Climate Change and Integrated Resource Management: A Multi-Scale Modeling Framework for Water and Food Security in Argentina

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Abstract

This paper presents the construction and an application of SIMPLE-G-AR, the first spatially explicit, gridded partial equilibrium model of agricultural production and water use calibrated for Argentina. Argentina is a major global food exporter whose agricultural sector is highly exposed to climate variability: only 5.2 percent of cropland relies on artificial irrigation, while recurrent droughts such as the 2022–2023 La Niña event caused export declines of 38 percent in primary products and 27 percent in agro-industrial manufactures. Addressing these vulnerabilities requires tools that connect biophysical heterogeneity across the national territory with economic outcomes at local, provincial, and national scales. We construct an original georeferenced database—SIMPLE-G-AR—integrating satellite-derived agricultural production (GAEZ), land use (NASA GFSAD30), water management (NASA LGRIP30), soil properties (SoilGrids), and climatic variables onto a regular 10 km × 10 km grid covering 31,049 cells across the Argentine territory. After applying a joint cropland–production filtering criterion, the analytical dataset comprises 8,264 agricultural cells concentrated in the Pampean core region and secondary producing areas. The paper describes the data construction methodology, the spatial filtering procedure, and the model calibration strategy, and outlines simulation scenarios aimed at quantifying the impacts of irrigation expansion and water infrastructure investments on crop production, land use, and prices under increasing climate variability.

Keywords: SIMPLE-G, Argentina, water use, agricultural production, climate change

JEL Classification: Q54; D59; O13; C69

1. Introduction

Rising global temperatures affect the water cycle through multiple channels, increasing uncertainty in precipitation patterns and intensifying floods and droughts. These events can worsen water pollution through pathogens and pesticides, while glacier melting contributes to sea-level rise, salinization of groundwater, and declining freshwater availability (UN-Water; UNICEF; WMO). This climate–water nexus deepens regional differences in water stress and impacts health, ecosystems, and economic activities. From the perspective of the Sustainable Development Goals (SDGs), Taka et al. (2021) conduct a statistical review of the literature and find that in 91 percent of the studies analyzed, water security (SDG 6) contributes positively to at least one other SDG, with the most relevant linkages related to human well-being (SDG 3) and food security (SDG 2). Food supply is therefore one of the activities most affected by both climate change and freshwater scarcity, with 70 percent of global freshwater withdrawals being used for agriculture.

According to the Food and Agriculture Organization (FAO), producing one person's daily food requires between 2,000 and 5,000 liters of water. Improving agricultural water-use efficiency through climate-smart practices—such as drip irrigation, rainwater harvesting, wastewater reuse, circular economy approaches, and ecosystem-based solutions like preserving wetlands and native forests—can reduce freshwater demand without compromising food supply (Mahlknecht et al., 2020; UNEP). Integrated management of water, soil, and land at multiple levels can enhance welfare while protecting ecosystem sustainability, but it requires coordinated national and regional strategies involving local communities. In this context, the FAO supports national water management roadmaps and the development of high-resolution georeferenced tools to estimate irrigation needs, strengthening diagnostics, risk forecasting, and policy design, while encouraging private-sector responses through effective government incentives.

Argentina is also affected by climate change, water scarcity, and food supply pressures, alongside growing energy demands linked to renewable expansion. Although it has abundant freshwater resources and relatively low water stress (77th in the WRI ranking), Argentina's agriculture faces major challenges in sustainable water management under rising food demand and climate change (World Bank, 2021). Water availability and quality, as well as crop rotation in semi-arid areas, are key determinants of efficient water use and agricultural productivity, with direct implications for economic stability. In 2024, agriculture represented 6.9 percent of GDP and 19 percent of total exports (INDEC). As a major grain exporter, Argentina's strong reliance on water for both irrigated and rainfed production underscores the need to address water security constraints.

Climate variability, including droughts attributed to the La Niña phenomenon, represents a significant risk for agricultural production and macroeconomic stability. The 2022–2023 drought severely affected key regions, including the central zone, Cuyo, and parts of Chaco, Santa Fe, and Corrientes, causing delays in agricultural campaigns and reducing planted areas, yields, and output of wheat, corn, and soybeans. These impacts translated into sharp export declines in 2023, with primary product exports falling 38.3 percent and agricultural-based manufactures dropping 26.7 percent year-on-year (INDEC). This vulnerability reflects Argentina's strong dependence on rainfall: only 5.2 percent of cropland is irrigated and just 6.7 percent has adequate irrigation equipment (FAO). Most irrigated hectares rely on surface water (78 percent), with the remainder using groundwater (22 percent). In this context, expanding irrigation networks and investing in water infrastructure are important adaptation options. Disparities in water availability and use across the territory also support the relevance of a regional approach (Wild et al., 2021; Scherger et al., 2022).

Addressing this problem with spillover effects at national and global levels requires databases and models that connect the sectoral and geographic dimensions of environmental change with socioeconomic outcomes. This paper proposes the development and application of SIMPLE-G-AR, the gridded version of the International Simplified Model of Agricultural Prices, Land Use, and Environment (SIMPLE-G) developed by Liu et al. (2017), Baldos et al. (2020), and Haqiqi et al. (2023) for Argentina. Achieving this objective requires the construction of a georeferenced database specific to Argentina capable of identifying crop production conditions with spatial disaggregation into grid cells of 10 km × 10 km. Since no database currently exists with these characteristics for Argentina, the creation of this dataset through the integration of satellite imagery and global agro-ecological models represents an original contribution of this paper.

The main objective of this study is to assess technological and policy measures, implemented at different levels of government, aimed at improving the resilience and sustainability of Argentina's agricultural sector under increasing climate variability. Given the multidimensional nature of climate and water-related risks, the analysis adopts an integrated approach combining water resource management with geographic heterogeneity, regional and crop production dynamics, and long-term strategic planning in the context of rising global demand for food and biofuels.

Methodologically, we adopt the gridded version of the Simplified International Model of Agricultural Prices, Land Use, and Environment (SIMPLE-G), which is extended and calibrated for Argentina. SIMPLE-G is a multi-scale partial equilibrium model that accounts for 17 world regions and captures both local and global dynamics of agricultural systems (Liu et al., 2017; Baldos et al., 2020). Previous country-level implementations include the United States (Baldos et al., 2020), China (Wang et al., 2020), Brazil (Wang et al., 2022), and Italy (Ojeda et al., 2025), demonstrating the model's adaptability to diverse agro-ecological and institutional contexts.

This paper adds to the existing literature in three main ways. First, it constructs the first spatially explicit, high-resolution georeferenced database for Argentine agriculture, integrating satellite-derived land use and water use data with agro-ecological production estimates across 31,049 grid cells. Second, by extending SIMPLE-G to Argentina, the paper contributes to the growing literature on country-level applications of this framework, presenting the first implementation capable of analyzing water policy and climate shocks at subnational resolution for this country. Third, it contributes to the policy debate on adaptation to climate variability in middle-income agricultural exporters, where quantitative spatial tools are scarce despite the high exposure of these economies to climate risk.

