}	0.80	–
$\text{DoD}_{\max}$	0.50	–	$\text{SoC}_{\min}$	0.20	–
V_{batt}	12	V	C_{batt}	255	Ah
h	30	m	ρ_w	1000	kg/m^3
g	9.81	m/s^2	GHI_{STC}	1000	W/m^2
α_{PV}	25	yr	α_{DG}	15	yr
α_{batt}	6	yr	δ	90	days
$A_{\max}$	100	ha	$W_{\max}$	10×10^6	m^3/yr
T	24	h	β_{CO_2}	2.68	kg/L
P_{tomato}	689.0	USD/ton	Y_{tomato}	15.0	ton/ha
P_{cassava}	200.0	USD/ton	Y_{cassava}	20.0	ton/ha
P_{maize}	414.3	USD/ton	Y_{maize}	3.0	ton/ha
L_{tomato}	0.73	jobs/ha	L_{cassava}	0.59	jobs/ha
L_{maize}	0.29	jobs/ha	–	–	–



(a) Normalized objective performance across scenarios.



(b) Resulting land distribution and technology sizing.

Fig. 3: Multi-objective optimization outcomes.

To examine how the relative importance of each objective affects the optimal configuration, eight weighting scenarios were defined. Scenarios 1–3 prioritize a single dimension (economic, environmental, and social), while Scenarios 4, 6, and 7 emphasize the economic objective with partial consideration of the others. Scenario 8 equally favors environmental and social criteria, and Scenario 5 assigns equal weights to all objectives, representing the balanced configuration. The optimization was implemented in CasADi v3.7.0 within MATLAB Figure 3a shows the normalized performance of the three objectives across the eight weighted-sum scenarios, highlighting clear trade-offs among economic, environmental, and social goals. Economic-oriented cases (1, 4, 6) minimize TAC but result in higher water use and lower employment, whereas environmentally and socially oriented scenarios (2, 3, 8) achieve lower CWC and greater employment at the expense of larger PV and storage capacities (see Fig. 3b). Land allocation reflects these trade-offs: maize prevails in cost-driven scenarios, while tomato and cassava dominate in sustainability-oriented ones, illustrating the balance between productivity and resource intensity. Scenario 5, with equal weighting of all objectives, provides the most balanced configuration, combining moderate cost (0.78 MUSD/year), low water consumption (849 m^3/ton), and the highest employment (66 jobs). This scenario harmonizes the three objectives while maintaining technical feasibility and is therefore selected for detailed analysis.

III. Results and Discussion

The weighted-sum optimization with equal weights allocate 50 ha each to tomato and cassava, for an annual production of 1750 tons. The resulting system integrates 939.8 kW of PV capacity, a 149 kW diesel generator, 334.1 kWh of battery storage, and a 38 kW pumping unit. Fig. 4a shows the system's hourly operation: energy demand peaks at 120 kW during irrigation periods, while PV generation peaks near 11:00, supplying daytime loads and charging the battery. The diesel unit operates mainly before sunrise, and the battery maintains supply balance, with the state of charge rising from 20% at midnight to full charge by 14:00 before discharging in the evening (see Fig. 4b). The total annual water demand, including residential use, reaches approximately 1.49×10^6 m^3. Economically, the system achieves a levelized cost of energy (LCOE) of 0.0545 USD/kWh, while renewables supply 77.5% of total electricity, confirming the diesel unit's backup role. Technically, demand is fully met without energy losses.

In addition, fourteen sensitivity scenarios were evaluated to assess the impact of parameter variations on the system. Scenario 1 reduces technology investment costs by 50%, resulting in a strong decrease in TAC. Scenarios 2–3 modify crop water requirements by ±50%, revealing that higher irrigation needs substantially increase both CWC and the energy required for pumping, which in turn demand larger PV and storage capacities. Scenarios 4–5 vary crop energy demand by ±50%, showing similar trends in TAC and generation sizing. Scenario 6 adjusts the irrigation schedule to coincide with daylight hours, slightly improving energy utilization efficiency. Scenarios 7–8 modify solar irradiation by factors of ×2 and ×0.5, respectively, leading to pronounced changes in TAC and PV sizing. Scenarios 9–10 double and halve residential water and energy demand, moderately affecting the TAC. Scenario 11 increases pumping-system efficiency to 95%, reducing TAC and diesel dependency, whereas Scenario 12 removes the land-allocation constraint, allowing greater crop specialization. Finally, Scenarios 13–14 double and halve both water and land availability, confirming that resource availability strongly affects the total cost and system configuration. The resulting percentage variations in the objectives and installed capacities are summarized in Figure 5.

