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Key Points:

- We developed an InSAR processing strategy that achieves basin-wide ~ 2 mm/year accuracy in the presence of up to 15 cm of tropospheric noise
- Sentinel InSAR results show that the Permian Basin's sharp increase in shale oil production has led to numerous surface deformation features
- InSAR subsidence patterns near Pecos can be modeled as dip slip over multiple normal faults and discretized cylindrical reservoir compaction

Supporting Information:

- Supporting Information S1

Correspondence to:

S. Staniewicz,
scott.stanie@utexas.edu

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InSAR Reveals Complex Surface Deformation Patterns Over an 80,000 km² Oil-Producing Region in the Permian Basin

Scott Staniewicz¹ , Jingyi Chen¹ , Hunjoo Lee² , Jon Olson² , Alexandros Savvaidis³ , Robert Reedy³, Caroline Breton³ , Ellen Rathje⁴ , and Peter Hennings³ 

¹Department of Aerospace Engineering and Engineering Mechanics, The University of Texas at Austin, Austin, TX, USA, ²Hildebrand Department of Petroleum and Geosystems Engineering, The University of Texas at Austin, Austin, TX, USA, ³Bureau of Economic Geology, The University of Texas at Austin, Austin, TX, USA, ⁴Department of Civil, Architectural, and Environmental Engineering, The University of Texas at Austin, Austin, TX, USA

Abstract Here we used Sentinel-1 interferometric synthetic aperture radar (InSAR) data acquired between November 2014 to January 2019 to map how the basin's surface has deformed in response to fluid injection and extraction. While our stacking approach has low complexity, its accuracy increases with the Sentinel-1 data volume. With an automated outlier removal algorithm, we achieved ~ 2 mm/year accuracy across the basin in the presence of up to ± 15 cm tropospheric noise. We observed numerous subsidence and uplift features near active production and disposal wells, with the maximum deformation rate occurring in 2018 when production peaked. The most important deformation signatures are linear patterns that extend tens of kilometers near Pecos, TX, where a cluster of increased seismic events was cataloged by the Texas Seismological Network (TexNet). Our elastic modeling results demonstrate that fluid extraction and dip slip along normal faults are potential causes for the observed seismicity and deformation patterns.

Plain Language Summary Over the past decade, breakthroughs in horizontal drilling and hydraulic fracturing have made the Permian Basin one of the most productive oil fields in the world. Using spaceborne interferometric synthetic aperture radar (InSAR), we mapped how the Permian Basin's land surface has deformed from oil and gas production activities. We developed a new processing technique to mitigate tropospheric noise associated with turbulent variations, which allows us measure ground changes with millimeter-level accuracy. We observed numerous subsidence and uplift features near active production and disposal wells. The observed deformation rate is the highest in 2018 when the largest volume of oil and gas was produced in the basin. The InSAR-observed subsidence patterns over the Pecos area can be modeled as dip slip over multiple normal faults and discretized cylindrical reservoir compaction. The implication for the scientific community, as well as a broader sector of stakeholders, is that the increase in high-quality satellite-based data now allows us to monitor vast areas for subsurface stress and pore pressure changes in oil-producing regions.

1. Introduction

The Permian Basin stretching from eastern New Mexico and covering most of West Texas has become the United States's largest producer of oil and gas over the past decade, largely due to advances in shale recovery technologies. Injection or withdrawal of fluids from the subsurface can induce earthquakes along existing faults (Ellsworth, 2013; Simpson et al., 1988), and an increased rate of low-magnitude earthquakes has been observed along with the increase in hydrocarbon production in West Texas (Atkinson et al., 2016; Ellsworth, 2013; Frohlich et al., 2016, 2019; Lomax & Savvaidis, 2019; Savvaidis et al., 2020; Skoumal et al., 2020). While petroleum production and wastewater injection volumes have been rising throughout the basin, the recently cataloged earthquakes are spatially clustered (supporting information section S1). One significant cluster is near Pecos, TX, where increased seismic activity began in 2009 and climbed to more than 2,000 earthquakes in 2017 (Frohlich et al., 2019). To better understand the causes of these earthquakes and to assess the likelihood of infrastructure damage and safety concerns, the State of Texas funded the Texas Seismological Network (TexNet) to record earthquakes down to $M_{2.0}$ across the state since 2017 (Savvaidis et al., 2019). TexNet seismic data will be most meaningful when combined with knowledge of the

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subsurface (Academy of Medicine et al., 2017; Council, 2013); however, measuring the subsurface at a basin scale is both expensive and technically challenging.

