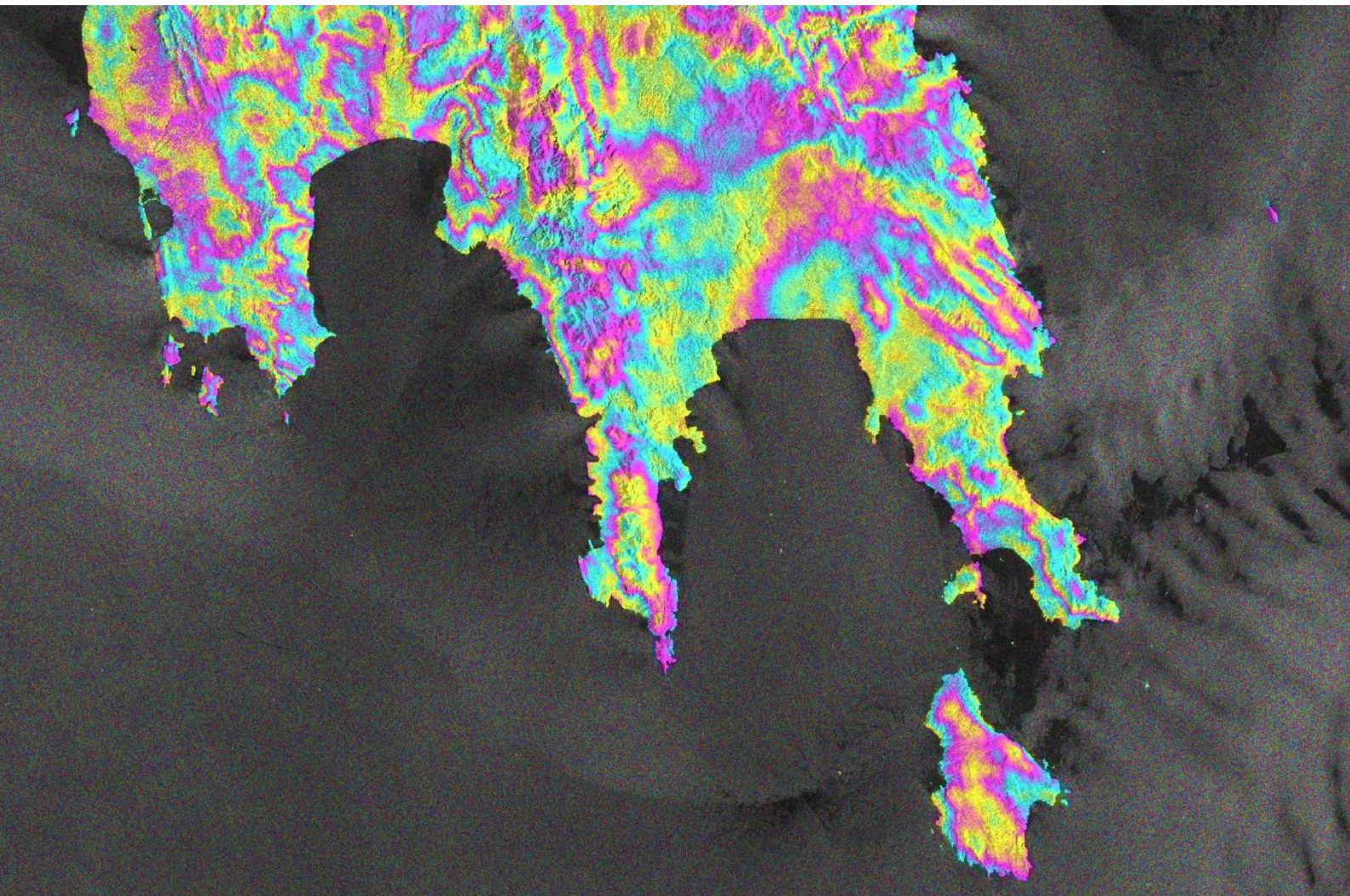


# **InSAR Technique to Assess and Monitor the Land Subsidence Induced by Overexploitation of Groundwater, Gialova lagoon catchment, Greece**

Swetha Thulasi Veedu



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GG9121 Geochemistry, Degree Project 45 HE credits  
Series: Master's Programme in Geological Sciences - NMGE0  
(120hp)  
Spring term 2025  
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## ABSTRACT

The efficiency of Sentinel-1 data, InSAR-Small Baseline Subset (SBAS) technique, and Mintpy tools in identifying potential land subsidence zones and observing subsidence patterns is well known in the scientific literature of remote sensing. This study applied advanced InSAR techniques to freely accessible Sentinel-1 satellite data to analyse land deformation patterns during 2016 and 2017 in the Gialova catchment, Greece. The investigation of spatiotemporal characteristics of land subsidence in the Gialova catchment revealed widespread subsidence, with certain limited zones exhibiting a rebound effect. The cumulative displacement patterns indicated significant subsidence, reaching up to -2.8 cm in 2016 and -4 cm in 2017. Notably, the subsidence trend at well location 23, which reached -4 cm, showed a strong correlation ( $R^2=0.64$ ) with lagoon salinity. This correlation suggests a synchronous decline in aquifer levels, restricting the influx of fresh groundwater into the lagoon. Furthermore, the cumulative subsidence trend observed from the alluvial and conglomerate aquifers (well locations 23 and 9) demonstrated a weak correlation ( $R^2 < 0.02$ ) with rainfall events, including under a 3-week lag analysis. Minor day-to-day variations in subsidence and temporary uplifts noticed from the time series pattern reflects elastic response of aquifer system. This finding suggests a delayed hydrological response of the aquifer and validates that the globally recognized human induced factor—overexploitation of groundwater resources—plays a significant role in land subsidence within the study area. Given that land subsidence poses threats to infrastructure, aquifer systems, and ecological environments, detailed monitoring studies integrating InSAR-derived land subsidence data with groundwater level measurements are essential for the sustainable management of the Gialova catchment and its lagoon.

**Keywords:** InSAR, Land subsidence, ASFOpenSARLab, Mintpy

## ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my supervisor, **Dr. Fernando Jaramillo**, for his continuous support, insightful guidance, and encouragement throughout the progress of this thesis. I would like to acknowledge **Professor Volker Brüchert**, course coordinator at the **Department of Geological Sciences**, for his support and for facilitating the academic framework that made this research possible.

Special thanks are also extended to **Jesús Martín Marañón Eguívar**, PhD scholar at the **Department of Physical Geography**, for his generous help and advice on various aspects of the work.

I am grateful to **Stockholm University**, the **Department of Geological Sciences**, and the **Department of Physical Geography**, where this thesis is being completed, for providing the academic environment and resources necessary to carry out this research in the **Gialova region**.

Finally, I would like to express my deepest gratitude to my **husband** and **daughter** for their unwavering support, patience, and encouragement throughout this journey. Their love and understanding have been a constant source of strength and motivation during the course of this work



# Table of Contents

|                                                                           |    |
|---------------------------------------------------------------------------|----|
| 1. INTRODUCTION .....                                                     | 6  |
| 1.1 Hypothesis, aim and objectives .....                                  | 6  |
| 1.1.1 Relevance of the study .....                                        | 6  |
| 2. BACKGROUND.....                                                        | 7  |
| 2.1 Land subsidence .....                                                 | 7  |
| 2.2 Synthetic Aperture Radar (SAR).....                                   | 8  |
| 2.3 Interferometric Synthetic Aperture Radar (InSAR) .....                | 9  |
| 2.4 Interferogram and Mintpy: Miami InSAR Time Series in Python .....     | 12 |
| 2.5 The use of InSAR to detect groundwater changes .....                  | 12 |
| 3. MATERIALS AND METHODS .....                                            | 13 |
| 3.1 Study region.....                                                     | 13 |
| 3.2 Sentinel-1 dataset collection.....                                    | 15 |
| 3.2.1 On-demand InSAR preprocessing in ASF HyP3 .....                     | 15 |
| 3.3 Burst InSAR SBAS- processing in Mintpy .....                          | 16 |
| 3.3.1 Softwares and conda environment setup.....                          | 17 |
| 3.3.2 InSAR-Small Baseline Subset (SBAS) processing.....                  | 17 |
| 3.3.2.1 Phase unwrapping.....                                             | 18 |
| 3.3.2.2 Interferograms access and subset.....                             | 18 |
| 3.3.2.3 Load Hyp3 data to Mintpy.....                                     | 18 |
| 3.3.2.4 Spatial coherence-based network modification.....                 | 19 |
| 3.3.2.5 Unwrapping error correction.....                                  | 20 |
| 3.3.3 Time series inversion and plotting .....                            | 21 |
| 3.4 Precipitation and Salinity data.....                                  | 22 |
| 3.5 Statistical analysis.....                                             | 22 |
| 4. RESULTS.....                                                           | 23 |
| 4.1 Spatial and Temporal coherence analysis.....                          | 23 |
| 4.2 Land subsidence spatial characteristics .....                         | 25 |
| 4.3 Time Series Analysis of land subsidence at selected groundwater ..... | 27 |
| extraction site                                                           |    |
| 4.3.1 Time series of land subsidence and rainfall during 2016.....        | 27 |
| 4.3.1.1 Land subsidence and temporal changes in lagoon salinity-2016..... | 29 |
| 4.3.2 Time series of land subsidence and rainfall during 2017.....        | 29 |

|                                                                            |    |
|----------------------------------------------------------------------------|----|
| 4.3.2.1 Land subsidence and temporal changes in lagoon salinity- 2017..... | 30 |
| 4.4 Statistical analysis: linear regression .....                          | 30 |
| 5. DISCUSSION .....                                                        | 32 |
| 5.1 Geospatial assessment of areas vulnerable to land subsidence .....     | 32 |
| 5.2 Interpreting land subsidence in relation to rainfall .....             | 33 |
| 5.3 Effect of land subsidence on lagoon salinity .....                     | 34 |
| 6. CONCLUSION.....                                                         | 35 |

## **LIMITATIONS OF STUDY**

## **FUTURE RECOMMENDATIONS**

# List of Figures and Table

- Figure 1.** The basemap of Gialova lagoon catchment with stream network, olive groves, groundwater extraction wells and DEM (Digital Elevation Model)
- Figure 2.** Hydrogeological units with groundwater extraction points
- Figure 3.** Preview of potential interferogram pairs chosen for the study in the ASF vertex
- Figure 4.** Interferogram network plot of 2016 shows total interferograms generated and average spatial coherence
- Figure 5.** The Interferograms networks of a) 2016 and b) 2017 and interferograms with low coherence selected to remove (red dashed line)
- Figure 6.** General workflow of the InSAR processing for displacement data
- Figure 7.** Spatial coherence distribution over the study region shows good coherence ranges between 0.5 and ~0.95 during 2016 (a) and 2017 (b)
- Figure 8.** Temporal coherence distribution over the study region shows good coherence ranges between 0.5 and 1.0 during 2016 (a) and 2017 (b)
- Figure 9.** Surface displacement of the Gialova lagoon catchment during a) 2016 and b) 2017 the variants of brown pixel indicate subsidence
- Figure 10.** Surface displacement of the Gialova lagoon catchment during a) 2016 and b) 2017 the variants of brown pixel indicate subsidence
- Figure 11.** Classified surface displacement of the Gialova lagoon catchment during 2016 (a) and 2017 (b) shows spatial extension of subsidence and uplift
- Figure 12.** Subsidence pattern at well location 23 in relation to Rainfall and lagoon salinity during 2016
- Figure 13.** Subsidence pattern at well location 9 in relation to Rainfall and lagoon salinity during 2017
- Figure 14.** Subsidence pattern at well location 23 in relation to Rainfall and lagoon salinity during 2017
- Figure 15.** Linear regression plots showing effect of rainfall on cumulative displacement at two well locations during 2016 and 2017 (a) location 9 and (b) location 23
- Figure 16.** Linear regression plots showing relationship between cumulative displacement and lagoon salinity at well locations during 2017 a) location 9 and b) location 23
- Table 1** Major subsidence pattern observed and the total area affected during the study period

# InSAR Technique to Assess and Monitor the Land Subsidence Induced by Overexploitation of Groundwater, Gialova lagoon catchment, Greece

## 1. INTRODUCTION

Land subsidence is a significant global geohazard, and a review of 290 related studies reveals that 47% of the most subsidence susceptible regions are coastal aquifers and river deltaic plains (Bagheri et al., 2021). The hydroclimatic and anthropogenic driven water demand cause stress on the confined and unconfined aquifer systems and are irreversible from the compaction and land subsidence (Galloway & Burbey, 2011). The scenario of continuous lowering of piezometric surface of successive aquifers due to its over exploitation along with drought conditions has been reported in several regions of Greece since 1980's (Sideri et al., 2010). Studies used InSAR techniques (Papadopoulou et al., 2019; Karatzetzou et al., 2021) have demonstrated that areas with sustained pumping, such as the Thermaikos Gulf and regions of Central Macedonia, Greece experience measurable ground deformation.

In Mediterranean regions, where agricultural areas dominated by olive cultivation are particularly vulnerable to land subsidence due to intensive use of groundwater for irrigation (Bianchini et al., 2015). Using InSAR techniques the land subsidence over agricultural land was noticed in the Tuscany region, the key olive producing region, Italy (Bianchini et al., 2015). Olive trees are drought tolerant and can survive with limited water but studies have shown that proper irrigation significantly improves the yield, profitability and oil quality (Dag et al., 2018; Gucci et al., 2009). The three-phase system is one of the most widely used modern olive oil extraction methods by olive mills, especially in Greece, where approximately 70% of olive mills employ this system (Sygouni et al., 2019) and uses up to 130 litres of water per 100 kg of olives (Foti et al., 2021). When such oil extraction methods and irrigation rely completely on groundwater for optimal production without the proper management of water resources can lead to land subsidence due to groundwater depletion (Tzanis & Daskalaki, 2020).

The Gialova lagoon, located in the southwestern Peloponnese (Greece), is one of the country's most ecologically significant coastal wetlands, also part of a wider Natura 2000 site. The lagoon was once sustained by a balance of freshwater and saltwater inputs, primarily fed by the Xerolagados stream and Tyflomitis springs. The main land use type in the lagoon catchment is olive groves. Xerolagados stream, one of the main sources of freshwater, in the catchment has been polluted by untreated olive mill wastewater (OMW) and the olive mills operating even at highlands makes easy entry of the pollutants to the streams originating from there. All these factors increased the region's reliance on groundwater for agricultural activities, tourism, and domestic purposes. Overexploitation of groundwater can increase the risk of land subsidence and thereby flooding and sea water intrusion to the coastal aquifer systems and lagoons and leads to adverse impacts on socio economic development.



