Chapter 7
Behavioral Parameters: Capturing Geospatial Heterogeneity in Economic Decisions and Responses

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Tackling fundamental environmental and societal challenges requires a comprehensive geospatial understanding of the interactions among food, agriculture, land, water, and environmental systems. However, this understanding must be achieved with a keen eye on spatial heterogeneity, as environmental responses to economic and policy interventions, resource availability, and climate change are rarely uniform across landscapes. Failure to consider spatial variation can lead to flawed models, misguided policies, and unintended consequences.

To address this challenge, this chapter introduces a geospatial dataset that includes economic behavioral parameters. This dataset is specifically designed for spatially heterogeneous analyses within gridded economic modeling focused on land, water, and environmental sustainability. The dataset incorporates key parameters such as land supply elasticity, water supply elasticity, land conversion possibilities, and substitution elasticity, offering detail and resolution for capturing the spatial responses of production systems to economic and environmental drivers.

Economic parameters are rarely available at gridded scales, yet they are essential for modeling how different regions within a landscape will respond to changes. By integrating these parameters with readily available environmental and economic data, researchers can unlock new avenues for analyzing and predicting spatially differentiated land-use change, water resource allocation, and agricultural production under various sustainability scenarios.

This chapter describes the construction of the SIMPLE-G-US dataset with all crops composite, highlighting its specific advantages and unique aspects in spatially heterogeneous analysis. Through examples, the application of the dataset is showcased in Part IV, demonstrating its potential to contribute to gridded economic modeling. Other internally consistent SIMPLE-G datasets include the global dataset

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(Haqiqi et al. 2022), the corn–soy dataset (Sun et al. 2020, Liu et al. 2023), and the Brazil dataset (Wang et al. 2022, 2024).

Parameters in the model represent behavior leading to the dynamics of the SIMPLE-G system. The model parameters in each simulation are fixed and are usually obtained from other studies or empirical estimations. Table 7.1 summarizes the main parameters used in the model. We describe some of these parameters in the following sections.

1 Regional Parameters

This section introduces the data sources for regional parameters that determine how price changes and income growth influence food selection, how consumers choose between domestic and imported goods, and how livestock and processed food sectors adjust their inputs in response to changing prices.

1.1 Consumer Demand

Consumer demand elasticities, which govern how consumers react to food price changes and income growth, are based on the work of Muhammad et al. (2011), who use cross-section international data to estimate food demand systems spanning the full range of national per capita incomes. To capture the impacts of dietary upgrading in the model, equations relating the price and income elasticities of food demand to the log of per capita incomes are embedded in the model. The estimation of these linkages is described in Hertel and Baldos (2016).

1.2 Spatial Reallocation and Trade Elasticities

Armington-type elasticity parameters are important components of the model. Armington substitution elasticities measure the degree of substitutability between imported and domestic goods or between goods from different sources of origin. Hertel et al. (2007) estimate the Armington substitution elasticities for GTAP sectors based on bilateral transport costs among a subset of countries. The average elasticity for crops is around 3. However, these estimates are subject to uncertainty and sensitivity. It is advisable to use a range of values or conduct sensitivity analyses when applying these elasticities in trade models. We also assume a symmetric value of 3 on the export side.