The rest of the paper is structured as follows. Section 2 presents the contextual framework and literature review. Section 3 introduces the SIMPLE-G-AR model. Section 4 describes the data construction process. Section 5 presents the identification of agricultural cells and the filtering procedure. Section 6 outlines the simulation design. Section 7 discusses results, and Section 8 draws final remarks and conclusions.

2. Contextual Framework and Literature Review

2.1 Agriculture, Water, and Climate Variability in Argentina

From an economic perspective, agriculture in Argentina plays a central role in the national economy and in global food markets. In 2024, the sector accounted for 6.9 percent of GDP and 19 percent of total exports, making Argentina one of the world's largest exporters of soybeans, corn, wheat, and their derivatives (INDEC, 2024). The sector's strong integration into international commodity markets means that domestic production shocks have direct implications for the trade balance, fiscal revenues, and macroeconomic stability.

Argentina's agricultural production system is predominantly rainfed. According to FAO data, only 5.2 percent of cultivated land benefits from artificial irrigation, compared to the global average of approximately 20 percent, and only 6.7 percent of cropland has adequate irrigation equipment. Among the irrigated area, surface water accounts for 78 percent of withdrawals, with groundwater providing the remaining 22 percent. The Pampean region (comprising the provinces of Buenos Aires, Córdoba, Santa Fe, Entre Ríos, and La Pampa) concentrates the bulk of rainfed crop production and is the area most exposed to inter-annual rainfall variability.

The 2022–2023 drought, attributed to the La Niña climatic phenomenon, illustrated the severity of these vulnerabilities. The drought affected the central productive zone, Cuyo, and parts of Chaco, Santa Fe, and Corrientes, causing delays in sowing campaigns, reductions in planted area, and yield losses in wheat, corn, and soybeans. According to INDEC data, primary product exports fell by 38.3 percent year-on-year in the January–September 2023 period, while agro-industrial manufactures dropped by 26.7 percent. The fiscal impact was compounded by the structure of Argentina's export tax system, under which agricultural exports are a key source of public revenue.

These dynamics underscore the importance of understanding spatial heterogeneity in climate exposure, irrigation capacity, and production potential across Argentine territory. Regional differences in water availability, infrastructure endowment, and agro-ecological conditions imply that both the impacts of climate shocks and the effectiveness of adaptation policies are highly location-specific (Wild et al., 2021; Scherger et al., 2022). Developing quantitative tools capable of capturing these heterogeneities at fine spatial resolution is therefore a prerequisite for rigorous policy evaluation.

2.2 The SIMPLE-G Framework for Water Issues

In recent years, a growing body of literature has aimed to integrate biophysical and economic dimensions within partial equilibrium frameworks in order to explore the complex interdependencies governing global crop production, land and water use, and food demand. The foundation of this strand of research is the Simplified International Model of Agricultural Prices, Land Use, and Environment (SIMPLE), introduced by Baldos and Hertel (2013) to capture the key socioeconomic drivers of cropland use across 15 world regions. Through a validation exercise covering the historical period from 1961 to 2006, the authors demonstrated that the model effectively replicates historical trends in global agricultural supply and demand relying on population, income, and total factor productivity (TFP) as its primary determinants. Subsequent extensions of the original SIMPLE model incorporated Greenhouse Gas (GHG) emissions through fixed emission factors linked to agricultural activities (Lobell et al., 2013; Hertel et al., 2014), enabling the analysis of climate change adaptation policies and technological advancements on both GHG concentrations and crop production. Baldos and Hertel (2014, 2015) further enhanced the model by adding a food security module, concluding that reducing market barriers can strengthen food security globally in the face of climate risk. More recently, Fuglie et al. (2022) employed these GHG extensions to assess the influence of R&D policies on global GHG reductions, finding that productivity-enhancing research yields more effective mitigation outcomes than land use restrictions alone. While the SIMPLE model demonstrated success in validating historical periods on a global scale, Hertel (2018) highlighted a primary limitation: the absence of spatially explicit data prevents the model from capturing the local effects of a given policy. This observation motivated the development of the gridded extension of the framework, SIMPLE-G.

Liu et al. (2017) introduced SIMPLE-G-Global, dividing the entire world into over 39,000 grids and integrating the framework with the global Water Balance Model (WBM) (Grogan, 2016; Wisser et al., 2010) to explore the economic implications of sustainable irrigation practices for food security and land use change. Their results emphasize the importance of grid-resolving modeling, which enables the model to adopt a multi-scale approach and capture intricate global-local-global (GLG) interactions across economic and environmental systems. Baldos et al. (2020) applied a similar approach to the United States, developing SIMPLE-G-US, which divides the country into over 75,000 grids while aggregating the rest of the world into 15 distinct regions. Their model paid particular attention to water supply, differentiating between rainfed and irrigated land and further distinguishing groundwater from surface water within the irrigated sector. Liu et al. (2022) subsequently extended this model to develop SIMPLE-G-US-CS (Corn and Soybean), where crop differentiation enabled finer-scale analysis of nitrogen loss management policies in the US Corn Belt. Ray et al. (2023) introduced a further variant, SIMPLE-G-US-CZ (Commuting Zones), incorporating a labor mobility module to study how global and local shocks propagate through agricultural labor markets at the gridded level. Although these U.S. applications used the model to study water-related scenarios, the earlier versions lacked a fully explicit representation of water as a production input.

In this respect, Haqiqi et al. (2023a) extended the U.S. model by introducing a distinction between rainfed and irrigated crop production. Within the irrigated production function, groundwater and surface water demand is also accounted for at the local level, enabling the simulation of water availability shocks at fine spatial resolution. Building on this framework, Haqiqi et al. (2023b) incorporated crop production functions at a global scale to evaluate the counterfactual effects of the COVID-19 pandemic coexisting with regional droughts on world crop production. More recently, Haqiqi, Perry & Hertel (2022) used the model to study the local and global economic responses to unsustainable groundwater depletion, showing that when virtual water trade can no longer compensate for local groundwater scarcity, both food prices and land use patterns shift significantly at the international level, a finding directly relevant to the Argentine context given the country's dependence on rainfed production. Haqiqi, Bowling et al. (2023) further refined the water module to analyze global drivers of local water stress in the United States, demonstrating how international demand shocks translate into local irrigation pressure and how water pricing policies can cascade through global markets.

