Fine-scale spatiotemporal variation in subsidence across California’s San Joaquin Valley explained by groundwater demand

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Abstract

Achieving sustainable agricultural groundwater use remains a significant challenge worldwide in part because data on groundwater withdrawals are limited. A new generation of interferometric synthetic aperture radar (InSAR) data provide high spatial- and temporal-resolution measurements of subsidence and uplift of the earth’s surface, which are known to reflect change in groundwater storage below. Here, we establish for the first time a quantitative link between local irrigation water demand and InSAR-derived vertical land surface displacements in California’s San Joaquin Valley, with the goal of increasing the utility of remotely sensed displacements for understanding and managing groundwater at fine scales. We relate 100 m, sub-monthly displacements to estimates of irrigation water demand generated from land cover and weather data by performing a suite of physical process-motivated statistical analyses that leverage (i) temporal variations in surface water supplies created by climate, and (ii) spatial variations in water demand created by different land uses. Between 2015 and 2017, cultivated land experienced up to seven times the total subsidence, and up to nine times the dry year subsidence rate, of uncultivated land. In uncultivated areas, subsidence rates differed minimally across dry and wet years. In contrast, within cultivated areas, dry year subsidence rates were more than double wet year rates, indicating increased agricultural groundwater pumping under diminished precipitation and surface water supplies. Mean subsidence, and the marginal response of subsidence to water demand, were greatest for cultivated lands and for field and pasture crops in particular, and were also proportional to distance from surface water supply infrastructure. These findings demonstrate that land surface observations have the potential for use in the quantification of connected surface water and groundwater processes at policy-relevant scales.

1. Introduction

Management of freshwater resources is critical to global water and food security [1, 2]. In agricultural regions like California’s Central Valley, variability in surface water availability can be mitigated through groundwater use. However, overdraft of groundwater aquifers in agricultural regions is common, and is both difficult to diagnose in the short term and to manage in the longer-term [3–7]. These difficulties stem from geophysical uncertainty associated with quantifying available groundwater [8] and from a dearth of groundwater usage data at policy-relevant spatial and temporal scales [9–12]. Without comprehensive groundwater reporting, scientists, planners, and policymakers must rely on sparse monitoring wells and low-resolution satellite data [3, 13] to estimate changes in groundwater stores. The need for improved groundwater monitoring systems is even more pressing under climate change, as rising imbalance between surface water supply and demand is projected to increase pressure on groundwater resources in agricultural regions worldwide [7, 14, 15].

Interferometric synthetic aperture radar (InSAR) is a remote sensing technology used to map land surface displacement at high spatial and temporal resolutions, and which has great potential to address gaps in groundwater monitoring. To date, InSAR has been used to attribute land surface subsidence and uplift to seasonal groundwater extraction and recharge over select aquifers [16–22]; to estimate permanent loss
in aquifer storage due to subsurface compaction in California’s Central Valley [23–25]; to quantify large aquifer volume changes [26]; and to improve the capacity of the Gravity Recovery and Climate Experiment (GRACE) mission to provide local groundwater storage estimates [27]. The high spatial resolution and increased temporal sampling of newer satellite-based InSAR platforms [28] provide an opportunity to better understand how both geophysical and human factors contribute to land surface displacement dynamics.

We explore the potential of InSAR to be used as a tool for agricultural groundwater monitoring and management at local scales. In the California Central Valley, despite abundant discussion and debate concerning the sustainability of the region’s uniquely diverse specialty crop production [29–32], there exist no publicly accessible, fine-scale measurements of either surface water or groundwater withdrawals, rendering direct attribution of subsidence to water use difficult. Similarly, while land subsidence over large spatial scales has long been linked to groundwater pumping to meet agricultural water demand in the region [3, 23, 33, 34], to date it has not been possible to infer the intensity of local groundwater use from surface displacement, and it remains challenging to relate local subsidence to agricultural irrigation [21]. Here we combine new, high-resolution observations of vertical land surface displacement derived from InSAR [35] with climate and land cover data to attribute—at fine scale and for the first time—different rates and patterns of land surface displacement in the San Joaquin Valley to the differential groundwater demand generated by different land uses and associated irrigation.