Over the decades, various management strategies, and other human activities, have disrupted the Gialova lagoon's natural hydrology and study suggest a more holistic approach for future sustainable management of the lagoon by considering climate scenario, land uses and topography (Maneas et al., 2019). During the 2016-2018 the freshwater input to the Gialova lagoon was about 40% from precipitation and 60% from surface and groundwater sources and the lagoon was poorly connected with the freshwater resources (Mazoni et al., 2020). The over exploitation of groundwater resources along with drought conditions could trigger the aquifer storage, accelerate the aquifer compaction, and increase the further risk of land subsidence in the region. Land subsidence can cause significant threats to the hydrological connectivity in the whole Gialova catchment and to the Gialova lagoon in the semi-arid coastal zone. It will directly affect not only the groundwater resources but also the freshwater inflow to lagoon and its sustainable management from the high salinity and even hypersaline conditions.

## **1.1 Hypothesis, aim and objectives**

Hypothesis 1: During the period 2016-2017 there has been land subsidence in the hydrological catchment of the Giolava Lagoon due to groundwater over extraction and hydroclimatic variability

Hypothesis 2: Since increasing salinity in the lagoon is related to drier conditions and over extraction (i.e., less freshwater inflow), there should exist a temporal relationship between land subsidence and salinity

The study aims to perform a Land Subsidence (LS) analysis of the Gialova catchment during 2016 and 2017 with the aid of InSAR techniques, a) to interpret whether groundwater overexploitation is the potential drivers of LS and b) to identify the impacts of LS on the lagoon salinity during the study period.

The main objectives are,

1. To conduct a time series analysis (2016-2017) of land subsidence in the Gialova catchment and to identify the zones/regions more vulnerable to subsidence.
2. Integration of InSAR derived ground displacement results with rainfall data to evaluate its relationship with the land subsidence.
3. Interpretation of relationship between the land subsidence and the lagoon salinity.

### **1.1.1 Relevance of the study**

Research efforts aimed at detecting and monitoring land deformation in Greece have predominantly focused on Northern Greece, relying on geotechnical, geological, and hydrological data (Leontarakis, K., & Pytharouli, S. (2020). A limited number of studies utilized advanced InSAR remote sensing techniques (Papadopoulou et al., 2019; Karatzetzou et al., 2021) to identify the land subsidence. According to Karatzetzou et al., 2021 the significant subsidence zones (up to  $-30$  mm/year) identified in Thessaloniki plain are mostly in agriculture areas and spatially correlated well with the groundwater decline due to

overexploitation of groundwater. There remains a notable lack of research focused on the southern regions, particularly the Peloponnese peninsula including the Gialova catchment focused on the land subsidence resulting from groundwater extraction. Gialova catchment, hosting agriculturally intensive zones of olive groves and vulnerable coastal aquifers, has not been systematically analyzed to date for land subsidence using remote sensing techniques such as InSAR applied to Sentinel-1 data. Application of modern technologies including cloud computing services, python scripts and geospatial techniques enables efficient collection, processing, and analysis of data to get LS in centimeter level precision.

## **2. BACKGROUND**

According to the EASAC (European Academies Science Advisory Council) report and the previous studies the groundwater resources of 14 water regions, including the Peloponnese, of Greece is under stress (Voudouris et al., 2005). In many regions of Greece, the excessive exploitation of groundwater over recent decades has led to a significant decline in water table levels and a gradually developing hazard associated with this depletion is land subsidence. (Loupasakis., 2020). Monitoring land subsidence in a coastal lagoon catchment can provide a comprehensive framework for the integrated and sustainable management of land and water resources. The relevant literatures referred for this particular thesis work were listed below under each subheading.

### **2.1 Land subsidence**

Land Subsidence is the temporary or permanent deformation of the earth's surface due to various natural and human induced processes, it can cause significant threats to topography, surface infrastructures, human safety and sustainable development. According to UNESCO Working Group on Land Subsidence (WGLS) the land-level lowering or land subsidence is a major threat throughout the world and addressed in the programme of International Hydrological Decade, 1965-1974 (Raymond L. Nace., 1980). The first international symposia on Land Subsidence (LS) were held in Tokyo in 1969 to improve and disseminate knowledge about it. As part of the UNESCO's Land Subsidence International Initiative (LaSII) the Land Subsidence Symposium convenes approximately every 5-year period. The enhanced scientific understanding and technical knowledge required to identify the natural and anthropogenic land subsidence and related hazards in order to improve the long-term sustainable living conditions (TISOLS, 2023). The natural causes for the land subsidence are tectonic reactivation of structural features, sediment compaction, volcanism, earthquake, and landslides (Galloway et al., 2016). To alleviate the land subsidence the anthropogenic factors such as, mining, tunnelling, oil and gas exploration, rapid urbanisation causing overloading on the land surface, have significant role and the most important and critical is land subsidence due to long-term groundwater exploitation (Gao et al., 2016). Climate change is also an increasing concern and significant factor for LS especially in the arid and semi-arid regions (Naghbi et al., 2022) due to frequency of drought and its pressure on the aquifer system.

In the context of Global climate change and anthropogenic pressure the Land Subsidence (LS) is a significant global problem, which causes threats to topography, aquifers, surface

infrastructures, human safety, economy of society and sustainable development (Samsonov et al., 2014). All over the world, in several regions, the grave problem due to the over exploitation of groundwater is groundwater level declination and it leads to permanent loss of aquifer storage and LS (Vasco et al., 2021). In Central Mexico the higher consumption of groundwater resources caused compaction of the aquifer system and resulted in rapid LS which is detected by ALOS InSAR Time-Series method (Chaussard et al., 2014). In the Western Songnen Plain from long term subsidence analysis (2014-2019) the annual LS rate and maximum deformation rate is observed to be as -3.14 mm/a and -22.05 mm/a and the longest subsidence period observed on July 1/2016 until August 10/2018 (Zheng et al., 2022) and the subsidence caused mainly by groundwater pumping. In the Western United States, the machine learning approach estimated that 2.0 km<sup>3</sup>/yr of groundwater storage was lost roughly over the period from 2015–2016 and observed the highest LS in areas with thick sedimentary deposits (>500 m) and dense agricultural land use (Smith and Majumdar 2020).

The highest deformation rates of -20.34 mm/year are observed in Western Thessaly region, Greece, using the groundwater resource data and Random Forest (RF) method (Ilia et al., 2018). The sea water invasion associated with the land subsidence phenomena has been recorded since 1964 in the Kalochori-Sindos region and later on ground truth and satellite-based studies highlighted it (Stiros, 2001, Costantini et al., 2016). The time series analysis of 250 interferograms from ERS and ENVISAT data (1993-2010) identifies LS and rebound in Northern Greece, particularly around Kalochori and Sindos (Nikos et al., 2016). Loupasakis (2020) provided a comprehensive overview of subsidence in aquifer systems across Greece, including Thessaly plains, Thessaloniki, Amyntaio basin, and Crete, documented intensive subsidence tied to irrigation and mining abstraction, with rebound observed in areas where pumping was suspended. From the InSAR-derived subsidence in the Gulf of Corinth (Greece) the linear correlation with rainfall shows weak correlation and correlated well with aquifer level (Raucoules et al., 2008).

## **2.2 Synthetic Aperture Radar (SAR)**

The Synthetic Aperture Radar (SAR) remote sensing is an active microwave remote sensing technique and the principle behind is the sensor transmits a microwave (radio) signal towards the target and detects the backscattered portion of the signal (Tsyganskaya et al., 2018a). The SAR system can operate in various frequency bands with specific characteristics for specific applications (Pepe et al., 2017) and most commonly used SAR frequency bands are X-band (8-12GHz), C-band (4-8GHz), L-band (1-2GHz). The common and more widely used SAR satellites are Sentinel-1A/B (C-band), RADARSAT 2 (C-band), ALOS-2 (L-band), TerraSAR-X (X-band) and upcoming NISAR will carry both L-band and S-band SAR (Rosen et al., 2018). The pulse carrier wavelengths of each band are 3cm, 6cm, and 24cm for the X, C, S and L bands respectively to acquire information of the Earth surface from the received backscattered RADAR signals (Ulaby et al., 1981). The SAR data have a wide variety of applications such as, flood monitoring, crop mapping and monitoring, soil moisture content estimation, oil spill monitoring, cryospheric/glaciological applications, forest studies, wetland studies and SAR interferometry for subsidence monitoring etc (Balzter et al., 2015).

The European Union's Copernicus Earth observation mission launched Sentinel-1A and 1B in 2014 and 2016 with wide global coverage, open data access and interferometric capabilities. The revisit time is 6 days by combining 1A and 1B and 12 days with only one satellite operational, the Sentinel-1B is not operational since December 2021 (Hill et al., 2021). The Sentinel-1 data is collected and provided by the dual polarization SAR instrument which operates in the C-band range of 5.405 GHz (Crosetto et al., 2016). Due to the very good penetration capacity of C-band frequency range it can operate in any weather condition, as it has the capability of penetrating through the darkness, clouds, snow and rain and to provide higher spatial resolution data of the Earth's surface (Huang et al., 2017). The four exclusive acquisition modes the Sentinel-1 SAR data operates is Strip Map (SM), Interferometric Wide Swath (IW), Extra Wide Swath (EW) and the IW mode will allow to combine a large swath width (250 km) with a moderate geometric resolution (5m x 20m) (Torres et al., 2012). Interferometric Wide Swath (IW) of the Sentinel-1 TOPSAR mode is split into 3 bursts IW1, IW2 and IW3. The Level-0 products of the data take by each mode is the base product consisting compressed and unprocessed data with auxiliary information to support processing of Level-1 and Level-2 high level data's (European Space Agency., 2013).

The Sentinel-1 data have a wide range of applications from land to sea monitoring (marine tracking, sea ice and ice sheet) and through various worldwide studies it has been proved its significance. For wetland studies; wetland mapping, flood monitoring, wetland health assessment and water extent change detection (Sahour et al., 2022). Sentinel-1 data have been used to monitor the natural disaster like landslides or subsidence (Torres et al. 2012) analysis and interpretation of ground deformation associated with volcanoes, earthquake and groundwater extraction (González et al. 2015, Grandin et al. 2016, Motagh et al. 2017; Sowter et al. 2016). The key features of Sentinel-1, open and free access, IW mode, high global coverage, short repeat cycle and consistent acquisition strategy with high resolution, make it ideal for ground deformation monitoring (Bui et al., 2021).

### **2.3 Interferometric Synthetic Aperture Radar (InSAR)**

Interferometric synthetic aperture radar (InSAR), an effective geodetic technique that uses the different phases of two SAR images acquired at different orbit positions or at different times to provide land deformation measurements over large areas with precision in the millimeter to centimeter range (Richard et al., 1998). InSAR, a SAR satellite data-based technique with wide applications and demonstrated its ability to attain information on Earth surface deformation (Rosen et al. 2000). In Synthetic Aperture Radar (SAR) interferometry, the key quantity of interest is the phase difference ( $\Delta\phi = \phi_2 - \phi_1$ ) between two SAR acquisitions. Phase ( $\phi$ ) is a crucial property of the microwave signals used in SAR, which represents the position of the wave within its oscillation cycle (Hanssen R.F., 2001). Typically, phase is measured in radians, ranges from 0 to  $2\pi$  and is sensitive to the path length that the radar signal travels (between the radar antenna and the ground target). This phase difference encodes information about surface displacement, topography, or atmospheric effects (Massonnet et al., 1998) and each SAR image is a complex-valued signal, where each pixel is represented as:

$$S(x,y)=A(x,y)e^{j\phi(x,y)}$$

Here:

- $A(x,y)$  denotes the amplitude of the backscattered signal at location  $(x,y)$
- $\phi(x,y)$  is the radar signal phase
- $j=\sqrt{-1}$  is the imaginary unit.

The **interferogram generation** is the significant step for further analysis and it is formed by multiplying the first image by the complex conjugate of the second image (Just and Bamler 1994).

If  $S1(x,y)$  and  $S2(x,y)$  be the complex SAR images acquired at two different times, the interferogram,  $I(x,y)$ , is formed by  $I(x,y)=S1(x,y) \cdot S2^*(x,y)$ . The phase estimation of the interferogram is universally using the same fundamental principle the arctangent (Gatelli et al., 1994) of the imaginary and real parts of the complex-valued interferometric signal:

$$\phi = \arg(I) = \arctan\left(\frac{I_i}{I_r}\right), \text{ This formula provides the wrapped phase in the range } (-\pi, \pi]$$

Since this is a direct mathematical result of forming an interferogram, it is consistently applied across all InSAR processing platforms, whether open-source, commercial, or cloud-based. Most common commercial InSAR softwares are ENVI SARscape, SARproz, DORIS- Delft Object-oriented Radar Interferometric Software, and GAMMA software (Perissin et al. 2011, Sahraoui et al. 2006, Werner et al. 2000). The OpenSAR lab is a cloud based InSAR platform or workflow environment hosted by NASA Alaska Satellite Facility (ASF) to integrate various InSAR tools (Vaka & Rao, 2023). ASF Hyp3 (Hybrid Pluggable Processing Pipeline) is a cloud-based processing platform developed by the Alaska Satellite Facility (ASF DAAC 2024) that allows users to generate analysis ready InSAR products from Synthetic Aperture Radar (SAR) data by requesting processing on-demand (Li et al., 2021). Hyp3 can generate INSAR\_GAMMA, INSAR\_ISCE\_BURST, RTC (Radiometrically Terrain Corrected), and Amplitude Change Detection (ACD) data products (ASF DAAC., 2024). To generate and process the InSAR interferograms, the common open-source softwares available are ISCE- InSAR Scientific Computing Environment, SNAP- Sentinel Application Platform, GMTSAR- InSAR processing system based on Generic Mapping Tools, StaMPS- Stanford Method for Persistent Scatterers, EZ InSAR- Easy Interferometric Synthetic Aperture Radar, PyRate- Python tool for estimating velocity and time-series from InSAR data, GIANT- Generic InSAR Analysis Toolbox, and PySAR- Python-based SAR (Hrysiewicz et al., 2023). The PySAR was an early Python tool developed for time-series InSAR analysis and is now deprecated and succeeded by MintPy software (Miami InSAR Time Series in Python), which is more advanced, actively maintained, and has broader capabilities (Zhang et al., 2019). All these methods are generally more cost-effective, time-efficient, and capable of providing continuous monitoring of land deformation compared to traditional techniques.