IV. Concluding Remarks

This paper proposes an integrated framework for the planning and optimization of agro-energy systems within the

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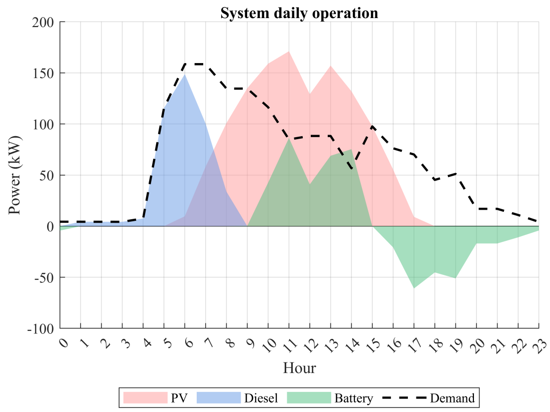
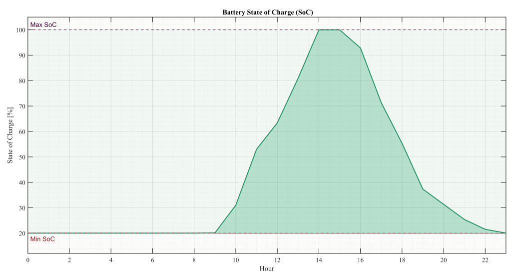


(a) Hourly power generation and demand.



(b) Battery state of charge throughout the day.

Fig. 4: Daily operation of the agro-energy system.

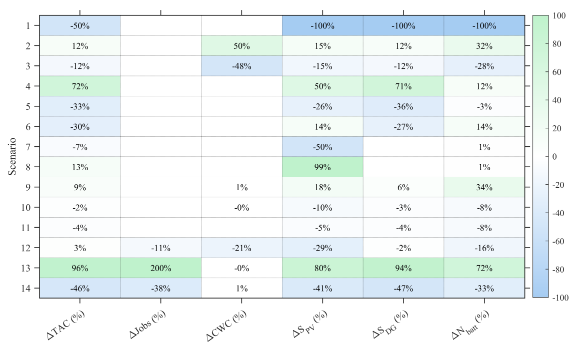


Fig. 5: Heatmap of relative variations (%) across sensitivity scenarios with respect to the baseline.

Water–Energy–Food (WEF) nexus. By coupling system modeling with multi-objective optimization, the approach jointly allocates land, energy, and water resources under realistic operational constraints. The results demonstrate the framework's ability to capture interdependencies among resources and infrastructure, leading to balanced configurations that reduce costs and water use while enhancing employment opportunities. The proposed approach is especially relevant in rural and decentralized contexts, where water extraction, energy generation, and agricultural production depend on shared and capacity-limited infrastructures. Moreover, it provides a replicable tool to support sustainable planning in rural settings and is adaptable to different contexts, although its formulation and resulting optimal solutions depend on local resource availability and data constraints. Future research will incorporate temporal variability and battery degradation to improve the long-term accuracy of system performance, as well as extend the analysis to alternative multi-objective optimization techniques, such as the ϵ-constraint method.

References

[1] National Intelligence Council, "Global trends: Alternative worlds," tech. rep., National Intelligence Council, 2012.

[2] FAO, IFAD, UNICEF, WFF, WHO, *The State of Food Security and Nutrition in the World 2021: Transforming Food Systems for Food Security, Improved Nutrition, and Affordable Healthy Diets for All*. Rome: FAO, 2021.