The San Joaquin Valley is an ideal location for probing agricultural groundwater dynamics. There is cultivation of irrigated specialty crops in the valley, with surrounding land dominated by rainfed native grass and shrub lands (figure 1 (a), (b)). The valley features an extensive surface water supply infrastructure network (i.e. canals) through which surface water deliveries to agricultural users for irrigation vary substantially from year to year: in wet years, users may receive up to 100% of their surface water allocations, while in critically dry years, they may receive 0% [21, 36, 37]. The valley is located over an aquifer system composed of coarse sand and gravel stratified with fine clay and silt [38]. An impermeable clay layer known as the Corcoran Clay divides portions of the aquifer vertically into an upper unconfined and lower confined layer, although various confining or semi-confining layers exist throughout the valley [38, 39]. While the extents and connectedness of aquifer hydrogeologic features are not precisely mapped throughout the valley, the aquifer may be conceptualized generally as a semi-confined system for which groundwater pumping can induce subsidence [24].

In the valley, growers pump groundwater to supplement missing surface water supplies in dry years where possible [4, 23, 37]. Therefore, we examine the land surface displacement record from a drought period (2015 - 2016), during which there were minimal surface water deliveries, and a record-breaking wet period (2016 - 2017), during which deliveries returned. Differences between surface water availability in dry and wet periods (figure 2(a)), and variability in water demand associated with different land uses (figure 1 (c, d) and figure 2 (b)), allow us to attribute heterogeneity in land surface displacements in both space and time (figure 1 (c, f)) to land cover types and their associated groundwater demand.

Here, we begin with a description of our conceptual model (section 2.1), the data (section 2.2), and the methods used to conduct three sets of empirical analyses (section 2.3). We then discuss results from the three analyses: we provide descriptive analyses of displacement and its variation across different land cover types (section 3.1); we evaluate the capacity of water demand to explain spatiotemporal variation in land surface displacement across the region and across wet and dry time periods (section 3.2), as well as across different land cover types and levels of access to surface water supply infrastructure (section 3.3). Additionally, we explore a suite of supplementary analyses designed to address potential sources of uncertainty in the attribution of land surface displacement to groundwater demand (section 3.4).

2. Methods and data

2.1. Conceptual model

We adopt an idealized conceptual model to motivate and structure our statistical analysis. The model integrates our understanding of the mechanics driving land surface displacement with the fundamentals of surface water hydrology (Supplementary Text S1 (stacks.iop.org/ERL/15/104083/mmedia)). We consider displacements \( dD/dt \) to be the sum of two responses: a local poroelastic displacement response \( dD_p/dt \), which arises from local changes in pore pressure caused by change in groundwater storage [40] (stores of water in subsurface pore spaces); and a broad, potentially non-local elastic load response \( dD_s/dt \), which arises from changes in the downward force of stored surface and subsurface water on the solid earth, reflecting motion opposite to that induced by poroelastic effects [41–44]. Thus, displacements are related to groundwater storage (equations (S1)–(S2)). Where groundwater is pumped from confined or semi-confined aquifers, as in the San Joaquin Valley [16, 24], the elastic load effect is overwhelmed by the poroelastic effect [42]. We therefore assume that observed displacement reflects poroelastic effects over regions of active groundwater pumping (\( dD/dt = dD_p/dt \) and elastic load effects...
elsewhere \((dD/dt = dD_e/dt)\). Artificial groundwater storage, or managed aquifer recharge, is limited in our study region and therefore not considered in our analysis.