## 2.4 Interferogram and Mintpy: Miami InSAR Time Series in Python

Phase unwrapping is a critical step in most SAR-based deformation studies, particularly in InSAR and time-series InSAR methods such as SBAS and PSInSAR as it enables the conversion of ambiguous wrapped phase measurements into continuous phase values that are essential for accurate deformation estimation (Berardino et al., 2002 and Ferretti et al., 2001). The coregistered and unwrapped interferogram stacks can be generated by various InSAR tools (such as, Hyp3, ARIA, ISCE, FRInge, GAMMA, SNAP etc) with common workflow steps but different methods and algorithms (Rosen et al., 2012; Wegmüller et al., 2016; JPL, 2021). Coherence plays a crucial role in Interferometric Synthetic Aperture Radar (InSAR), serving as a key metric for assessing the quality and reliability of interferograms. Spatial coherence, refers to the similarity of radar signals across neighboring pixels within a single SAR acquisition and it helps to evaluate phase noise and signal consistency (Zebker and Villasenor., 1992). Temporal coherence describes how consistent the radar signal remains between multiple observations over time. A low temporal coherence suggests decorrelation—caused by temporal changes (e.g., vegetation growth, water movement), geometric distortions, or system noise and areas with high coherence are more reliable for accurate displacement measurement (Touzi et al., 1999)

Mintpy is a python 3 software to read the beforehand generated stack of interferograms and primarily it uses the SBAS (Small Baseline subset) technique for InSAR analysis and developed by researchers at the University of Miami (Karamvavis and Karathanassi., 2020). The geospatial tools like Mintpy are available on the community driven collection of conda packages like 'conda-forge'. For the SBAS InSAR time series analysis of the Fernandina volcano at Galápagos Islands-Ecuador, for the potential larger earthquakes associated with the faults on San Francisco Bay and for the studies along Owens Valley, California earthquake sequences the ISCE2/topsStack, ARIA tool, and Hyp3 InSAR processors were utilised on Sentinel-1 data (Yunjun et al., 2019, Chaussard et al., 2015, Xu et al., 2021). ASF Hyp3 processed sentinel-1 data used to perform Mintpy-time series analysis of the ground deformation in Semarang area, Central Java and the approximate subsidence rate of -0.87 cm/year was observed from 2014 to 2023 (Agustan et al., 2023).

## 2.5 The use of InSAR to detect groundwater changes

Groundwater changes and ground movement monitoring studies conducted for the administrative area of Greater London demonstrate that InSAR derived land movement values range from -6 to +6 mm/year and average groundwater loss estimated to be 9.003 MCM/year (Agarwal et al., 2020). The high groundwater extraction induced land subsidence is found in the study by Hung et al. (2011) in southwestern Taiwan and the land subsidence rate is well correlated with the declining groundwater level. A strong correlation ( $R = 0.886$ ) was observed between variations in groundwater levels and ground deformation retrieved using the PSInSAR technique in the context of urban expansion in Lucknow City, India. These results demonstrate that InSAR provides a robust and scalable approach for the continuous assessment of land

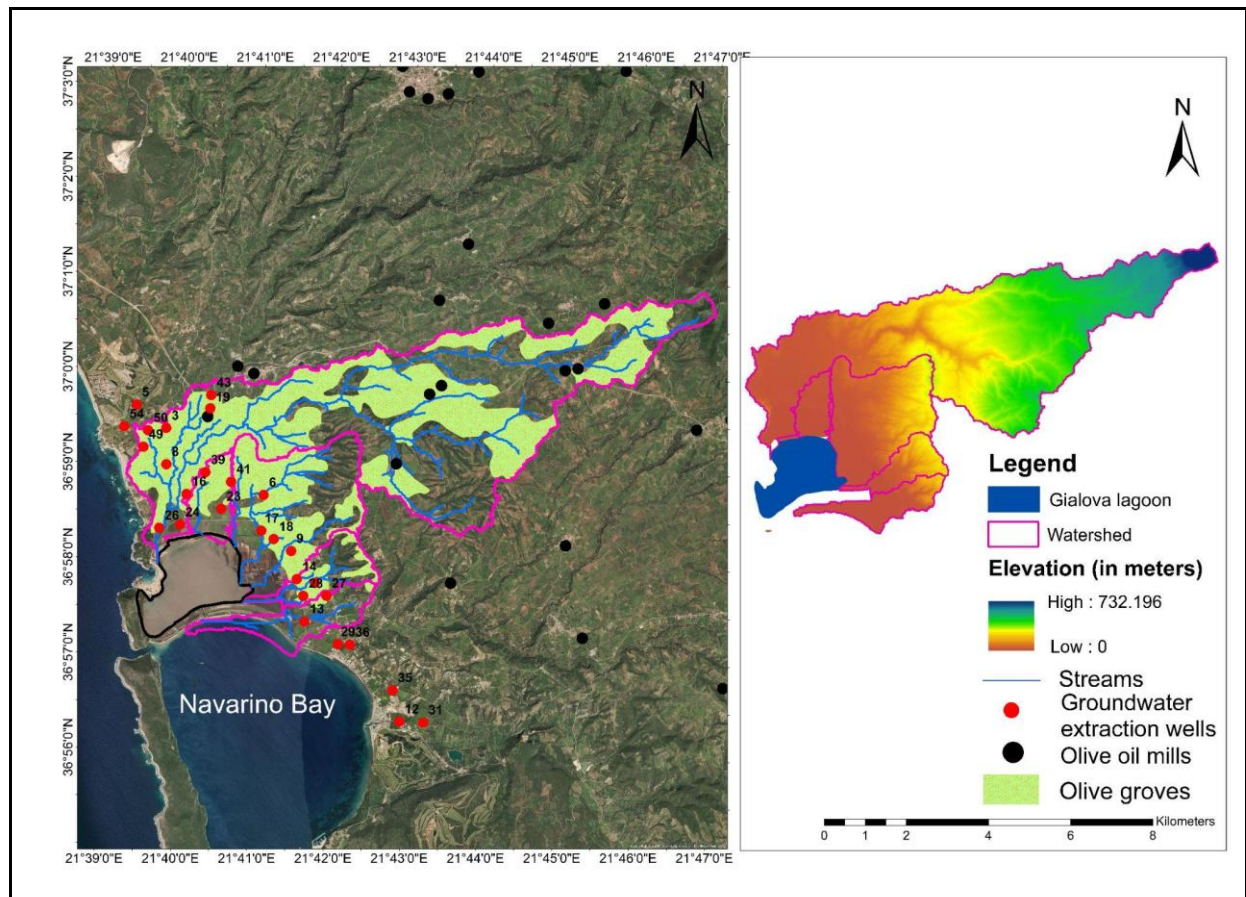


deformation induced by groundwater stress and can be effectively applied in other urban environments (Kumar et al., 2022).

### **3. MATERIALS AND METHODS**

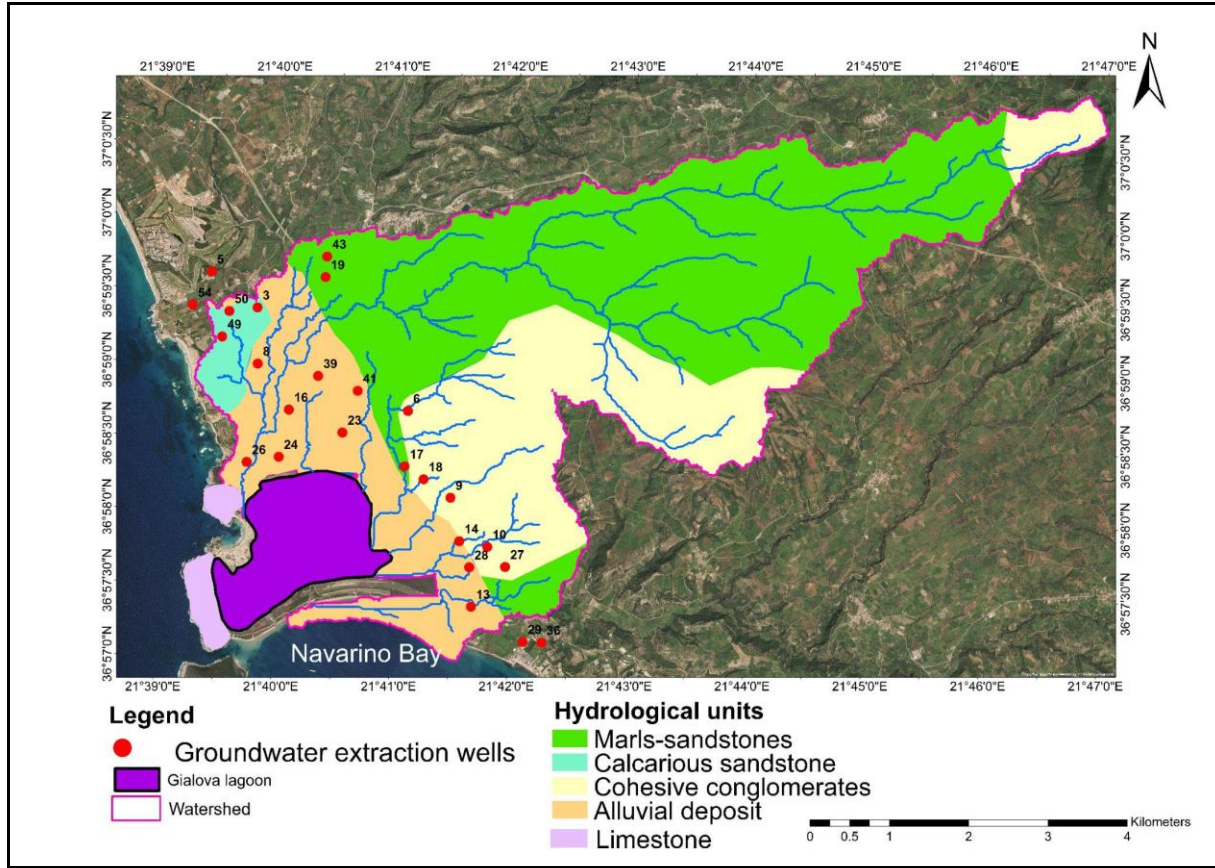
#### **3.1 Study region**

The Gialova Lagoon catchment (36.32 km<sup>2</sup>), in the southwestern coast of Greece, lies between latitudes 37°1'30"N & 36°55'30"N and longitudes 21°40'E & 21°41'E that enjoys a typical Mediterranean climate with hot and dry summers, mild and wet winters. The mean annual precipitation, evaporation and temperature is 695mm, 889mm and 18°C. The major surface water resources, Xerolagados stream, in this hydrological catchment is mounting at an elevation of 700 m (above MSL) (Figure 1) and the Tyflomitis spring is located at an elevation of 4m. Human interventions began in the late 1950's which diverted the flow of these freshwater inputs into the Voidokilia bay and Navarino bay. The main economy has been linked to agriculture municipality extracting significant quantities of groundwater per year to meet the needs of the population. The major land use type is olive groves and there are a total of 6 olive oil mills (Figure 1) in the catchment of the Gialova Lagoon; these mills are assumed to pollute the Xerolagados stream. There are another four additional mills just outside of the delineated catchment. The major hydrogeological units of the region are Limestone, Flysch, Conglomerates, Calcareous Sandstone, and Alluvial deposits (Holocene) (Figure 2). The groundwater extraction/well sites shape files were collected and two groundwater extraction wells (9 and 23) located at an elevation of 5m and 6m (above MSL) selected for this study to carry out time series displacement analysis (Figure 2). The extraction well 23 is in the alluvial formation and well 9 is in conglomerate formation (Figure 2).



**Figure 1.** The basemap of Gialova lagoon catchment with stream network, olive groves, olive mills, groundwater extraction wells and DEM (Digital Elevation Model)

The Gialova lagoon of Tyflomitis-Xerolagados hydrological catchment is one of the country's most ecologically significant wetlands spanning 225.5 hectares and an additional 0.85 hectares by the surrounding marshes to the East, it provides vital habitats for numerous species, including migratory birds, many of which are endangered. The geological age of this stable low energy environment, Gialova lagoon, is estimated to be 3300 years ago (Aubuin., 1959). The lagoon was once sustained by a balance of freshwater and saltwater inputs, primarily fed by the Xerolagados stream and Tyflomitis springs. The human intervention that started as part of the drainage projects severely altered the lagoon's hydrological connectivity and since it became difficult to maintain the brackish water conditions and to support the wetland's rich biodiversity (Emmanouilidis et al., 2018, Maneas et al., 2019). Eventually, the lagoon has experienced increasing salinity and hypersaline conditions which has devastated local plant and animal populations.



**Figure 2.** Hydrogeological units with groundwater extraction points

## 3.2 Sentinel-1 dataset collection

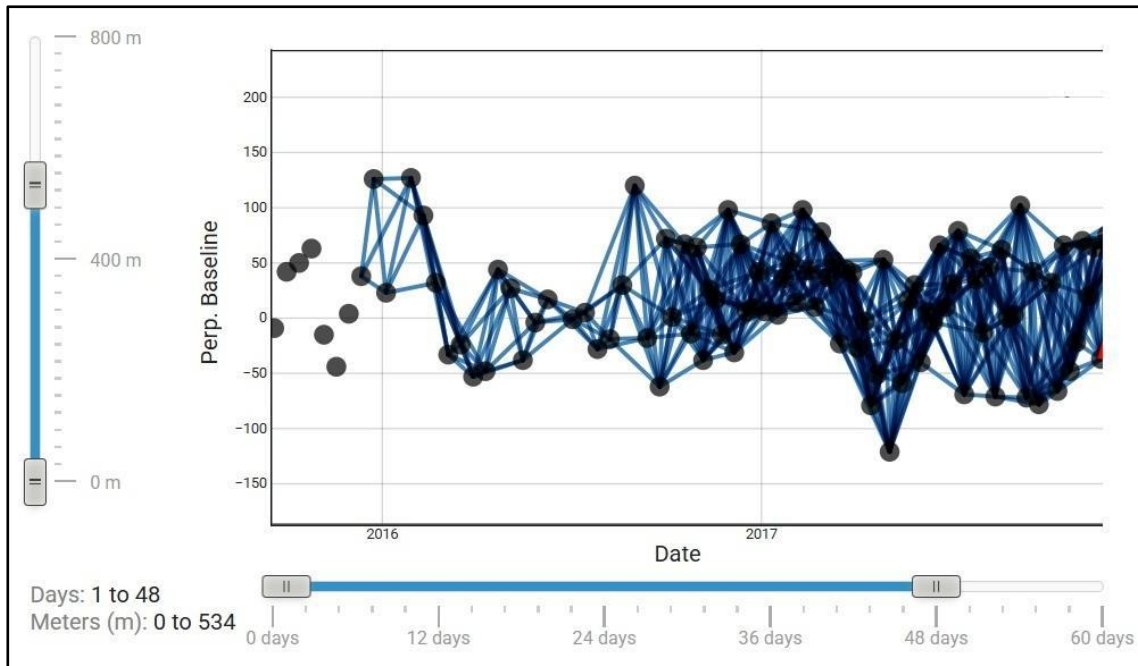
For this study, the Single Look Complex (SLC) Level-1 Sentinel-1(S1) Burst images collected from the ASF (Alaska Satellite Facility, URL: <https://search.asf.alaska.edu/#/>) which has free access. The S1 Bursts dataset in ASF Vertex is in a testing or early-access phase and the advantage is that it allows the users to download a single burst from the Sentinel-1 SLC without having to download the entire SLC that contains it. The advantage of INSAR\_ISCE\_BURST data is the unwrapping error correction can be performed only with this data. The Geographic search for two years from 15 December 2015 to 31 December 2017 has filtered 250 scenes with 946 files The SLC level-1 IW3 Burst data file generated in VV polarization which was acquired in the ascending orbit number 175 selected as reference scene to make product pairs for interferometry.

