Can Geospatial Data Help Explain Rising Agricultural Land Prices?

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August 2026

Abstract

Agricultural land prices have increased substantially in recent decades, raising concerns about land availability and farm profitability. There is limited evidence on the relative importance of the factors driving these trends. This study applies a hedonic pricing model to cadastral parcel transaction data from the Netherlands to estimate the relative contribution of various determinants of agricultural land prices, such as parcel characteristics, regulatory pressure, competition from alternative land uses, and price speculation as well as geospatial data on soil quality and climate risk. The analysis examines how the capitalization of these factors varies across parcels and over time. This study improves our understanding of agricultural land markets and the economic forces that shape farmland prices at the parcel level.

1 Introduction

As the world population continues to grow, land has become increasingly scarce. As a finite resource, land is in growing demand for urban, agricultural, and forestry uses (Lambin and Meyfroidt, 2011; Gomiero, 2016; King et al., 2023; Anisimov, 2026), contributing to record-high land prices. In the Netherlands, agricultural land prices are among the highest in Europe and the world (Eurostat, 2025). Competing land uses are further strained by locational shocks such as the energy transition, the Dutch housing crisis, and recent EU reforms to nitrogen derogation rules (van der Hoek, 2024), which limit manure application and increase costs and uncertainty in livestock-intensive regions. Together, these factors have contributed to sharp increases in land prices.

Rising agricultural land prices have important implications for the structure and competitiveness of the agricultural sector. Because land represents a primary production input and a major component of farm wealth, changes in land values affect farm expansion, entry opportunities for young farmers, and long-term investment decisions. When agricultural land prices increase faster than agricultural returns, farmland ownership becomes increasingly dependent on expectations about future land prices rather than current productive capacity, potentially altering incentives within agricultural land markets (Falk, 1991; Clark et al., 1993).

Capitalization of increasing land prices can also influence the adoption of regenerative and nature-based farming practices. These systems often require changes in land management, including investments in soil health, biodiversity enhancement, and ecosystem restoration, while associated benefits typically develop over longer time horizons. Higher agricultural land prices increase financial pressure on farmers, strengthening incentives to maximize short-term returns from land, and potentially reducing the attractiveness of practices with delayed economic benefits. Understanding the factors driving agricultural land prices is therefore important for assessing the economic conditions under which alternative farming systems can be adopted.

In general, the literature suggests that soil fertility, commodity prices, and crop input prices have been key determinants of land prices (Agosta et al., 2025). However, increasing opportunity costs of land, driven by energy development and urban expansion, have also influenced agricultural land prices in various parts of the world, including North America (Uematsu et al., 2013; Borchers et al., 2014; Cai et al., 2024), South America (Sills and Caviglia-Harris, 2009; Donoso et al., 2013), and Europe (Maddison, 2000; Sklenicka et al., 2013; Lehn and Bahrs, 2018; Tezcan et al., 2020). In the United States, farmland values increased at a compound annual growth rate of 5.8% during the period 2019–2024, or 2.0% in real terms after adjusting for inflation (Callahan, 2026).

Despite increasing public concern, there is limited empirical understanding of the specific drivers behind the increase in agricultural land prices in the Netherlands. Existing studies (Needham, 1992; Koomen et al., 2004; Diogo et al., 2015; Levkovich et al., 2018) often analyze aggregate trends without disentangling the relative contributions of parcel characteristics, soil characteristics, climate risk, regulatory pressure, competition from

alternative land uses, and price speculation. This study addresses this gap by quantifying the effects of these factors on agricultural land values over time using individual-level transaction data.

The objective of this study is to identify the factors that contribute to variation in agricultural land prices in the Netherlands and to examine how their importance differs across municipalities and over time. Building on a hedonic pricing framework, we link cadastral land price data to parcel characteristics, soil characteristics, climate risk, regulatory conditions, alternative land uses, and price speculation. The main contribution of this paper to the literature is twofold: first, we incorporate geospatial climate risk and soil quality data into the analysis of agricultural land prices; second, we study land prices at the individual parcel level using cadastral parcel data. As a robustness check, we also estimate a Manski model or a restricted Manski model to account for potential spatial dependence in agricultural land prices and observed covariates (Manski, 1993), and to assess whether spillover effects from nearby parcels are present. Hence, this study provides new evidence on the mechanisms driving the agricultural land market.

2 Literature Review

Land is often analyzed in the broader economics and finance literature as an asset whose value reflects expected future rents, conversion possibilities, and the option to wait before development. In the real-options tradition, Titman (1985) show that uncertainty can raise land prices because development is irreversible and owners may optimally delay conversion. Cunningham (2006) provide empirical support for this mechanism in a parcel-level study of the Seattle metropolitan area, where they test whether higher house-price uncertainty delays development and raises vacant land prices. More broadly, Shiller (2007) argues that housing markets are shaped by expectations, supply conditions, and market psychology rather than fundamentals alone. This perspective is useful for thinking about agricultural land markets as well, since land prices reflect expectations about future scarcity, urban development pressure, and speculative demand.

A second strand of the literature emphasizes land not only as a productive asset, but also as a financial object that affects collateral, debt capacity, and investment. Liu et al. (2013) argue that housing demand shocks can generate large land-price movements, and that when firms are borrowing constrained, these land-price changes feed into investment and generate broader macroeconomic fluctuations. Related evidence from Japan shows that collateral channels are important in transmitting shocks: Gan (2007) finds that declines in land-value substantially reduce firm debt capacity and corporate investment, while Kwon (1998) shows that monetary tightening lowers land prices and weakens collateral values. This is consistent with a=the financial accelerator mechanism in which declines in collateral values weaken borrowing capacity and thereby amplify shocks to investment and output. Rajan and Ramcharan (2015) provide similar evidence for U.S. agricultural land in the 1920s, showing that easier credit contributed to the land-price boom and that the subsequent tightening of credit made refinancing more difficult, which

helped push land prices downward. This broader finance literature is highly relevant for agricultural land markets, as it highlights the role of land as collateral and the potential for credit conditions to propagate through financial accelerator effects.

Agricultural land markets have traditionally been analyzed through the lens of agricultural productivity, but recent literature highlights the growing importance of spatial, regulatory, and socioeconomic factors in explaining farmland prices[1]. Agosta et al. (2025) provide a systematic review of agricultural land markets and identify intrinsic factors, such as soil fertility, water availability, and parcel characteristics, as well as extrinsic factors, such as urban pressure, demographic changes, and climate variation, as important determinants of farmland values. The authors note that only about 5% of the reviewed studies use cadastral parcel-level transaction data to analyze land prices. Since our study uses cadastral transaction data from the Netherlands, we aim to explain land prices, including any speculative component.