We describe local change in groundwater storage using a standard water balance framework that relates local storage change \(dS/dt\) to the difference between surface water inputs (precipitation, irrigation) and outputs (evapotranspiration, discharge) (equation (S3)). We combine the water balance model with our geophysical understanding of the displacement response, and consider idealized conditions representative of drought conditions in the San Joaquin Valley [36, 37]. This yields a simple proportionality between displacement and vegetation water demand, or the difference between evapotranspiration \(ET\) and precipitation \(P\): \(dD/dt = -\alpha(ET - P)\) (equations (S4)–(S6)), where \(\alpha\) is a proportionality

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**Figure 1.** Land cover, water demand, and vertical land surface displacement in California’s San Joaquin Valley and environs. (a) Location of the San Joaquin Valley study region (highlighted box) in California, with counties including Fresno, Kern, Kings, Madera, Tulare, and portions of adjacent counties (black lines) and the cultivated valley (within the red lines); (b) 2015–2017 static annual land cover classifications; annual rates of water demand \((PET - P)\) for dry (c) and wet (d) water years; annual rates of land surface displacement for dry (e) and wet (f) water years.
constant. Positive water demand results in negative displacement, or subsidence. When surface water deliveries are present, such as in interim seasons or wet periods, we expect the opposite: either reduced rates of subsidence or, in some cases, uplift via recharge.

This conceptual model relates groundwater storage change to displacement using a proportionality constant ($\alpha$), which is a function not only of the poroelastic and elastic responses, but also various aspects of the subsurface (e.g. geology, soil composition) [25] and land use practices (e.g. soil management, irrigation methods) (equations (S7) and (S8)). Due to this heterogeneity in surface and subsurface features across the study region, we relied on a large-sample statistical approach that was purposefully designed to average over this heterogeneity [45], and thereby illustrate key dynamics present across the study region. Thus, our empirical analysis is focused on exploiting variation in high-resolution observational data (section 2.2), through which we explore the capacity of a simple linear relationship (section 2.3) to reveal fundamental features of an otherwise complex connected surface and groundwater system.

2.2. Data
Our primary data include vertical land surface displacements, land cover classifications, and vegetation water demand for irrigation (‘water demand’). Our vertical land surface displacement data are observations at a 100 m x 100 m spatial resolution and 6 - 48 day (19 day average, 24 day mode) temporal resolution. Displacement data are a combination of two independent and complementary geodetic datasets: synthetic aperture radar (SAR) acquisitions from the European Space Agency’s Sentinel-1 missions [28, 46–48], which are corrected using available continuous Global Positioning System (cGPS) stations [49] following the cGPS-enhanced InSAR method [35] (Supplementary Text S2.1). We formatted 50 spatiotemporal displacement estimates (Supplementary figure S1 and Supplementary table S1) between April 1, 2015 and October 23, 2017 as cumu-
relative vertical land surface change relative to April 1, 2015 (mm, ‘total’ displacement), and rates of change (mean mm/day within 6-48 day measurement periods; displacement ‘rate’). Our land cover data are classifications [50, 51] grouped into seven categories aligned with those used in land use surveys [52] and with irrigation practices [53] (Supplementary figure S2). We limit our analysis to areas whose land cover types remain unchanged over our study period, and consider areas with oil wells [54] separately. These land cover types and their percentage of the valley (1.2 million grid cells total), are as follows: fruit and nut crops, e.g. deciduous, citrus, and vineyard crops (33%); native vegetation (30%); urban land (13%); idle land (10%); field crops, e.g. corn, cotton, and soy (6%); pasture crops excluding pasture grasslands, e.g. alfalfa and switchgrass (4%); oil fields (3%); and truck crops, e.g. tomatoes, lettuce, and melons (1%). Because we lack fine-scale information on water supply, we generate an estimate of water demand as the difference between potential evapotranspiration and precipitation ($PET - P$). $PET$ is the product of daily 2 km resolution reference evapotranspiration [55] (http://cimis.casix.ucdavis.edu/cimis/), and vegetation-specific coefficients [56] matched to the annual 30 m land cover data [50, 51]; from $PET$, we subtracted daily 4 km precipitation [57] (Supplementary Text S2.2). Additionally, we constructed a measure of proximity to artificial surface water supply infrastructure (e.g. canals) (Supplementary Text S2.3 and Supplementary figure S3) [58, 59]. Ancillary data include: soil infiltration characteristics [60]; elevation [61]; well water table depth measurements [62]; and annual groundwater use amounts reported by agricultural water districts [63, 64].