### 3.2.1 On-demand InSAR preprocessing in ASF HyP3

The ASF on demand SAR preprocessing service is currently available only for the Sentinel-1 dataset and which is utilised for this study (Alaska Satellite Facility, 2022). The data were processed using ASF's on-demand HyP3 processing system and this processing pipeline is based on the Interferometric Synthetic Aperture Radar (InSAR) Scientific Computing Environment (ISCE), which is particularly well-suited for burst-mode Sentinel-1 data. The

INSAR\_ISCE\_BURST option generates interferograms at the burst level, preserving the temporal and spatial structure required for accurate time-series analysis using tools like MintPy. The ASF vertex SBAS tool supports the Mintpy SBAS method by identifying and previews the potential interferograms will be generated using SBAS parameters for time series analysis (Figure 3).

On the ASF DAAC-SBAS (Small Baseline Subset) tool the interferograms are chosen based on the two important parameters, perpendicular baseline and temporal baseline. Interferometric pairs with moderate temporal (48 days) and small perpendicular baselines were selected to optimize coherence in a coastal region characterized by vegetation cover and seasonal precipitation. Although Sentinel-1 has a 12-day repeat cycle with single sensor and 6 days with twin sensors (Sentinel 1A and 1 B) the interferometric pairs with a 48-day temporal baseline were selected to balance data availability and coherence in a coastal environment, while minimizing temporal decorrelation. Through ASF's on-demand HyP3 processing system preprocessed interferograms generated for a period from 30 November 2015 to 30 December 2017.



**Figure 3.** Preview of potential interferogram pairs chosen for the study in the ASF vertex

### 3.3 Burst InSAR SBAS- processing in Mintpy

The ASF Hyp3 processed the raw sentinel data and performed co-registration, topographic phase removal, interferogram generation, phase unwrapping and generated outputs as GeoTIFFS. Several high-level processing steps were still necessary and were performed using the OpenSARLab jupyter book data recipes/scripts (Annexure1). Therefore, the HyP3-generated pairwise interferograms were then used as input for time-series analysis in MintPy (Miami InSAR Time Series in Python). The steps including before time series analysis are:

- Software Environment setup



- Loading and formatting HyP3 GeoTIFF products into MintPy's HDF5 structure
- Network inversion to derive displacement time series
- Selection of a reference point and reference date
- Residual error correction, including unwrapping jump detection and orbital ramp removal
- Optional tropospheric correction using external weather models (e.g., ECMWF via CDS API)
- Temporal coherence-based masking
- Visualization of surface deformation trends and generation of products such as cumulative displacement and average velocity maps

### 3.3.1 Softwares and conda environment setup

For this study, a Linux-based InSAR processing environment was set up on a Windows system using Ubuntu 24.04.1 via the Windows Subsystem for Linux (WSL2) to ensure compatibility with open-source tools such as MintPy. The MintPy version 1.6.1 was installed through a Conda-based environment following community-supported installation recipes from OpenSARLab (ASF, 2023) and the installation recipe provided by Gareth Funning (2023). Required Python packages, including MintPy and PyGMT, were managed using a custom environment.yml file to ensure reproducibility.

To support automated data access, credentials for Earthdata and Dataspace were securely stored using a netrc file. Additionally, ISCE environment paths were configured to enable compatibility with the topsApp.py workflow. ARIA-Tools and Jupyter kernel integration were included to streamline the processing and visualization workflow within Jupyter notebooks. This setup enabled efficient Sentinel-1 time-series InSAR analysis with a reproducible and portable workflow.

### 3.3.2 InSAR-Small Baseline Subset (SBAS) processing

The mathematical principles and equations in the SBAS method enable the processing and analysis of InSAR data and the extraction of displacement time series while minimizing errors and selecting high-quality data for inversion. Here's a concise explanation of each step involved in Mintpy-SBAS processing with the fundamental equations. The core principle behind the InSAR technique lies in analyzing the total interferometric phase difference ( $\Delta\phi$ ) between two SAR acquisitions, which encodes information related to ground surface displacement, topography, atmospheric conditions, and system noise (Aminjafari et al., 2024, Ferretti et al., 2007). The general InSAR phase equation by considering sensitive components (removing or minimizing these components significant to isolate the deformation signal) can be written as:

$$\Delta\phi = \phi_{\text{def}} + \phi_{\text{topo}} + \phi_{\text{atm}} + \phi_{\text{orb}} + \phi_{\text{noise}} \dots \text{Eq (1)}$$

[ $\phi_{\text{def}}$  deformation signal,  $\phi_{\text{topo}}$  topographic phase,  $\phi_{\text{atm}}$  atmospheric delays,  $\phi_{\text{noise}}$  instrumental and decorrelation noise]

### 3.3.2.1 Phase unwrapping

The estimated phase is inherently ambiguous by integer multiples of  $2\pi$ , this is because the radar phase is wrapped, meaning it can only be measured within the interval  $(-\pi, \pi]$ . This ambiguity must be resolved to extract meaningful geophysical quantities such as surface deformation or elevation, the process is called phase unwrapping (Hanssen R. F., 2001). For burst-based processing, HyP3 leverages the ISCE2 software package, which integrates the SNAPHU (Statistical-Cost, Minimum Cost Flow, Network-Flow Algorithm for Phase Unwrapping) tool. Burst-Based InSAR processing workflow employs a Minimum Cost Flow (MCF) approach (Alaska Satellite Facility (ASF) but includes the generation of a connected components file. This file is valuable for identifying and mitigating phase unwrapping errors, especially in areas with low coherence or complex deformation patterns. In the MCF approach the interferogram is represented as a graph, where nodes correspond to residues and edges represent possible connections (branch cuts) between residues (Costantini., 1998). Each possible connection between residues has an associated weight/cost, typically based on the length or quality of the path. The goal is to minimize the total weight of connecting all residues.

### 3.3.2.2 Interferograms access and subset

In this stage, the script starts by importing essential libraries for handling and visualizing geospatial data. Some examples of these are geopandas which handles vector data, rasterio for raster data, and shapely which can perform geometric operations. Then the script establishes a working directory to perform the analysis and copies the InSAR-SBAS project files from the user's ASF Vertex account.

Next, it checks the existence of other essential supplemental data, such as DEM data, azimuth angle map, and incidence angle map. Such data sets are critical for enhancement of InSAR results in the MintPy processing system (Fattahi et al., 2017). They can be used to correct for topographic effects, geometric distortion, and signal sensitivities. They are provided to make the processing pipeline more robust and reliable with respect to deformation measurements. As such, these files are considered essential optional components in the HyP3 workflow, particularly for detailed and accurate InSAR analyses with MintPy.

To define the spatial extent for the analysis, the script provides interactive subsetting methods. These include drawing a bounding box, selecting overlapping coverage, or inputting geospatial data in formats such as WKT or shapefiles. For this study, the Gialova catchment area (see Figure 1) was identified as the focus of interest. Its shapefile was incorporated into the script to accurately constrain the area prior to subsetting, thereby optimizing the processing workflow for localized deformation analysis in MintPy.

### 3.3.2.3 Load Hyp3 data to Mintpy

A coregistered unwrapped 165 and 211 interferograms for the years 2016 and 2017, respectively, along with pixel wise geometry files (DEM, incidence and azimuth angles) were loaded into MintPy environment. Next step converts multiple GeoTIFF products into two

HDF5 files: geometryGeo.h5, which contains spatial metadata and look angle information, and ifgramStack.h5, which stores the interferometric time-series data. This conversion is performed only once, allowing for repeated configuration and testing of time-series parameters without reprocessing the input stack. After loading, the original GeoTIFF files can optionally be deleted to save disk space, as they are no longer required for further analysis.

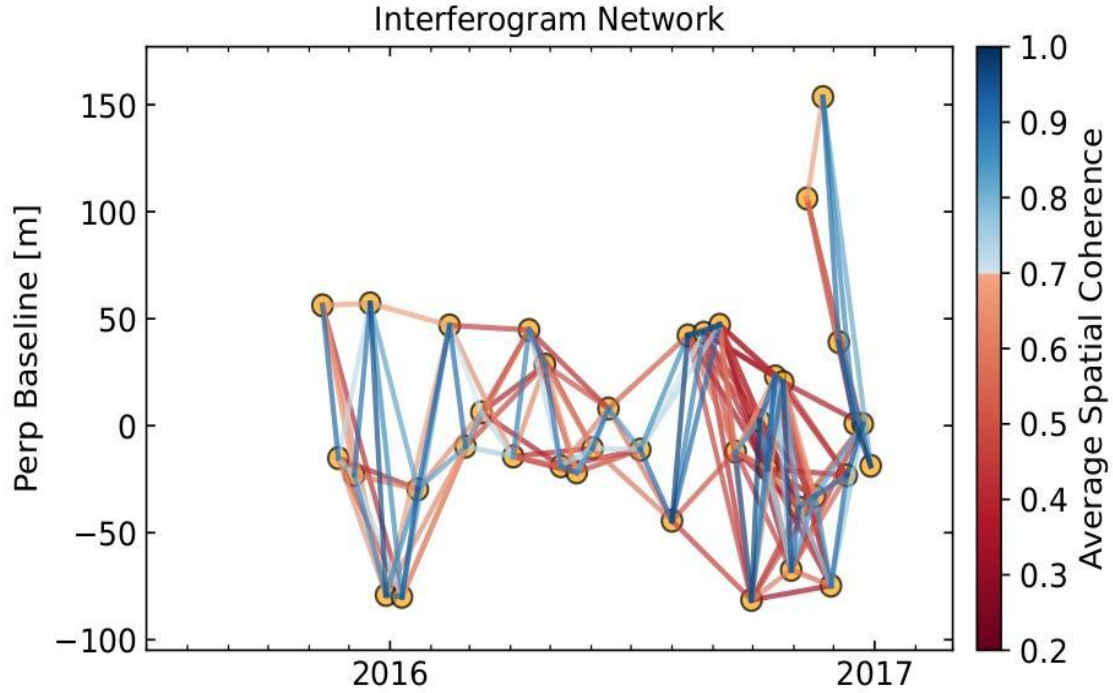
### 3.3.2.4 Spatial coherence-based network modification

Although Yunjun et al. (2019) proposed a coherence-based network optimization using a minimum spanning tree (MST) with the inverse of average spatial coherence (ASC) as weights. The MintPy processing workflow follows a simplified interferogram filtering step using the built-in modify\_network function. Therefore, in this study before running the modify\_network step, the smallbaselineApp.cfg configuration file is edited manually [mintpy.modify\_network.wrapError Threshold < 0.5] to remove interferograms affected by low coherence or unwrapping anomalies. The plot of the interferogram network (Figure 4 & 5) generated displays perpendicular baselines over time and the average spatial coherence between image pairs. The coherence matrix shows the average spatial coherence between image pairs, where values closer to 1.0 (in dark blue) indicate higher coherence (Fig 5 a & b) and thus more reliable phase information but some lower-coherence links (reddish tones) are also present (Figure 4). The majority of interferograms for the year 2017 exhibit higher coherence >0.7 and are considered for further analysis (Figure 5b). Interferograms generated for 2016 from 39 acquisitions show more reddish tone links (Fig 4) due to low coherence and through the modify\_network function removed 60 low-quality interferograms of 2016 (Figure 5 a) to improve robustness of the SBAS inversion.