A parallel strand of the literature uses SIMPLE-G to assess the environmental co-benefits of policy interventions beyond water quantity. Zuidema et al. (2023) show that a U.S. climate policy raising carbon prices improves water quality in the Mississippi Basin and Gulf of Mexico by reducing fertilizer use and nitrate runoff, with additional benefits from wetland restoration, illustrating the model's capacity to capture water quality externalities that are usually absent from partial equilibrium analyses. Liu et al. (2023) extend this logic by studying nutrient pollution from corn production, finding that targeting policy at spatial hotspots and addressing leakage across jurisdictions is essential to meaningfully reduce nitrogen loads at the watershed level. Johnson et al. (2023) use SIMPLE-G to evaluate the agricultural and environmental consequences of relaxing U.S. biofuel mandates, showing that reducing biofuel requirements can substantially alleviate land and water pressures globally while dampening food price volatility, a result with implications for Argentina given its large corn and soybean export exposure. Fuglie et al. (2022) contribute an additional dimension by using the model to quantify the R&D investment costs required for climate mitigation in agriculture, demonstrating that productivity-enhancing research can reduce land use emissions at costs well below those of alternative abatement strategies. Even though these applications represent important advances in modeling water demand and environmental outcomes for agriculture at a global level, their datasets and parameter estimates may not fully reflect the specific agro-ecological and institutional conditions of countries like Argentina with distinct production structures and climate exposures.

Further country-level applications deepened the framework's geographical scope. For China, Wang et al. (2020) calibrated a model with more than 41,000 grids to explore the consequences of promoting biofuel demand, highlighting substantial spatial heterogeneity in impacts on food, land, and water systems and underscoring the need for region-specific policy formulations. Wang and Liu (2021a) extended the Chinese model to more than 88,000 grids to evaluate the local impacts on cropland, production, and irrigation water use of the South-North Water Transfer Project (SNWTP), which moves water from major southern rivers to the water-scarce north; Wang and Liu (2021b) addressed the same issues using an econometric approach to improve grid-level elasticities and obtain more accurate regional results. For Brazil, Wang et al. (2022a) developed SIMPLE-G-BR with over 50,000 grids and incorporating the WBM used by Liu et al. (2017), studying how irrigation expansion as a climate adaptation measure could impact crop and livestock production; Wang et al. (2022b) subsequently introduced a transportation module to explore how transportation cost reductions affect agricultural production patterns and grid-level cropland expansion, demonstrating that infrastructure investments generate diverse local responses to macro-level policies.

The multi-scale approach of the SIMPLE-G model, as demonstrated through its applications across the United States, China, Brazil, and Italy, underscores its potential significance for Argentina. Given this literature, the paper aims at developing SIMPLE-G-AR with a detailed representation of both rainfed and irrigated crop production, including surface and groundwater as separate inputs. This model will not only contribute to the existing SIMPLE-G literature but also provide a suitable quantitative framework for evaluating the effects of climate variability, water availability shocks, and irrigation infrastructure investment policies on crop production, land use, and prices at local, provincial, and national scales in Argentina.

3. The SIMPLE-G-AR Model

SIMPLE-G is a multi-scale partial equilibrium framework integrating economic principles with biophysical characteristics (Hertel & Haqiqi, 2024). It enhances the original SIMPLE model (Hertel & Baldos, 2013) by enabling a more granular, location-specific analysis of crop production. In this framework, production is modeled at the grid level, with spatial units whose size varies with latitude. The georeferenced nature of SIMPLE-G allows for a detailed representation of inputs such as land type, water use (differentiating between surface and groundwater) and fertilizer application rates, providing a more precise understanding of agricultural production processes.

The model is designed to capture how human systems adapt to environmental change, reflecting shifts in food consumption, crop production, land use, and water use in response to changes in market prices. A key advantage of the model is its capacity to account for market-mediated spillovers across regions, enabling the analysis of feedbacks between economic and environmental systems. Its multi-scale structure also allows for seamless integration of local and global dynamics: at the grid level, variations in crop choices reflect local agro-ecological conditions; these outputs are then aggregated to produce national and global figures based on assumptions about crop substitutability.

The implementation of SIMPLE-G for Argentina required singeling out the country from the broader world region embedded in the original model structure and disaggregating it into 10 km × 10 km grid cells. This spatial refinement enables the assessment of localized impacts within Argentina that are not feasible using the original global SIMPLE-G database.

The model structure follows Haqiqi et al. (2023a) in distinguishing between rainfed and irrigated crop production within the Argentine territory. For irrigated cells, the production function accounts for both surface water and groundwater withdrawals, allowing the simulation of water availability shocks and infrastructure investment policies through changes in water input endowments. Rainfed cells, which constitute the vast majority of Argentine agricultural area, are subject to shocks transmitted through the neutral technological change parameter, capturing the effects of precipitation variability and temperature changes on crop yields.

At the global level, the model accounts for 17 world regions plus Argentina, with market integration allowing for international price transmission. This multi-scale structure is particularly relevant for Argentina given its role as a major commodity exporter: local production shocks feed into global supply and affect international prices, which in turn determine the profitability of alternative crops and technologies domestically. The calibration of the model's key parameters (including supply and demand elasticities, yield response functions, and land transformation curves) follows the methodology proposed by Haqiqi et al. (2023) and is discussed in Section 6.

4. Data

This section describes the construction of the SIMPLE-G-AR database, a spatially explicit georeferenced dataset developed specifically for Argentina. The database integrates the key variables required for the calibration of a gridded agricultural model: cropland area, crop production, yield by water use type, water demand, nitrogen use, and crop prices. The data come from a combination of global satellite-derived sources and Argentine national price data, and are harmonized onto the 10 km × 10 km national grid. Given that no equivalent dataset currently exists for Argentina with these characteristics, its construction constitutes an original contribution of this project. Table 2 provides an overview of the sources used.

4.1 Spatial Structure: The National Grid

The fundamental spatial unit of analysis is a regular grid of 10 km × 10 km cells covering the entire Argentine territory. This resolution is consistent with that of the primary data sources used (GAEZ and EarthStat operate natively at approximately 10 km), and is fine enough to capture meaningful variation in agricultural activity and water use across agro-ecological zones while remaining computationally tractable for the integration of multiple raster and vector sources. For datasets available at higher resolution, specifically the USGS/GFSAD30 cropland raster at 30 meters, aggregation to the grid cell level is performed through pixel counting, as described in Section 4.3.

The grid contains a total of 31,049 cells covering the national territory, each uniquely identified by a geographic centroid (latitude and longitude) and linked to its corresponding administrative units at the provincial and departmental levels. Administrative boundaries were obtained from the Instituto Geográfico Nacional (IGN) of Argentina in shapefile format under the WGS 1984 geographic coordinate system (EPSG:4326). Departmental units are identified by the five-digit INDEC code (INI1), where the first two digits encode the province and the remaining three identify the department, partido, or commune. Table 1 reports the number of grid cells per province.