Interferometric synthetic aperture radar (InSAR) has been routinely used for mapping surface deformation over wide areas with millimeter-to-centimeter accuracy (Bürgmann et al., 2000; Massonnet et al., 1993). These surface deformation measurements can be used to derive information about Earth's subsurface, estimate the distribution of fault slip, and infer associated seismic risk (Elliott et al., 2016; Huang et al., 2017; Segall, 2010). Within Texas, Shirzaei et al. (2016) reported indications of surface uplift due to wastewater injection near a 2012 *M*4.8 earthquake, though limited validation for the ALOS data was available at this site near Timpson, TX (Semple et al., 2017). Kim and Lu (2018) detected multiple deformation bowls within the Delaware Basin related to wastewater injection, CO₂ injection, and hydrocarbon production using Sentinel-1 InSAR data. Zheng et al. (2019) incorporated InSAR-derived surface deformation data into a poroelastic model to analyze the geomechanical processes near an uplift signal in northern West Texas. They discovered that the observed surface deformation was likely caused by injection well leakages, rather than pressure increases at the planned injection depth, and the leaks may have contributed to freshwater contamination. Most recently, Deng et al. (2020) used ascending Sentinel-1 line-of-sight (LOS) measurements to infer pore pressure change and Coulomb failure stress change at three sites in the southern Delaware Basin. They suggested that certain groups of earthquakes are likely induced by fluid injection but noted that local rock structure and media properties are key controls on the area's susceptibility to induced seismicity.

Previous InSAR studies demonstrated the use of InSAR surface deformation data for understanding causes of induced seismicity; however, these studies only focused on study areas ~60-by-60 km or smaller, and basin-wide InSAR surface deformation data with detailed uncertainty quantification are needed for assessing the likelihood of induced seismicity risk. Since InSAR tropospheric noise variance increases with the distance away from the reference point (Emardson et al., 2003), it is difficult to expand the InSAR spatial coverage to the entire Permian basin while retaining millimeter level accuracy. In this study, we show that the increasing quantity and quality of Sentinel-1 synthetic aperture radar (SAR) data allow us to average thousands of interferograms and mitigate strong tropospheric noise. Additionally, we developed an outlier detection algorithm that removes InSAR measurements corrupted by severe tropospheric noise (e.g., storms and heat waves) and reduces InSAR measurement uncertainty by another factor of 2, down to 1–3 mm/year across the basin. Our results were validated by independent GPS measurements recorded at 13 permanent ground stations. The InSAR-observed subsidence patterns over the Pecos area can be modeled as dip slip over multiple normal faults and discretized cylindrical reservoir compaction. Our InSAR deformation maps are now available through the Center for Integrated Seismicity Research (CISR) for the broader scientific community. This data set, when combined with physics-based reservoir and fault modeling, can produce insights into the causes of induced seismicity. Furthermore, these surface deformation data products can be used to assess the areal effectiveness of the oil and gas production, a measure for estimating which regions of a reservoir are being depleted most quickly. InSAR techniques now provide a low-cost method to assist oil and gas operations and risk management at a basin scale.

2. Methods

2.1. InSAR Data Processing Strategy

Using a geocoded single look complex (SLC) processor (Zebker, 2017; Zheng & Zebker, 2017), we processed 91 ascending (Path 78, Frames 94–104) and 82 descending (Path 85, Frames 483–493) Sentinel-1 scenes acquired between November 2014 and January 2019 (Figure 1). We generated more than 7,000 interferograms with 120 m pixel spacing and a maximum temporal baseline of 800 days. No spatial baseline threshold was imposed in the interferogram formation. Because few decorrelation artifacts were presented, we were able to unwrap all interferograms without additional spatial filtering using the Statistical-cost, Network-flow Algorithm for Phase Unwrapping (SNAPHU) (Chen & Zebker, 2001). We removed long-wavelength phase ramps, possibly due to residual orbit errors or long-wavelength tropospheric noise, using a planar phase model. Comparable interferograms can be generated using other processors such as the InSAR Scientific Computing Environment (ISCE) (Rosen et al., 2012).

