Impact of Land Subsidence on Housing Sale Values: Evidence from the San Joaquin Valley, California

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ABSTRACT *This study assesses the impact of land subsidence on housing sale values in the San Joaquin Valley, California. The study uses home sale transactions and vertical land-surface displacement data from interferometric synthetic aperture radar techniques. Using fine-scale fixed effects, matching, and a repeat-sales approach, our results indicate that land subsidence resulted in a 2.4%–5.8% reduction in housing sale values, with the largest reductions occurring in areas where substantial subsidence occurred. Such findings may have implications for groundwater management and can potentially help inform policy design to mitigate the causes and impacts of land subsidence.* (JEL R21, Q51)

1. Introduction

Land subsidence (LS) is defined as the gradual settling or sudden sinking of land surface that is caused mainly by removing groundwater from aquifer systems of certain hydrogeological settings (Bagheri-Gavkosh et al. 2021). Direct impacts include infrastructure damage and reduced storage capacity of the affected aquifer system. Indirect impacts include increased flood risk (frequency, depth, duration), which is further exacerbated in coastal regions because of sea-level rise; alteration of natural environments, such as wetlands, riparian corridors, stream gradients, and water depths and temperatures; and ground failures (fissures), which can damage infrastructure as well as provide direct pathways for contaminant-laden surface water to reach groundwater (Dixon et al. 2006; Mazzotti et al. 2009; Minderhoud et al. 2020; Dinar et al. 2021; Kok and Costa 2021; Josset et al. 2024).

Most known studies to date, and an increasing rate of publication in recent years, have focused on global estimates (Wu, Wei, and D'Hondt 2022) and local estimates (Amin et al. 2022; Hussain et al. 2022) of subsidence rates in various locations, such as cities in coastal regions, deltas, and areas where extensive pumping of groundwater from susceptible aquifer systems takes place. A unique study by Saputra, Spit, and Zoomers (2019) estimated household-level LS adaptation costs by documenting the repair expenditures undertaken by low-income households in the suburbs of three major cities in Indonesia.

Because data are scant and difficult to obtain and incorporate into existing analytical frameworks, only a few studies estimate the potential economic and social costs of LS. A recent work by Ndahangwapo, Thiam, and Dinar (2024) developed a dynamic economic optimization model for groundwater utilization and assessed various policy tools to mitigate overexploitation externalities. They apply the model to an LS-affected aquifer, the Dendron aquifer system, in South Africa. Another recent work by Esteban et al. (2024) developed and applied an optimal control model of groundwater extractions under conditions of LS, demonstrating its use under several policy interventions in the Alto Guadalentín aquifer system in the Segura River basin of Spain.

An earlier work by Kok and Costa (2021) proposes a standardized framework for economic cost assessment of LS in economic sectors along the lines of direct and indirect

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effects, and market and nonmarket effects. However, the authors have not demonstrated the use of their framework in any of the LS cases known around the world. Herrera-García et al. (2021) documented the distribution of LS globally and provided initial estimates of the potential exposed GDP. They reviewed existing information and identified that, due to groundwater depletion, LS occurred at 200 locations in 34 countries between 1961 and 2018. They estimated that potential subsidence threatens 12 million km^2 (8%) of the global land surface with a probability higher than 50%. The authors suggest that the cumulative potential subsidence area (focusing only on high to very high potential subsidence regions) amounts to 2.2 million km^2, or 1.6% of the global land area, with 1.2 billion inhabitants (19% of the global population) and has a risk-exposed GDP of $8.19 trillion, or 12% of the global GDP. Although these are "proxy" estimates, the magnitude is substantial. Additional approaches and estimates can help inform policy development to potentially mitigate the economic and social impacts of LS in the present and future.

LS can have major impacts on urban settings. As stated by Gambolati and Teatini (2021, viii), "Land subsidence, that is, the loss of land elevation, is a major geomechanical process that threatens the viability and sustainable development of many millions of people throughout the world, especially in but not restricted to, coastal and highly urbanized areas. The most severe cases of land subsidence are associated with groundwater overdraft." This statement also supports the empirical assessment in Herrera-García et al. (2021). This observation may partly explain the surge in studies of the extent of LS in urban centers (e.g., Hu et al. 2013; Chaussard et al. 2021; Amin et al. 2022; Hussain et al. 2022; Wu, Wei, and D'Hondt 2022).

Damages associated with LS to urban settlements and hardships faced by people in affected areas can be documented in terms of the extent of the impact, such as the number of buildings or length of roads affected. Still, little has been published on the dollar value of such impacts. Published work mainly uses data on housing sales in areas in cities affected by LS, using the hedonic pricing method to estimate the dollar value loss on housing sale values in different vicinities to the LS epicenter (Yoo and Perrings 2017; Willemsen, Kok, and Kuik 2020). Such housing sale data are readily available in countries where markets for real estate transactions exist. Estimating the value loss to the housing market from LS allows the aggregation of value losses across a region or a state and can be used by policy makers as a reference to a public investment aimed at addressing LS damages.

Most of the previous work on impact of LS on the residential sector used data from a city or a small region. In this article, we apply the hedonic pricing method to a large region with a large range of characteristics to evaluate the economic impact of LS by examining the market value of single-family residential homes in the San Joaquin Valley (SJV) counties, California, from 2015 to 2021.[1] Our research encompasses transaction data, incorporating housing sale value and characteristics (ATTOM Data Solutions 2023), and vertical land-surface displacement data obtained through interferometric synthetic aperture radar techniques (TRE ALTAMIRA 2021a, b). Our findings indicate that LS reduces housing values from 2.4% to 5.8%. Notably, the values of homes where higher subsidence rates occurred had more substantial reductions. Our analysis also suggests heterogeneity in the impact of LS on housing values, with areas with a population that have a higher percentage of bachelor's degree and areas with less subsidence in the earlier periods observing a larger impact of LS on housing sales value. Our findings suggest that, on average, subsidence resulted in a reduction of $6,689 (in low-subsidence rate areas) to $16,165 (in high-subsidence rate areas) in housing values. Considering the overall impact on housing values in SJV

[1] In this study, the term "housing sale value" refers to the total transaction value of the entire property, encompassing the home's physical structure and its surrounding lot, which may include a yard, garden, pool, and other outdoor amenities. It represents the aggregate value of all components within the property boundaries and serves as a comprehensive indicator of the property's overall market price. Studied SJV counties include San Joaquin, Stanislaus, Merced, Madera, Fresno, Kings, Tulare, and Kern.

counties that are impacted by LS, we find that subsidence would result in a aggregate loss of $1.87 billion.

2. Background

The Hedonic Method and Literature Review

The model we use for estimating the impact of LS on housing sale value is a traditional hedonic pricing method (HPM) model, the foundations of which were developed in the twentieth century (Waugh 1929; Court 1939; Griliches 1971; Sheppard 1999). The HPM is used to estimate the economic value of an ecosystem or environmental service that directly impacts the market price for homes. HPM can be used to measure positive (e.g., parks, recreational sites) and negative (e.g., noise, air or water pollution, Superfund sites, LS) effects of environmental (dis)amenities on home prices. Examples of HPM in a similar context include the impact of floods (e.g., Graff Zivin and Neidell 2009; Atreya, Ferreira, and Kriesel 2013; Scott et al. 2014; Bakkensen, Ding, and Ma 2019; Beltrán, Maddison, and Elliott 2018; Ortega and Taṣpınar 2018; Bakkensen and Ma 2020; Gibson and Mullins 2020; Hennighausen and Suter 2020; Graff Zivin, Liao, and Panassie 2023), wildfires (e.g., Stetler, Venn, and Calkin 2010; Hansen and Naughton 2013; McCoy and Walsh 2018; Koo and Liang 2022; Paudel 2022; Shi et al. 2022), and air, noise, and water pollution (e.g., Ridker and Henning 1967; Smith and Huang 1995; Kim, Phipps, and Anselin 2003; Chay and Greenstone 2005; Guignet, Northcutt, and Walsh 2015; Sullivan 2016; Singh, Saphores, and Bruckner 2018; Morano et al. 2021; Tang and Niemeier 2021; Christensen, Keiser, and Lade 2023) on housing sale value. Additional applications of HPM to environmental externalities can be found in Palmquist and Smith (2002).