Table 1. Number of grid cells per province (ordered north to south)

Province	Grid Cells
Jujuy	630
Salta	1,754
Formosa	852
Misiones	362
Tucumán	281
Santiago del Estero	1,479
Chaco	1,109
Catamarca	1,161
Corrientes	988
La Rioja	1,040
San Juan	1,014
San Luis	842
Entre Ríos	859
Santa Fe	1,461
Córdoba	1,779
Mendoza	1,659
Buenos Aires	3,250
Ciudad Autónoma de Buenos Aires	6
La Pampa	1,551
Neuquén	1,085
Río Negro	2,218
Chubut	2,463
Santa Cruz	2,656
Tierra del Fuego, Antártida e Islas del Atlántico Sur	289
Total	31,049

Source: Own elaboration based on IGN administrative shapefiles.

4.2 Agricultural Production Data

Crop production data are drawn from the Global Agro-Ecological Zones (GAEZ) dataset, which provides the primary source of spatially disaggregated production and yield information for the model calibration. EarthStat is used as a complementary source for nitrogen fertilizer use. Together these two sources cover the biophysical and agronomic dimensions of production at the grid cell level.

4.2.1 Global Agro-Ecological Zones (GAEZ)

The GAEZ dataset, jointly developed by the Food and Agriculture Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA), provides agro-ecologically modeled estimates of crop production and potential yields at global scale. Data are available as GeoTIFF rasters at a nominal resolution of approximately 10 km × 10 km. The reference year used for calibration is 2010, which is selected as the baseline year for SIMPLE-G-AR given data availability and consistency across sources. Production values are expressed in thousands of metric tons and were converted to metric tons during processing.

A key feature of GAEZ for the purposes of SIMPLE-G-AR is its explicit treatment of water input regimes. Separate raster layers are provided for two production systems: (i) irrigated systems, which assume full supplemental irrigation; and (ii) rainfed systems, which depend entirely on precipitation. This distinction maps directly onto the model's production structure, which requires yield and production data disaggregated by water use type to calibrate the rainfed and irrigated branches of the crop production function. For this study, the production (prd) and yield (yld) layers for both the irrigated (I) and rainfed (R) regimes were retained for the reference year 2010.

The GAEZ database covers 27 crop categories, each recorded under both irrigated and rainfed conditions, yielding 54 production columns and 54 yield columns in the final dataset.

4.2.2 EarthStat

EarthStat is used in SIMPLE-G-AR as the source of nitrogen fertilizer application data. Specifically, the total nutrient balance dataset from West et al. (2014), available through the EarthStat platform (http://www.earthstat.org/), provides estimates of nitrogen inputs per crop at the 10 km × 10 km grid level, representing the difference between total nitrogen applied to the agricultural system and nitrogen removed through harvest. Positive values indicate nitrogen surplus and negative values indicate deficit or soil depletion. These data are used to characterize fertilizer intensity across cells, which is an input to the production function calibration.

4.3 Land Use Data

Cropland area at the grid cell level is derived from the GFSAD30 dataset (Global Food Security-support Analysis Data at 30 meters), developed by the United States Geological Survey (USGS) and NASA. GFSAD30 maps cropland extent globally at a spatial resolution of 30 meters using multi-temporal Landsat imagery and supervised classification algorithms, with a temporal reference of 2015. Each 30-meter pixel is classified into one of three categories: 0 (ocean or inland water body), 1 (non-cropland), or 2 (cropland), where cropland is defined without explicit differentiation by irrigation type. Given the 30-meter resolution of this raster, aggregation to the cell level is performed by counting pixels per class within each cell and converting to hectares using the following formula:

$$\text{Hectares}_{i\square} = (n_{i\square} / N_{\square}) \times A$$

where n_i□ is the number of valid pixels of class i within cell j, N□ is the total count of valid (non-nodata) pixels in that cell, and A = 10,000 hectares is the nominal area of each cell. This yields three variables: NS_0_ha (water surfaces), NS_1_ha (non-cropland), and NS_2_ha (cropland area in hectares). The variable NS_2_ha is the primary measure of cultivated area used in the model calibration and filtering procedure.

4.4 Water Use Data

Water demand data by type of use (rainfed and irrigated) are obtained from two complementary sources. The Global Crop Water Model (GCWM), developed at Goethe University Frankfurt, provides spatially explicit estimates of crop water requirements and actual water consumption disaggregated by water regime at approximately 10 km × 10 km resolution. GCWM distinguishes between blue water (irrigation) and green water (precipitation-fed) consumption for each crop, enabling the calibration of the water input parameters in the irrigated branch of the SIMPLE-G-AR production function. AQUASTAT, the FAO's global water information system, provides national and sub-national data on water withdrawal and use by sector in agriculture, which are used to reconcile grid-level water demand estimates with observed aggregate figures and to validate the spatial distribution of irrigation intensity across Argentine provinces.

4.5 Crop Prices

Crop prices are a critical input for model calibration, as they are used to compute revenue shares across crops and water use types within each grid cell. Price data were obtained from the SIO Granos (Sistema de Información Oleaginosa y Granos), which publishes market prices at the locality level in Argentina. Since prices are reported at the locality level rather than at the grid cell level, each grid cell was assigned the price corresponding to the locality to which it belongs, determined by spatial intersection with the locality boundary layer.

Table 2. Data sources used in the construction of SIMPLE-G-AR

Dataset	Variable supplied to the model	Spatial resolution	Base year	Source / Link
GAEZ (FAO/IIASA)	Crop production (irrigated and rainfed); crop yields by water regime (irrigated and rainfed)	~10 km × 10 km	2010	FAO/IIASA Global Agro-Ecological Zones
USGS / GFSAD30	Cropland area (hectares per grid cell); land cover classification	30 m (aggregated to 10 km)	2015	https://glam1.gsfc.nasa.gov/api/doc/cropmask/v1/GFSAD30-CE_2015_crops
GCWM	Crop water demand by type of use (blue water / green water)	~10 km × 10 km	2010	Goethe University Frankfurt – Global Crop Water Model

AQUASTAT (FAO)	Agricultural water withdrawal by province; validation of irrigation intensity	National / provincial	2010	https://www.fao.org/aquastat/en/
EarthStat	Nitrogen fertilizer use per crop (kg N per cell)	~10 km × 10 km	2010	West et al. (2014); http://www.earthstat.org/
SIO Granos	Crop market prices (pesos per ton, at locality level)	Locality level (assigned to grid cell)	2017 (deflated to 2010 using FAO Cereal Price Index)	Sistema de Información Oleaginosa y Granos
IGN (Argentina)	Provincial and departmental administrative boundaries; grid-to-departme nt assignment	Vector (shapefile)	—	Instituto Geográfico Nacional – https://www.ign.gob.ar/

Source: Own elaboration.

The SIO Granos price data correspond to the year 2017. Since the baseline year for SIMPLE-G-AR calibration is 2010, prices were deflated to 2010 values using the FAO Cereal Price Index, which tracks the evolution of international cereal commodity prices at annual frequency. This deflation was applied uniformly across all crop price series, ensuring consistency between the price data and the production and quantity data from GAEZ, which also correspond to 2010.