Several studies have examined agricultural land markets and land-use dynamics in the Netherlands using different methodological approaches. Needham (1992) develops a theoretical framework for studying Dutch land prices in publicly supplied land markets, emphasizing the role of institutional arrangements and land supply constraints. Koomen et al. (2004) use a land-use simulation model to analyze future agricultural land allocation, while Diogo et al. (2015) develop an economic theory-based modeling framework that explains agricultural land-use patterns through local utility maximization. More recently, Levkovich et al. (2018) apply a hedonic pricing approach to study the effect of spatial planning regulations on land values, focusing on zoning classifications and parcel characteristics. Although these studies provide important information on Dutch land markets, there is limited empirical evidence on how parcel and soil characteristics, regulatory pressure, competition from alternative land uses, and price speculation are jointly capitalized into agricultural transaction prices.

Hedonic pricing models are commonly used to estimate the implicit value of individual land characteristics and provide a suitable framework for analyzing these factors. Maddison (2000) applies a cross-sectional hedonic pricing model to agricultural land markets in England and Wales, examining how parcel characteristics, population density, soil classification, climate conditions, and elevation are capitalized on farmland values. Vural and Fidan (2009) also relies on cross-sectional variation to analyze agricultural land markets in Turkey, highlighting the importance of parcel and soil characteristics. Extending this approach to pooled cross-sectional datasets, Khan et al. (2015) analyze agricultural land prices in Pakistan during the period 2013-2015, controlling for locational, agricultural and environmental characteristics. Sheng et al. (2018) employ a pooled cross-sectional framework covering the period 2009-2011 to examine how improvements in transport infrastructure are reflected in farmland prices in Australia. Together, these studies demonstrate

[1]Land value refers to the appraised worth of land based on its physical characteristics, contextual factors, and income-generating potential, whereas land price is the actual amount agreed upon in a market transaction. The two may differ because transaction prices can reflect speculation, market distortions, and incomplete information (Agosta et al., 2025).

the applicability of hedonic pricing models that analyze how different land characteristics are reflected in agricultural land values.

Agricultural policies and regulatory changes represent another important determinant of farmland values, as policy incentives and restrictions can be capitalized on land prices. In the Netherlands, the phase-out of the EU derogation exemption under the Nitrates Directive started in 2022 and will be fully eliminated by 2026 (van der Hoek, 2024). The removal of this exemption lowers the amount of manure that dairy farmers can apply per hectare, potentially creating additional demand for agricultural land as farmers require more land to maintain existing livestock production levels.

In addition to policy developments, increasing competition for land from alternative uses has also been identified as an important determinant of agricultural land values. A large body of literature focuses on urbanization pressure and urban sprawl, measured through population density (Lehn and Bahrs, 2018; De Noni et al., 2019b), distance or travel time to urban centers (Sklenicka et al., 2013; Delbecq et al., 2014; Lehn and Bahrs, 2018; Wineman and Jayne, 2018; **?**), and urban-rural classifications (Uematsu et al., 2013; Chen et al., 2018). This source of land-use competition is particularly relevant in the Netherlands, where limited land availability and high population density create strong competition between agricultural and urban land uses.

The transition to green energy represents another source of alternative land-use pressure, as agricultural land is increasingly considered for renewable energy production. Haberl et al. (2014) highlight land-use competition from bioenergy production, while Tsai et al. (2019) and Lee et al. (2021) examine how the expansion of solar energy production can affect agricultural land values. This is increasingly relevant as renewable energy targets create additional demand for land suitable for energy infrastructure.

The literature on agricultural land prices contains relatively limited work that explicitly utilizes geospatial data. Agosta et al. (2025) find that only 2% of the publications in their systematic review include geospatial factors, although several studies (Bastian et al., 2002; Samarasinghe and Greenhalgh, 2013; De Noni et al., 2019a; Giuffrida et al., 2023) estimate spatial econometric hedonic pricing models, building on the framework of Manski (1993); Anselin (1988); Kelejian and Prucha (1998); Elhorst (2010). These approaches are motivated by the fact that nearby parcels may display similar prices or be affected by shared local shocks, implying spatial autocorrelation and potential spillover effects. This is especially relevant in settings with geospatial data, where distance, neighborhood structure, and local market conditions can be incorporated through a spatial weights matrix.

This paper contributes to the literature on land prices in two ways. First, we utilize cadastral parcel-level data on agricultural land prices in the Netherlands to perform a pooled cross-sectional hedonic pricing model. This framework allows us to examine how parcel characteristics, soil characteristics, climate risk, regulatory pressure, and alternative land use affect farmland values. Second, the study incorporates geospatial data on soil quality and climate risk at the parcel level, allowing us to account for parcel-level heterogeneity in these factors and to better identify their contribution to farmland prices.

3 Theoretical Framework

Agricultural land is a heterogeneous asset whose land price reflects the discounted stream of expected future returns generated by its underlying characteristics. Under hedonic pricing theory, land is viewed as a bundle of productive, environmental, and locational attributes that are capitalized into market prices. Buyers therefore bid not only for the land itself but also for the characteristics that determine its expected profitability.

The productive capacity of farmland depends on its underlying natural capital. Soil quality influences agricultural productivity through fertility, nutrient availability, drainage, and water retention capacity, while hydrological conditions determine exposure to drought and waterlogging. Because these characteristics affect expected yields and production risk, they are expected to be reflected in farmland prices.

Farmland prices are also influenced by competing land uses. Urban expansion, population growth, and renewable energy development increase the opportunity cost of agricultural land by creating alternative uses that may generate higher economic returns. Expectations regarding future conversion opportunities therefore increase demand for strategically located parcels and may be capitalized into agricultural land prices.

Government regulation may alter the price of agricultural land by changing production constraints and expected future returns. Policies that increase the scarcity of productive land or raise the demand for additional acreage among agricultural producers are expected to affect land prices through capitalization of anticipated future profits.

In addition to fundamental determinants, farmland prices may also reflect extrapolative expectations. When market participants expect recent price appreciation to continue, past price growth may itself stimulate current demand, leading prices to deviate from values implied solely by productive fundamentals. Such feedback mechanisms have been documented in asset markets and may also arise in agricultural land markets.

These considerations motivate an empirical specification in which farmland prices are modeled as a function of productive characteristics, environmental conditions, regulatory exposure, competing land uses, and market expectations.