We performed analyses at the spatiotemporal resolution of the displacement data by using modal and median resampled values of land cover and water demand. Our analysis exploits variation across two dimensions. First, temporal differences between dry and wet time periods figure 2(a) represent extremes in surface water supply [36]. We defined the dry period to be April 1, 2015 - October 4, 2016 (22 observations) and the wet period to be October 5, 2016 - October 23, 2017 (28 observations). The dry period spans more than a single water year (October - September of either 2015-2016 or 2016-2017), due to our inclusion of additional April-September 2015 displacement observations to more closely balance the number of wet and dry period observations. Second, spatial differences between land cover types figure 2(b) represent differences in water demand. We split the study region into broad cultivated and uncultivated land regions using the extent of the cultivated alluvial valley [65] as a boundary (figures 1(a) and (b)), and 2(b). Where noted, we use either the full study region or the subset cultivated valley, as well as the land cover types therein.

2.3. Empirical analyses

Our analysis proceeds in three parts. First, we evaluate how displacement dynamics are differentiated by land cover. We provide summary statistics of displacement for different land cover types for the entire study period, and wet and dry year periods separately. We also calculate the correlation between displacement and water demand rates at the grid cell level across the full study region, which identifies unique temporal dynamics of displacement and water demand within areas with either strong positive or negative correlation, and identifies the land cover types that generate those dynamics. See Supplementary Text S3.1 for details.

Second, we explore the capacity of water demand to directly explain variation in displacement. We empirically model displacement as a linear function of water demand in the cultivated valley at the grid cell level, and for wet and dry time periods separately. This analysis yields estimates of grid-cell level mean displacement rates, mean change in displacement with a change in water demand, and the fraction of variation in displacement explained by water demand. See Supplementary text S3.2 and equation (S9) for details.

Third, we evaluate how displacement response to water demand varies by land cover. We again model displacement as a linear function of water demand for separate wet and dry periods, but at the land cover type group level. This analysis yields estimates of land cover type- and time period-specific mean displacement rates, and mean change in displacement with a change in water demand. Lastly, we model displacement as a linear function of water demand interacted with land cover type and a measure of proximity to surface water supply infrastructure (Supplementary Text S2.3 and Supplementary figure S3). This allows simulation of displacements for each land cover type across a range of water demand rates, as well as for low and high levels of access to surface water supply infrastructure. See Supplementary Text S3.3 and equations (S10)–(S12).

Our attribution of heterogeneity in displacement to land cover and associated groundwater demand faces several possible sources of confounding. Therefore, we explore the capacity for variation in displacement with land cover to be attributable to variation in other features of the environment, scale, or model specification (Supplementary Text S3.4). Additionally, while there exist records of groundwater levels and withdrawals in the San Joaquin Valley, those that are publicly accessible are not temporally and/or spatially consistent across our large study region. Therefore, we only briefly explore the capacity of displacements to be used directly alongside a limited set of well water table depth measurements (Supplementary Text S3.4.5) and annual groundwater use amounts reported by agricultural water districts (Supplementary Text S3.4.6).
3. Results and discussion