The coverage of GPS permanent stations in West Texas is sparse, and there are 14 permanent GPS stations (Figure 1) that recorded daily east, north, and up (ENU) surface deformation measurements (Blewitt et al., 2018). After removing the common tectonic motion, all GPS stations showed little surface deformation

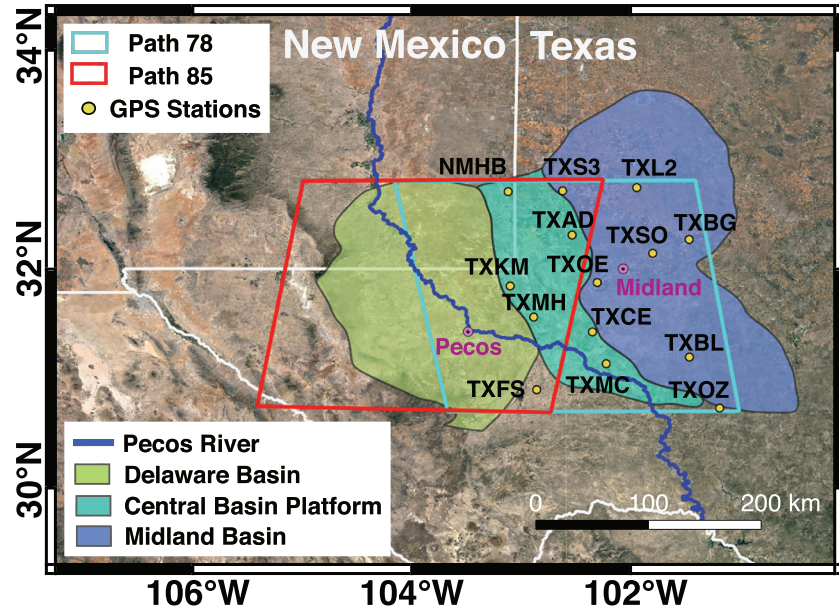


Figure 1. GPS and InSAR data coverage over the Permian Basin. Yellow dots indicate GPS permanent stations. Teal and red boxes indicate ascending Path 78 and descending Path 85 paths of Sentinel 1 InSAR coverage, respectively. Each path contains over 80 SAR acquisitions, leading to over 3,500 interferograms per path at 120 m pixel spacing.

(0–3 mm/year) between November 2014 and January 2019. We chose the GPS station TXKM as the reference point for both ascending and descending InSAR data, and we used the remaining 13 stations as controls to assess InSAR measurement uncertainty as described in section 2.3.

2.2. Solutions for Cumulative Surface Deformation Over Time

An interferogram measures surface deformation that occurred between the two SAR acquisition times along the radar LOS direction (Hanssen, 2001). We employed a stacking approach (Sandwell & Price, 1998) to calculate the average LOS velocity v_{avg} of each ground pixel over a time period of interest T as

$$v_{avg} = \frac{\sum_{i \in G} d_i}{\sum_{i \in G} t_i} \quad (1)$$

where G is a subset of interferograms that were formed using two SAR scenes acquired within the time period T . The LOS measurement (in cm) and the temporal baseline of the i th interferogram in G are written as d_i and t_i , respectively. Comparable LOS velocity estimates can be produced using the Small Baseline Subset (SBAS) approach (Berardino et al., 2002) with a constant velocity (linear deformation) model (supporting information section S5).

In this study, we solved for the average LOS velocities over three periods of interest: November 2014 to January 2017, November 2014 to January 2018, and November 2014 to January 2019. Over each period T_j , we computed the cumulative LOS surface deformation over this period as the product of $v_{avg,j}$ and T_j . We also solved for the vertical and eastward deformation in the region where path 78 and 85 overlap (supporting information section S2). To account for the large variation in look angle within one Sentinel-1 Interferometric Wide (IW) swath image, we used the LOS unit vector at each pixel location (Figure S2) in the LOS decomposition.

2.3. Errors in InSAR Surface Deformation Estimates

The phase of an interferogram can be written as (Zebker & Villasenor, 1992; Zebker et al., 1994, 1997)

$$\Delta\phi = \frac{4\pi}{\lambda} \Delta d_{LOS} + \Delta\phi_{orb} + \Delta\phi_{decor} + \Delta\phi_{unwrap} + \Delta\phi_{dem} + \Delta\phi_{iono} + \Delta\phi_{tropo} + \Delta\phi_n \quad (2)$$

where λ is the radar wavelength and Δd_{LOS} is the surface deformation along the radar LOS direction. The noise terms include orbital errors, phase decorrelation, unwrapping errors, DEM inaccuracies, ionospheric and tropospheric artifacts, and other residual noise terms that are typically an order of magnitude smaller