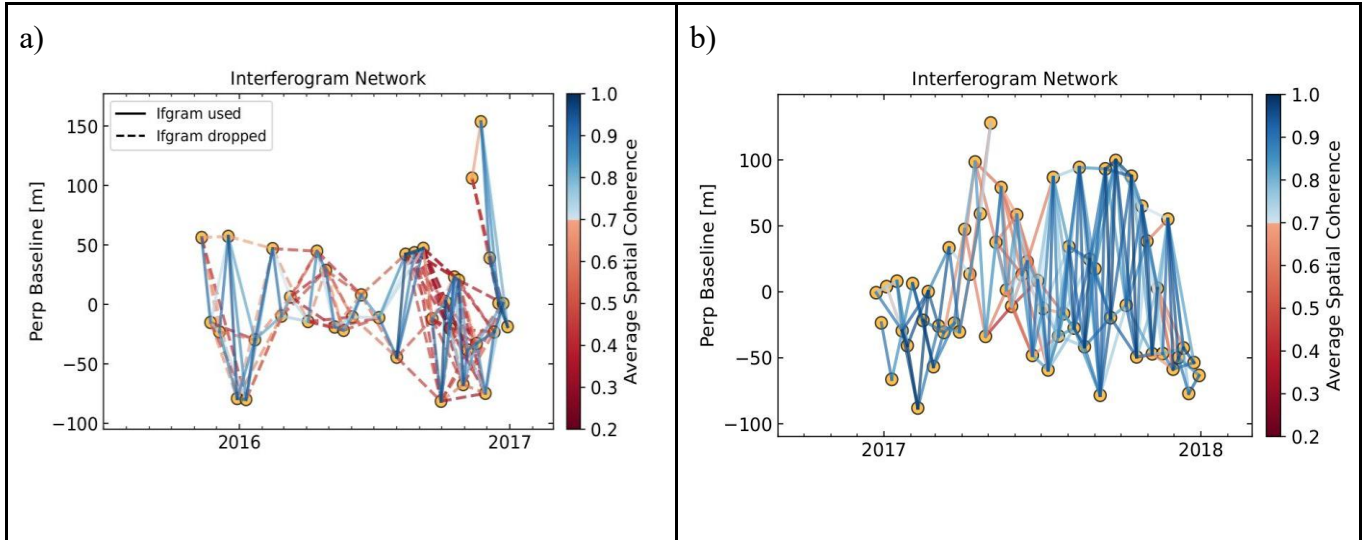
Coherence  $\gamma_p$  measures the quality of the interferogram by comparing the similarity between two SAR images. The coherence for a pixel 'p' is calculated by equation 2 and the coherence scale is a normalized value ranging between 0 and 1.

$$\gamma_p = \frac{|\sum_{t=1}^N S_{p,t1} S_{p,t2}|^2}{\sum_{t=1}^N |S_{p,t1}|^2 \sum_{t=1}^N |S_{p,t2}|^2} \dots\dots\dots \text{Eq (2)}$$

[ $S_{p, t1}$  and  $S_{p, t2}$  are the complex reflectivity values at pixel 'p' for acquisitions 1 and 2, and N represents the number of coherent pixels]



**Figure 4.** Interferogram network plot of 2016 shows total interferograms generated and average spatial coherence



**Figure 5.** The Interferograms networks of a) 2016 and b) 2017 and interferograms with low coherence selected to remove (red dashed line)

### 3.3.2.5 Unwrapping error correction

The unwrapped phase files (\*\_unw\_phase.tif) and associated connected component masks (\*\_conncomp.tif) in the interferogram.h5 file indicates that the phase unwrapping was already completed during ASF HyP3 processing. As such, no additional unwrapping step was required within MintPy, allowing the analysis to proceed directly to the Phase Unwrapping error correction (optional), baseline network modification, tropospheric (optional) and topographic



correction and finally plot the unwrapped inverted time-series with respect to a reference acquisition date.

In InSAR time-series analysis, phase measurements are inherently relative. To ensure consistency, all interferograms must be referenced to a common pixel, known as the reference point. Adding a reference point is a critical step in InSAR time series analysis using MintPy, and it is done before unwrapping error correction, the step before time-series inversion. Providing the coordinates of a known stable location either automatically (by choosing the pixel with the highest average spatial coherence) or manually is a significant step before the phase unwrapping error correction and network inversion (Hooper et al., 2007). In this study, manually selected a reference pixel (latitude and longitude of 36.997558 and 21.725181) on the northern part of the catchment which is stable and no sign of deformation is present, and having an average spatial coherence of 0.8.

### **3.3.3 Time series inversion and plotting**

The network of differential unwrapped interferograms was inverted using the `invert_network` step in MintPy to estimate the time-series of displacement for each pixel. This step inverts the unwrapped phase measurements to the deformation time series. This inversion reconstructs surface displacement over time with respect to a reference acquisition date. By default, MintPy selects the first acquisition as the temporal reference unless otherwise specified. The inversion is typically done using a Weighted Least Squares (WLS) method, which minimizes the L2 norm of the phase residuals, giving more weight to interferograms with higher spatial coherence (Shankar et al., 2023). The result of this process is a pixel-wise time-series of displacement values, representing the change in radar line-of-sight (LOS) distance over time. These values are converted from radians to meters, reflecting the cumulative surface motion from the radar toward (positive) or away from (negative) the satellite, i.e., Subsidence in case of vertical deformation (Luyen et al., 2021)

The inversion was applied to geocoded unwrapped phase data using the default dataset (`unwrapPhase`) and coherence-based masking. The `temporalCoherence.h5` file was used to create a mask (`maskTempCoh.h5`) by setting a threshold of 0.7, ensuring that only reliable pixels (with high coherence) are used in the inversion. The output files are `time series.h5` (displacement time series for each acquisition date) `temporalCoherence.h5` (Average temporal coherence per pixel) `numInvIfgram.h5` (Number of interferograms used per pixel in the inversion). The temporal coherence data generated during the inversion step is then used to get reliable pixels and to plot the spatial distribution of temporal coherence (Figure 9). Then generated python code to get the displacement time series data of the two chosen well sites from the study region, Gialova lagoon catchment (Appendix IV). All these outputs were essential for subsequent tropospheric delay and topographic corrections.

#### **3.3.3.1 Tropospheric delay and Topography correction**

Tropospheric delay is the significant noises in the InSAR data caused by the variations in atmospheric water vapour and pressure (Zebker et al., 1997). In Mintpy the

“correct\_troposphere” step runned by setting `mintpy.troposphericDelay.method = era5` in configuration file to remove the errors using the external weather model data such as, ERA5 (Zhou & Liu, 2021). This method integrates pressure, temperature, and humidity data from the ERA5 dataset to model and subtract the atmospheric signal from the interferometric phase. Then the output file is `timeseries_ERA5.h5` with improved accuracy of the displacement time series data. The topography or DEM error correction, this step removes the static elevation signal like sinks (-ve values) in the Digital Elevation Model and fill it. The residual topographic phase in the uncorrected DEM data can be misinterpreted as displacement. The `correct_topography` step in the MintPy workflow was executed and it removed the residual topographic effects that can bias the time series analysis (Hooper et al., 2004).

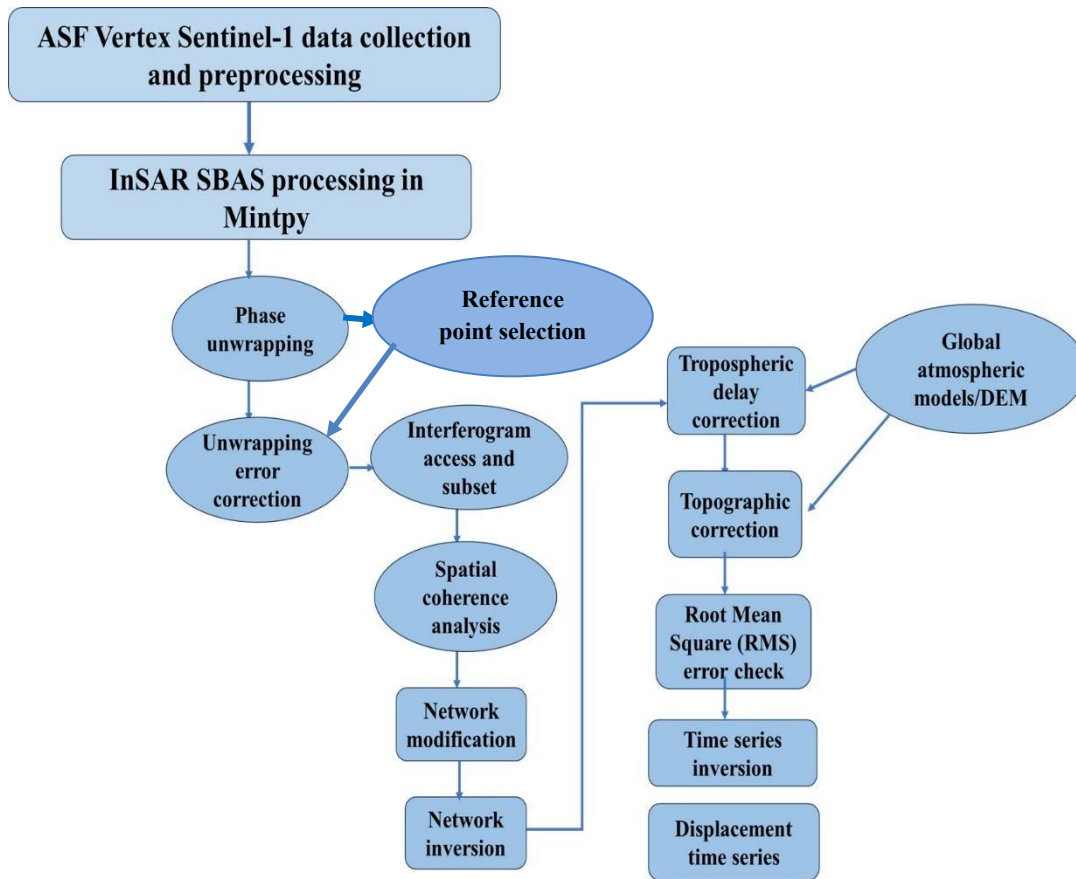
The next step is to run the code to evaluate the Root Mean Square (RMS) error of the interferometric time series. This allows for the identification and removal of acquisitions with high noise levels. After applying the necessary corrections and performing the RMS analysis, the time series inversion script repeated again to produce a refined dataset for further analysis.

### **3.4 Precipitation and Salinity data**

Precipitation and evaporation rate data were taken from Manzoni (2020). The original dataset has daily values; however, to integrate with the time series displacement data, satellite revisit days values were needed. To create the necessary dataset, the sum of 6 days and 12 days was considered for 2016 and 2017 and was put into a new set (Appendix IA). Salinity data collected from the same publication; however, in this case, the average of all the 6 days and 12 days values for each year was recorded in the new dataset. These datasets covered the months from April 2016 until December 2017, and can be found in Appendix IB. The missing rainfall data for the January to April 2016 collected from the ERA5 hourly data on Single Levels from 1959 to Present dataset provided by the Copernicus Climate Data Store (CDS), produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It offers global, hourly estimates of atmospheric, land, and oceanic variables, and is widely used in climate and weather research. To access this hourly temporal resolution data, a copernicus CDS account is needed.

### **3.5 Statistical analysis**

Numerous studies have employed linear regression techniques to quantify the correlation between land subsidence and other environmental variables. Pacheco-Martínez et al., (2013) carried out linear regression analysis between groundwater level and subsidence and interpreted subsidence of 8 cm/year in areas with declined groundwater level due to over exploitation. The environmental impact of land subsidence in Jakarta, Indonesia interpreted using InSAR time series analysis, and correlated it with the hydrogeological and anthropogenic factors through regression analysis (Chaussard et al., 2013).

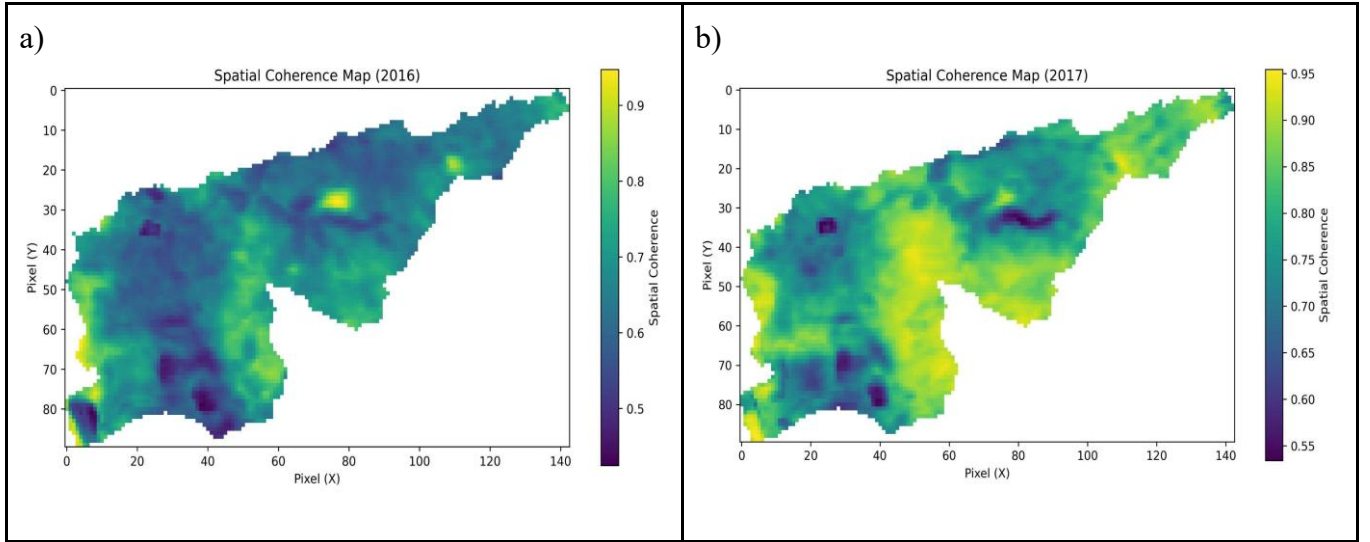


**Figure 6.** General workflow of the InSAR processing for displacement data

## 4. RESULTS

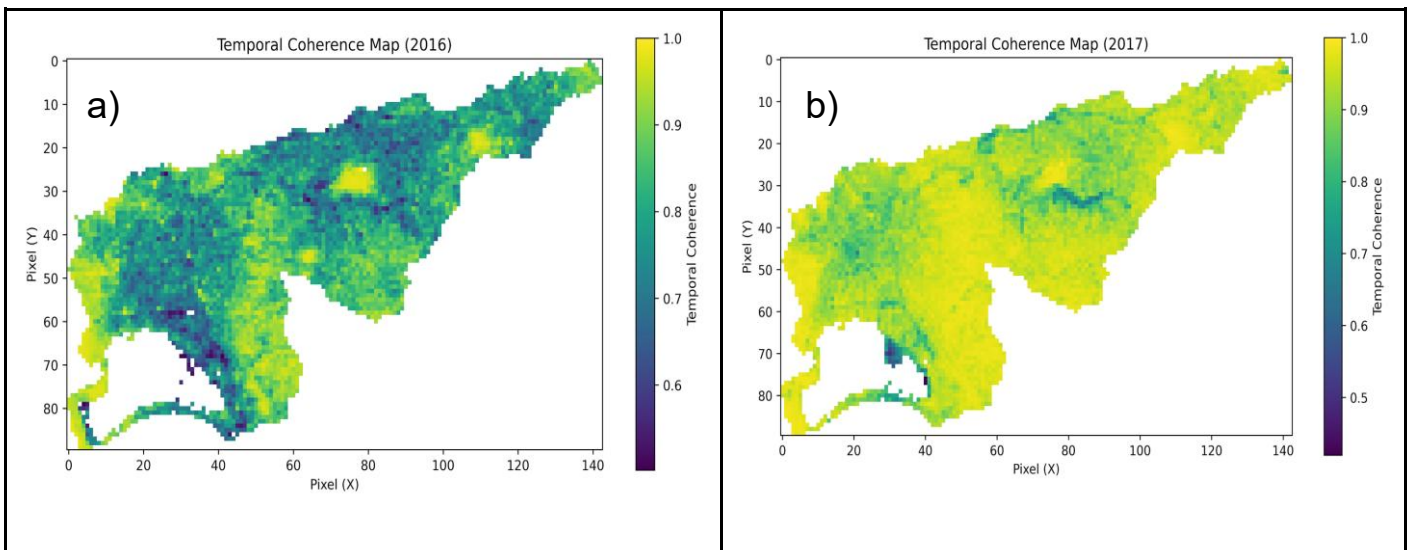
### 4.1 Spatial and Temporal coherence analysis

To ensure the reliability of the interferometric results, low-coherence interferograms were excluded during preprocessing. Consequently, the spatial coherence map (Fig 7 a & b) derived from the 2016 and 2017 datasets indicates overall good coherence across the Gialova catchment, with values predominantly above 0.5. This indicates that the preserved pixels exhibit sufficient signal quality for displacement monitoring over the Gialova lagoon catchment. The coherence map highlights stable and consistent signal return areas by high coherence (bare ground or built-up areas) supporting the validity of subsequent displacement estimates.