3.1. Displacement dynamics differentiated by land cover

Statistical summaries over the cultivated valley reveal meaningful differences across land cover types, including different crops. Cumulative totals and average rates of displacement, expressed as the median of grid cell observations within each land cover type for the full time series, vary significantly across land cover types (figure 3 (a, b)). The largest cumulative magnitudes of subsidence occurred in the dry year and for field crops, followed by pasture crops, truck crops, and fruit and nut crops (figure 3(c)). For example, there was a median 272 mm of total cumulative subsidence for field crops over the study period, and a dry water year subsidence rate of 131 mm/year. For fruit and nut crops, there was a median 62 mm of total subsidence over the study period, and a dry water year subsidence rate of 31 mm/year. In contrast, for uncultivated lands (idle, native, urban, and oil), subsidence totals over the study period were between 4 and 38 mm, and dry water year rates of subsidence were between 5 and 14 mm/year. The lesser subsidence of fruit and nut crops relative to other crops is unexpected given high reported volumes of water consumption by fruit and nut crops in California. The area of land cultivating fruit and nut crops, which is large relative to field crops (33% vs. 6% of the cultivated valley), can nevertheless consume a greater total volume of water. For all cultivated lands, the subsidence rates experienced in the dry year were more than double that of the wet year, whereas dry and wet year subsidence rates for uncultivated lands differed only by up to 9%. Agricultural land types experienced an additional 20-88 mm of subsidence in the dry year relative to the wet year, indicating how much subsidence may be attributable to surface water deficits in a drought year.

In general, land cover types with the greatest relative subsidence are those with higher positive water demand (figure 3(b)). Water demand is greatest for field crops, followed by truck, pasture, and then fruit and nut crops (figure 3(b), top). In general, we expect land cover types with greater relative water demand (e.g. field crops vs. fruit and nut crops) to have greater groundwater withdrawal and associated subsidence. However, differences in the amount of water applied as irrigation between agricultural land types are determined both by differences in physiological water demand and the efficiency of irrigation (section 2.1 and Supplementary Text S1). Field and pasture crops characteristically use irrigation methods that are less efficient and higher-volume (gravity-driven methods such as flood and furrow) than those used by fruit and nut crops (micro-sprinkler and drip irrigation) [66]. Thus, irrigation methods can increase or decrease the relative intensity of irrigation water use beyond what would be expected according to water demand alone. For example, pasture crops have only a slightly greater water demand than fruit and nut crops (figure 3(b), top), but are generally irrigated less efficiently [66]. This may explain the relatively greater subsidence during dry periods over pasture crops than water demand alone suggests (figure 3(b), bottom).

Correlation between time series of land surface displacement and water demand (figure 4 (a)) illustrates seasonal (phase) alignments between displacements and water demand that we expect based on the conceptual water balance model, and the presence or absence of poroelastic effects in agricultural and non-agricultural land, respectively (section 2.1 and Supplementary Text S1). Negative correlation indicates displacement that is out of phase with water demand (figure 4(b), blue lines), which is expected in areas where groundwater pumping results in subsidence during the dry summer season (during positive water demand). This pattern appears predominantly over cultivated land (figure 4(c), top). Positive correlation indicates that displacement is in phase with water demand (figure 4(b), orange lines), a pattern that occurs almost exclusively over rain-fed native vegetation (figure 4(c), bottom). Furthermore, the amplitude of the out-of-phase displacement signal, which corresponds to agricultural land cover, is greater than that of the in-phase non-agricultural displacement signal. Thus, cultivated areas are distinguishable from uncultivated areas according to the relationship between displacement and water demand. Additionally, the spatial extent of strong negative correlation increases in dry relative to wet periods (Supplementary figure S4), suggesting an observable increase in the spatial extent of agricultural reliance on groundwater during the dry period.