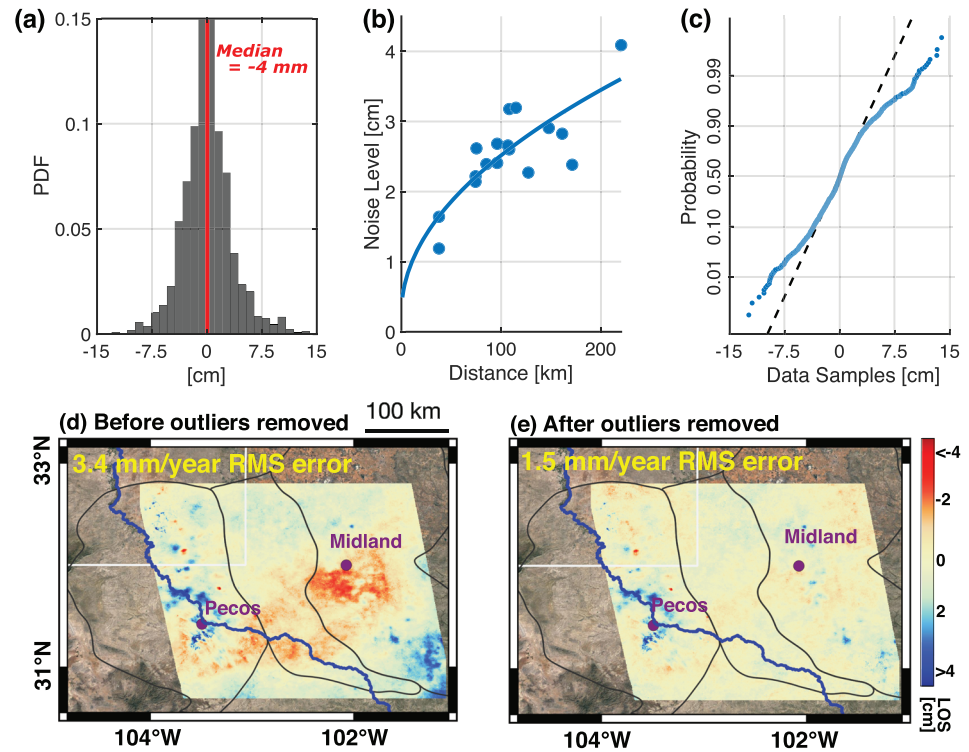


Figure 2. (a) LOS measurements (in cm) of all ascending interferograms at the GPS station TXMC. The distribution has a near zero median (-4 mm) and a standard deviation of 3.2 cm. Due to the absence of substantial deformation signals, the standard deviation of the distribution is a measure of LOS turbulent tropospheric noise. (b) The standard deviation of random tropospheric turbulent noise at 13 control locations (blue dots), which increases as the square root of the distance from the InSAR reference point (blue line). (c) A comparison between the tropospheric noise distribution at TXMC with a normal distribution. Dashed line connects the 1st and 3rd quartiles of the data. Troposphere noise following a normal distribution would match the dashed line, and non-Gaussian tails (we noted as outliers) are present. Cumulative ascending LOS deformation solutions (November 2014 to December 2017) (d) before and (e) after excluding InSAR outlier measurements. Note that 1.1 cm cumulative error over 3 years is equivalent to 3.5 mm/year RMS error in the velocity estimate.

than the error terms listed here. Following the processing strategy outlined in section 2.1, $\Delta\phi_{orb}$, $\Delta\phi_{decor}$, and $\Delta\phi_{unwrap}$ were either removed or negligible in our data set. Because the relatively flat Permian Basin is located in the middle latitudes, $\Delta\phi_{dem}$ and $\Delta\phi_{iono}$ are not substantial (Fattahi & Amelung, 2013; Liang et al., 2019). For the remainder of this section, we focused on evaluating and mitigating the impact of tropospheric noise on the West Texas Sentinel-1 data.

Tropospheric noise $\Delta\phi_{tropo}$ consists of a stratified component that correlates with topography (Doin et al., 2009) and a turbulent component that is random at time scales longer than one day (Emardson et al., 2003). In supporting information section S3, we show that the stratified tropospheric errors in our Sentinel-1 data are minimal. We further examined interferograms at the 13 control locations. For example, LOS measurements of the ascending interferograms at pixels near the GPS station TXMC show a near zero median (-4 mm) and a standard deviation of 3.2 cm (Figure 2a). Due to the absence of substantial deformation signal at this station, the standard deviation of the LOS distribution is a measure of turbulent tropospheric noise. We found that the median LOS turbulent error is close to 0 (no systematic noise bias) at all GPS control stations. The standard deviation of the turbulent noise increases as the square root of the distance from the InSAR reference point (Figure 2b). Furthermore, we compared the LOS turbulent noise distribution observed at each GPS station to a normal distribution using a normal probability plot (Filliben, 1975). We discovered that non-Gaussian tails (outliers) are present (e.g., Figure 2c) as a result of severe tropospheric noise (e.g., storms or heat waves). Identifying and removing these InSAR measurement outliers is crucial for achieving millimeter level accuracy.