Table 7.1 Parameters in the gridded model

Parameter	Description	Source
Supply elasticities		
η^L	Cropland supply elasticity	Empirical estimations (Villoria et al. 2023)
η^{GW}	Groundwater supply elasticity	Empirical estimations (Haqiqi et al. 2023)
η^{SW}	Surface water supply elasticity	Empirical estimations (Haqiqi et al. 2023)
η^N	N fertilizer supply elasticity	Uniform value (Baldos et al. 2020)
η^H	Other agricultural inputs supply elasticity	Uniform value (Baldos et al. 2020)
QCET land allocation parameters		
τ	QCET transformation elasticity parameter for land allocation	Empirical estimations for each class of water rights*
Substitution elasticities		
σ	Substitution elasticity between fertilizer and other inputs composite	Based on yield response to fertilizer from Agro-IBIS (Liu et al. 2023)
σ^{HLW}	Substitution elasticity between water-land composite and other inputs composite	Empirical estimations of intensive margin*
σ^{LW}	Substitution elasticity between water and land	Based on yield response to deficit irrigation*
σ^W	Substitution elasticity between water and other irrigation inputs	Based on irrigation technology and crop mix*
σ^{SG}	Substitution elasticity between groundwater and surface water	Uniform value (Baldos et al. 2020)
Subregional Armington parameters		
φ	Substitution possibility between varieties of aggregated crop outputs of grid cells	International trade literature (Hertel et al. 2007)
κ	Substitution possibility between varieties of aggregated crop outputs of subregions	International trade literature (Hertel et al. 2007)
Consumer and trade elasticities		
ω	Imports substitution elasticity	International trade literature (Hertel et al. 2007)
ψ	Export transformation elasticity	Symmetric to imports
α	Demand elasticity parameter	Muhammad et al. (2011)
β	Demand elasticity parameter	Muhammad et al. (2011)
σ^V	Substitution elasticity in livestock production sector	Calibrated to target historical changes in feed use (see Baldos and Hertel 2012)
σ^F	Substitution elasticity in processed food sector	Zero value (i.e., fixed proportion in production)
Other parameters		
Multiple parameters	Water quality and nitrogen leaching	Based on leaching response to fertilizer from Agra-IBIS (Liu et al. 2023)
Multiple parameters	Greenhouse gas emissions factors	Based on GTAP and other sources (Aguiar et al. 2019)
Multiple parameters	Nutrition and food security parameters	Following Neiken (2003) (Baldos and Hertel 2013)

(Note: * shows the work in progress)

1.3 Input Substitution Elasticities for Livestock and Processed Food Sectors

The input substitution elasticity for the livestock sector is based on the historical calibration documented in Baldos and Hertel (2012) over the period from 2001 to 2006. Feed use consumption, taken from FAOSTAT, for high income regions is targeted by adjusting the input substitution elasticity. Processed food sectors assume the Leontief production function given zero values for these substitution elasticities.

2 Gridded Parameters

This section describes the data sources for parameters that determine the spatially heterogeneous agricultural decisions. They include parameters related to supply of agricultural inputs (land and water) and demand of inputs derived from agricultural production from Constant Elasticity of Substitution (CES) functions.

2.1 Cropland Supply Parameters

The cropland supply function determines the willingness to supply cropland at a given level of land rents. The main parameter in this function is the supply elasticity, which represents the percentage change in cropland supply as a response to a 1% change in average cropland rent. Regional cropland supply elasticities are taken from the SIMPLE model, and gridded land supply elasticities for the United States are based on the statistical model developed by Villoria and Liu (2018) using gridded data from the Americas. This elasticity was estimated based on the propensity of land to be converted to crop cultivation from other uses (including pasture and forestry) conditional on the profitability of land while controlling for agroecological conditions. In the model, this parameter ranges from 0 to 0.755. A larger value indicates a greater likelihood of switching to cropland from other uses for a given increase in cropland rents.

2.2 Cropland Conversion (Transformation) Parameters

A quantity-preserving constant elasticity of transformation (QCET) function determines the allocation of land to irrigated and rainfed activities. The transformation elasticity parameter determines the percentage change in the ratio of each land type in response to a 1% change in relative rents to the two activities. This parameter shows the flexibility of converting cropland to irrigated or rainfed production. In the United States, this parameter is estimated following Jame et al. (2017) based on local water rights law. Different water rights can restrict the extension or intensity of irrigation at one location. For this estimation, we employ county level information from the USDA, including cash rents for irrigated and nonirrigated cropland as well as total irrigated and nonirrigated cropland area by county. We assume that all the grid cells in a county follow the estimated parameter for that county.

2.3 Water Supply Parameters

The water supply elasticity determines how the economic supply of water will change in response to changes in the price or value of water. Without observing market price behavior, it is difficult to estimate this parameter. Thus, we use hydrological information to create a database of water supply elasticities based on availability and current withdrawals. We assume that water supply at each grid cell is limited by hydrological constraints. Figure 7.1 illustrates two examples. This form of water supply function is slowly increasing at the beginning (up to A) and then rapidly increasing (after B) when approaching the asymptote (C). With adverse changes in hydroclimatic conditions, the cost schedule may shift to S_2 (depending on the natural supply of water).