3.2. Water demand explains variation in displacement

We used a grid cell—level regression analysis (equation S9) to evaluate the extent to which spatial variation in water demand corresponds to spatial variation in displacement, across all land cover types within the cultivated valley. We assess spatial patterns in the direction and magnitude of mean displacement (figure 5(a), (d)), the marginal response of displacement to water demand figure 5(b), (e), and the degree to which water demand variation explains displacement variation figure 5(c), (f). Differences between dry (figure 5 top) and wet (figure 5 bottom) periods illustrate differences between cases of limited and abundant surface water supply in the growing season, respectively. Mean displacement, the marginal displacement response to water demand, and explained variance were all of greater magnitude in the dry period, suggesting greater relative reliance on groundwater throughout the valley. Meanwhile, there was substantial spatial variability in
this water demand - displacement relationship. For example, negative displacement (subsidence) and displacement sensitivity to water demand were reduced but still present in the wet period in southwestern Tulare county (dark red and purple regions in figure 5(a) and (b), respectively), while there was uplift and greatly diminished displacement sensitivity in the Westlands region of southwestern Fresno county (dark gray and light purple regions in figure 5(d) and (e), respectively).

In terms of the regression design, mean displacement (the intercept) and the marginal response of displacement to water demand (the slope) are independent from one another. Therefore, these results imply that even when local averages are accounted for, negative marginal responses of displacement to water demand (greater subsidence with greater water demand) have an extremely coherent spatial structure consistent with intensively farmed areas of the valley. Furthermore, the percent of variance in displacement that is explained by water demand (R-squared) is exceptionally high—up to 95%—in these same areas of the valley, even though displacement is not independent from other features of the environment, such as geology and soils, which are not accounted for in the empirical model. In the dry period, in areas with R-squared values ranging between 70%–95% (orange and red in figure 5(c)), water demand is the primary, or exclusive, driver of subsidence. In areas with lower R-squared values, including cultivated areas in the wet period (figure 5(f)), remaining unexplained spatial variability is likely due to surface water supply.
3.3. Displacement response to water demand varies by land cover

First, we used a land cover type—level regression analysis (equation S10) to evaluate the extent to which land use—specific water demand explains land use—specific displacement in the valley, and within separate dry (figure 6(a)) and wet (figure 6(b)) periods. Average dry period rates of subsidence (figure 6(a), horizontal axis), and the average marginal response of displacement to change in water demand (figure 6(a), vertical axis), are both greater for those land cover types that also demonstrated greater cumulative subsidence and rates over time (figures 3(a) and (b)). For example, for field and pasture crops, average rates of displacement are not only more negative, but the marginal displacement response to increased water demand is also more negative, relative to other land cover types. Furthermore, the magnitudes of subsidence and marginal displacement response to water demand were reduced for all land cover types during the wet period (figure 6(b)), when surface water supplies were available.

Second, we used fitted regression coefficients to simulate displacement across a realistic range of water demand (equation S11, Supplementary figure S5), and across both levels of water demand and levels (5th and 95th percentiles) of proximity to surface water supply infrastructure (equation S12), again within separate dry (figure 6(c)) and wet (figure 6(d)) periods. Without accounting for proximity to surface water infrastructure (equation S11), we observe that subsidence rates increase with water demand for agricultural land cover types in the dry period, as well as for select agricultural lands in the wet period, but to a lesser degree (Supplementary figure S5). Thus, agricultural lands in general are more sensitive to water demand in dry periods, but only select agricultural land cover types (field, pasture crops) remain sensitive in wet periods.

Accounting for access to surface water supply infrastructure (equation S12), which is done using a measure of the intensity of proximal artificial surface water features such as canals (Supplementary figure S3), reveals additional dynamics. The use of the surface water source intensity measure as a proxy for surface water supply was necessitated by the absence of spatially-explicit measurements of surface water deliveries at the resolution of our displacement or water demand datasets (Supplementary Text S2.3). The 5th percentile of water source intensities took a value of zero, indicating areas where no grid cells in the surrounding 5 km region contained artificial surface water supply infrastructure features; the 95th percentile took a value of 0.22, indicating areas where 22% of grid cells in the surrounding 5 km region contained an artificial surface water supply feature. In the dry period, subsidence increased with water demand for agricultural land cover types in areas with both low and high artificial water source intensities (figure 6(c)), when the measure of those intensities did not indicate access to surface water, as deliveries were limited or non-existent in that period. In contrast, in the wet period, when surface water deliveries returned, subsidence only continued to increase with water demand in areas with low artificial water source intensities—or in areas lacking surface water supply infrastructure. We note that figures 6(c) and (d) present a subset of land cover types in order to
Figure 5. Spatial structure in the relationship between displacement and water demand. Maps show estimates from simple ordinary least squares regression of displacement rates on water demand rates at the grid cell-level in the cultivated valley (within the red lines), using observations within dry (April 1, 2015 – October 4, 2016, n = 22 per cell, a–c) and wet (October 5, 2016 – October 23, 2017, n = 28 per cell, d–f) time periods. (a, d) The intercept, or average displacement rate; (b, e) the slope, or average change in the displacement rate with a unit increase in the water demand rate; (c, f) the R-squared, or the fraction of variation in displacement explained by water demand.