Because severe tropospheric noise may only affect a portion of a SAR image, we identified InSAR measurement outliers at each pixel independently as follows. Given N SAR acquisitions, there are up to $N - 1$ InSAR LOS measurements at a pixel of interest that contain the common tropospheric noise of the k th SAR scene. We defined $u_{k,n}$ as the n th such LOS measurement, and $\bar{u}_k$ as

$$\bar{u}_k = \frac{1}{N-1} \sum_{n=1}^{N-1} |u_{k,n}| \quad (3)$$

We labeled $u_{k,n}$ (for all n) as outlier measurements if $\bar{u}_k > \text{median}(\bar{\mathbf{u}}) + 4\sigma_{\text{MAD}}$, where $\bar{\mathbf{u}} = [\bar{u}_1, \dots, \bar{u}_N]$, and $\sigma_{\text{MAD}} = 1.483 \cdot \text{MAD}(\bar{\mathbf{u}})$. Here we employed a robust statistics measure, the median absolute deviation (MAD), for estimating the spread of data samples in the presence of outliers (Hampel, 1974; Rousseeuw & Hubert, 2011). Given a vector $\mathbf{x}$ that contains M data samples, $\text{MAD}(\mathbf{x})$ is defined as

$$\text{MAD}(\mathbf{x}) = \text{median} \left(|x_m - \text{median}(\mathbf{x})| \right)_{m=1, \dots, M} \quad (4)$$

where x_m is the m th data sample.

To evaluate the performance of our InSAR processing strategy, we projected GPS data recorded at 13 control stations onto the LOS directions to use as ground truth. The differences between InSAR and GPS inferred average LOS velocities were used as a measure of the uncertainty in the InSAR surface deformation solutions (supporting information section S4). We found that stacking reduces the impact of random Gaussian turbulent noise by $\sim \sqrt{N}$, where N is the number of SAR acquisitions. The outlier removal algorithm further reduces the uncertainty in the LOS velocity estimates by a factor of 2, down to 1–3 mm/year across the basin. For example, the average InSAR velocity along the ascending LOS direction between November 2014 and January 2018 shows a root-mean-square (RMS) error of 3.4 mm/year before the outlier removal and 1.5 mm/year after the outlier removal. The presence of InSAR measurement outliers resulted in long-wavelength artifacts (~ 100 km and greater) in the cumulative deformation solutions (e.g., Figure 2d), which were automatically mitigated through the pixel-based outlier removal algorithm (e.g., Figure 2e). Additionally, we compared InSAR LOS deformation solutions as derived from (1) the stacking method, (2) a SBAS linear deformation model with L_1 and L_2 -norm penalty functions, and (3) unregularized and regularized SBAS deformation time series (supporting information section S5). These InSAR time series algorithms can be implemented using software packages such as Generic InSAR Analysis Toolbox (GIANt) (Agram et al., 2013), STAMPS (Hooper et al., 2012), and LiCSBAS (Morishita et al., 2020). Removing the detected outliers leads to more accurate and consistent surface deformation solutions in all three cases.

3. Results and Discussion

3.1. Surface Deformation in the Permian Basin

The Sentinel-1 cumulative LOS deformation solutions reveal numerous surface deformation features over the oil-producing region in the Permian Basin (Figure 3). From the ascending geometry, we observed no substantial deformation in the Central Basin Platform, where oil and gas are mostly produced from conventional reservoirs. In the Midland and Delaware Basins, we observed an accelerating surface deformation rate between November 2014 and January 2019, which coincides with the sharp rise of oil production from unconventional reservoirs in 2017 and 2018. For example, a 30 km² area northwest of Pecos shows approximately 0.5 cm cumulative LOS deformation between November 2014 and January 2017, 1.5 cm between November 2014 and January 2018, and over 5.5 cm from November 2014 to January 2019. The greatest number of observable signals is present in 2018 when peak production occurred in the region. Similarly, from the descending geometry, we find no substantial deformation in the Central Basin Platform and an increasing rate of surface deformation in the Delaware Basin.