Only a few studies exist that focus on applying HPM to estimate the impact of LS on residential housing sale value. Among the few available studies, Willemsen, Kok, and Kuik (2020) used house-level data to examine the impact of the subsidence rate on housing prices in Rotterdam and Gouda, the Netherlands. They use data of uniform subsidence rates for whole neighborhoods, "differential" subsidence data by building, and subsidence rate of the "surrounding" area in relation to a given house. The results suggest that uniform subsidence rate has the largest impact on housing values, with an approximately 6% reduction in sale price, while "differential" and "surrounding" subsidence show 2% and no effect, respectively.

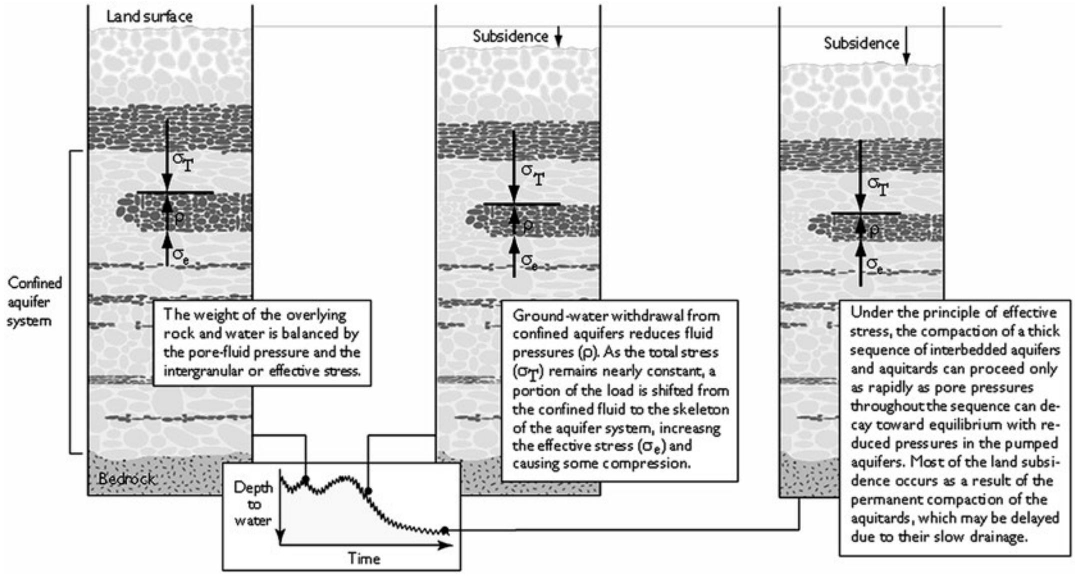
Yoo and Frederick (2017) estimated the impact of LS and associated earth fissures on residential housing sale value in Maricopa County, Arizona. Using 82,716 housing sale values between 2004 and 2010, they estimated a fixed effects quantile regression model predicting the impact of LS and earth fissures on housing sale values. Findings suggest that LS and earth fissures negatively impact housing values, varying statistically across different distributions of housing prices. Impacts are found to be more manifested at higher-priced homes, whereas they are statistically insignificant at substantially lower-priced homes. In another study also in Maricopa County, Yoo and Perrings (2017) estimated a fixed effects hedonic price model, similar to the one in Yoo and Frederick (2017) but emphasizing future LS and earth fissures. Findings indicate that existing and future LS and earth fissures reduced housing values. The mean value of homes located in LS landscapes was lower than those located outside LS landscapes.

Mechanics of Groundwater Pumping–Induced LS

LS attributed to groundwater pumping occurs in many aquifer systems that are at least partly composed of unconsolidated fine-grained sediments and have undergone extensive groundwater development (Poland 1984). The relation between changes in pore-fluid pressure and compression of the aquifer system is based on the principle of effective stress (Terzaghi 1925), as shown in Figure 1.

The pore structure of a sedimentary aquifer system is supported by the system's granular skeleton, and the groundwater's

Figure 1
Principle of Effective Stress and Its Relationship to Groundwater Levels, Aquifer-System Compaction, and Land Subsidence



Source: Galloway, Jones, and Ingebritsen (1999).

Note: Subsidence of the land surface is a result of a decrease in pore-fluid pressure (ρ) and resulting increase in effective stress (σe) in fine-grained material under conditions of total stress (σT) in a one-dimensional, fluid-saturated geologic medium.

pore-fluid pressure that fills the intergranular pore space expands or contracts in response to groundwater-level changes. Seasonally fluctuating groundwater levels can result in a few centimeters of elastic (reversible) LS and uplift. Long-term groundwater-level decline can result in a onetime release of "water of compaction" from the pore spaces of fine-grained sediments. Accompanying this release of water is a predominantly inelastic (permanent) reduction in the pore volume of the compacted fine-grained sediments, and hence, an overall reduction of the aquifer system volume, which is expressed as LS (Galloway, Jones, and Ingebritsen 1999).

The concepts reviewed here collectively form the aquitard-drainage model, which provides the theoretical basis of many subsidence studies related to groundwater, oil, and gas production. For a review of the history of the aquitard-drainage model, see Holzer (1998); for a complete description of aquifer-system compaction, refer to Poland (1984); and for a review and selected case studies of LS caused by aquifer-system compaction in the United States, refer to Galloway, Jones, and Ingebritsen (1999).

Development of the Groundwater Resource and Associated LS in the SJV

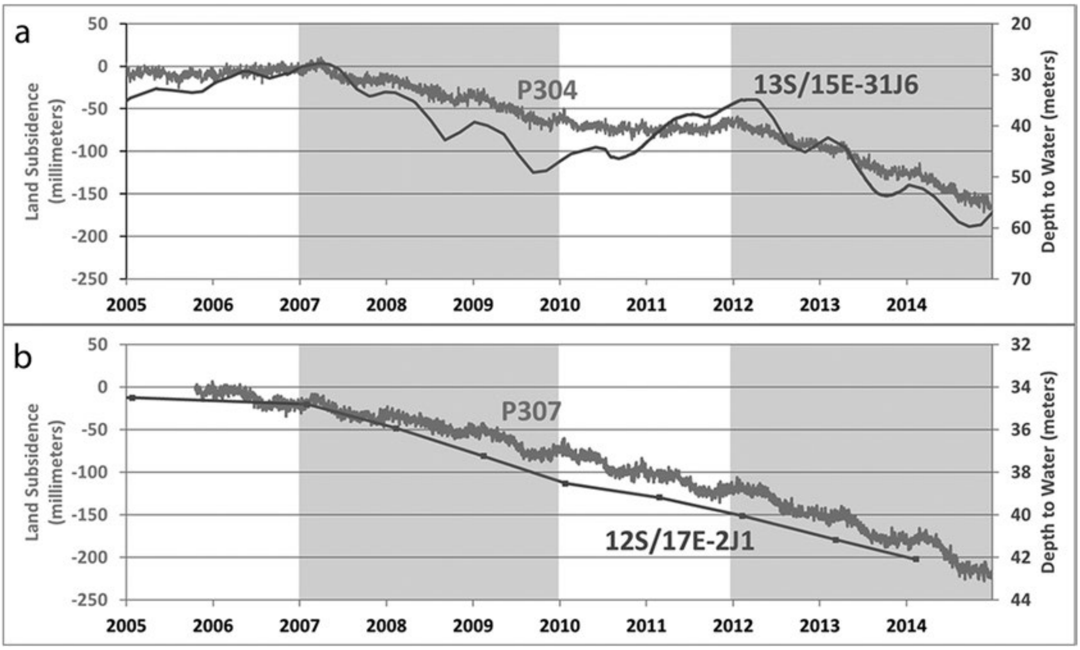
The SJV has a long history of LS caused by groundwater development. In some parts of the valley, groundwater was heavily relied on to irrigate agricultural crops. The extensive groundwater withdrawal from the unconsolidated SJV deposits lowered groundwater levels and caused widespread LS.