4 Methods

Building on the hedonic pricing framework, which assumes that agricultural land prices reflect the capitalization of underlying land attributes, we empirically estimate the determinants of farmland prices using repeated cross-sectional data on agricultural land transactions in the Netherlands. Since individual parcels are not repeatedly observed over time, we estimate a pooled cross-sectional ordinary least squares (OLS) model with municipality and year fixed effects. This approach allows us to examine how the variation in parcel characteristics, soil characteristics, regulatory pressure, competing land uses, and market expectations is reflected in observed cadastral transaction prices. The baseline specification is given by

$$\ln(P_{imrt}) = \alpha + \beta L_i + \gamma S_i + \phi R_i + \theta C_{mt} + \lambda E_{mt} + \rho U_{mt} + \tau D_i + \eta \Delta \ln(\bar{P}_{r,t-1}) + \mu_m + \delta_t + \varepsilon_{imrt}, \tag{1}$$

where P_{imrt} denotes the transaction price per hectare of agricultural parcel i in municipality m in COROP region r and year t.

4.1 Parcel characteristics

The vector L_i contains parcel-level characteristics, including parcel size and parcel size squared. Parcel size and its squared term capture the nonlinear relationship between parcel size and land prices, allowing us to assess potential economies of scale. Following Ritter et al. (2020), we adopt a log-linear-squared functional form. Other parcel-level characteristics include buyer and seller type, but this data will be obtained from the cadastral parcel transaction data.

4.2 Soil characteristics

Similar to Vural and Fidan (2009), the vector S_i contains parcel-level soil characteristics, including clay content (g/kg), silt content (g/kg), sand content (g/kg), soil organic carbon (dg/kg), pH level (pH $\times$ 10), and total nitrogen (cg/kg) in the top 0 to 30 cm of the soil. These variables capture time-invariant differences in the biophysical quality of land across parcels and are included as baseline controls in the hedonic specification. The soil variables are derived from SoilGrids, which provides modeled estimates of soil properties based on available soil observations and environmental covariates. As such, the SoilGrids variables should be interpreted as proxy measures of underlying baseline soil chemistry and physical conditions rather than as direct time-varying observations of management-induced soil changes. Soil texture, measured through the relative shares of clay, silt, and sand, influences water retention, drainage capacity, nutrient availability, and the suitability of the land for different agricultural activities (Joshi et al., 2026). The soil organic carbon captures the fertility of the soil by improving nutrient cycling, water-holding capacity, and soil structure, increasing the productive capacity of agricultural land (Lal, 2016). The pH level measures soil acidity and affects nutrient availability and crop growth conditions (Barrow and Hartemink, 2023). Finally, total nitrogen captures the major forms of nitrogen present in the soil and is a key driver of leaf and stem growth in plants (Novoa and Loomis, 1981). Together, these soil characteristics represent the natural productive capacity of agricultural land and are therefore expected to be capitalized into farmland prices.

4.3 Climate risk

The vector R_i captures parcel-level drought- and waterlogging risk. It includes the variables GLG_i, GLG_i^2, GHG_i, and GHG_i^2, where GLG denotes the average lowest ground-

water levels (in centimeters) and GHG stands for the average highest groundwater levels (in centimeters). We expect a nonlinear relationship between land prices and groundwater levels because the marginal effects of GLG and GHG are unlikely to be constant across their ranges. Very dry conditions can reduce crop productivity through water stress, while very wet conditions can lower productivity through waterlogging and poor soil aeration. As a result, land prices may respond more strongly at extremes than would be implied by a simple linear specification. The drought risk (GLG) is measured by the 30-year average of LG3, where LG3 is defined as the average of the three lowest groundwater levels in a hydrological year, measured in centimeters[2], while a sampling frequency of twice per month, approximately on the 14th and the 28th. The waterlogging risk (GHG) is measured analogously as the 30-year average of HG3, where HG3 is defined as the average of the three highest groundwater levels in a hydrological year, also measured in centimeters and observed twice per month.

4.4 Regulatory pressure

The variable C_{mt} captures heterogeneous exposure to the manure derogation phase-out. We exploit municipality variation in exposure to the policy using a continuous difference-in-differences specification, where municipalities with higher pre-policy cow density are expected to be more exposed to the regulatory change. The interaction term compares changes in agricultural land prices after the policy change across municipalities with different levels of pre-policy cow density and is defined as:

$$C_{mt} = Post2022_t \times CowDensity_m, \tag{2}$$

where $Post2022_t$ equals one after the start of the manure derogation phase-out and zero otherwise. The density of cows at the municipal level is measured using livestock density in 2020 prior to the policy change and is defined as

$$CowDensity_m = \frac{Cows_{m,2020}}{AgriLand_{m,2020}}, \tag{3}$$

where $Cows_{m,2020}$ is the number of cows in municipality m in 2020 and $AgriLand_{m,2020}$ is the total agricultural area in hectares in 2020.

A key assumption in our continuous difference-in-differences specification is that municipalities with different levels of pre-policy cow density would have followed parallel price trends in the absence of the manure derogation phase-out. Since the treatment variable cow density is continuous, we assess this assumption using an event study specification that interacts $CowDensity_m$ with year indicators. The pre-policy coefficients provide a direct check for differential trends before 2022.

We estimate the following event study specification:

[2]It is the distance from the ground surface to the groundwater level.

$$\ln(P_{imt}) = \alpha + \sum_{\tau \neq 2021} \beta_\tau \left(\mathbb{1}[t = \tau] \times CowDensity_m \right) + \mu_m + \delta_t + X'_{imt}\gamma + \varepsilon_{imt}, \quad (4)$$

where 2021 is the omitted reference year. If the parallel trends assumption holds, the coefficients for the pre-policy years should be statistically indistinguishable from zero. Based on our hypothesis, we expect the post-2021 coefficients to be positive, indicating stronger price increases in municipalities with higher pre-policy cow density after the phase-out of the derogation.

The variable $D_{1,i}$ captures parcel-level spatial exposure and is time-invariant. It represents the distance from parcel i to the nearest Natura 2000 region, reflecting potential regulatory pressure as well as the risk of biodiversity impacts. Parcels located closer to Natura 2000 regions may face stronger regulatory pressure and may be associated with a higher likelihood of biodiversity harm. The variable $D_{1,i}$ is included in the vector D_i.

4.5 Land competition

The vector E_{mt} captures competing land demand associated with solar and wind development, using measures of municipal solar and wind energy intensity. Increasing solar and wind deployment may affect agricultural land prices through higher demand for land from energy-related uses, particularly nonresidential solar capacity and wind power infrastructure. Municipalities with a higher solar capacity or a greater density of wind turbines may therefore experience stronger competition between agricultural production and renewable energy installation.