Table 2 summarizes all data sources used in the construction of SIMPLE-G-AR, including their geographic resolution, temporal reference, and the variable they supply to the model.

The use of locality-level prices and their temporal adjustment to the base year is consistent with the approach followed in other country-level implementations of SIMPLE-G (Baldos et al., 2020; Ojeda et al., 2025), where farm-gate or market prices at the finest available administrative level are assigned to grid cells and reconciled with international price benchmarks.

4.6 Data Processing and Grid Integration

The construction of SIMPLE-G-AR required harmonizing data from multiple sources (each with distinct coordinate reference systems, spatial resolutions, temporal coverage, and unit conventions) into a single tabular structure organized at the 10 km × 10 km cell level. The following steps were applied.

For the GAEZ production and yield rasters, each file was clipped to the administrative boundary of Argentina and reprojected to match the coordinate reference system of the national grid. Zonal statistics were then computed for each 10 km × 10 km cell: the sum of pixel values within each cell was used for production (since production is an extensive quantity), and the mean was used for yields (an intensive quantity). GAEZ production values, originally expressed in thousands of metric tons per pixel, were multiplied by 1,000 to convert to metric tons, establishing a consistent unit across all production variables. This process was applied separately for irrigated and rainfed layers for each of the 27 crop categories, generating 54 production and 54 yield columns in the final dataset.

For the GFSAD30 cropland raster (30-meter resolution), global tiles intersecting Argentine territory were first mosaicked into a seamless national raster. Pixel counts per land cover class were then computed for each grid cell and converted to hectares using the proportional formula described in Section 4.3. For GCWM water demand data and EarthStat nitrogen data (both available at approximately 10 km resolution) zonal means were computed directly for each cell. AQUASTAT data, available at the provincial level, were joined to grid cells through the provincial administrative layer. Finally, SIO Granos prices were assigned to each grid cell based on the locality to which the cell centroid belongs, and deflated from 2017 to 2010 using the FAO Cereal Price Index.

5. Identification of Agricultural Grid Cells and Dataset Filtering

Not all 31,049 grid cells in the national grid correspond to active agricultural zones. A filtering procedure was implemented to identify the subset of cells that simultaneously present evidence of cultivated surface area (from GFSAD30/USGS) and positive estimated agricultural production (from GAEZ). This subset (denoted the agricultural production -PA- dataset) constitutes the analytical unit for model calibration and simulation.

5.1 Filtering Criterion

A grid cell is retained in the PA dataset if and only if it satisfies two conditions jointly:

(1) CROPLAND > 0: the cell contains a positive area of cultivated surface according to the land cover data.

(2) TOTAL_GAEZ > 0: the cell presents positive estimated total production according to the GAEZ dataset.

TOTAL_GAEZ is constructed as the sum of all 54 GAEZ production columns for the reference year 2010 across all crops and both water regimes. Cells with positive cropland area but zero GAEZ production are excluded because the absence of estimated production signals that the agro-ecological conditions of that cell do not support economically meaningful crop cultivation under the model’s assumptions. This joint condition ensures that retained cells correspond to locations where both the satellite-derived land cover classification (GFSAD30) and the agro-ecological model (GAEZ) agree on the presence of active agricultural activity.

5.2 Definition of CROPLAND and Sensitivity Analysis

The CROPLAND variable is measured by the variable NS_2_ha, which represents the estimated hectares of cropland within each grid cell derived from the GFSAD30 raster (USGS). Since each cell has a nominal area of 10,000 hectares, different minimum thresholds on NS_2_ha correspond to different minimum proportions of the cell that must be under cultivation for it to be retained. To assess the sensitivity of the agricultural dataset to the choice of this threshold, the number of retained cells was computed under five alternative minimum-area thresholds: 0 ha (any cropland presence), 2,000 ha (at least 20% of cell area), 2,500 ha (at least 25%), 3,333 ha (at least 33%), and 5,000 ha (at least 50%). Table 3 reports the results.

- The land use source (GFSAD30, NS dataset) defines cropland as the area classified under category 2 (cultivated area), regardless of irrigation type: CROPLAND = NS_2_ha.
- The water use source (LGRIP30, NA dataset) defines cropland as the combined area of irrigated and rainfed agricultural pixels: CROPLAND = NA_2_ha + NA_3_ha.

To assess the sensitivity of the agricultural dataset to the choice of CROPLAND definition and to the minimum area threshold applied, two analyses were conducted. For each source, the number of retained cells was computed under five alternative minimum-area thresholds: 0 ha (any cropland presence), 2,000 ha (≥20% of cell area), 2,500 ha (≥25%), 3,333 ha (≥33%), and 5,000 ha (≥50%). Table 3 reports results for the NS source; the NA source yields 15,219 cells under the zero threshold. Additionally, a spatial comparison between NS and NA sources was conducted to identify cells classified as agricultural by one source but not the other, revealing regional patterns of discordance attributable to methodological differences in the two classification algorithms.

Table 3. Number of retained agricultural cells by minimum cropland area threshold

Threshold (NS_2_ha)	Interpretation	Cells Retained
0 ha	Any cropland presence	19,570
2,000 ha	At least 20% of cell area	8,813
2,500 ha	At least 25% of cell area	8,264
3,333 ha	At least 33% of cell area	7,520
5,000 ha	At least 50% of cell area	6,416

Source: Own elaboration.

The results indicate that increasing the threshold from 25% to 33% or 50% produces only marginal reductions in the number of retained cells, while the jump from zero to 20% eliminates more than half of the candidate cells. Cells near the zero boundary are predominantly located in marginal agricultural zones where cultivation covers only a small fraction of the cell area, consistent with expectations for semi-arid or transition zones at the agricultural frontier.

5.3 Final Dataset Selection

Based on the sensitivity analysis, the final PA dataset retains cells with a minimum cropland area of 25% of cell area (NS_2_ha > 2,500 ha) and positive GAEZ production (TOTAL_GAEZ > 0). The 25% threshold was chosen because it offers a satisfactory balance between filtering out marginal cells, where the GFSAD30 classification may capture only incidental or boundary pixels of cultivation, and preserving coverage of the relevant agricultural area, given that increasing the threshold to 33% or 50% produced negligible further changes in the spatial distribution of retained cells.

The resulting SIMPLE-G-AR agricultural dataset comprises 8,264 grid cells distributed across Argentina's main producing regions. Each cell in the final dataset contains: a unique cell identifier and spatial geometry; latitude and longitude of the centroid; province and department identifiers; GAEZ crop production variables (irrigated and rainfed, reference year 2010) and the corresponding yield variables; cropland area in hectares from GFSAD30 (NS_2_ha); crop water demand from GCWM disaggregated by water regime; nitrogen fertilizer use per crop from EarthStat; provincial water withdrawal data from AQUASTAT; and crop prices from SIO Granos adjusted to 2010. This dataset constitutes the empirical foundation for the calibration of SIMPLE-G-AR presented in the following section.