Long-term groundwater-level declines have resulted in a vast onetime release of "water of compaction" from compacting silt and clay layers in the aquifer system, causing the widespread LS that has contributed to one of the single largest alterations of the land surface attributed to humankind (Galloway, Jones, and Ingebritsen 1999).

Partially in response to these groundwater-level declines and subsidence, an extensive

Figure 2

Land Subsidence and Groundwater Levels in California, 2005–2014: (a) Mendota; (b) Madera



Sources: Luhdorff and Scalmanini Consulting Engineers and the US Geological Survey for well data; University Navigation Satellite Timing and Ranging Consortium for continuous global positioning system (CGPS) data.

Note: CGPS station P304 and well 13S/15E-31J6 show groundwater-level decline and subsidence during drought periods near Mendota. CGPS station P307 and well 12S/17E-2J1 show groundwater-level decline and subsidence during drought periods and nondrought periods near Madera. Shaded periods represent calendar years affected by increased pumping.

surface-water delivery system was developed to redistribute some of the water from north to south and east to west. Surface-water imports from the Central Valley Project's Delta-Mendota Canal (DMC) since the early 1950s and the State Water Project's California Aqueduct since the early 1970s resulted in a decrease in groundwater pumping in some parts of the valley, which was accompanied by a steady recovery of water levels and a reduced compaction rate in some areas. The increased availability of surface water helped facilitate the continued growth of the agricultural industry. However, because the availability of surface water varies substantially from year to year and season to season, agriculture, as it grew, developed a reliance on groundwater for irrigation. During the droughts of 1976–1977 and 1987–1992, diminished deliveries of imported surface water prompted increased pumping of groundwater to meet irrigation demands. This increased pumping resulted in water-level declines and periods of renewed compaction. Following these droughts, recovery to predrought water levels was rapid, and compaction virtually ceased (Galloway, Jones, and Ingebritsen 1999).

Similarly, during the droughts of 2007–2009 and 2012–2016, groundwater pumping increased in some parts of the valley. Groundwater levels declined during these periods in response to increased pumping, approaching or surpassing historical low levels, which caused compaction (Figure 2a). In contrast to the earlier droughts, water-level declines and resulting subsidence did not stop in some areas after the droughts and instead continued declining and subsiding, respectively (Figure 2b). Surface-water deliveries did not meet demand even in nondrought years, partly because of increased operational requirements of the delivery systems and increased demand associated with changes in land use, both of which contributed to a more persistent dependence on groundwater despite climatic conditions. Furthermore, some places where increased demand has occurred have not had sufficient access to surface water, leading to subsidence in areas that historically had small amounts or no known subsidence.

Impact of LS on Housing Sale Values and Infrastructure

LS has direct and indirect impacts on housing sale values. Subsidence can cause structural damage to homes, such as cracking foundations, walls, and floors. This kind of damage directly decreases a property's value and can make it difficult to sell without costly repairs. In addition, homeowners may face higher insurance premiums if an area is known for subsidence issues. In some cases, insurance companies might limit coverage for subsidence damage, making it harder for homeowners to protect their investments. This can be a deterrent for potential buyers. Furthermore, the risk associated with subsidence can make an area less attractive to potential home buyers and real estate investors. Such reduced demand may lead to a decrease in home values.

Subsidence can damage local infrastructure, including roads, sewage systems, and water lines. The costs for repairing such damages can lead to higher taxes or utility fees for residents, making the area less attractive to potential buyers. Due to the increased risk, lenders may hesitate to approve mortgages for properties in areas with substantial subsidence. This can reduce the pool of potential buyers.

LS signifies groundwater overdraft, which can and has resulted in legislation regulating water usage, which can affect productivity in agricultural regions like the SJV. A decline in the agricultural economy can have a broader impact on the local economy and housing sale values. Groundwater pumping that resulted in renewed aquifer-system compaction and LS has caused operational, maintenance, and construction design problems for the California Aqueduct, the DMC, and other water-delivery and flood-control canals in the SJV. Subsidence has reduced the flow capacity and freeboard of several canals that deliver irrigation water to farmers and transport floodwater out of the valley; structural damages have already required millions of dollars worth of repairs, and more repairs are likely to be needed in the future.[2] Even small amounts of subsidence in critical locations, especially where canal gradients are small, can impact canal operations. On the DMC between the canal intakes near Tracy and the San Luis Reservoir, where less than 15 mm of subsidence occurred during 2007–2010 (Sneed, Brandt, and Solt 2013), deliveries during a five-day window of opportunity to recharge the reservoir in spring 2014 fell short because of reduced flow capacity.[3]

Contribution of the Study

This study presents several distinct changes compared with previous work on the use of HPM to assess the impact of LS on housing sale values. Our study is the first investigation of the impacts of subsidence on the housing market in SJV, where subsidence rates ranged from 0 to 0.3 m/yr during 2015–2021. By addressing this knowledge gap, we contribute insights into the economic consequences of LS for homeowners in the SJV. One significant enhancement we introduce is the use of highly detailed and precise measurements of subsidence afforded by InSAR data. This advanced technique enables us to use subsidence data at a much finer spatial and measurement granularity. Consequently, we are able to accurately assign a subsidence value for each house within a 100 × 100 m area, enhancing the precision of the analysis.

Furthermore, our study incorporates transaction data spanning six years from multiple counties in California. This extensive dataset enables us to observe and analyze the potential causal impact of subsidence using fine-scale fixed effects, matching techniques, and a repeat-sales approach. By leveraging these

[2] Bob Martin, San Luis and Delta-Mendota Water Authority, and Chris White, Central California Irrigation District, pers. comm., 2010.

[3] Bob Martin, San Luis and Delta-Mendota Water Authority, pers. comm., 2014.

robust methodologies, we strengthen the credibility and reliability of our findings.

Finally, we explore the heterogeneous impact of LS on housing sale value, segmenting properties into different groups to discern how LS impacts vary by community educational level and exposure to subsidence in earlier periods. We extend our examination to include the heterogeneity in the impacts based on subsidence rate, distinguishing areas with low- and high-subsidence rates to better understand the varying degrees of these effects on housing value. By taking these factors into account, our study aims to provide a comprehensive understanding of the heterogeneous impact of LS on housing sale value, which can help inform policy- and decision-making for sustainable groundwater and land resources development in areas that may be susceptible to LS.

3. Data Sources and Descriptive Statistics

To conduct the analysis, we gathered comprehensive data on LS rates and housing sale value and characteristics during 2015–2021 for counties in SJV. Here we outline the data sources and present some descriptive statistics.