Nonresidential solar capacity density is defined as

$$SolarCapacityDensity_{mt} = \frac{InstalledSolarCapacity_{mt}^{nonresidential}}{MunicipalityArea_m}, \quad (5)$$

where $InstalledSolarCapacity_{mt}^{nonresidential}$ denotes the installed non-residential solar capacity measured in kilowatts in municipality m and year t, and $MunicipalityArea_m$ denotes the total area of the municipality measured in hectares.

Wind turbine density is defined as

$$WindTurbineDensity_{mt} = \frac{NumberOfWindTurbines_{mt}}{MunicipalityArea_m}, \quad (6)$$

where $NumberOfWindTurbines_{mt}$ denotes the total number of wind turbines installed in municipality m and year t, and $MunicipalityArea_m$ denotes the total area of the municipality measured in hectares.

Due to data availability limitations, the solar capacity variable captures total nonresidential solar deployment rather than exclusively utility-scale solar parks located on agricultural land. As a result, this measure should be interpreted as a broader indicator of solar development pressure rather than a direct measure of agricultural land conversion for solar energy production.

Similar to Lehn and Bahrs (2018), the variable U_{mt} is the population density in municipality m in year t, measured as the total number of inhabitants divided by the municipality's total surface area. It is a proxy for the municipality-level urbanization pressure and competing demand for land for residential, commercial, and infrastructure development. Higher population density may increase the price of agricultural land by increasing the expectation of future development opportunities.

The variable $D_{2,i}$ captures parcel-level spatial exposure and is time-invariant. Following a similar specification as in Delbecq et al. (2014) and Lehn and Bahrs (2018), it represents the distance from parcel i to the nearest urban center, reflecting accessibility to urban markets and conversion pressure from nearby development. Parcels located closer to urban centers may face stronger conversion pressure and greater demand from competing land uses. The variable $D_{2,i}$ is included in vector D_i.

4.6 Financial speculation on land

To account for financial acceleration and feedback effects in agricultural land markets, the empirical specification includes lagged regional price growth, $\Delta \ln(\bar{P}_{r,t-1}) = \ln(\bar{P}_{r,t-1}) - \ln(\bar{P}_{r,t-2})$, as an additional explanatory variable. This term proxies for extrapolative expectations, capturing the extent to which current land prices may respond to recent appreciation in the local market rather than only to parcel characteristics, soil characteristics, and other observed fundamentals, in a manner similar to Shiller (2007). A positive coefficient on this variable would indicate that recent price increases are capitalized into current land prices, consistent with a feedback mechanism in which past price growth reinforces subsequent demand and further price appreciation. Macroeconomic financial conditions, such as interest rates, are absorbed by the year fixed effects because they do not vary across municipalities.

4.7 Fixed effects

Municipality fixed effects, μ_m, control for time-invariant differences between municipalities, including persistent differences in geography, agricultural specialization, and local land market conditions. Year fixed effects, δ_t, absorb national shocks common to all municipalities, such as inflation, interest rates, agricultural commodity prices, and aggregate land price trends. The main effects of $Post2022_t$ and $CowDensity_m$ are absorbed by the year- and municipality fixed effects, respectively. The error term is denoted by ϵ_{imt}. Standard errors are clustered at the municipality level.

The study provides an assessment of the determinants of agricultural land price dynamics in the Netherlands. By quantifying how parcel characteristics, soil characteristics, climate risk, regulatory pressure, competition from alternative land uses, and financial speculation are reflected in land prices, the research provides insights into the economic forces shaping agricultural land markets.

4.8 Robustness

To account for potential spatial dependence in agricultural land prices, we estimate a Spatial Durbin Model (SDM) as a robustness check (Anselin, 1988). The SDM is a highly attractive specification because it simultaneously captures endogenous interaction effects (via the spatial lag of the dependent variable) and exogenous interaction effects (through the spatial lags of the covariates). The SDM specification is given by:

$$\ln(P_{imrt}) = \rho W_t \ln(P_{imrt}) + \beta X_{imrt} + \theta W_t X_{imrt} + \mu_m + \delta_t + \varepsilon_{imrt}, \tag{7}$$

where the dependent variable is allowed to depend on a spatially lagged version of itself. The coefficient ρ captures the degree of endogenous interdependence in land prices across nearby parcels. Here, W_t denotes the spatial weights matrix in year t, which defines the relevant neighborhood structure and assigns weights to nearby observations. The vector X_{imrt} contains all covariates included in the baseline hedonic specification (1), and the associated coefficients β measure their direct effects on land prices. The term $W_t X_{imrt}$ includes the spatial lags of these regressors, with coefficients θ, allowing characteristics of neighboring parcels or surrounding areas to affect the price of a given parcel. By explicitly modeling both the spatial lag of the dependent variable and the spatial lags of the covariates, the SDM absorbs unobserved spatial processes, including irrigation access, water availability, or clustered profitability shocks (e.g., pests or disease), thereby mitigating omitted variable bias.

5 Data

This study constructs a pooled cross-sectional dataset of agricultural land transactions in the Netherlands by combining cadastral parcel transaction data with parcel, geospatial, municipal, and regional level data. The parcel-level data includes parcel characteristics and the distance from the parcel to the nearest city and nearest Natura 2000 area. The geospatial-level data consists of soil characteristics and climate risk measures. The municipality-level data comprises cow density in 2020, biodiversity density over the past 70 years, as well as wind turbine density, solar capacity density, and population density for the period 2012 to 2025. The regional level data includes extrapolative expectations of land prices. Each observation in the dataset corresponds to an individual agricultural land transaction i observed in municipality m and region r in year t. The dataset includes 342 municipalities and 40 regions and covers the period 2012-2025.