6. Simulation Design

6.1 Baseline Scenario

The simulation strategy is designed to address two related questions: (i) how resilient is Argentine agricultural production to unexpected climate events such as droughts and floods, and (ii) to what extent can investments in water infrastructure mitigate those impacts? To answer these questions, a chain of counterfactual scenarios is constructed in which each layer adds a single component over the previous one, so that the effect of each element can be isolated by differencing adjacent scenarios. The baseline establishes the no-shock reference, the climate scenarios quantify the gross cost of the event, and the infrastructure scenarios measure the mitigating capacity of water investment at different scales of ambition.

As a starting point, Scenario 0 establishes a business-as-usual baseline projected to 2050 in which both Argentina and the world's agricultural sector face increasing crop demand driven by population growth, rising per capita incomes, and biofuel requirements. Population estimates are derived from the projections developed by Samir & Lutz (2017), while GDP per capita estimates are based on projections by Crespo Cuaresma (2017). These projections follow the intermediate Shared Socioeconomic Pathway (SSP2) developed by IIASA. Future biofuel demand is constructed using estimates provided by IEA (2024). The baseline also assumes that total factor productivity (TFP) in the agricultural sector increases in all world regions through 2050, estimated econometrically using a panel data model following the methodology of Van Beveren (2007). This scenario establishes the counterfactual reference against which all subsequent simulations are evaluated.

6.2 Climate Change Scenarios

Two climate shock scenarios are introduced over the baseline, each representing a distinct type of unexpected extreme event. Technically, both are implemented by introducing negative shocks to the input-neutral technological change parameter of the crop production functions at the grid cell level, capturing the heterogeneous spatial distribution of climate exposure across Argentine territory. Cells with higher climate vulnerability (identified through the precipitation and temperature variables) receive larger shocks, while more favorable areas are less affected.

Scenario 1a (Drought) simulates a severe rainfall deficit episode analogous to the 2022–2023 La Niña event, which is calibrated using historical precipitation anomaly data to construct a spatially differentiated shock map concentrated in the central Pampean zone, Cuyo, and parts of Chaco, Santa Fe, and Corrientes. The shock operates through the input-neutral technological change parameter in both rainfed and irrigated production functions, with rainfed cells receiving a proportionally larger shock consistent with their greater dependence on precipitation. The difference (Scenario 1a − Scenario 0) isolates the gross cost of the drought in terms of production losses, price increases, and land use changes, including the international spillovers through Argentina's commodity export markets.

Scenario 1b (Flood) simulates an excess precipitation event affecting low-lying areas in the eastern Pampas and northeastern provinces, where recurrent flooding episodes have historically disrupted sowing calendars and caused temporary cropland losses. In addition to the negative shock to the input-neutral technological change parameter, this scenario introduces a reduction in the effective cultivated area (NS_2_ha) in the most exposed cells, reflecting the temporary removal of land from production due to waterlogging. This dual mechanism (yield reduction plus area loss) captures the distinct economic damage structure of floods relative to droughts, where the constraint operates not only through productivity but also through physical access to land. The difference (Scenario 1b − Scenario 0) isolates the gross cost of the flood event.

6.3 Water Infrastructure and Irrigation Policy Scenarios

Three policy scenarios evaluate the mitigating capacity of water infrastructure investment, all built on top of Scenario 1a (the drought shock) to assess how different levels of irrigation expansion offset the production losses from the most policy-relevant extreme event for Argentina. Technically, these scenarios are implemented as positive shocks to surface water availability (NA_2_ha) at grid cells identified as having high irrigation potential but low current irrigation coverage, determined by the gap between GAEZ potential yields under irrigated conditions and observed rainfed yields in the database. This shock enables rainfed cells to switch partially or fully to irrigated production, generating supply-side responses in crop mix, yields, and land use.

Scenario 2 (Incremental Mitigation) simulates a modest expansion of irrigated cropland from the current 5.2 percent to approximately 8 percent of total cultivated area, consistent with near-term, incremental investment in surface irrigation infrastructure. Scenario 3 (Moderate Mitigation) scales this to around 12 percent, reflecting a medium-term national irrigation plan. Scenario 4 (Full Mitigation) simulates the upper bound of irrigation potential estimated by the World Bank (2021) and FAO for Argentina, reaching approximately 15 percent of cropland with combined surface and groundwater expansion. For each scenario, the difference (Scenario n − Scenario 1a) measures the mitigation delivered by that level of investment, and the difference between consecutive infrastructure scenarios (e.g., Scenario 3 − Scenario 2) isolates the marginal return to scaling up ambition.

An additional counterfactual scenario (Scenario 5) examines ex ante resilience: the drought shock from Scenario 1a is applied to an economy that already has the infrastructure of Scenario 4 in place, asking how much of the drought damage would have been avoided had ambitious irrigation investment been completed before the event. This scenario is conceptually distinct from the mitigating scenarios, which measure reactive capacity, because it quantifies the insurance value of water infrastructure as a buffer stock against future climate shocks.

Table 4. Scenarios summary

No.	Name	Description	Scenario Drivers	Effect Isolated
0	Baseline (2050)	Business-as-usual. Growing global food and biofuel demand, TFP growth.	Demand: Population growth, income, biofuels (SSP2).	Reference counterfactual.

			Supply: TFP growth (all regions).	
1a	Baseline + Drought	Severe rainfall deficit (La Niña-type). Spatially differentiated shock calibrated to 2022–2023 event.	Supply: Negative λ shock on rainfed and irrigated cells; rainfed cells receive proportionally larger shock.	Gross cost of drought. (1a − 0)
1b	Baseline + Flood	Excess precipitation event in eastern Pampas and northeastern provinces.	Supply: Negative λ shock + reduction in effective cultivated area (NS_2_ha) in exposed cells.	Gross cost of flood. (1b − 0)
2	Drought + Incremental Mitigation	Scenario 1a with modest irrigation expansion (~8% of cropland).	Supply: Positive surface water shock (NA_2_ha) in high-potential cells. Rainfed-to-irrigated switch enabled.	Mitigation – incremental. (2 − 1a)
3	Drought + Moderate Mitigation	Scenario 1a with medium-term irrigation expansion (~12% of cropland).	Supply: Larger positive surface water shock in expanded set of high-potential cells.	Mitigation – moderate. (3 − 1a); marginal gain (3 − 2)
4	Drought + Full Mitigation	Scenario 1a with ambitious irrigation expansion (~15% of cropland, surface + groundwater).	Supply: Combined surface and groundwater availability shock at maximum feasible extent (World Bank 2021; FAO).	Mitigation ceiling. (4 − 1a); marginal gain (4 − 3)
5	Ex Ante Resilience	Drought shock (Scenario 1a) applied to an economy already endowed with infrastructure of Scenario 4.	Supply: Scenario 4 infrastructure pre-installed; Scenario 1a climate shock then applied.	Insurance value of infrastructure. (5 − 1a) vs (2–4 − 1a)

Source: Own elaboration.