Withdrawal of water is constrained by the maximum amount of water available in each grid cell after subtracting nonagricultural water use. We assume that the supply elasticity of water varies by grid cell and depends on the ratio of water extracted relative to the sustainable extraction level (R). We assume a three-parameter Fréchet function for water supply with calibrated parameters ω_0, ω_1, ω_2, ω_3:

$$\varepsilon_g = \omega_0 + \frac{\omega_1}{\left(\omega_2 + R_g\right)^{\omega_3}}, \tag{7.1}$$

where R is calculated as the ratio of annual withdrawal to annual groundwater recharge or as the ratio of annual withdrawal to annual available surface water. We calibrate this supply function separately for surface water and groundwater at each grid cell based on economic and hydrologic information, including annual water withdrawal for crop irrigation, the sustainable extraction level of water by source, and the estimated value of water, as described previously.

Haqiqi et al. (2023) have calibrated the gridded water supply schedules for the continental United States to the benchmark year 2010 based on the ratio of groundwater withdrawal to groundwater recharge (Gleeson et al. 2016; Reitz et al. 2017). For the US grid cells, the water supply elasticity is calculated using the withdrawal-to-recharge ratio and the empirically estimated parameters ω_0, ω_1, ω_2, and ω_3. These values are estimated using water withdrawal data from the USGS for 2010 and the