In the northern Delaware Basin, where large volumes of oil production and wastewater disposal occurred, the ascending and descending LOS deformation patterns are similar. This means that the observed deformation in this region is primarily vertical (Figures 4b and 4e). The observed subsidence or uplift features between November 2014 and January 2019 are ~ 1 –4 cm. In the southern Delaware Basin, Deng et al. (2020) solved for the cumulative LOS surface deformation between November 2014 and February 2019 (~ 100 km by 60 km) using the ascending Sentinel-1 data (Path 78 Frames 99 and 100). In this study, we found that the

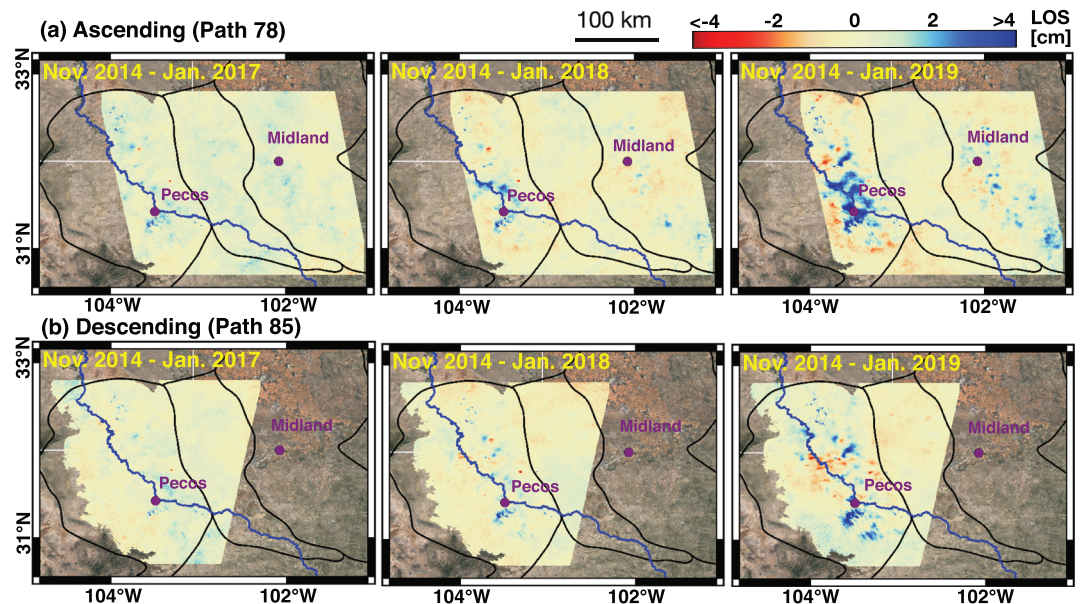


Figure 3. Cumulative LOS deformation (November 2014 to January 2017, November 2014 to January 2018, and November 2014 to January 2019) as inferred from Sentinel-1 (a) ascending Path 78 and (b) descending Path 85 data over an 80,000 km² oil-producing region of the Permian Basin. Here a subsidence or eastward deformation signal leads to a positive LOS measurement in the ascending geometry, and a subsidence or westward deformation signal leads to a positive LOS measurement in the descending geometry. Areas with >1,200 m altitude are masked due to the low oil production activity in mountainous regions.

observed magnitudes of the ascending and descending LOS deformation are different (Figure 3), which suggests that both horizontal and vertical deformation occurred in this region. Previous studies near Mesquite, Nevada, have shown that confined aquifer pumping in the presence of faults can produce complex asymmetrical deformation patterns with a nontrivial horizontal component (Burbey, 2008). In the Pecos area, the largest subsidence patterns (~13 cm over 4 years) occurred ~15 km south of Pecos, and the largest eastward motion (~3–4 cm over 4 years) occurred near the town of Pecos along a line transect (Figures 4c and 4f). The observed linear deformation patterns parallel the inferred favorable fault plane orientation (a strike angle ~300° lining up with the measured S_{Hmax} direction) proposed by Lund Snee and Zoback (2018), and they also align with a cluster of recent shallow earthquakes (<3 km depth) cataloged by TexNet.

3.2. Implications for Geomechanical Modeling

Based on fault plane solutions derived from recent seismic activity and the faulting stress regime interpretations (Lund Snee & Zoback, 2018), the Pecos area is in a normal faulting regime. We employed an elastic dislocation model (Okada, 1992) to demonstrate that the presence of dip-slip normal faults can produce the observed linear subsidence patterns in this area (Figure 5a). We solved for the dip angle, depth, width along the dip direction, and slip magnitude of four normal faults by best fitting the forward model to InSAR vertical deformation observations, minimizing the sum of squared residuals and maximizing the r -squared values (Y. Du et al., 1992) (supporting information section S6). The optimal solution suggests that the depth of the faults ranges from 0.9 to 1.5 km, which is shallower than most of the TexNet recorded earthquakes (2–6 km in depth). Possible explanations for this discrepancy include (1) the existence of aseismic fault slippage being responsible for the observed surface deformation (McGarr & Barbour, 2018), (2) bias in earthquake depth estimation in the TexNet catalog (Lomax & Savvaidis, 2019), and (3) systematic modeling errors associated with representing a mechanically layered earth as a homogeneous half space (Y. Du et al., 1992).