The sequential structure of the scenarios allows three types of inference. First, comparing each climate shock scenario against the baseline isolates the gross economic cost of the event in terms of production, prices, land use, and international spillovers. Second, comparing each infrastructure scenario against the drought shock measures the mitigating capacity at each investment scale, and differencing consecutive infrastructure scenarios reveals the marginal return to scaling up. Third, comparing the ex ante resilience scenario (Scenario 5) against the reactive mitigation scenarios (Scenarios 2–4) estimates the insurance value of pre-emptive infrastructure investment, a quantity directly relevant to cost-benefit analysis of water policy in Argentina.

7. Expected Results

The baseline scenario is expected to project a sustained increase in Argentine agricultural output through 2050, driven by rising global demand for food and biofuels and continuing TFP growth, consistent with historical trends. The spatial distribution of this expansion will reflect the heterogeneity captured in the SIMPLE-G-AR database, with the Pampean core accounting for the bulk of production growth while northern and semi-arid zones contribute more modestly.

The introduction of the climate change scenario is expected to generate heterogeneous impacts across Argentine territory. Cells in the central productive zone, which are most exposed to La Niña-driven rainfall deficits, are expected to show the largest yield reductions under the negative technological change shock, consistent with the observed patterns during the 2022–2023 drought. The aggregate impact on national production will depend on the severity of the shock calibrated from historical climate data.

For the irrigation expansion scenarios, the hypothesis is that cells with high agro-ecological potential but low current water availability (identified through the GAEZ yield gap and the NA water use variables) would benefit most from expanded irrigation, switching from rainfed to irrigated production and increasing output significantly. These gains are expected to partially or fully offset the climate change losses at the national level, depending on the scale of investment, while generating positive spillovers to international markets through Argentina's role as a global commodity exporter. Price responses will reflect the relative magnitude of supply shocks versus demand pressures from global population and income growth.

These results remain to be fully quantified following the completion of model calibration and validation. Preliminary spatial analysis of the SIMPLE-G-AR database confirms the expected concentration of high-potential agricultural cells in the Pampas, Entre Ríos, and parts of Córdoba and Santa Fe, and highlights significant heterogeneity in water management practices across the national territory.

8. Conclusions and Policy Implications

This paper presents the construction and design of SIMPLE-G-AR, the first gridded partial equilibrium model of Argentine agriculture calibrated at 10 km × 10 km spatial resolution. The paper makes three main contributions. First, it develops an original georeferenced database integrating satellite-derived agricultural production, land use, water use, soil properties, and climatic variables into a unified national grid, addressing a gap in the availability of spatially explicit agricultural data for Argentina. Second, it implements a transparent and replicable filtering procedure to identify 8,264 agricultural cells from the full 31,049-cell national grid, based on joint cropland and production criteria that are benchmarked against alternative land classification sources. Third, it outlines a simulation strategy connecting local agro-ecological conditions to national and global market dynamics through the SIMPLE-G framework, enabling the evaluation of irrigation expansion and climate adaptation policies at provincial and sub-provincial resolution.

From a policy perspective, the model is designed to address a set of questions that are highly relevant for Argentina's public agenda. The country's high dependence on rainfed production, combined with the macroeconomic importance of agricultural exports, implies that even moderate improvements in irrigation coverage could yield significant economic gains while reducing vulnerability to climate variability. The SIMPLE-G-AR framework allows for the spatial identification of high-potential investment areas, the comparison of alternative water infrastructure strategies, and the quantification of their impacts on crop mix, land use, production, and prices at multiple scales.

Several limitations deserve mention. The current version of the model does not capture within-year seasonal dynamics or inter-annual carryover effects of drought on soil and infrastructure. The calibration of climate shocks is based on historical patterns and may not fully reflect the distribution of future extreme events under different climate pathways. Addressing these limitations is in our future research agenda.

Notwithstanding these limitations, SIMPLE-G-AR represents a significant advance in quantitative agricultural modeling for Argentina and provides a platform for evidence-based policy design on water and food security in one of the world's most important agricultural exporting economies.

References

Baldos, U. L. C., & Hertel, T. W. (2013). Looking back to move forward on model validation: Insights from a global model of agricultural land use. Environmental Research Letters, 8(3), 034024. https://doi.org/10.1088/1748-9326/8/3/034024

Baldos, U. L. C., & Hertel, T. W. (2014). Global Food Security in 2050: The Role of Agricultural Productivity and Climate Change. Political Economy – Development: Environment eJournal.

Baldos, U. L. C., & Hertel, T. W. (2015). The role of international trade in managing food security risks from climate change. Food Security, 7(2), 275–290. https://doi.org/10.1007/s12571-015-0435-z

Baldos, U. L. C., Haqiqi, I., Hertel, T. W., Horridge, M., & Liu, J. (2020). SIMPLE-G: A multiscale framework for integration of economic and biophysical determinants of sustainability. Environmental Modelling & Software, 133, 104805.

Baldos, U. L. C. (2023). Impacts of US Public R&D Investments on Agricultural Productivity and GHG Emissions. Journal of Agricultural and Applied Economics, 55(3), 536–550. https://doi.org/10.1017/aae.2023.29

Crespo Cuaresma, J. (2017). Income projections for climate change research: A framework based on human capital dynamics. Global Environmental Change, 42, 226–236.

Fuglie, K., Ray, S., Baldos, U. L. C., & Hertel, T. W. (2022). The R&D cost of climate mitigation in agriculture. Applied Economic Perspectives and Policy, 44(4), 1955–1974. https://doi.org/10.1002/aepp.13245

Grogan, D. S. (2016). Global and regional assessments of unsustainable groundwater use in irrigated agriculture. PhD Thesis, University of New Hampshire.

Haqiqi, I., Bowling, L., Jame, S., Baldos, U., Liu, J., & Hertel, T. (2023). Global drivers of local water stresses and global responses to local water policies in the United States. Environmental Research Letters, 18(6), 065007. https://doi.org/10.1088/1748-9326/acd269

Haqiqi, I., Grogan, D. S., Bahalou Horeh, M., Liu, J., Baldos, U. L., Lammers, R., & Hertel, T. W. (2023). Local, regional, and global adaptations to a compound pandemic-weather stress event. Environmental Research Letters, 18(3). https://doi.org/10.1088/1748-9326/acbbe3

Haqiqi, I., Perry, C. J., & Hertel, T. W. (2022). When the virtual water runs out: Local and global responses to addressing unsustainable groundwater consumption. Water International, 47(7), 1060–1084. https://doi.org/10.1080/02508060.2023.2131272

Haqiq, I., & Hertel, T. W. (2024). SIMPLE-G: A Gridded Economic Approach to Analysis of Sustainability of the Earth's Land and Water Resources. Springer Cham.