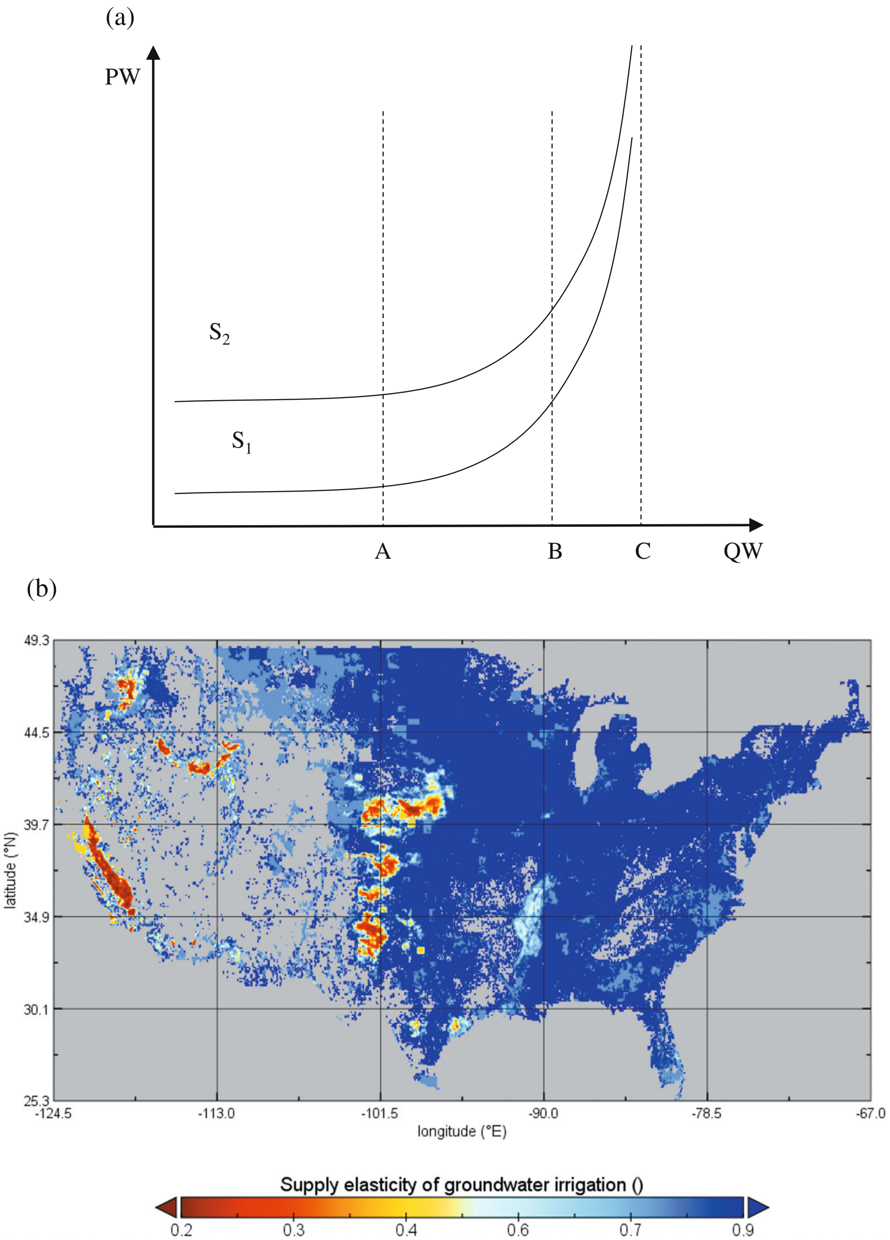

Fig. 7.1 (**a**) Economic supply for water with maximum availability determined by asymptote C. (**b**) Estimated groundwater elasticities in the continental United States

estimated value of water (Haqiqi et al. 2016). In this version, ω_1 is 0.50, ω_2 is 0.30, ω_3 is 0.45, and ω_0 is 0 for groundwater and −0.05 for surface water. Then, we apply the estimated function to all the grid cells to determine the unique water supply elasticity for each grid cell. The information about groundwater recharge is taken from the Annual Estimate of Recharge (Reitz et al. 2017). Figure 7.1b shows the supply elasticity based on the ratio of groundwater withdrawal to local recharge around the year 2010. The red color shows the locations with a very rapid depletion of groundwater which are mostly in California and the Ogallala Aquifer. For some locations, more groundwater is withdrawn in 1 year than flows in as over 10 years. The High Plains Aquifer, the Central Valley of California, the Snake River Basin, and western Washington show dramatic levels of unsustainability based on this index.

Using previous versions of SIMPLE-G, researchers have taken other approaches for estimating these elasticities. Haqiqi et al. (2018) consider variable water supply elasticity (i.e., the elasticity would adjust depending on the distance to the asymptote). These authors calculate the maximum surface water available at each grid cell after subtracting nonagricultural water use from locally generated runoff (Wolock 2003) while maximum available groundwater available was determined with groundwater stock (Gleeson et al. 2016; Befus et al. 2017).

2.4 Elasticities of Substitution in Crop Production

The substitution elasticity between N fertilizer and other inputs is an important parameter in the model. This elasticity determines the likely changes in N application rate in response to change in relative price of N fertilizer. We estimate this parameter for each grid cell, following Liu et al. (2023) to establish a framework for estimating this parameter. We begin by obtaining the yield response functions from Agro-IBIS, then combine this response function with estimated yields of irrigated and nonirrigated crops to find the substitution elasticity for irrigated and rainfed crop production (Liu et al. 2023).

2.5 Other Parameters

Liu et al. (2018) have estimated leaching parameters from Agro-IBIS to construct a nutrient-leaching module for all the grid cells in SIMPLE-G-US. This nonlinear leaching function shows that nutrient leaching will increase quadratically when N application rate increases. The parameters are specific to the unique biophysical characteristics of each grid cell, including soil type, irrigation, and land cover (Liu et al. 2023).

3 Summary

Considering geospatially heterogeneous behavioral parameters is important for understanding the interactions among agriculture, land, water, and environmental systems. We introduced a geospatial dataset of economic parameters specifically designed for analysis within gridded economic modeling. This dataset includes key parameters—such as land supply elasticity, water supply elasticity, land conversion possibilities, and substitution elasticity—that allow researchers to capture the spatial responses of production systems to economic and environmental drivers.

The chapter described the construction and sources of the SIMPLE-G-US dataset, which encompasses all crops in a composite commodity. The regional parameters determine how price changes and income growth influence the production and consumption of goods and services in different regions. The gridded parameters determine local decisions and economic responses to policies and shocks. This dataset is an example of how to employ biophysical information to calibrate and estimate parameters required in analyzing and predicting spatially differentiated decisions. We encourage researchers to consider the spatial variation in economic parameters and to incorporate this knowledge into their analyses to address the complex challenges associated with food, agriculture, land, water, and environmental systems.

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