highlight patterns specific to agricultural lands. Displacements for oil fields, a non-agricultural land type, should not be sensitive to the proximity of surface water supply networks, other than through the collocation of those oil fields with agricultural land that is sensitive to water supply. As anticipated, the slope for oil fields with low proximity to surface water infrastructure does not change between dry and wet periods as it does for agricultural land; the slope for oil fields with high proximity is consistent with collocated agricultural land. This analysis demonstrates that the sensitivity of agricultural land subsidence to water demand is diminished with proximity to surface water supply networks, but only in wet periods when surface water is in fact accessible through those networks. This supports our understanding that water demand satisfied by pumping groundwater drives subsidence, and does so variably across different land cover types.

3.4. Attribution of variability in displacement to water demand

All robustness analyses generated results consistent with our primary findings. Alternative regression model specifications demonstrate that systematic differences in displacement and displacement sensitivity to water demand by land cover type are robust to model specification (Supplementary figures S6 and S7, Supplementary table S2, and Supplementary Text 3.4.1). For example, even when accounting for variation in proximity to artificial surface water supply infrastructure (Supplementary figures S3 and S8), soil infiltration characteristics \[60\], elevation \[61\], longitude and latitude, the field and pasture crop displacement responses in the dry period remain more negative than those of other land cover types (figure S6). Thus, key differences in displacement sensitivity to water demand by land cover type are not explained by those other features. Despite deviation in some estimates (e.g. we obtain variable results for truck crops and idle land, for which there are fewer samples and uncertain classification, respectively), it remains clear that subsidence rates are more sensitive to increased water demand, and subsidence is greater for agricultural land cover types, and in dry relative to wet periods.

While agricultural land cover types are relatively well-mixed spatially across the larger study region, there exists some degree of spatial segmentation by land cover type, which motivated analysis within a subset area of the valley. For the subset analysis, displacement remains differentiated by land cover type, with field and pasture crop subsidence totals and rates exceeding those of fruit and nut and other non-agricultural land cover types (Supplementary figure S9 (b, c)). In our analysis accounting for spatial correlation in displacement, we replicated our main descriptive analyses using displacement data adjusted for spatial correlation, and also replicated our land cover type-level regression analysis through bootstrap sub-sampling of the study region. In both analyses, the relative relationships between displacement for
Figure 6. Displacement and displacement sensitivity to water demand by land cover type, and simulations across water demand and proximity to surface water infrastructure. (a), (b) Regression coefficients (points) from linear regressions of displacement on water demand for different land cover types (colors), and within dry (a, April 1, 2015 - October 4, 2016) and wet (b, October 5, 2016 - October 23, 2017) periods. Coefficients and 95% confidence intervals (point thickness) show the expected displacement response to change in water demand (vertical axis) and mean displacement rates (horizontal axis). (c), (d) Predictions (lines) and 95% confidence intervals (line thickness or shaded regions) show predicted rates of displacement (vertical axis) for different rates of water demand (horizontal axis), and for contrasting intensities of proximal artificial surface water supply infrastructure (line type). Predictions were generated using the fitted coefficients of a linear regression of displacement on water demand interacted with land cover type (color) and intensities of proximal surface water infrastructure (line type), and within dry (c) and wet (d) periods. (a), (b) calculations include all grid cells in the cultivated valley; (c), (d) includes a sub-sample (10^5) of displacement grid cells in the cultivated valley.