Data Sources

LS Data

We used LS data derived from spaceborne InSAR techniques for this study. InSAR is a satellite-based, remote-sensing technique that can detect land-surface displacement at high spatial and measurement resolutions. Synthetic aperture radar (SAR) data are produced by reflecting radar signals off a target area and measuring the two-way travel time back to the satellite. In SAR uses, two SAR scenes of the same area taken at different times and "interferes" (differences) them, resulting in maps called interferograms that can be processed to show vertical land-surface displacement between two points in time.

We downloaded InSAR data representing measurements of vertical land-surface displacement for California between July 2015 and December 2021 from the California Department of Water Resources ArcGIS REST Services directory (California Department of Water Resources 2023). The vertical displacement estimates were derived from SAR data collected by the European Space Agency Sentinel-1 satellite constellation and processed by TRE ALTAMIRA under contract with the California Department of Water Resources. The Sentinel-1 InSAR data were processed for more than 200 groundwater basins in California, including the SJV (Appendix Figure A1), and calibrated using vertical displacement data from continuous global positioning system stations. The resulting time-series data consist of vertical displacement values for point locations on a grid with 100 m spacing, with values representing averages of vertical displacement measurements in the immediate 100×100 m^2 areas of each point. Annual raster data were generated at monthly time steps from interpolating the point data using an inverse distance weighted method with a maximum search radius of 500 m. Gaps in the spatial coverage of the point data are areas with insufficient data quality (TRE ALTAMIRA 2021a, b).

The quality of the InSAR results was assessed by statistical comparison of the InSAR-based vertical displacement point time-series data to data from ground-based CGPS stations that were not used for calibrating the InSAR data and CGPS stations that were used for calibrating InSAR data in Northern California (Towill 2022). The statistical comparison followed the methodology for positional accuracy of geospatial data derived from various surveying methods developed by the Federal Geographic Data Committee (1998). The resulting analysis indicated that InSAR data accurately measured vertical displacement of California's ground surface to within 18 mm for the period January 1, 2015–October 1, 2022, at the 95% confidence interval. This statement of accuracy is based on the assumptions that the number, distribution, and characteristics of CGPS checkpoint locations provide a representative sample of the entire study area and of the whole InSAR dataset and that the CGPS data constitute an independent source of higher accuracy. This statement of accuracy applies to the statewide dataset and may vary for regional or localized area subsets (Towill 2022).

Housing Sale Values and Characteristics

We used transaction records of all homes sold in 58 counties in California from January 2002 to December 2021 from ATTOM Data Solutions (2023), a national real estate data provider. The data included details such as the home sale transaction price (converted to 2021 dollars), exact street address, parcel boundaries, square footage, year built, lot size, number of rooms, number of bathrooms, number of stories, and amenities such as a pool. LS data for this study area are available from July 2015 to December 2021, and we restricted the use of the housing transaction data accordingly. Using the location and boundaries of the sold homes and the 100 × 100 m raster grid LS data from the California Department of Water Resources (DWR), we calculated the annual LS rate for each home at the time of the sale. Appendix Figures A1 and A2 depict the amounts of vertical ground surface displacement between July 2015 and December 2021 and the homes sold between 2015 and 2021.

Land Use and Other Related Data

To account for the impact of agricultural-related economic activities in the vicinity of each house, we followed Auffhammer et al. (2020) and calculated the proportion of land designated for agricultural use within 5-km radii of each house using the US Geological Survey (USGS) 2019 National Land Cover Database (NLCD) (Dewitz 2021).[4] We identified homes in each groundwater sub-basin using groundwater basin and sub-basin boundary data from the DWR (California DWR 2023). A sub-basin is created by dividing a groundwater basin into smaller units using geologic and hydrologic barriers or, more commonly, institutional boundaries. Using sub-basin boundaries, we could control the spatial dependence of housing prices. The assumption behind this specification is that agricultural operations often use groundwater sources for at least part of applied irrigation, and thus homes in agricultural areas are more likely to face LS impacts.

To identify homes that do not have access to piped drinking water, we followed the approach of London et al. (2021) and Muehlenbachs, Spiller, and Timmins (2015) and used data on public water systems service area boundaries and identified the 419 municipal water suppliers throughout California from the State Water Resources Control Board (California DWR 2023) with the assumption that any housing outside these suppliers' service areas is groundwater (private well) dependent (Lee, Nemati, and Dinar 2021, 2022; London et al. 2021). The assumption is that houses that depend on private wells in LS areas (which tend to be fairly shallow compared with municipal or irrigation wells) may face water security issues. Finally, we calculated the distance from each home's centroid to the nearest highway and the nearest major city boundary, following the methodology of Auffhammer et al. (2020). These two variables indicate the hedonic value of the housing from being in preferred locations.

We collected house-level weather data from the parameter-elevation regressions on independent slopes model data, which provides information on a 4 × 4 km grid for 2015–2021 (Schlenker and Roberts 2009). Our primary weather variables include annual mean temperature, where we use the average of the maximum (Tmax) and minimum (Tmin) temperatures, as well as annual average precipitation. Last, we use US Census Bureau data at the block group level to incorporate information on educational attainment (measured as the percentage of households with a bachelor's degree or higher) and regional economic activity related to agriculture, captured by the percentage of the labor force employed in the agricultural sector.

[4] The NLCD, which is managed by USGS, was the source of the land cover data. This database provides 30 m resolution information on land surface features and changes using Landsat Thematic Mapper technology. The NLCD data include 15 categories, such as open water, developed (including open space, low-, medium-, and high-intensity development), barren land, forest (evergreen, deciduous, and mixed), shrub/scrub, grassland, pasture/hay, cultivated crops, and wetlands (woody and emergent herbaceous).

Table 1
Number of Counties and Areas Affected by Land Subsidence in the San Joaquin Valley, California, 2015–2021

	No. of Counties with Subsidence	Total Subsidence Area (km^2)	Area Under Low Subsidence (km^2)[a]	Area Under High Subsidence (km^2)[b]
2015	7	11,100	8,497	2,603
2016	7	6,652	6,629	23
2017	8	8,260	7,167	1,093
2018	7	6,280	6,271	9
2019	7	10,885	10,075	810
2020	7	10,936	9,119	1,817
2021	7	12,262	9,895	2,367

Note: Subsidence occurred in parts of the counties, not entire counties.
[a] Low subsidence is < 0.18 m per year.
[b] High subsidence is ≥ to 0.18 m per year.

Descriptive Statistics

As shown in Table 1, there are eight counties in the SJV where LS occurred in parts of each county during the study period: San Joaquin, Stanislaus, Merced, Madera, Fresno, Kings, Tulare, and Kern (Appendix Figure A2). By examining homes sold in a geographically continuous area, we mitigate potential variations stemming from different market dynamics and external factors that could exist across discontinuous regions. Table 1 provides summaries of subsidence in California, specifically presenting information on the number of counties with subsidence and the corresponding subsidence areas. The table presents data for different years, allowing for a comparison of two categories of subsidence rates and affected areas over time. For example, during 2015–2016, which was a severe drought year in California, the total subsidence area in SJV was 11,100 km^2. Within this area, 8,497 km^2 were in areas where a low-subsidence rate range of less than 0.18 m/year occurred, whereas 2,603 km^2 were where a high-subsidence rate range (more than 0.18 m/year) occurred. In comparison, during the wet years 2018–2019, the total subsidence area was reduced to 6,280 km^2, where 6,271 km^2 were in the low-subsidence area, and only 9 km^2 were in the high-subsidence area.

Table 2 provides summaries of observable variables for housing sales, specifically comparing different categories based on the presence and rate of subsidence. The table includes descriptive statistics, such as mean and standard deviation for each variable for the full sample in SJV counties, those with no-subsidence areas, and those in areas of low- and high-subsidence rates at the time of sale. We observe that there are statistically significant differences in the observable variables, such as distance to the nearest city and highway, number of bedrooms, housing age, and percentage of agriculture between those homes in no-subsidence areas versus those in areas of low- and high-subsidence rates.