After removing the best fit deformation associated with dip-slip faulting (Figure 5b), there is still ~2 cm residual subsidence in the Pecos area (e.g., Figure 5f). Given that shallow groundwater production was minimal in this region for the time period of interest (Deng et al., 2020), we introduced an elastic reservoir compaction model (Geertsma, 1973) to our geomechanical analysis (supporting information section S7). We implemented two layers of multiple cylindrical reservoirs corresponding to reported locations and depths of well clusters in the Delaware Mountain Group (DMG) and Wolfcamp reservoirs, which account for most of

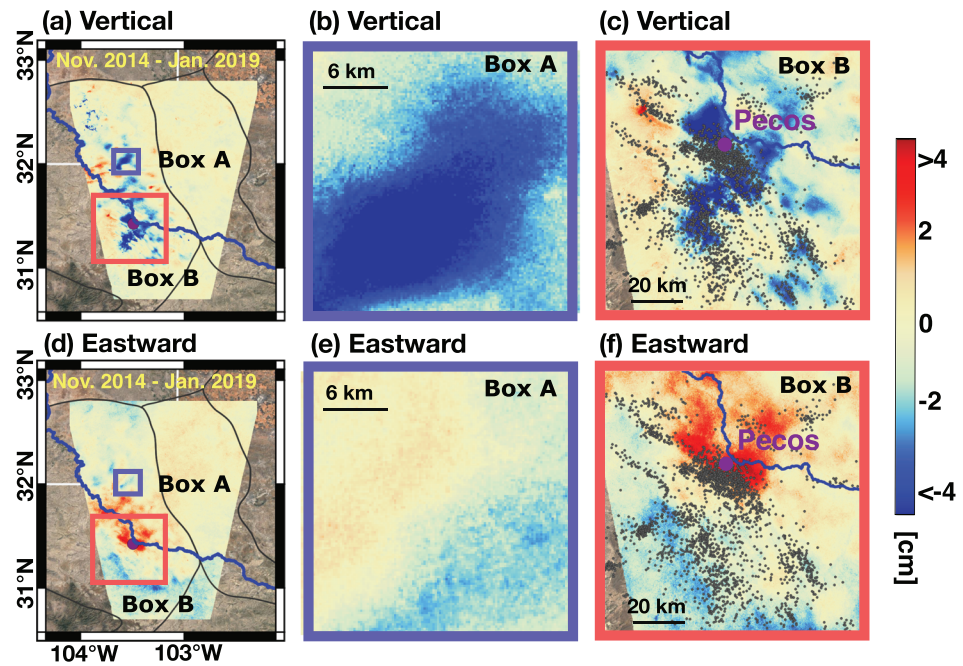


Figure 4. (a) Cumulative vertical deformation between November 2014 and January 2019 over the region where Sentinel-1 Path 78 and Path 85 overlap. A zoomed-in view of Box A in the northern Delaware Basin and Box B in the southern Delaware Basin are shown in panels (b) and (c), respectively. (d) Cumulative eastward deformation between November 2014 and January 2019 over the region where Sentinel-1 Path 78 and Path 85 overlap. A zoomed-in view of Box A in the northern Delaware Basin and Box B in the southern Delaware Basin are shown in panels (e) and (f), respectively. In the southern Delaware Basin, the observed vertical and eastward deformation (panels c and f) show linear patterns along with earthquake hypocenters (gray dots) detected by TexNet in 2018.