5.1 Parcel-level data

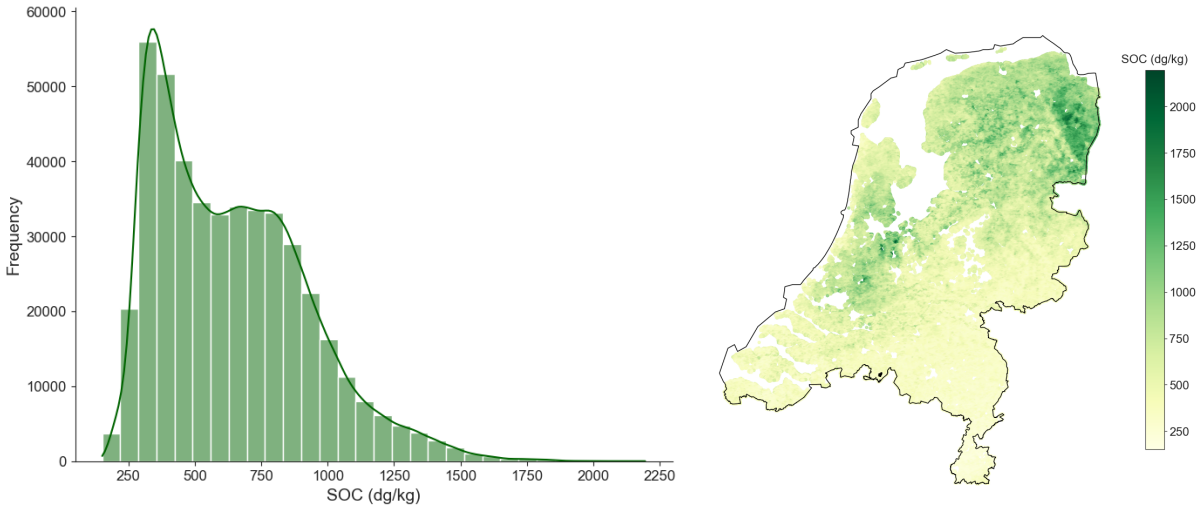
Cadastral parcel transaction data will be obtained from the Kadaster and include agricultural land prices, parcel size, and transaction-specific characteristics. Land prices are measured as the natural logarithm of transaction prices per hectare.

The distance to the nearest city will be calculated as the shortest absolute distance from each sold parcel to the nearest city with at least 10,000 inhabitants. The distance to the nearest Natura 2000 region will be calculated as the shortest absolute distance from each sold parcel to the nearest Natura 2000 region. These calculations will be performed in QGIS once the cadastral transaction data have been obtained.

5.2 Geospatial-level data

Soil characteristics, including clay, silt, and sand content, as well as organic carbon, pH, and nitrogen in the soil, were obtained from SoilGrids, which uses a digital soil mapping approach based on Quantile Random Forest trained on approximately 230,000 global soil profile observations to generate soil property estimates at a spatial resolution of 250 meters. The geospatial-level data is considered time-invariant. Figure 1 presents the concentration of soil organic carbon content (fine earth fraction) in dg/kg at a depth level of 0-30cm.

Figure 1: SOC concentration on agricultural land

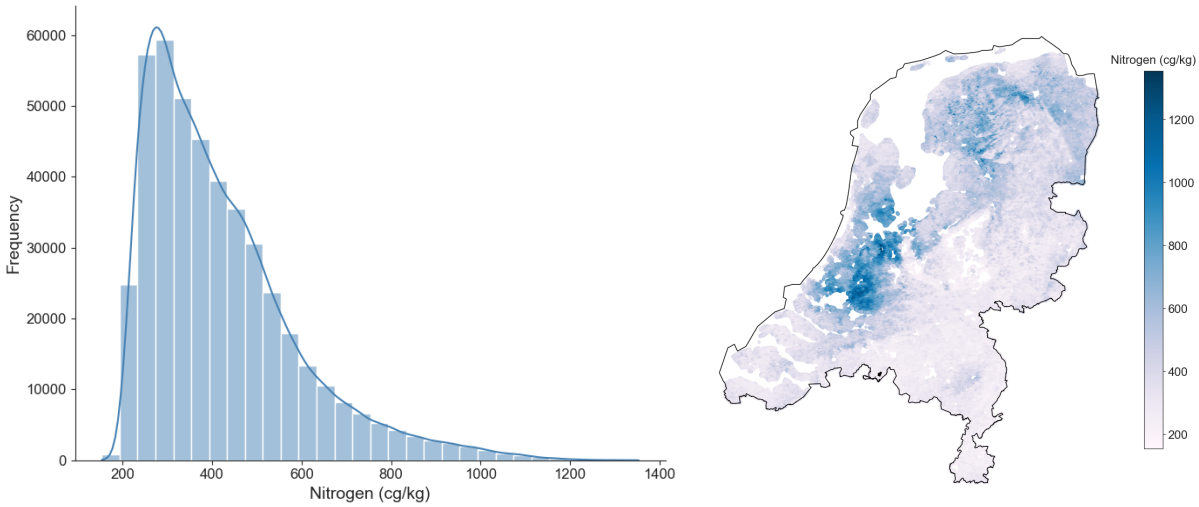


(a) SOC distribution

(b) SOC map

Figure 2 displays the total nitrogen in cg/kg at a depth level of 0-30cm.

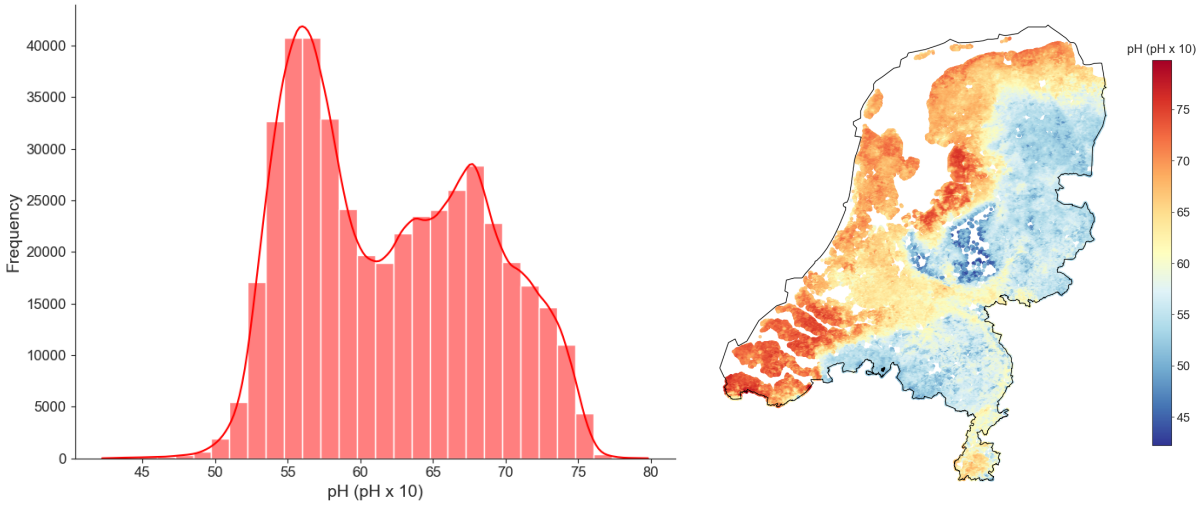
Figure 2: Nitrogen concentration on agricultural land



(a) Nitrogen distribution (b) Nitrogen map

Figure 3 shows soil pH in water measured in pH x 10 (to convert to pH values divide by 10) at a depth level of 0-30cm.