4. Empirical Strategy and Results

The basic principle of the HPM is that the price of a market good is related to its characteristics or the services it provides. For example, the price of residential housing reflects the characteristics of that property (e.g., distance from the center of the town, pool, building style, neighborhood, environmental amenities or disamenities). Thus we can assign value to the individual characteristics of housing or another good by looking at how the price people are willing to pay for it changes when its characteristics change. A basic model looks like the following:

$$P = f(H, N, E, F) \quad [1]$$

In equation [1], the housing sale price (P) is influenced by several factors. The housing variables (H) encompass characteristics such as year built, size in square footage, number of rooms, presence of a fireplace or pool, and more. The neighborhood variables (N) encompass aspects like crime level, school quality,

Table 2
Observable Variables for Housing Sale in the San Joaquin Valley, California

	Full Sample (SJV)		No Subsidence		Low Subsidence[a]		High Subsidence[b]	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Sales price ($1,000 and 2021 dollars)	319	188	324	183	281	212	240	223
% agriculture (5 km)	0.07	1.73	0.06	1.54	0.17	2.84	0.13	1.95
Groundwater dependent	15.48	36.17	14.88	35.59	19.60	39.70	22.08	41.49
Distance to highway (km)	1.99	2.15	2.07	2.23	1.40	1.38	1.37	0.90
Distance to city (km)	0.85	4.03	0.90	4.22	0.54	2.18	0.51	2.33
% agriculture employed	8.05	9.79	7.59	9.34	10.82	12.12	15.51	11.26
Temperature (°C)	17.79	1.09	17.78	1.17	17.80	0.30	18.14	0.21
Precipitation (mm)	266.89	112.83	272.19	116.77	234.78	67.52	181.58	36.11
Age (years)	37.69	25.38	38.02	25.45	35.06	24.35	37.65	27.18
No. of bedrooms	3.21	0.93	3.23	0.88	3.04	1.25	3.05	0.97
No. of baths	2.02	0.82	2.02	0.81	1.97	0.88	1.89	0.61
Story	1.10	0.53	1.11	0.52	1.07	0.56	1.05	0.66
Pool (%)	16.86	37.44	16.74	37.33	18.28	38.65	14.25	34.96
Observations	275,122		241,894		29,234		3,994	

Note: This table reports sample means, with sample standard deviations.
[a] Low subsidence is < 0.18 m per year.
[b] High subsidence is ≥ to 0.18 m per year.

proximity to recreational areas, and more. The environmental variables (E) include pollution levels (air, water, noise), visibility, LS, and so on. In addition, the model incorporates fixed effects (F), such as county fixed effects, sub-basin fixed effects, and sales-year fixed effects, which account for variables that have a constant effect across observations. By controlling all attributes except one, we can isolate the impact of that specific variable on the dependent variable.

This article examines the effects on housing sale value related to proximity to areas with observed LS. Examining the effects of housing sale value related to proximity to areas with observed LS may highlight potential issues related to direct physical housing damage from subsidence, groundwater availability, or changes in local employment availability and economic activities. Notably, LS (mostly permanent) in the SJV during a past drought (2012–2016) occurred due to the overdraft of groundwater in areas with high water demand for agriculture and associated highest groundwater-well density (Faunt et al. 2016; Jeanne et al. 2019). It is helpful to consider a broad range of unobservable attributes that may be related to the housing and proximity to the LS areas.

In this study, three different empirical methods—fine-scale fixed effects on the full sample, fine-scale fixed effects on the matched sample, and fixed effects using repeat-sales data—are used in estimating the impact of LS on the housing sale value. The use of fixed effects allows for the control of unobservable factors affecting all homes alike that may lead to biased estimators, using house-level location and transaction data to identify the effects of LS on the housing sale value. County and sub-basin fixed effects, along with sales-year models, are incorporated to eliminate bias and control for common trends. The matching method is employed to address potential omitted variable bias that are not addressed using fixed effects and improve causal inference by comparing similar homes within and outside the subsidence area, where we restricted the matched control and treatment units to be in the same geographic area (e.g., city, sub-basin, or county boundaries). Finally, as a robustness check, we use a repeat-sales model by restricting the sample to homes sold twice during the study period. A repeat-sales approach is designed to estimate property value changes over time by comparing the same property's sale prices across different points in time. Since our variable of interest, LS, is time-varying, estimating a repeat-sales approach with parcel fixed effects seems to be ideal from a causal identification standpoint.

A house fixed effect in our main specification controls for time-invariant parcel-specific observable and unobservable variables that may bias our analysis.

Fixed Effects with Full Sample

As noted above, the primary challenge to estimating the impact of LS on housing sale value is that there may be unobservable factors related to subsidence and housing value, which, if unaccounted for, would lead to omitted variable bias in our estimator. The dataset of house-level location and transaction data allows us to include various fixed effects and control for unobservable factors. Our empirical strategy identifies the impacts of LS in a given year at two levels of intensity on housing sale value at the parcel-year level, using spatial and intertemporal variation in transaction value and subsidence intensity.

First we consider a parsimonious fixed effects specification for log transaction value:

$$\begin{aligned} ln\ P_{it} &= \alpha + \theta Subsidence_{it} + \beta X_{it} \\ &\quad + \lambda_t + \varphi_c + \vartheta_b + \varepsilon_{it}, \end{aligned} \quad [2]$$

where $ln\ P_{it}$ is the natural log of housing sale value for housing location i and year t. The variable of interest is LS ($Subsidence_{it}$), an indicator variable that takes the value of one if the housing is located in an area affected by LS and zero otherwise. X_{it} is a vector of control variables, such as the size of the house, the number of bedrooms, and the presence of a pool. We use county (φ_c) and sub-basin (ϑ_b) fixed effects to eliminate bias in our estimates that may arise from unobserved time-invariant characteristics of counties and sub-basins, which affect housing sale value, such as location and quality of public services, that may affect the value of the housing in the presence of LS. In addition, we incorporate year dummies (λ_t) to control for common trends that affect all homes in the sample at the same time, such as changes in interest rates or macroeconomic conditions. ε_{it} is the error term, which captures the impact of unobservable factors specific to each housing in each time period, such as individual preferences.

Table 3 presents the results of the average effect of LS presence on housing value using the fixed effects regressions. The log of transaction value is the dependent variable in all specifications. Bootstrapped standard errors for all the specifications are shown in parentheses. Standard errors are clustered at the level of the zip code to account for within–zip code serial correlation in the error term and produce consistent standard errors in the presence of such association (Bertrand, Duflo, and Mullainathan 2004). Our analysis uses various control variables and fixed effects to examine the relationship between subsidence and housing value. In columns (1)–(4) of Table 3, we include a binary variable called "subsidence," which takes a value of one if the housing experienced any level of subsidence at the time of sale and zero otherwise.

Column (1) of Table 3 presents the baseline fixed effects model corresponding to equation [2], where we include year, county, and sub-basin fixed effects. These fixed effects collectively control for time-invariant characteristics at the county and sub-basin levels and common time shocks across all observations. The estimated impact of LS on housing sales prices is –0.065. In column (2), we include county-by-year and sub-basin-by-year fixed effects, which account for time-varying local conditions such as changes in the labor market. This allows us to better isolate the effect of subsidence on housing values by conditioning on local economic changes—such as shifts in employment or activity related to droughts—in specific county or sub-basin areas. Using this specification, the estimated impact of LS on housing sales price is –0.073.