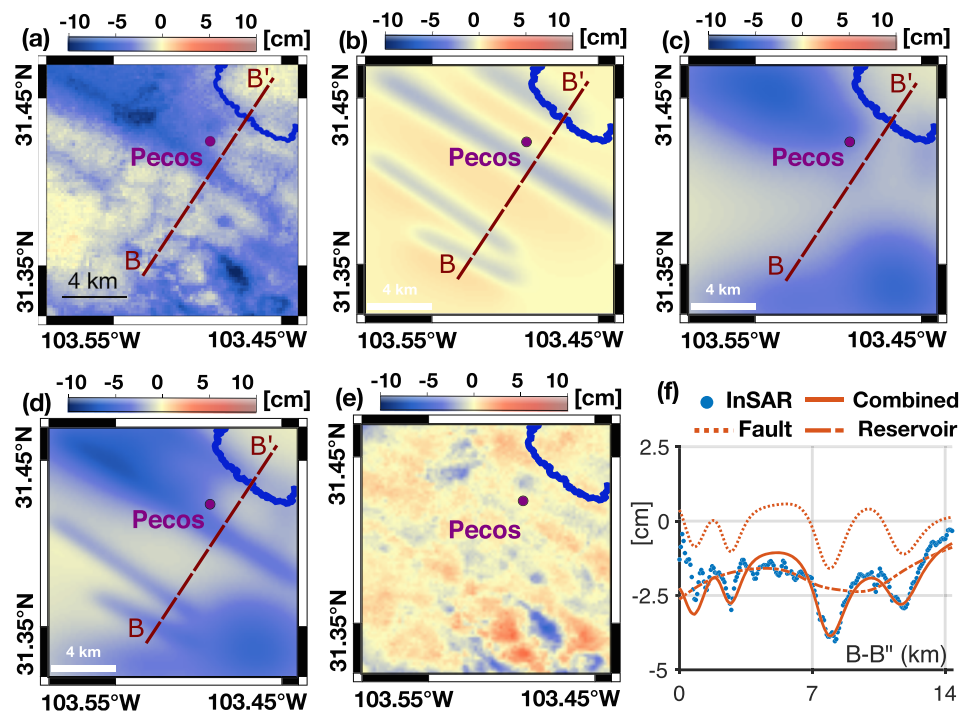


Figure 5. (a) InSAR-observed cumulative vertical deformation between November 2014 and January 2019 in the Pecos, TX, area. (b) Modeled vertical deformation associated with four dip-slip faults. (c) Modeled vertical deformation associated with reservoir compaction. (d) Modeled total vertical deformation associated with four dip-slip faults and reservoir compaction (panels b and c). (e) Difference between InSAR-observed and model-predicted vertical deformation (panels a–d). (f) Difference between InSAR-observed and model-predicted vertical deformation along the B-B' transect.

the recent oil and gas production in the region. We discretized the DMG layer based on a cluster of production wells predominantly perforated over a depth range of 1.5–1.8 km. The Wolfcamp wells are completed over a depth range of 3–3.6 km. We employed an objective function inversion method to solve for the reservoir pressure depletion pattern that best fit the InSAR-observed subsidence (Figure 5c) (J. Du & Olson, 2001).

An important conclusion of this study is that both fault slip and reservoir inflation or compaction can produce observable surface deformation over an 80,000 km² oil-producing region of the Permian Basin. The InSAR-observed subsidence patterns over the Pecos area can be modeled as slip over multiple faults and discretized cylindrical reservoir compaction (Figures 5d–5f). We note that InSAR subsidence data alone can constrain all pertinent fault and reservoir parameters in our normal faulting and reservoir compaction models. The InSAR-observed cumulative surface deformation patterns, which show larger horizontal component than the model prediction, suggest that other factors, such as strike-slip faulting and heterogeneity in subsurface properties, may play a role. There have been extensive studies on how reservoir compaction and inflation and fault slippage alter stress fields in the subsurface and produce surface deformation (Y. Du et al., 1992; Geertsma, 1973; Khakim et al., 2012; Okada, 1992; Segall, 1992; Vasco & Ferretti, 2005; Vasco et al., 2008). InSAR surface deformation can be combined with this knowledge to evaluate fluid recovery efficiency and monitor disposal wells at low cost. Furthermore, these high-quality geodetic measurements are readily available to complement the TexNet seismic catalog for assessing the likelihood of fault motion and induced earthquake risks in Texas.

Data Availability Statement

Sentinel-1 single look complex (SLC) images can be accessed from the Alaska Satellite Facility (ASF) DAAC. NASA Shuttle Radar Topography Mission (SRTM) 30 m DEM data (Nasa, 2013) were used for removing topographic phase from interferograms. Equivalent quality interferograms can be produced using other processors such as ISCE (Rosen et al., 2012) or GMTSAR (Sandwell et al., 2011). Permian InSAR cumulative surface deformation solutions (November 2014 to January 2017, November 2014 to January 2018, and November 2014 to January 2019) are available at the Texas Data Repository (<https://doi.org/10.18738/T8/AVDBOJ>). GPS data were provided by the Texas Department of Transportation and processed by the Nevada Geodetic Laboratory (<http://geodesy.unr.edu/>) (Blewitt et al., 2018). The TexNet earthquake catalog is available online (at <https://www.beg.utexas.edu/texnet/catalog>). Oil production and injection data were processed from IHS Markit and are available through the Center for Integrated Seismicity Research (CISR). Aggregate production and injection volumes are available through Texas Railroad Commission (<https://www.rrc.state.tx.us/>). Mapping figures were created using the QGIS software (Team, 2020).

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