**Figure 7.** Spatial coherence distribution over the study region shows good coherence ranges between 0.5 and ~0.95 during 2016 (a) and 2017 (b)

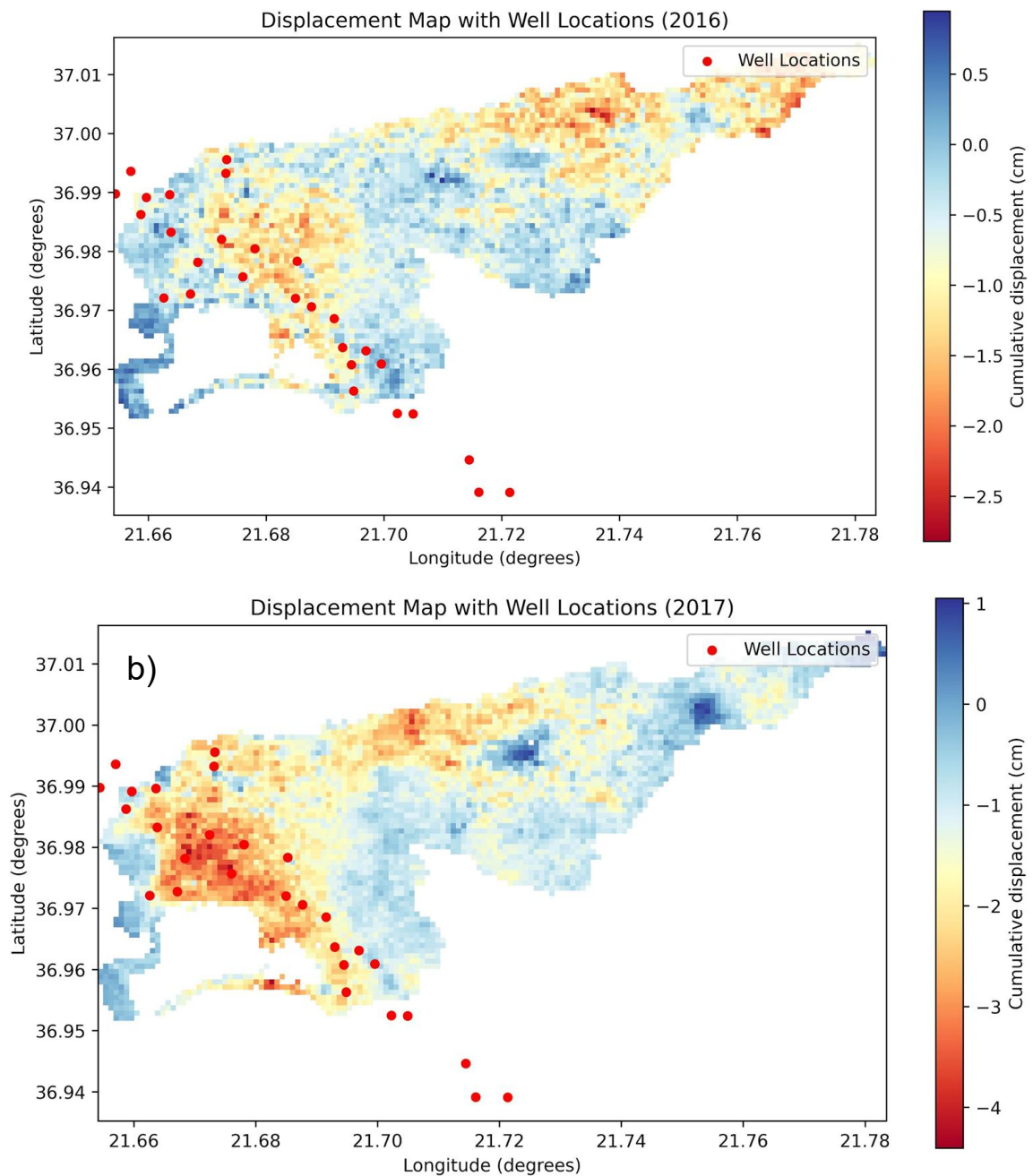
The temporalCoherence.h5 file was used to create a mask (maskTempCoh.h5) by setting a threshold of 0.5, ensuring that only reliable pixels (with high coherence) are used in the inversion. This filtering resulted in 5,133 reliable pixels across the study area. The temporal coherence map (Fig 8 a & b) derived from the 2016 and 2017 datasets indicate overall good temporal coherence across the Gialova catchment, with values predominantly above 0.5. Two pixels/points selected for the time series analysis show good spatial and temporal coherence  $>0.6$ . As generating and processing time series for all wells would be computationally intensive, selected the wells situated in different hydrogeological units. The one well in the alluvial formation and the other in the cohesive conglomerate, allowing for a comparative analysis of displacement behaviour across different geological settings.



**Figure 8.** Temporal coherence distribution over the study region shows good coherence ranges between 0.5 and 1.0 during 2016 (a) and 2017 (b)

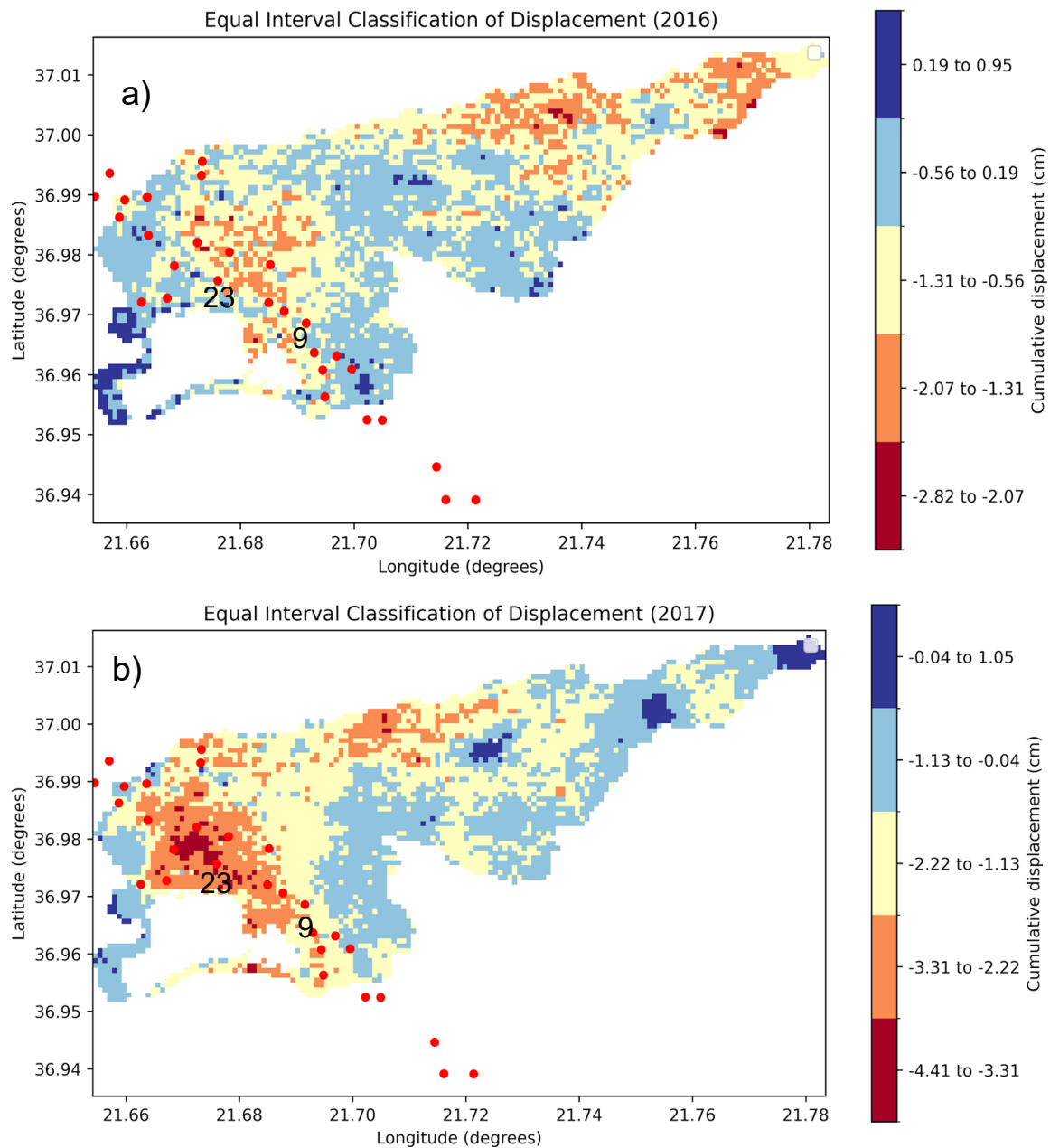
## 4.2 Land subsidence spatial characteristics

A high-resolution deformation map for the Gialova lagoon catchment was successfully generated from the Sentinel-1 SAR data for the years 2016 and 2017 (Figure 9 a & b). As depicted in Figures 9 a&b, the cumulative surface displacement ranges from -2.5 to 0.5 cm (Figure 9a) and -4 to 1 cm (Figure 9b) during 2016 and 2017, respectively. The groundwater extraction points (wells) from the coastal region are overlaid on the displacement map, and the corresponding displacement values (in centimeters) (Figure 9 a&b) were derived from the corresponding InSAR pixel coordinates.



**Figure 9.** Cumulative surface displacement observed in the Gialova lagoon catchment during a) 2016 and b) 2017 and two wells (23 & 9) selected for time series analysis

To interpret the significant localized subsidence regions/zones the displacement maps were classified on an equal interval basis. The cumulative displacement map of 2016 is then classified into 5 zones and the three zones of negative values spanning from -2.82 to -2.07cm, -2.07 to -1.3 cm, -1.31 to -0.56 cm, and two zones varying from -0.56 to 0.19 cm and 0.19 to 0.95 cm (Fig 10a). The classified cumulative displacement map for the year 2017 ranges from -4.41 to -3.31 cm, -3.31 to -2.22 cm, -2.22 to -1.13 cm, -1.13 to 0.04 cm and 0.04 to 1.05 (Fig 10b). From the Google Earth imagery, the areas with high observed subsidence are predominantly covered by mature and young olive groves, along with land likely used for irrigated forage or row crops.



**Figure 10.** Classified surface displacement of the Gialova lagoon catchment during 2016 (a) and 2017 (b) shows spatial extension of subsidence and uplift



### **4.3 Time Series Analysis of land subsidence at selected groundwater extraction sites**

This section presents the displacement time series analysis of the selected well locations derived from InSAR analysis, after inverting the network of differential unwrapped interferograms of 39 and 62 acquisition dates during 2016 and 2017 (Appendix IA and IB). The Python script was used to select pixel coordinates (66, 41) for well location 6 and (54, 23) for well location 23 for the analysis. The proximity of well location 23 from the lagoon is 0.6 km and well location 9 is 1 km. The well location 9 is chosen due to its proximity to the Tyflomitis spring, the major fresh water source of the lagoon. To explore potential environmental drivers of the observed ground displacement, rainfall data from the corresponding period were analysed to assess any correlation between precipitation events and ground movement. Additionally, lagoon salinity data from the same time frame were examined to investigate whether land displacement may be a triggering factor for hypersaline conditions in the lagoon.

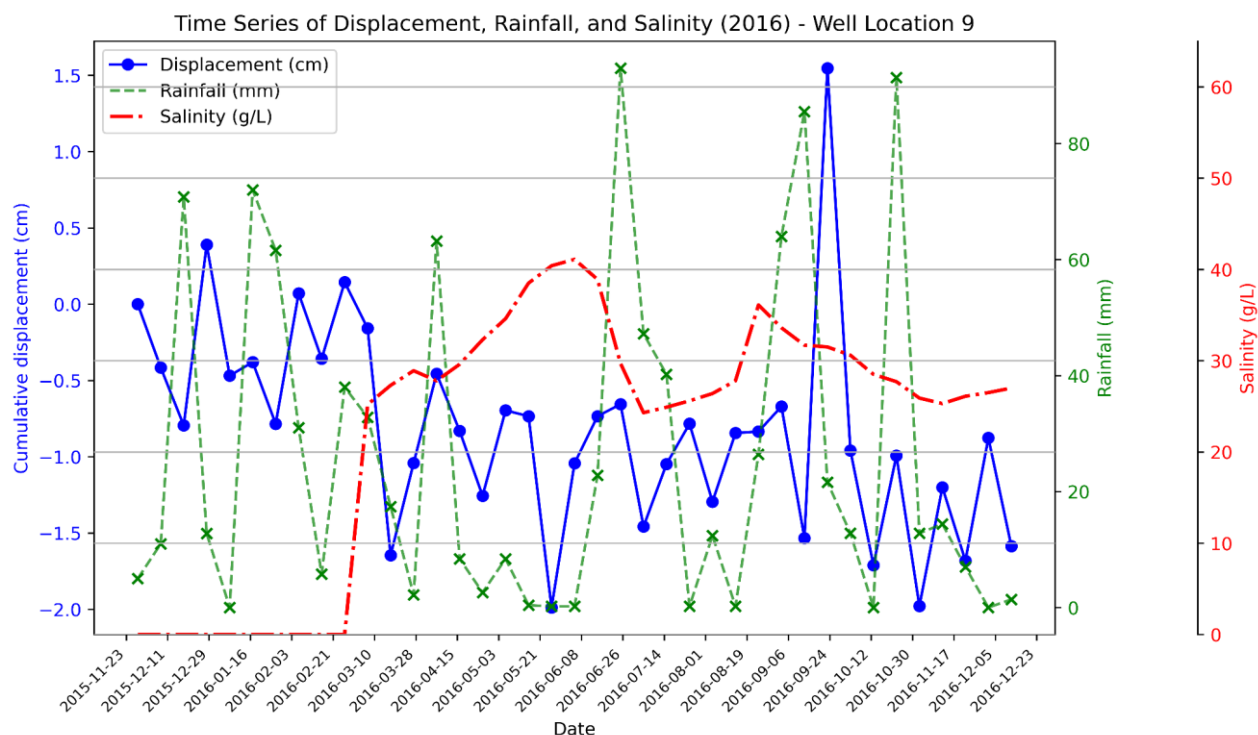
#### **4.3.1 Time series of land subsidence and rainfall during 2016**

The precipitation data of the study period collected and incorporated to land subsidence time series to evaluate the potential correlation between the variables. The time series data of well locations 9 and 23 (Figures 11 & 12) demonstrates ground displacement patterns over the year 2016. The rainfall dataset consists of 39 precipitation measurements ((Figures 11 & 12) recorded at approximately 10-day intervals over the course of 2016. Each value represents the average rainfall in millimeters accumulated during the respective interval. Rainfall values throughout the year 2016, ranged from near-zero values during dry spells (May to August) and > 40 to 100 mm (Figure 11 & 12) during late autumn and winter months (November, December, January).