In column (3), we add observable house characteristic variables (living area size, number of bedrooms, bathrooms, and stories, age of the housing, presence of a pool) and other control variables, including the percentage of agricultural land use in the surrounding area (5 km) and the distance to the closest highway and city (km). Comparing the results of this specification with those of column (2), we find that the point estimate for the subsidence effect in column (3) moves closer to zero, where the estimated impact is –0.024.

Our preferred specification, in column (4), includes house-specific characteristics,

Table 3
Log Sale Price on Subsidence in the San Joaquin Valley, California: Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Subsidence	−0.065***	−0.073***	−0.024***	−0.025***	
	(0.005)	(0.005)	(0.004)	(0.004)	
Low subsidence (< 0.18 m/year)					−0.024***
					(0.004)
High subsidence (≥ 0.18 m/year)					−0.058***
					(0.008)
Year fixed effects	Yes	No	No	No	No
County fixed effects	Yes	No	No	No	No
Sub-basin fixed effects	Yes	No	No	No	No
County-year fixed effects	No	Yes	Yes	Yes	Yes
Sub-basin-year fixed effects	No	Yes	Yes	Yes	Yes
Housing characteristics	No	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	Yes
Weather controls	No	No	No	Yes	Yes
% agriculture employed	No	No	No	Yes	Yes
Average sales value	278,713	278,713	278,713	278,713	278,713
Observations	275,122	275,122	275,122	275,122	275,122
R-squared	0.205	0.209	0.621	0.635	0.635

Note: Each column represents a separate regression using a different combination of controls and fixed effects. The dependent variable in all regressions is the log sale price. Standard errors are in parentheses and clustered at the zip code level with 1,000 bootstrap repetitions. The number of zip codes is 256. Housing characteristics include the year built, number of bedrooms, bathrooms, stories, and the presence of a pool. Other controls include the percentage of agriculture (5 km) and the distance to the closest highway and city (km). Weather variables include mean annual temperature and total precipitation. We include the square terms of temperature and precipitation to account for the nonlinear relationship between home values and weather variables.

***$p < 0.10$.

county-by-year and sub-basin-by-year fixed effects, and additional control variables for weather conditions. These include mean annual temperature, total precipitation, and their squared terms to capture the potential nonlinear relationship between home values and weather. We also control for agricultural labor market activity using the percentage of the population employed in the agricultural sector at the US Census Bureau block group level. This variable, combined with the county-by-year and sub-basin-by-year fixed effects, helps capture time-varying local conditions. For example, groundwater withdrawals may interact with local economic activity—such as agricultural employment—which can independently influence housing prices and be distinct from the direct costs of subsidence. Including this variable also helps account for regional labor market dynamics that could otherwise bias the estimates. Using this specification, the estimated impact of LS on housing sales price is −0.025. In other words, on average, homes in subsidence-affected areas sell for approximately 2.5 percentage points less than control homes, ceteris paribus. Based on the average sales value of $278,713, this translates to an estimated reduction of about $6,967 in home value.

As shown earlier, the standard errors are clustered at the zip code level to account for within-community spatial correlation. We use zip codes as a conservative proxy for community boundaries. As a robustness check, we cluster the standard errors at the water agency and city levels. Given the relatively small number of clusters (256 zip codes, 66 water agencies, or 174 cities), adjusting for spatial correlation becomes particularly important, as clustered standard errors may otherwise be underestimated. In addition to bootstrapping the standard errors, a feasible alternative is to compute Conley standard errors, following the approach suggested by Conley (1999). The results of these additional checks are in Appendix Table A1. As shown, the significance level of the estimated impact remains consistent across the different methods, although the estimated standard errors vary slightly.

Note that the subsidence variable above measures any level of subsidence regardless of its intensity. There might be nonlinear effects of LS on housing value where the impact is larger for higher subsidence rates. To test this hypothesis, we can define the LS variable using a categorical indicator with a set of indicator variables that represent different categories of subsidence. Thus, the equation becomes

$$ln\ P_{it} = \alpha + D'_{it}.\Gamma + \beta X_{it} + \lambda_t + \varphi_c + \vartheta_b + \varepsilon_{it}. \quad [3]$$

D'_{ist} represents a vector of indicator variables representing subsidence intensity in the housing location i at year t. To assess subsidence levels, we use a two-category classification system: low-subsidence rate and high-subsidence rate (defined for this study using California DWR definitions).[5] Low subsidence is defined as subsidence rate less than 0.18 m per year; high subsidence is defined as subsidence rate that is equal to or exceeds 0.18 m per year. As a reference point, the base category is defined as "no subsidence." Column (5) of Table 3 presents the nonlinear impacts of LS on housing sale value. As indicated in this column, the estimated the impact of LS on homes sales value in areas of high-subsidence rates in the SJV is –0.058. Furthermore, our analysis revealed that homes in areas of low-subsidence rates exhibit a discernible impact, albeit at a relatively lower magnitude. Specifically, the estimated impact of LS on home sales value in this category is –0.024. These observations highlight the varying degrees of impact subsidence can have on housing sale value in the SJV. Understanding these distinctions can help determine the implications of subsidence on the real estate market and potential mitigation strategies.

In addition to the definition for distinguishing high- and low-subsidence areas, we applied several alternative methods to define the thresholds. The threshold used previously (0.18 m) corresponds approximately to the top decile of the dataset. Here, we explore three alternative thresholds: the 90th percentile (0.19 m), the first quartile (0.13 m), and the median value (0.09 m). The results based on these alternative definitions are in Appendix Table A2.

Consistent with our earlier findings, using the 90th percentile as the cutoff yields similar results. As shown in column (2) of Appendix Table A2, the estimated impact of low LS on housing sale prices is –0.024, while the estimated impact in high-subsidence areas is –0.064. When using the first quartile or the median subsidence rate as the threshold, we observe a nonlinear relationship; however, the difference in estimated impacts between low- and high-subsidence areas becomes smaller.

Fixed Effects with Matched Sample

To address potential omitted variable bias and strengthen causal inference, we use a matching method as an additional econometric approach to estimate the impact of LS on house sales value. As discussed already, subsidence can affect individual properties—by damaging foundations or increasing insurance premiums—and broader community infrastructure—by compromising water-delivery systems and roads. To isolate the effect of subsidence on individual home values, we structure the matching approach so that treated and comparison homes are located in the same community. In other words, we compare homes in subsidence-affected areas to similar homes outside those areas but in the same region, thereby controlling unobservable community-level factors that could be correlated with subsidence.

For the matching process, we use a range of housing characteristics, including the year built, number of bedrooms and bathrooms, number of stories, and presence of a pool. We incorporate geographic variables such as the distance to the nearest city and highway and the percentage of agricultural land use within a 5 km radius. These covariates are chosen to account for the likelihood of subsidence and factors influencing housing values.

[5] We used data from the California DWR to determine the 0.18 m (0.6 ft.) threshold. DWR categorizes subsidence into eight levels. We used the three highest categories to define high subsidence (i.e., –0.6 ft. and below) and distinguish it from low subsidence. More details are available at https://sgma.water.ca.gov/webgis/?appid=SGMADataViewer#landsub.

To perform the matching, we use nearest-neighbor (1:5) Mahalanobis covariate matching with replacement. This method allows us to select a group of comparison homes outside the subsidence area that closely resemble the treated homes in the subsidence area in terms of observable characteristics (Rosenbaum and Rubin 1983; Stuart 2010). We used three different definitions of community boundaries: city, sub-basin, and county. In each case, we restricted the matching sample to select comparison units based on the observed characteristics, but only from within the same geographic boundary. That is, in the first specification, matches were drawn only from the same city; in the second, from the same sub-basin; and in the third, from the same county. This approach allows us to isolate the effect of LS while holding constant broader community-level factors that may influence housing prices.