different agricultural land cover types, and specifically negative displacement (subsidence) during dry months, were retained (Supplementary figures S10 and S11). When incorporating land cover classification error into the main descriptive analyses, the magnitudes of displacement for land cover types varied. However, the relative rankings of agricultural land cover types remained the same (Supplementary figure S2 and Supplementary table S3).

Through comparison of displacement and monitoring well water table depth data (Supplementary Text S3.4.5), we found that displacement observations extracted at well locations were more correlated with each other than were the water table depth observations at those same well locations. However, temporal patterns in displacement were generally consistent with well water table depths (albeit lagged, as observed in previous research [18]). Both the well and displacement data similarly distinguished between agricultural and non-agricultural land types (Supplementary figure S13). It is nevertheless apparent that the information provided by point-located well data is fundamentally different in nature from that of gridded InSAR, despite general correspondence. In our analysis of annual groundwater use amounts reported by agricultural water districts that were incorporated into Groundwater Sustainability Agencies (GSA) following the passage of California’s Sustainable Groundwater Management Act (SGMA) in 2014 [67], we found that volumes of displacement over GSAs were a fraction of the total groundwater withdrawal volumes, and that this fraction varied substantially between GSAs, and over time within individual GSAs (Supplementary Text S3.4.6). In 2015 and 2016, annual total volumes of displacement over GSAs ranged between 13% and 21% of reported groundwater use by volume, and displacement patterns varied substantially across adjacent agencies.
(Supplementary figure S14). Displacement is a function not only of groundwater withdrawals (themselves a function of irrigation demand and water use efficiency), but also long-term recharge rates, aquifer properties, and subsurface geology—all of which vary in space and time [12, 16, 18, 24, 25, 68]. Nevertheless, comparisons such as these demonstrate opportunity for evaluating subsidence data alongside other datasets and models of the aquifer system, which have the capacity to benefit local-level monitoring efforts, the assessment of permanently reduced storage capacity, and the identification of opportunities for managed aquifer recharge.

4. Conclusion

Improved groundwater management at local to regional scales requires high quality data at those scales. InSAR is a promising source of spatially consistent, high-quality geophysical data that is relevant to water resources management because it records the land surface response to water storage changes at unprecedented spatial and temporal resolutions. Due to the variable resolution and availability of data on other factors that drive land surface change, including but not limited to land and irrigation management practices and subsurface geology, the promise of InSAR lies in our ability to combine it with other sources of geophysical and social data to answer water policy-relevant questions. Here, we provide a preview of the power of such a synthesis, demonstrating that spatial patterns of subsidence and their relationship to agricultural cultivation and associated water demand are clear and robust. Our findings suggest that policy levers supporting sustainable groundwater management might benefit from consideration of the groundwater use intensity of crop selection, not only the difficult-to-define sustainability of groundwater extraction from within aquifer boundaries that remain uncertain and that are costly to delineate [69]. As California is representative of high-producing, semi-arid and irrigation-dependent systems worldwide, coordinated efforts to link subsidence, groundwater and surface water use, and crop production data across comparable spatiotemporal scales have tremendous global potential to advance groundwater monitoring and management.

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All data, including raw SAR images and cGPS position data, are freely available from public sources (as referenced) and processed GlnsAR data products are available from the Zenodo repository at http://10.0.20.161/zenodo.3968902. All data processing, analyses, and visualizations were done in the R programming environment [70]. Analysis and visualization scripts are available upon request to the authors. Burney and Levy were supported by NSF-NIFA INFEWS/T1 Grant #1639318, Neely was supported by NASA Grant 80NSSC18K1422, and Borsa was supported by NASA Grant NNX16AR07G.

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