Figure 3: pH concentration on agricultural land

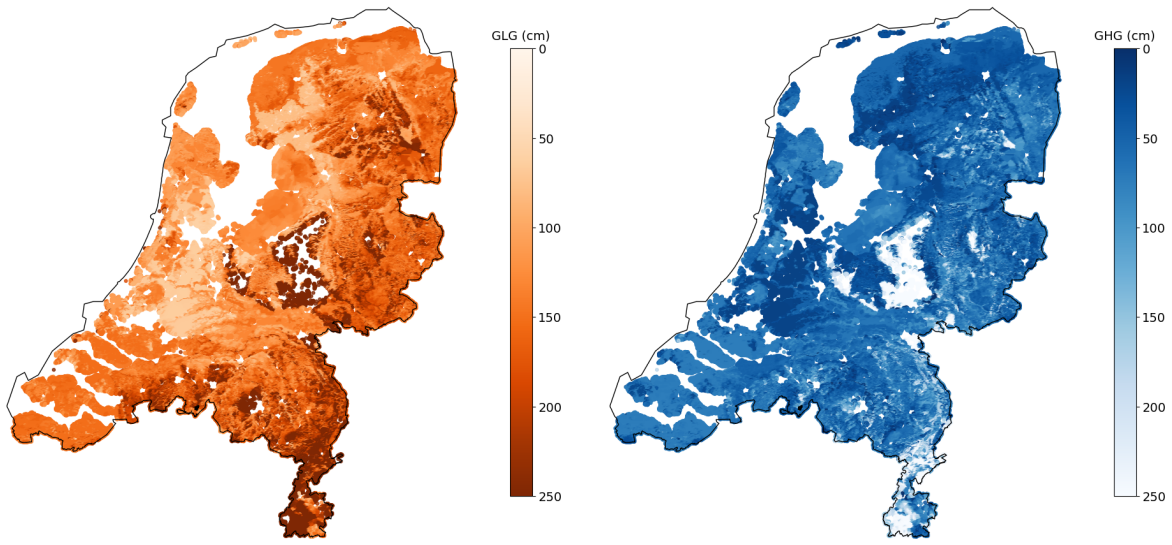


(a) pH distribution (b) pH map

Climate risk is examined by exploiting the geospatial variation in GLG and GHG to capture drought and waterlogging risk, respectively. The data on GLG and GHG are from the Bodemkaart, which is compiled by Wageningen Environmental Research. Figure 4 presents drought and waterlogging risks in the Netherlands, based on estimates of GLG and GHG from a groundwater dynamics model (De Gruijter et al., 2004). GLG and GHG are measured in centimeters. Darker colors indicate higher risk in both maps.

Table 1 presents descriptive statistics for the geospatial variables capturing soil characteristics and climate risk. When we obtain the individual transaction data, we will link

Figure 4: Climate risk on agricultural land



(a) Drought risk

(b) Waterlogging risk

each sold parcel to the parcel- and soil characteristics in the spatial dataset.

Table 1: Descriptive statistics of geospatial data

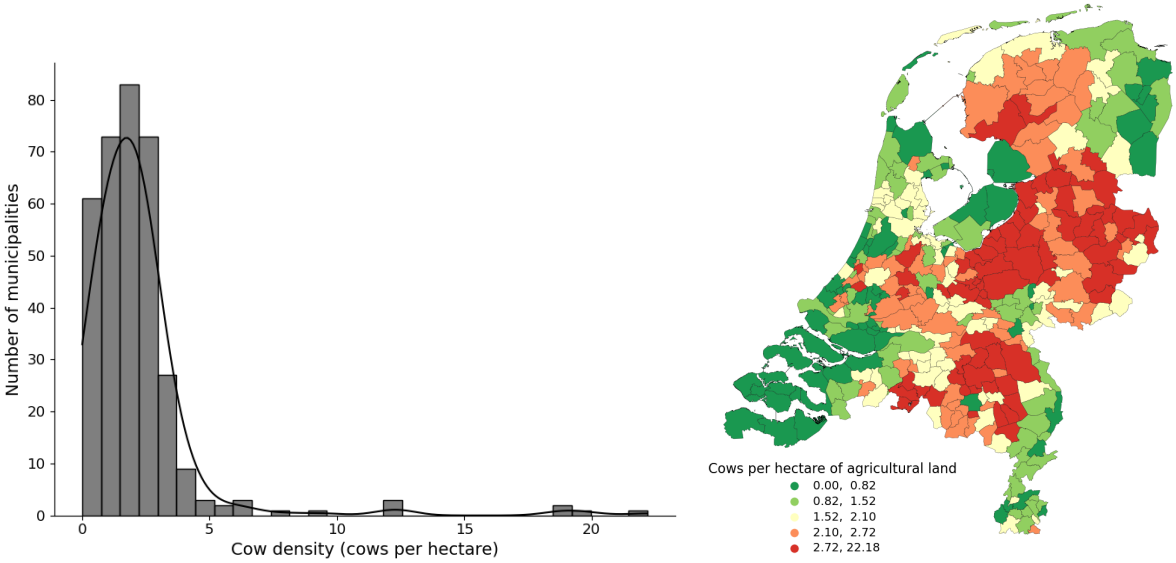
Variable	Count	Mean	Median	Std. dev.	Min.	Max.
Sand (g/kg)	448,459	460.14	418.91	235.22	32.52	935.89
Silt (g/kg)	448,459	320.27	327.00	132.57	18.59	779.26
Clay (g/kg)	448,459	219.40	234.13	112.64	27.49	629.85
Nitrogen (cg/kg)	448,459	420.75	380.16	169.19	153.63	1,353.37
pH (pH × 10)	448,459	62.09	61.55	6.44	42.21	79.80
SOC (dg/kg)	448,459	637.78	596.88	284.50	150.93	2,195.16
GLG (cm)	448,459	143.62	140.00	45.32	0.00	254.00
GHG (cm)	448,459	61.88	56.00	38.83	0.00	254.00

5.3 Municipality-level data

To measure the regulatory pressure from the phase-out of the EU manure derogation policy in the Netherlands, we use data from Statistics Netherlands (CBS). The policy indicator is constructed as a dummy variable equal to one from 2022 onward, capturing the announcement and implementation period of the gradual reduction of the derogation rule. To measure differences in exposure to this policy change between municipalities, we construct a measure of cow density using agricultural structure data obtained from Statistics Netherlands (CBS). Cow density is defined as the number of cows per hectare of agricultural land in each municipality. Data on the number of cows and the total agricultural land area are collected annually and linked to each agricultural land trans-

action based on municipality and year. Figure 5a shows a histogram of the number of cows per hectare of agricultural land in the Netherlands. Figure 5b presents the spatial distribution of cows per hectare of agricultural land, classified into five quantiles across the Netherlands.