One important aspect of using matching methods is the balance of covariates before and after matching. To assess this balance, we used the absolute standardized difference in means, which is measured in units of the pooled standard deviation. This measure allowed us to determine whether the measured variables between the treated and control groups were balanced in the matched and unmatched samples, regardless of the sample size.

Appendix Figure A3 illustrates the standardized differences in the original and matched samples. Initially, we observed statistically significant differences in various characteristics between the treated and comparison groups. However, after performing the matching procedure, the observable variables of homes in the subsidence area became similar, on average, to those of homes outside the subsidence area. This improvement in balance among the groups indicates the effectiveness of the matching process.

Table 4 presents the results of the LS impact on transaction value using the matched sample. We replicate our preferred specification from column (4) of Table 3 and apply it to the matched subsample. First, we restrict the treated and comparison units to being from the same city. As shown in column (1) of Table 4, the estimated impact of LS on home sale values is −0.032. When we use sub-basin and county boundaries instead, the estimated impacts are −0.027 and −0.021, respectively. To put these estimates into perspective, based on the average sale values across the matched samples, the estimated reductions in home value are approximately $7,767, $6,657, and $4,940, respectively. These figures align closely with the previously reported estimate of $6,967 in column (4) of Table 3.

Table 4
Log Sale Price on Subsidence in the San Joaquin Valley, California: Matching

	City	Sub-basin	County
	(1)	(2)	(3)
Subsidence	−0.032***	−0.027***	−0.021***
	(0.008)	(0.007)	(0.006)
County-year fixed effects	Yes	Yes	Yes
Sub-basin-year fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
% agriculture employed	Yes	Yes	Yes
Average sales value ($1,000)	242,708	246,540	235,260
Observations	14,234	24,508	32,668
R-squared	0.527	0.556	0.556

Note: Each column represents a separate regression that limits treated and comparison units to the same geography. The dependent variable in all regressions is the log sale price. Standard errors are in parentheses and clustered at the zip code level with 1,000 bootstrap repetitions. The number of zip codes is 256. Housing characteristics include the year built, number of bedrooms, bathrooms, stories, and the presence of a pool. Other controls include the percentage of agriculture (5 km) and the distance to the closest highway and city (km). Weather variables include mean annual temperature and total precipitation. We include the square terms of temperature and precipitation to account for the nonlinear relationship between home values and weather variables.
***$p < 0.10$.

Fixed Effects with Repeat-Sales Sample

Last, we leveraged the repeat-sales sample from our parcel data—comprising 84,540 observations from 42,270 homes sold twice—to estimate a panel fixed effects model. As indicated in the literature, using repeat sales of the same property over time allows for better control of unobserved heterogeneity and is widely considered the gold standard in hedonic valuation (Bishop et al. 2020; Banzhaf 2021; Nolte et al. 2024). We restrict the sample to homes in the SJV that were sold exactly twice between 2015 and 2021. For this analysis, we include only homes that were located outside the subsidence area during both sales or those that transitioned from a nonsubsidence area to a subsidence area between sales.

Given that our variable of interest—LS—varies over time, a repeat-sales model with house fixed effects is well suited for causal inference. By incorporating house fixed effects in that main specification, we control for time-invariant, house-specific characteristics that could otherwise bias the results. Comparing multiple sales of the same house allows us to account for these unchanging factors and isolate the impact of variables that vary over time. In essence, the repeat-sales approach enables us to estimate the effect of environmental changes—specifically, LS—on housing prices (Kousky 2010; Beltrán, Maddison, and Elliott 2019; Palmquist 1982; Banzhaf 2021). Using a repeat-sales subsample, we estimate equation [2] but now account for house fixed effects. First, we consider a parsimonious fixed effects specification for log transaction value:

$$\begin{aligned} ln\ P_{it} &= \alpha + \theta Subsidence_{it} + \lambda_t \\ &\quad + \varphi_c + \vartheta_b + \delta_i + \varepsilon_{it}, \end{aligned} \qquad [4]$$

where $ln\ P_{it}$ is the natural log of housing sale value for house i at year t. The variable of interest is LS ($Subsidence_{it}$), which is an indicator variable taking the value of one if the housing is located in an area affected by LS and zero otherwise. Similar to equation [3], we use county (φ_c) and sub-basin (ϑ_b), and year (λ_t) fixed effects. We also control for house fixed effects (δ_i) to control for time-invariant characteristics. ε_{it} is the error term. Similar to our previous model, standard errors are clustered at the zip code level.

One potential issue with using a repeat-sales model is selection bias—houses sold more than once during the sample period may be systematically different from those sold only once. Although the repeat-sales model can improve the internal validity of the estimated effects by controlling for time-invariant factors, there may be issues about the external validity of the point estimates. To assess this issue, we compare the characteristics of the two samples. Appendix Table A3 presents summary statistics for homes sold more than once versus those sold only once. On average, homes in the repeat-sales sample have slightly higher sale prices ($372,000) than those sold only once ($336,000). Other observable characteristics are relatively similar across both groups, which help elucidate the external validity of the repeat-sales estimates.

The results from the repeat-sales model are presented in Table 5. The estimated coefficient for LS is negative, statistically significant, and consistent in magnitude with our previous estimates. In the first specification, we include house fixed effects along with county, year, and sub-basin fixed effects. The second specification adds interactions between county and sub-basin by year fixed effects to account for time-varying local conditions, such as changes in local economic

Table 5

Log Sale Price on Subsidence in the San Joaquin Valley, California: Fixed Effects with Repeat-Sales Data

	(1)	(2)	(3)
Subsidence	−0.027***	−0.031***	−0.032***
	(0.002)	(0.002)	(0.002)
Year fixed effects	Yes	No	No
County fixed effects	Yes	No	No
Sub-basin fixed effects	Yes	No	No
County-year fixed effects	No	Yes	Yes
Sub-basin-year fixed effects	No	Yes	Yes
House fixed effects	Yes	Yes	Yes
Weather controls	No	No	Yes
Average sales value ($1,000)	304,191	304,191	304,191
Observations	84,540	84,540	84,540
R-squared	0.731	0.741	0.741

Note: Each column in each panel represents a separate regression using a different combination of controls and fixed effects. The dependent variable in all regressions is the log sale price. Standard errors are in parentheses and clustered at the zip code level with 1,000 bootstrap repetitions. The number of zip codes is 218. Weather variables include mean annual temperature and total precipitation. We include the square terms of temperature and precipitation to account for the nonlinear relationship between home values and weather variables.

***$p < 0.10$.

Table 6
Log Sale Price on Land Subsidence (LS) in the San Joaquin Valley, California: Heterogeneous Impacts

	High Early LS Areas	Low Early LS Areas	High-Education Areas
	(1)	(2)	(3)
Subsidence	0.002	−0.024***	−0.052***
	(0.026)	(0.004)	(0.004)
County-year fixed effects	Yes	Yes	Yes
Sub-basin-year fixed effects	Yes	Yes	Yes
Housing characteristics	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
% agriculture employed	Yes	Yes	Yes
Average sales value ($1,000)	192,276	273,641	325,918
Observations	4,106	238,713	49,564
R-squared	0.576	0.634	0.652

Note: Each column represents a separate regression on a different subsample: (1) areas with substantial early subsidence, (2) areas with low early LS exposure, and (3) areas with a higher share of educated households. The dependent variable in all regressions is the log sale price. Standard errors are in parentheses and clustered at the zip code level with 1,000 bootstrap repetitions. The number of zip codes is 256. Housing characteristics include the year built, number of bedrooms, bathrooms, stories, and the presence of a pool. Other controls include the percentage of agriculture (5 km) and the distance to the closest highway and city (km). Weather variables include mean annual temperature and total precipitation. We include the square terms of temperature and precipitation to account for the nonlinear relationship between home values and weather variables.
***$p < 0.10$.

activity. Finally, our preferred specification incorporates weather variables in addition to all previous fixed effects. Across all specifications, the results remain robust. As shown in column (3) of Table 5, the estimated effect of LS on home sale value is −0.032.