[3] M. Li, V. P. Singh, Q. Fu, D. Liu, T. Li, and Y. Zhou, "Optimization of agricultural water–food–energy nexus in a random environment: an integrated modelling approach," *Stochastic Environmental Research and Risk Assessment*, vol. 35, pp. 3–19, 1 2021.

[4] E. M. Biggs, E. Bruce, B. Boruff, J. M. Duncan, J. Horsley, N. Pauli, K. McNeill, A. Neef, F. Van Ogtrop, J. Curnow, B. Haworth, S. Duce, and Y. Imanari, "Sustainable development and the water–energy–food nexus: A perspective on livelihoods," *Environmental Science & Policy*, vol. 54, pp. 389–397, 2015.

[5] D. Wichelns, "The water-energy-food nexus: Is the increasing attention warranted, from either a research or policy perspective?," *Environmental Science & Policy*, vol. 69, pp. 113–123, 2017.

[6] W. A. Hussien, F. A. Memon, and D. A. Savic, "An integrated model to evaluate water-energy-food nexus at a household scale," *Environmental Modelling & Software*, vol. 93, pp. 366–380, 2017.

[7] C. Zhang, X. Chen, Y. Li, W. Ding, and G. Fu, "Water-energy-food nexus: Concepts, questions and methodologies," *Journal of Cleaner Production*, vol. 195, pp. 625–639, 2018.

[8] E. N. Z. Mai, N. Inoue, and Y. Uenishi, "The food water energy nexus in agriculture: Understanding regional challenges and practices to sustainability," *Sustainability*, vol. 17, no. 10, 2025.

[9] X. Cai, K. Wallington, M. Shafiee-Jood, and L. Marston, "Understanding and managing the food-energy-water nexus – opportunities for water resources research," *Advances in Water Resources*, vol. 111, pp. 259–273, 2018.

[10] R. González-Bravo, M. Sauceda-Valenzuela, J. Mahlknecht, E. Rubio-Castro, and J. M. Ponce-Ortega, "Optimization of water grid at macroscopic level analyzing water–energy–food nexus," *ACS Sustainable Chemistry & Engineering*, vol. 6, no. 9, pp. 12140–12152, 2018.

[11] A. A. Medina-Santana, A. Flores-Tlacuahuac, L. E. Cárdenas-Barrón, and L. F. Fuentes-Cortés, "Optimal design of the water-energy-food nexus for rural communities," *Computers & Chemical Engineering*, vol. 143, p. 107048, 2020.

[12] L. G. Hernández-Pérez, X. G. Sánchez-Zarco, and J. M. Ponce-Ortega, "Multi-objective optimization method based on deterministic and metaheuristic approaches in water–energy–food nexus under uncertainty," *International Journal of Environmental Research*, vol. 16, no. 3, p. 33, 2022.

[13] D. Peña-Torres, M. Boix, and L. Montastruc, "Optimization approaches to design water-energy-food nexus: A litterature review," *Computers & Chemical Engineering*, vol. 167, p. 108025, 2022.

[14] A. Cusva-García, "Propuesta de una solución energética para una comunidad aislada en el caribe colombiano," undergraduate thesis, Universidad de los Andes, 2020.

[15] P. Soman, "How much water does my crop need?," *International Journal of Agriculture Sciences*, vol. 12, no. 23, pp. 10430–10433, 2020.

[16] D. Armstrong and M. Giblin, "Assessing your water resources." Wise Watering Irrigation Management Course notes, 2001. Department of Primary Industries, Parks, Water and Environment.

[17] S. Elsoragaby, A. Yahya, M. R. Mahadi, N. M. Nawi, and M. Mairghany, "Energy utilization in major crop cultivation," *Energy*, vol. 173, pp. 1285–1303, 2019.

[18] R. Kargwal, Yadvika, A. Kumar, M. K. Garg, and I. Chanakaewsomboon, "A review on global energy use patterns in major crop production systems," *Environmental Science Advances*, vol. 1, no. 5, pp. 662–679, 2022.

979-8-3315-8138-1