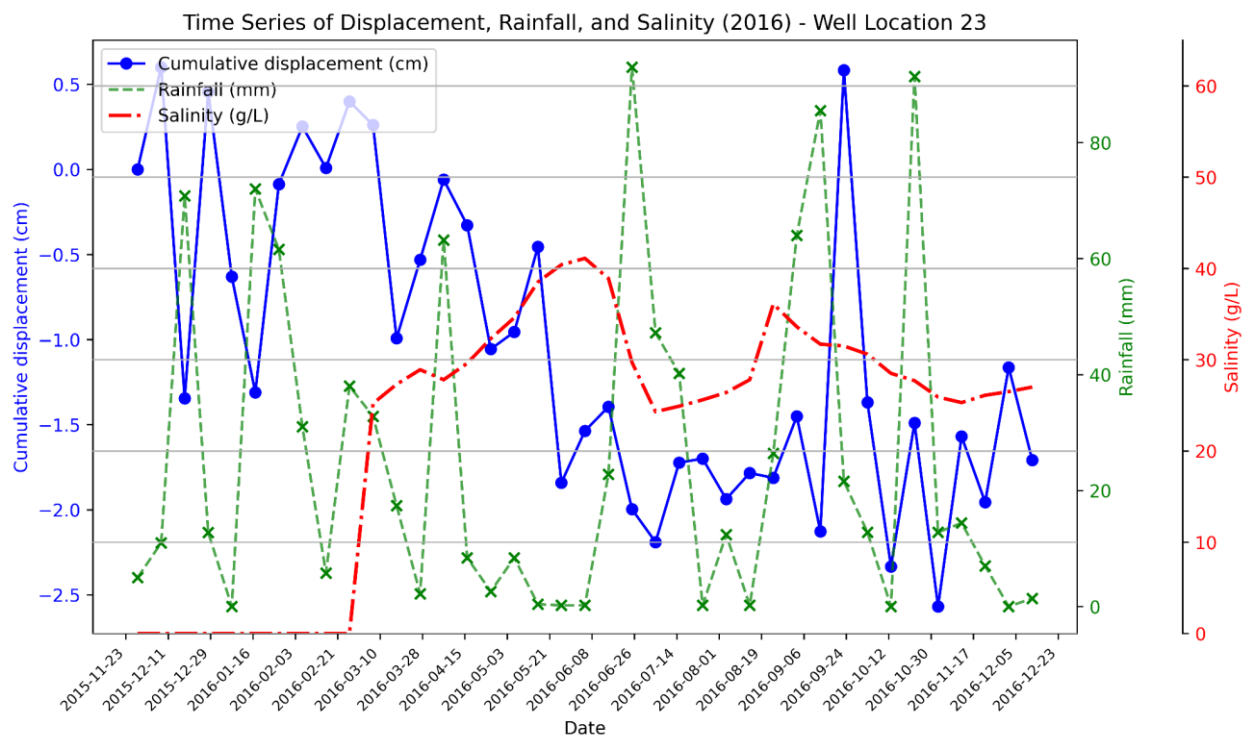
At well location 9 displacement is shown negative values primarily, and in time series the intermittent subsidence events reached nearly -2cm during March, May and October (Figure 11). Uplift events are limited and short-lived, the maximum uplift reached is 1.5 cm in between September 6th to 24th. This uplift occurred after the 12-day average rainfall event of 80mm in late August and early September.

During January 2016, the ground surface was approximately 0.3 to 0.5 cm above the reference level at well location 23 (Figure 12). This is followed by a sudden subsidence event in the middle of January (-1.3 cm). It is then followed by an uplift of +0.3cm in February. Then the steady downward trend begins in March (-1.0 cm) to September 6th (-1.5 cm). The maximum subsidence observed at location 23 is up to -2.5 cm in early October and late November. Then a sudden uplift to 0.5 cm in between September 6th to 24th after the high rainfall event of >80mm, indicating that surface recharge can temporarily reverse subsidence trends. Overall, the time series reflects a dynamic interplay between seasonal water availability and anthropogenic pressures.





**Figure 11.** Subsidence pattern at well location 9 in relation to Rainfall and lagoon salinity during 2016



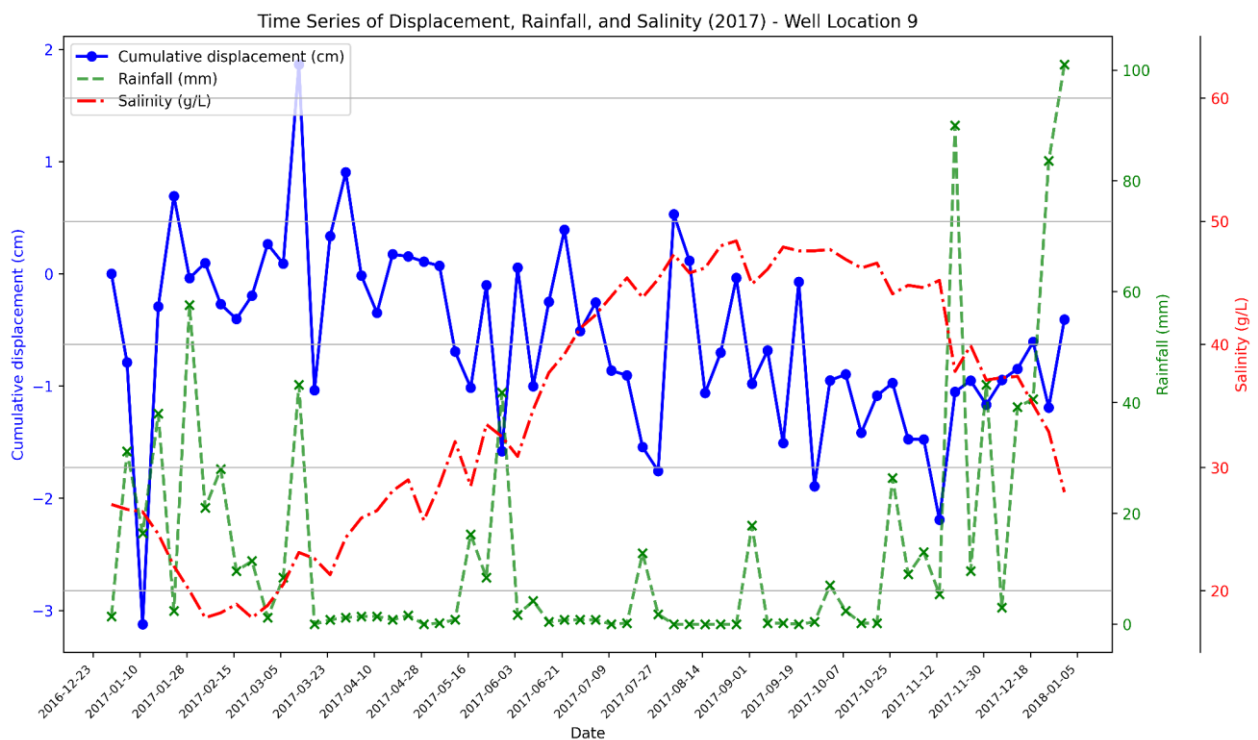
**Figure 12.** Subsidence pattern at well location 23 in relation to Rainfall and lagoon salinity during 2016

#### 4.3.1.1 Land subsidence and temporal changes in lagoon salinity-2016

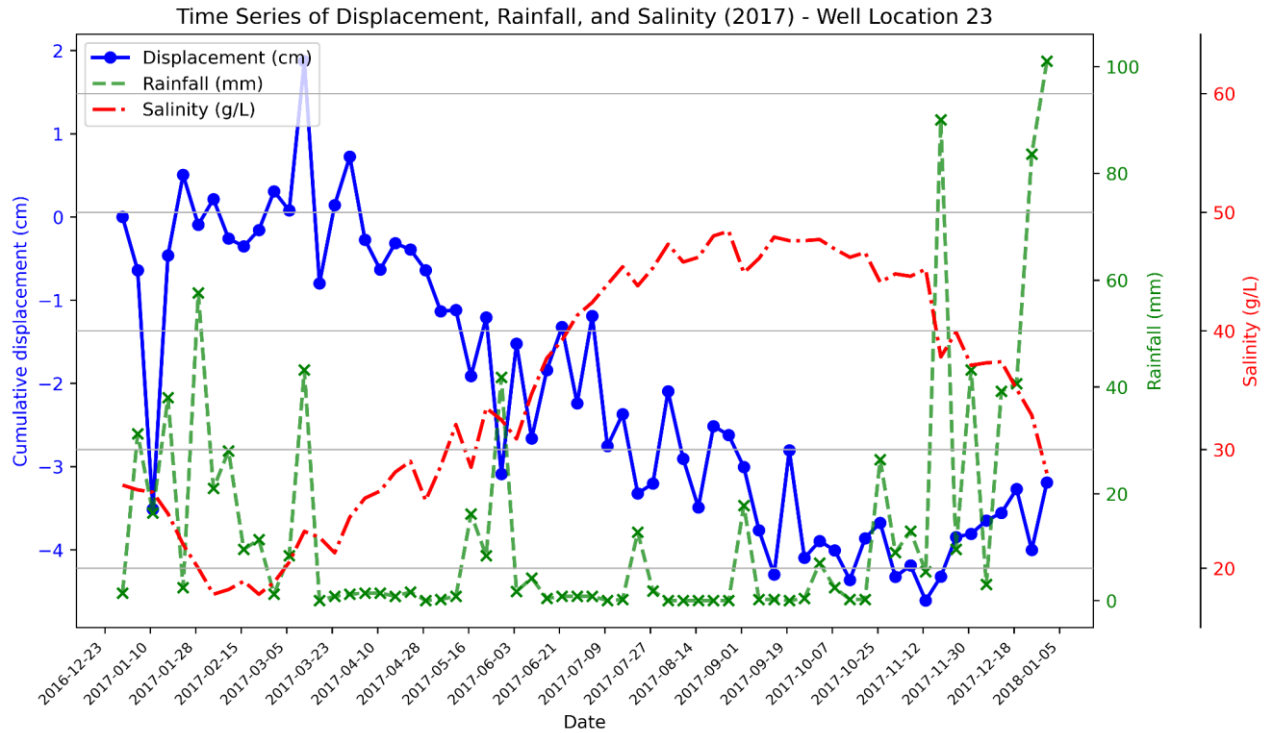
Salinity measurements begin in mid-March and show an increasing trend, peaking around May and early June (~40 g/L) and then to 30g/l approximately in late August to early September, followed by a gradual decline in salinity. During the peak salinity period the sudden increase in the land subsidence is observed at both locations 9 and 23 which reached up to -2cm and -2.5cm. The high rainfall events stabilized the salinity to 25-30 g/l by July till December. There is a simultaneous pattern of land subsidence and lagoon salinity during this whole period (July - December) suggests a common underlying stressor.

#### 4.3.2 Time series of land subsidence and rainfall during 2017

The time series data of well sites 9 and 23 (Figure 13 & 14) demonstrates ground displacement pattern over the year of 2017. At well location 9, there is notable subsidence of around -3 cm during the first part of January, which is followed by an uplift phase towards mid-March of close to +2 cm. In the subsequent months, the pattern is marked by slight upward and downward movements with minor changes in net displacement around the baseline. The greater total subsidence, from 0 cm to -4 cm, with no significant recovery observed in the well site 23 (Figure 14). From the rainfall data there are scattered rainfall events in the first half of the year, notable dry periods mid-year (May to October) and intense rainfall episodes in November and December, exceeding 100 mm in late December. Displacement measurements from both locations are aligned differently with the rainfall.