Figure 5: Cow density by municipality in 2020



(a) Cow density distribution

(b) Cow density map

The pressure from alternative land uses arises from both the transition to renewable energy and increasing urbanization pressure. To capture the renewable energy transition, we obtain data on renewable energy developments from Statistics Netherlands (CBS) and Windstats. For each municipality, we use the number of wind turbines and non-residential solar capacity over the period 2012 to 2025, and divide these by the total municipal surface area in square kilometers to construct wind turbine density and solar capacity density measures.

Urbanization pressure is measured at the municipality level using the number of inhabitants and municipal surface area, obtained from Statistics Netherlands (CBS). Table 2 reports descriptive statistics for the municipality-level variables. When we obtain the individual transaction data, we will merge the individual transaction data with the corresponding municipality-level data.

Table 2 reports descriptive statistics for the municipality-level variables capturing regulatory pressure and land competition. These characteristics will subsequently be merged with the parcel-level transaction data.

5.4 Regional-level data

The lagged regional price growth variable is constructed from transaction-level data that are currently being obtained. First, average land prices are calculated at the regional

Table 2: Descriptive statistics of municipality-level data

Variable	Observations	Mean	Median	Std	Min	Max
Cow density (cows/ha)	342	2.17	1.85	2.51	0.00	22.18
Wind density (wind turbines/km^2)	4,788	0.04	0.00	0.11	0.00	1.29
Solar density (kw capacity/km^2)	4,736	207.70	70.80	324.29	0.00	4,293.55
Population density (people/km^2)	8,208	874.86	459.88	1,028.89	22.69	6,900.49

level for each period. The variable is then measured as the difference in the logarithm of average regional land prices between two consecutive lagged periods. This variable captures recent price developments in the local land market.

6 Results

We are still working on the results.

7 Conclusion

8 Acknowledgement

This research was conducted in collaboration with ReGeNL, a consortium in the Netherlands focused on research into the potential of regenerative agriculture. The authors declare no other financial relationships or conflicts of interest.

Table 3: Data description

Variable	**Variable type**	**Level**	**Unit**	**Motivation**	**Source**
Land price	Continuous	Individual	ln(€/ha)	Dependent var	Kadaster
Parcel size	Continuous	Individual	ha	Economies of scale	Kadaster
Clay content	Continuous	Individual	g/kg	Soil characteristics	SoilGrids
Silt content	Continuous	Individual	g/kg	Soil characteristics	SoilGrids
Sand content	Continuous	Individual	g/kg	Soil characteristics	SoilGrids
Soil organic carbon	Continuous	Individual	dg/kg	Soil characteristics	SoilGrids
pH	Continuous	Individual	Index	Soil characteristics	SoilGrids
Nitrogen	Continuous	Individual	cg/kg	Soil characteristics	SoilGrids
GHG (Average highest water depth)	Continuous	Individual	cm	Waterlogging risk	Bodemdata
GLG (Average lowest water depth)	Continuous	Individual	cm	Drought risk	Bodemdata
Biodiversity per municipality	Continuous	Municipalicy	ct/km^2	Biodiversity measure	Laudius
Distance to Nature 2000	Continuous	Individual	km	Regulatory pressure / biodiversity risk	Calculation
EU manure derogation rule	Dummy	Municipality	Indicator	Regulatory pressure	Policy year
Number of cows	Continuous	Municipality	count	Regulatory pressure	CBS
Agricultural land	Continuous	Municipality	ha	Regulatory pressure	CBS
Nonresidential solar capacity	Continuous	Municipality	kW	Land competition	CBS
Number of wind turbines	Continuous	Municipality	count	Land competition	CBS
Distance to city	Continuous	Individual	km	Land competition	Calculation
Population density	Continuous	Municipality	people/km^2	Land competition	CBS

References

Agosta, M., Schimmenti, E., Di Franco, C. P., and Asciuto, A. (2025). Agricultural land markets: a systematic literature review on the factors affecting land prices. *Land*, 14(5):978.

Anisimov, O. (2026). Revisiting land banking in the era of land scarcity. *European Journal of Spatial Development*, 23(6).

Anselin, L. (1988). *Spatial econometrics: methods and models*, volume 4. Springer Science & Business Media.

Barrow, N. and Hartemink, A. E. (2023). The effects of ph on nutrient availability depend on both soils and plants. *Plant and Soil*, 487(1):21–37.

Bastian, C. T., McLeod, D. M., Germino, M. J., Reiners, W. A., and Blasko, B. J. (2002). Environmental amenities and agricultural land values: a hedonic model using geographic information systems data. *Ecological economics*, 40(3):337–349.

Borchers, A., Ifft, J., and Kuethe, T. (2014). Linking the price of agricultural land to use values and amenities. *American journal of agricultural economics*, 96(5):1307–1320.

Cai, X., Volpe, R., and Barraza, F. (2024). Farmland values in california. *Journal of ASFMRA*, pages 17–29.

Callahan, S. (2026). Land use, land value & tenure – farmland value. Retrieved August 10, 2026, from `https://ers.usda.gov/topics/farm-economy/land-use-land-value-tenure/farmland-value`.

Chen, Y.-H., Lee, C.-L., Chen, G.-R., Wang, C.-H., and Chen, Y.-H. (2018). Factors causing farmland price-value distortion and their implications for peri-urban growth management. *Sustainability*, 10(8):2701.

Clark, J. S., Fulton, M., and Scott Jr, J. T. (1993). The inconsistency of land values, land rents, and capitalization formulas. *American Journal of Agricultural Economics*, 75(1):147–155.

Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: Evidence for real options in seattle. *Journal of Urban Economics*, 59(1):1–31.

De Gruijter, J., van der Horst, J., Heuvelink, G., Knotters, M., and Hoogland, T. (2004). Grondwater opnieuw op de kaart; methodiek voor de actualisering van grondwaterstandsinformatie en perceelsclassificatie naar uitspoelingsgevoeligheid voor nitraat.

De Noni, I., Ghidoni, A., Menzel, F., Bahrs, E., Corsi, S., et al. (2019a). Exploring drivers of farmland value and growth in italy and germany at regional level. *Aestimum*, 74:77–99.

De Noni, I., Orsi, L., and Belussi, F. (2019b). Exploring drivers of farmland value and growth in italy and germany at regional level. *Aestimum*, 74:77–99.

Delbecq, B. A., Kuethe, T. H., and Borchers, A. M. (2014). Identifying the extent of the urban fringe and its impact on agricultural land values. *Land Economics*, 90(4):587–600.