Heterogeneity in the Impact

In this section, we conduct several heterogeneity analyses. First we present two sets of analyses aimed at identifying which locations are more likely to have become aware of the negative effects of LS. To explore this, we analyze two subsamples: one consisting of areas that experienced substantial subsidence in an earlier period and another of areas with minimal or no early exposure. We obtained regional-level data on LS exposure from the USGS and identified two sub-basins—Westside and Tule—as having experienced substantial subsidence in earlier periods (Sneed and Brandt 2015). These areas serve as our high early exposure group.

The impact of LS could be stronger in areas that did not experience high exposure in earlier periods. In other words, LS may be a stronger signal to homebuyers in regions where the subsidence rate was lower in the earlier periods. To test this, we estimate the same model used in column (4) of Table 3 for each subsample. The results are presented in columns (1) and (2) of Table 6. As shown, the impact of LS on housing sales is not statistically significant in areas with high early exposure. In contrast, the estimated impact in other regions is negative and statistically significant at −0.024.

In addition, we estimate our preferred specification for areas with a higher concentration of educated households, using a subset of block groups where at least 50% of the population holds a bachelor's degree or higher. Residents in these areas may be more likely to be aware of the impact of LS, and thus we might observe a stronger response in housing market outcomes. The results, presented in column (3) of Table 6, align with this consideration. In these areas with a greater percentage of population with bachelor's degree or higher, LS has a significantly larger negative impact on housing sale values, with an estimated coefficient of −0.052. This finding is consistent with the idea that populations with more levels of higher education may be more aware of and responsive to environmental risks.

5. Policy Analysis

To assess the magnitude of LS impacts, we conducted a detailed analysis using two rate categories of subsidence and mean transacted values for homes in the subsidence area. We used point estimates to provide an exercise on the average effect of subsidence on the housing sale value. In column (2) of Table 7, we present the results of this analysis. On average, being in a subsidence area leads to a reduction of $6,967 (using column (4) of Table 3 estimated impacts) in housing sale values. However, when we divide the subsidence area into the two rate groups—low- and high-subsidence rates—we find that housing values in the areas of low-subsidence rates experience an average reduction of $6,689, and housing values in the areas of high-subsidence rates face a much more significant impact, with an average reduction of $16,165. This shows that the severity of subsidence has a substantial effect on the magnitude of the reduction in housing sale value.

We aggregated these impacts and scaled them up to encompass the impact on all homes in the subsidence-affected area of the SJV. The total number of homes in the subsidence area is 207,040, with 49,750 falling into the high-subsidence rate category, and the rest in the low-subsidence rate category. When considering the overall impact on housing values in the SJV, we find that subsidence would result in an aggregate loss of $1.44 billion. Furthermore, using estimated impacts in column (5) of Table 3 and disaggregating the impact, we observe an aggregate loss of $1.87 billion. Overall, low-subsidence rates can lead to an aggregate loss of approximately $1.05 billion in housing values, whereas high-subsidence rates can significantly influence the impact, with a loss of approximately $0.80 billion in housing values (Table 7).

This study could help provide a basis for mitigation techniques to alleviate groundwater overdraft that leads to LS. We discuss two possible methods to address the impact of groundwater overdraft on aquifer depletion leading to LS (where applicable). One consideration could be to restrict pumping and reduce the likelihood of LS. This could be achieved by providing alternative water sources that do not affect groundwater levels, or potentially changing the uses of land, such as fallowing. Another method that has been practiced in recent years is managed aquifer recharge (MAR), in which water is returned on availability (e.g., floods, abundant precipitation) to recharge the aquifer. A study by Perrone and Rohde (2016) identified 136 MAR projects in California, with a range of objectives.[6] Of these, nearly 2% were projects that focused on LS mitigation, including several in the SJV, which shows median project costs above the median cost of all of the projects ($0.33/m^3/year; Perrone and Rohde 2016). This indicates that using MAR to mitigate LS can have associated costs, but no benefit-cost analysis was performed. A recent study by Reznik et al. (2022) evaluates MAR in the SJV without considering its mitigation effect on LS.

In 2014, California passed the Sustainable Groundwater Management Act (SGMA), which established a framework for sustainable, local groundwater management (California DWR 2023). The SGMA requires that each groundwater sub-basin designated by the California DWR as a high- or medium-priority sub-basin (which includes all the sub-basins in this study) develop and implement groundwater sustainability plans to help avoid and mitigate overdraft within 20 years. One of the six results listed in the SGMA is the potential for “significant and unreasonable

Table 7
Average and Aggregate Impacts from Land Subsidence in the San Joaquin Valley, California

	Average Impacts ($1,000)	Aggregate Impacts ($1,000)
Subsidence	6.967	$1,442,448
Low subsidence (< 0.18 m/year)	6.689	$1,052,113
High subsidence (≥ 0.18 m/year)	16.165	$804,209

[6] There are 11 benefit categories: banking groundwater, improving water quality, flood protection, protecting wetland habitat, increasing water supply, conjunctive use of groundwater and surface water, reducing greenhouse gases, reducing imported water, mitigating subsidence, increasing efficiency, and creating seawater barrier.

land subsidence." Implementation of the SGMA could help lessen or end subsidence-related loss of housing values in the SJV indicated in this study.

6. Discussion

Substantial LS has been observed in many parts of the world (Bagheri-Gavkosh et al. 2021; Herrera-García et al. 2021). Most published literature provides estimates of the physical causes and outcomes of LS, but little work has focused on economic and social consequences. In particular, little methodological and empirical research has been conducted on the perceived impact of LS on social and economic activities. Our findings contribute to the understanding of the extent of one line of LS impact on the urban sector. With rapid urbanization happening in many places, followed by economic expansion and increased demand for groundwater, the impact of LS through economic losses in urban centers is becoming evident. Economic damages can be reflected via several vectors of impacts (damages to public infrastructure, damages to private homes, reduction in sale prices of homes). Using data on LS severity from InSAR techniques and housing sale value from 2015 to 2021 in the SJV, we performed a wide-scale analysis of the impact of LS on housing sale values in the region. Our results indicate that LS resulted in a 2.4%–5.8% reduction in housing sale values.

Furthermore, we can conclude from the various analyses we conducted that there can be significant heterogeneity in the impact of LS across several scales. We found that higher-value homes are more sensitive to the LS impact, reflecting higher levels of loss to the housing sale values. We also found that regardless of the housing values, higher subsidence rates will result in larger losses. We found that LS, in aggregate, caused a loss of approximately \$1.44–\$1.87 billion in housing sale values in the impacted areas of the SJV.

As shown by Bagheri-Gavkosh et al. (2021) the main reason for LS in the SJV is related to the substantial overdraft of groundwater from aquifers for irrigation by agricultural activities. Therefore, mitigation of LS impacts can potentially be achieved by changing the magnitude of pumping of groundwater, changing land use designations that may result in losses to economic activities of the agricultural sector, or establishing MAR projects with multiple objectives, including LS mitigation. For example, MAR can use access water during certain periods (harnessing floods) or recycled urban wastewater to be reinjected into the aquifer year-round (Reznik et al. 2022).

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