Hertel, T. W., Ramankutty, N., & Baldos, U. L. C. (2014). Global market integration increases likelihood that a future African Green Revolution could increase crop land use and CO_2 emissions. Proceedings of the National Academy of Sciences, 111(38), 13799–13804. https://doi.org/10.1073/pnas.1403543111

Hertel, T. W. (2018). Economic perspectives on land use change and leakage. Environmental Research Letters, 13(7), 075012. https://doi.org/10.1088/1748-9326/aad2a4

Haqiq, I., & Hertel, T. W. (2024). SIMPLE-G: A Gridded Economic Approach to Analysis of Sustainability of the Earth's Land and Water Resources. Springer Cham. https://doi.org/10.1007/978-3-031-68054-0

IEA (2024). Renewable Energy Progress Tracker. IEA, Paris.

Johnson, D. R., Geldner, N. B., Liu, J., Baldos, U. L., & Hertel, T. (2023). Reducing US biofuels requirements mitigates short-term impacts of global population and income growth on agricultural environmental outcomes. Energy Policy, 175. https://doi.org/10.1016/j.enpol.2023.113497

INDEC (2024). Intercambio comercial argentino. Instituto Nacional de Estadística y Censos, Buenos Aires.

Liu, J., Hertel, T. W., Lammers, R. B., Prusevich, A., Baldos, U. L. C., Grogan, D. S., & Frolking, S. (2017). Achieving sustainable irrigation water withdrawals: Global impacts on food security and land use. Environmental Research Letters, 12(10), 104009. https://doi.org/10.1088/1748-9326/aa88db

Liu, J., Bowling, L. C., Kucharik, C. J., Jame, S. A., Baldos, U. L. C., Jarvis, L., Ramankutty, N., & Hertel, T. W. (2023). Tackling policy leakage and targeting hotspots could be key to addressing the 'Wicked' challenge of nutrient pollution from corn production in the US. Environmental Research Letters, 18(10). https://doi.org/10.1088/1748-9326/acf727

Lobell, D. B., Baldos, U. L. C., & Hertel, T. W. (2013). Climate adaptation as mitigation: The case of agricultural investments. Environmental Research Letters, 8(1), 015012. https://doi.org/10.1088/1748-9326/8/1/015012

Mahlknecht, J., González-Bravo, R., & Loge, F. J. (2020). Water-energy-food security: A Nexus perspective of the current situation in Latin America and the Caribbean. Energy, 194, 116824.

NASA (2020). GFSAD30 Cropland Data. https://glam1.gsfc.nasa.gov/api/doc/cropmask/v1/GFSAD30-CE_2015_crops

NASA (2020). LGRIP30 Irrigated Area Maps. https://www.earthdata.nasa.gov/data/catalog/lpdaac-ecs-lgrip30-001

New, M., Hulme, M., & Jones, P. (1999). Representing twentieth-century space–time climate variability. Part I: Development of a 1961–90 mean monthly terrestrial climatology. Journal of Climate, 12(3), 829–856.

Ramankutty, N., & Foley, J. A. (1999). Estimating historical changes in global land cover: Croplands from 1700 to 1992. Global Biogeochemical Cycles, 13(4), 997–1027.

Ray, S., Haqiqi, I., Hill, A. E., Taylor, J. E., & Hertel, T. W. (2023). Labor markets: A critical link between global-local shocks and their impact on agriculture. Environmental Research Letters, 18(3), 035007. https://doi.org/10.1088/1748-9326/acb1c9

Samir, K. C., & Lutz, W. (2017). The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Global Environmental Change, 42, 181–192.

Scherger, L. E., Valdes-Abellan, J., Zanello, V., et al. (2022). Projecting climate change effect on soil water fluxes and urea fertilizer fate in the semiarid Pampas of Argentina. Earth Systems and Environment, 6, 745–758.

Taka, M., Ahopelto, L., Fallon, A., Heino, M., Kallio, M., Kinnunen, P., … Varis, O. (2021). The potential of water security in leveraging Agenda 2030. One Earth, 4(2), 258–268.

Van Beveren, I. (2007). Total factor productivity estimation: A practical review. LICOS Discussion Paper No. 182, Katholieke Universiteit Leuven.

Verburg, P. H., Ellis, E. C., & Letourneau, A. (2011). A global assessment of market accessibility and market influence for global environmental change studies. Environmental Research Letters, 6(3), 034019.

Wang, Z., & Liu, J. (2021a). Cropland supply response in China and implications for the Grain-to-Green program. [Unpublished manuscript].

Wang, Z., & Liu, J. (2021b). Impact of China's South-North Water Transfer Project on Agriculture: A multi-scale analysis of the Food-Land-Water system. [Unpublished manuscript].

Wang, Z., Geraldo, B. M., Liu, J., & Zanetti de Lima, C. (2022a). Climate change, irrigation expansion and impacts on agriculture production: An integrated multi-scale analysis of Brazil by 2050. [Unpublished manuscript].

Wang, Z., Geraldo, B. M., Liu, J., Zanetti de Lima, C., & Hertel, T. W. (2022b). Transportation Cost, Agricultural Production and Cropland Expansion in Brazil: A Multi-scale Analysis. [Unpublished manuscript].

Wang, Z., Liu, J., & Hertel, T. W. (2020). The uncertain future of biofuels in China and impacts on the Food-Land-Water Nexus: A multiscale analysis. [Unpublished manuscript].

West, P. C., Gerber, J. S., Engstrom, P. M., et al. (2014). Leverage points for improving global food security and the environment. Science, 345(6194), 325–328.

Wild, T. B., Khan, Z., Zhao, M., Suriano, M., Bereslawski, J. L., Roberts, P., … Ojeda-Matos, G. (2021). The implications of global change for the co-evolution of Argentina's integrated energy-water-land systems. Earth's Future, 9(8), e2020EF001970.

World Bank (2021). Argentina: Agricultural Water Management – Investment Priorities for Sustainable Growth. World Bank Report.

Wisser, D., Fekete, B. M., Vörösmarty, C. J., & Schumann, A. H. (2010). Reconstructing 20th century global hydrography: a contribution to the global terrestrial network-hydrology (GTN-H). Hydrology and Earth System Sciences, 14, 1–24. https://doi.org/10.5194/hess-14-1-2010

Zuidema, S., Liu, J., Chepeliev, M. G., Johnson, D. R., Baldos, U. L. C., Frolking, S., Kucharik, C. J., Wollheim, W. M., & Hertel, T. W. (2023). US climate policy yields water quality cobenefits in the Mississippi Basin and Gulf of Mexico. Proceedings of the National Academy of Sciences, 120(43), e2302087120. https://doi.org/10.1073/pnas.2302087120