Diogo, V., Koomen, E., and Kuhlman, T. (2015). An economic theory-based explanatory model of agricultural land-use patterns: The netherlands as a case study. *Agricultural Systems*, 139:1–16.

Donoso, G., Cancino, J., Olguín, R., and Schönhaut, D. (2013). A comparison of farmland value determinants in chile between 1978-1998 and 1999-2008. *International Journal of Agriculture and Natural Resources*, 40(1):85–96.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial economic analysis*, 5(1):9–28.

Eurostat (2025). Agricultural land prices and rents – statistics. Retrieved October 27, 2025, from `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agricultural_land_prices_and_rents_-_statistics`.

Falk, B. (1991). Formally testing the present value model of farmland prices. *American Journal of Agricultural Economics*, 73(1):1–10.

Gan, J. (2007). Collateral, debt capacity, and corporate investment: Evidence from a natural experiment. *Journal of Financial Economics*, 85(3):709–734.

Giuffrida, L., De Salvo, M., Manarin, A., Vettoretto, D., and Tempesta, T. (2023). Exploring farmland price determinants in northern italy using a spatial regression analysis. *Aestimum*, 83:3–20.

Gomiero, T. (2016). Soil degradation, land scarcity and food security: Reviewing a complex challenge. *Sustainability*, 8(3):281.

Haberl, H., Mbow, C., Deng, X., Irwin, E. G., Kerr, S., Kuemmerle, T., Mertz, O., Meyfroidt, P., and Turner, B. (2014). Finite land resources and competition. *Rethinking global land use in an urban era*, 14:35–69.

Joshi, N., Kaur, R., Fahad, S., and Nawaz, T. (2026). Effects of soil texture and structure on nutrient chemistry and plant uptake. In *Sustainable Soil Chemistry and Plant Nutrition*, pages 251–270. Elsevier.

Kelejian, H. H. and Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The journal of real estate finance and economics*, 17(1):99–121.

Khan, S., Ali, G., Shah, S. A., Jan, A. U., Jan, D., and Fayaz, M. (2015). A hedonic analysis of agricultural land prices in pakistan's peshawar district. *Asian Journal of Agriculture and Rural Development*, 6(4):59–67.

King, R., Benton, T., Froggatt, A., Harwatt, H., Quiggin, D., and Wellesley, L. (2023). The emerging global crisis of land use. *How rising competition for land threatens international and environmental stability, and how the risks can be mitigated, Report. Royal Institute of International Affairs*.

Koomen, E. et al. (2004). Simulating the future of agricultural land use in the netherlands. *Economische en Sociale Geografie*, 96(2):218–224.

Kwon, E. (1998). Monetary policy, land prices, and collateral effects on economic fluctuations: evidence from japan. *Journal of the Japanese and International Economies*, 12(3):175–203.

Lal, R. (2016). Soil health and carbon management. *Food and energy security*, 5(4):212–222.

Lambin, E. F. and Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the national academy of sciences*, 108(9):3465–3472.

Lee, B., Chang, H.-H., and Wang, S.-Y. (2021). Solar power promotion plans, energy market liberalization, and farmland prices–empirical evidence from taiwan. *Energy Economics*, 99:105317.

Lehn, F. and Bahrs, E. (2018). Analysis of factors influencing standard farmland values with regard to stronger interventions in the german farmland market. *Land Use Policy*, 73:138–146.

Levkovich, O., Rouwendal, J., and Brugman, L. (2018). Spatial planning and segmentation of the land market: the case of the netherlands. *Land Economics*, 94(1):137–154.

Liu, Z., Wang, P., and Zha, T. (2013). Land-price dynamics and macroeconomic fluctuations. *Econometrica*, 81(3):1147–1184.

Maddison, D. (2000). A hedonic analysis of agricultural land prices in england and wales. *European Review of Agricultural Economics*, 27(4):519–532.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542.

Needham, B. (1992). A theory of land prices when land is supplied publicly: the case of the netherlands. *Urban Studies*, 29(5):669–686.

Novoa, R. and Loomis, R. (1981). Nitrogen and plant production. *Plant and soil*, 58(1):177–204.

Rajan, R. and Ramcharan, R. (2015). The anatomy of a credit crisis: The boom and bust in farm land prices in the united states in the 1920s. *American Economic Review*, 105(4):1439–1477.

Ritter, M., Hüttel, S., Odening, M., and Seifert, S. (2020). Revisiting the relationship between land price and parcel size in agriculture. *Land Use Policy*, 97:104771.

Samarasinghe, O. and Greenhalgh, S. (2013). Valuing the soil natural capital: a new zealand case study. *Soil Research*, 51(4):278–287.

Sheng, Y., Jackson, T., and Lawson, K. (2018). Evaluating the benefits from transport infrastructure in agriculture: a hedonic analysis of farmland prices. *Australian Journal of Agricultural and Resource Economics*, 62(2):237–255.

Shiller, R. J. (2007). Understanding recent trends in house prices and home ownership.

Sills, E. O. and Caviglia-Harris, J. L. (2009). Evolution of the amazonian frontier: Land values in rondônia, brazil. *Land use policy*, 26(1):55–67.

Sklenicka, P., Molnarova, K., Pixova, K. C., and Salek, M. E. (2013). Factors affecting farmland prices in the czech republic. *Land Use Policy*, 30(1):130–136.

Tezcan, A., Büyüktaş, K., and Aslan, Ş. T. A. (2020). A multi-criteria model for land valuation in the land consolidation. *Land use policy*, 95:104572.

Titman, S. (1985). Urban land prices under uncertainty. *The American Economic Review*, 75(3):505–514.

Tsai, Y.-H., Lin, T.-C., Lin, S.-Y., van Gasselt, S., Chen, C.-L., Hsu, C.-H., Lin, K.-Y., Liu, C.-H., Tsai, M.-C., and Xie, Z.-S. (2019). The effects of green energy production on farmland: A case study in yunlin county, taiwan. In *Land Use Change and Sustainability*. IntechOpen.

Uematsu, H., Khanal, A. R., and Mishra, A. K. (2013). The impact of natural amenity on farmland values: A quantile regression approach. *Land Use Policy*, 33:151–160.

van der Hoek, M. (2024). Dutch loss of manure derogation. USDA Voluntary Report.

Vural, H. and Fidan, H. (2009). Land marketing and hedonic price model in turkish markets: Case study of karacabey district of bursa province. *African Journal of Agricultural Research*, 4(2):71–75.

Wineman, A. and Jayne, T. S. (2018). Land prices heading skyward? an analysis of farmland values across tanzania. *Applied Economic Perspectives and Policy*, 40(2):187–214.