**Figure 13.** Subsidence pattern at well location 9 in relation to Rainfall and lagoon salinity during 2017



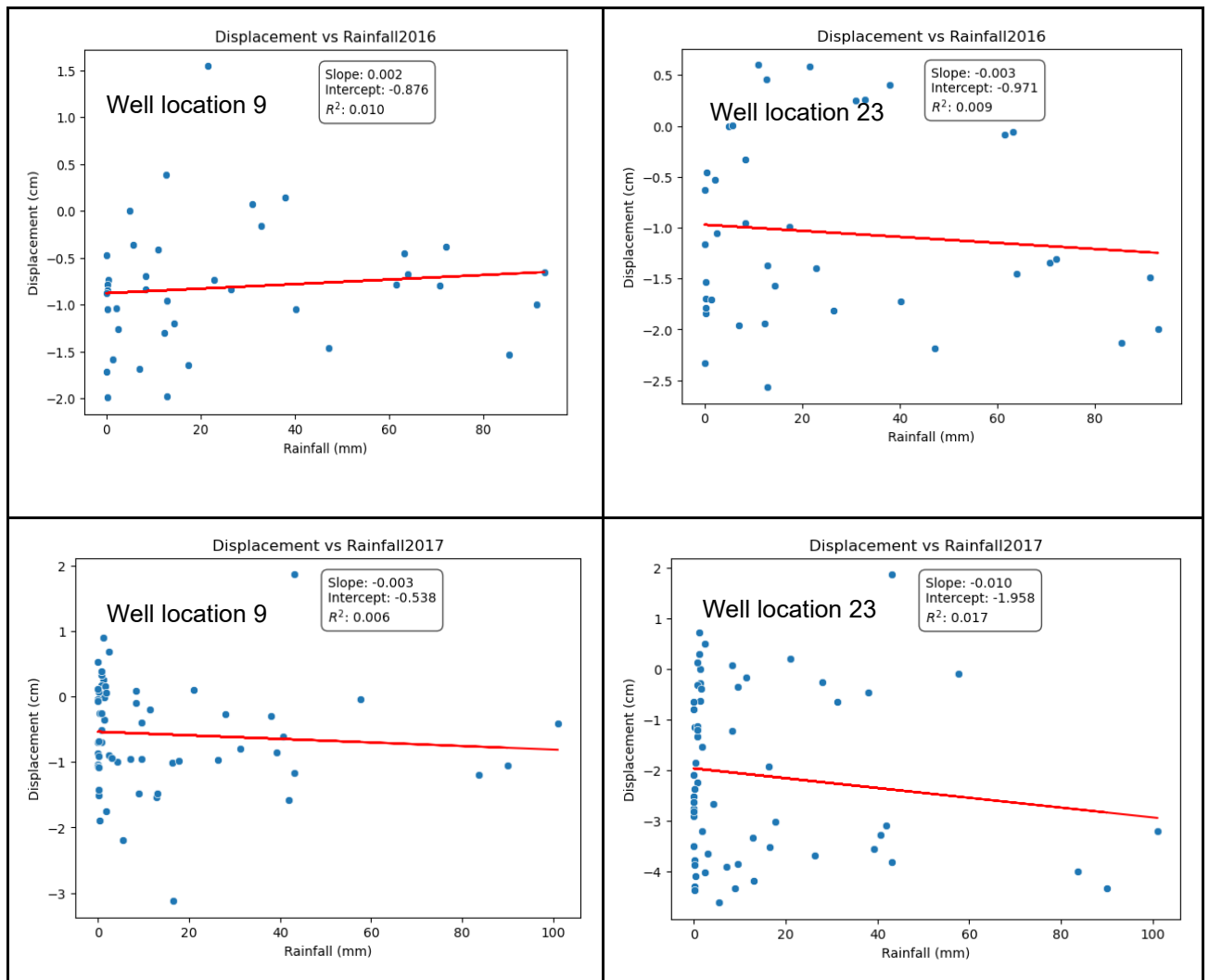
**Figure 14.** Subsidence pattern at well location 23 in relation to Rainfall and lagoon salinity during 2017

#### 4.3.2.1 Land subsidence and temporal changes in lagoon salinity- 2017

Salinity measurements are moderate (20–25 g/L) early in the year, January. Then in mid-March it shows an increasing trend, peaking around may and early June (~40 g/L) and then rise sharply in mid-year dry season around 48 g/L. During the peak salinity period a steadier downward trend in the land subsidence is observed at site 23 which was reaching up to -4cm. Following heavy rainfall events (e.g., late 2017), the lagoon salinity drops sharply to 28g/l, but ground uplift at both well locations is slow and limited (Figure 13 & 14).

### 4.4 Statistical analysis: linear regression

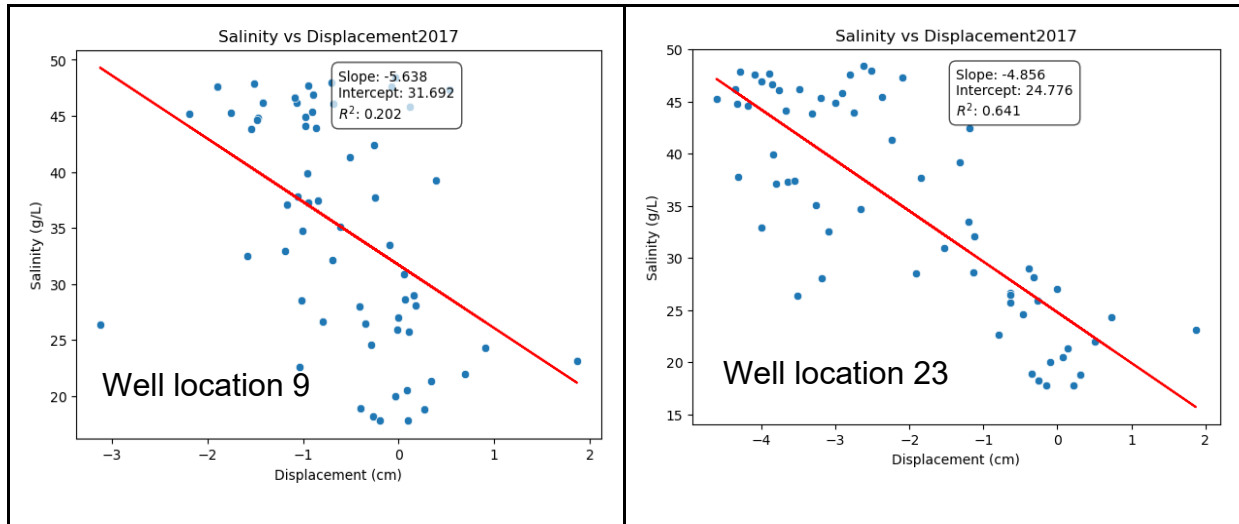
To assess the relationship between land displacement, rainfall and lagoon salinity, a simple linear regression analysis was performed. The regression analysis between rainfall and displacement at the two monitored wells revealed very weak correlations ( $R^2 < 0.02$ ) during 2016 and 2017 (Figure 15). The lagoon salinity value was missing for the initial period of 2016 and therefore it was not considered for the statistical analysis.



**Figure 15.** Linear regression plots showing the effect of rainfall on cumulative displacement at two well locations during 2016 and 2017 (a) location 9 and (b) location 23

The simple regression analysis between displacement and salinity for location 23 yielded a stronger negative correlation, with a slope of -4.856, a coefficient of determination ( $R^2$ ) of 0.641 (Figure 16b) and intercept of 24.77. It implies when the displacement is 0 cm then the lagoon salinity is 24.77 g/L and with respect to the subsidence the salinity also increases. It shows a relatively strong and consistent link between subsidence at this site and salinity changes in the lagoon system.

In contrast, Location 9 showed a weaker correlation (Figure 16a), slope = -5.638,  $R^2$  = 0.202, intercept = 31.692, suggests a more variable or indirect relationship between subsidence and lagoon salinity. This could be due to differences in hydrogeological settings or weaker hydrological connectivity with the lagoon system, leading to a less consistent influence of ground displacement on salinity dynamics.



**Figure 16.** Linear regression plots showing relationship between cumulative displacement and lagoon salinity at well locations during 2017 a) location 9 and b) location 23

## 5. DISCUSSION

Spatial and temporal coherence values above 0.6 are generally considered acceptable for InSAR time-series analysis, as they indicate sufficient phase stability across acquisitions to ensure reliable deformation measurements (Ferretti et al., 2001). These coherence metrics are critical for filtering out decorrelated or noisy pixels during processing. In addition to coherence assessment, the computation of the residual root-mean-square (RMS) error of the interferometric time series is also essential, as it helps to identify the acquisitions with high noise levels. The acquisition from 2016-11-17 exhibited the lowest RMS value (0.0010) and was therefore selected as the reference date for all displacement measurements. Conversely, the date 2016-11-11 exceeded 3 times the median RMS threshold (0.0081) and was consequently excluded from further analysis. For the 2017 period, the date 2017-02-09, having the minimum RMS value (0.0011), was selected as the reference date for displacement calculations. One acquisition (2017-01-04) exceeded 3 times the median RMS and was excluded from further analysis.

### 5.1 Geospatial assessment of areas vulnerable to land subsidence

The maximum land subsidence observed during 2016 was -2.82 to -2.07 cm (Figure 10a) and it covers an area of 0.14 km<sup>2</sup> in the northeastern part of the study region. The vulnerable zone of -2.07 to -1.31 cm subsidence was in the coastal region and northeastern part and the total area is of 1.92 km<sup>2</sup>. The zone of -1.31 to -0.56 cm spread in an area of 9.80 km<sup>2</sup> (Table 1).

The land subsidence vulnerability zonation map of 2017 (Figure 10b) shows that the zone of -4.41 to -3.31 cm subsidence covers an area of 0.66 km<sup>2</sup>. The zones of -3.31 to -2.22 cm, -2.22 to -1.13 cm, and -1.13 to -0.04 cm covers an area of 4.890 km<sup>2</sup>, 17.540 km<sup>2</sup> and 13.23 km<sup>2</sup> vice versa (Table 1). During 2017 the subsidence showed an increasing trend of up to 4.5 cm. The regions which were affected by the subsidence of <-2 cm in 2016 underwent subsidence

of -3 to -4.8 cm of subsidence during 2017. The spatial variability in land subsidence trends is due to the change in local hydrogeological units, land use and management factors (Peng et al., 2022).

Table1: Major subsidence pattern observed and the total area affected during the study period

| No. | Land subsidence (cm)-2016 | Area (km <sup>2</sup> ) | Land subsidence (cm)-2017 | Area (km <sup>2</sup> ) |
|-----|---------------------------|-------------------------|---------------------------|-------------------------|
| 1   | -2.82 to -2.07            | 0.14                    | -4.41 to -3.31            | 0.66                    |
| 2   | -2.07 to -1.31            | 1.92                    | -3.31 to -2.22            | 4.890                   |
| 3   | -1.31 to -0.56            | 9.80                    | -2.22 to -1.13            | 17.540                  |
| 4   | -0.5 to 0.19              | 24.24                   | -1.13 to -0.04            | 13.230                  |

The vulnerable zones of land subsidence in the Gialova catchment were mainly noticed in the regions where the main land use type is olive groves. The groundwater extraction points are scattered mainly through the subsidence observed region rather than the regions with no sign of subsidence ( $>0$  cm). It clearly gives an indication that the overexploitation of groundwater resources for the agricultural purposes is declining the aquifer water level, which leads to aquifer compaction and consequently land subsidence (cf. Famiglietti, 2014). Therefore, special emphasis was given to two groundwater extraction points (locations 9 and 23), located within the coastal alluvial and conglomerate aquifer systems of the region, to interpret the land subsidence time series patterns and identify the triggering factors. In a previous land subsidence study of the Sindos and Kalochori regions of Greece, the land subsidence phenomenon was observed from 1993 to 2000 but a rebound effect was noticed from 2003 to 2010 in agreement to recharge of aquifer and reduction of groundwater consumption (Sviggas et al., 2016).

## 5.2 Interpreting land subsidence in relation to rainfall

The time series plots of well locations 9 and 23 (Figures 11, 12, 13 and 14) illustrate the temporal evolution of ground displacement (cm), rainfall (mm), and lagoon salinity (g/L) over the years 2016 and 2017. The time series plot of each location clearly illustrates the cumulative displacement trend throughout the year concerning the displacement starting at 0 for the baseline acquisition date. Indicating progressive cumulative subsidence reaching approximately to -2 cm at location 9 and up to -2.5 cm at location 23 during 2016 with respect to zero displacements of 2015-11-23. The time series of 2016 shows a different pattern of displacement at each well location starting with a subsidence of -0.5cm at location 9 and with uplift of 0.5cm at location 23. During 2017 the cumulative displacement curve (Figure 11 to 14 blue line) shows alternating episodes of uplift and subsidence, with subsidence reaching approximately to -3 cm (locations 9) and -4cm (locations 23) with respect to zero displacement of 2016-12-23. Well Location 23 exhibits a more consistent cumulative subsidence pattern with fewer reversals, particularly from 2017 DOY 90 onward.

Notable subsidence events occurred even after the periods of significant rainfall (e.g., March, June, and October) during both years. The subsidence observed even after significant rainfall suggests a delayed response possibly linked to aquifer compaction or subsurface drainage dynamics likely associated with continuous groundwater abstraction. This behaviour is consistent with the findings of Burbey (2003), who demonstrated that time-series analysis of aquifer-system responses can reveal both elastic and inelastic deformation linked to groundwater fluctuations. Compared to Well Location 23, the displacement fluctuates between minor uplift and subsidence at Location 9 without a clearly sustained downward trend. These observed fluctuations point to a complex interaction of natural and anthropogenic factors such as, local-scale heterogeneities in lithology, recharge dynamics, or groundwater abstraction patterns (Galloway et al., 2011). The time series subsidence pattern observed at two selected wells are consistent with global trends where subsidence is significantly associated with high extraction rates. As indicated by Herrera-García et al. (2021) these human-induced processes as the leading cause of land subsidence risk globally.

The key observations from the regression analysis between rainfall and vertical displacement at two monitoring wells (well locations 9 and 23) over two years (2016 and 2017) show low  $R^2$  values (0.006 to 0.017). These values indicate that less than 2% of the variance in displacement can be explained by rainfall. Weak regression slopes (Figure 15) near zero and both positive and negative (e.g., slope = -0.003 or 0.002), which implies no consistent trend between increased rainfall and upward or downward displacement. Another regression analysis was conducted using a 3-week lag of rainfall as the predictor model yielded a very low  $R^2$  value of 0.022. This indicates that only about 2.2% of the variability in displacement can be explained by lagged rainfall. The analysis suggests that similar to Galloway's (1999) findings, short-term lagged rainfall does not significantly impact land displacement, highlighting the dominant influence of anthropogenic factors such as groundwater extraction on subsidence in the Gialova region.

### **5.3 Effect of land subsidence on lagoon salinity**

Previous studies (Manzoni et al., 2020) have documented the seasonal variability of lagoon salinity, with hypersaline conditions prevailing during summer and rapid salinity reductions following intense rainfall events. Therefore, a direct correlation analysis between rainfall and lagoon salinity was not repeated, as the relationship is already well established. Instead, in this study the analysis focuses on the interplay between land subsidence and lagoon salinity. The temporal correlation between lagoon salinity and land displacement at well Locations during 2016 shows a noticeable pattern, in which increases in salinity (g/L) tend to coincide with intensified land subsidence (negative displacement). For example, between June and September 2016, both salinity levels and subsidence depth increased simultaneously, with salinity peaking above 50 g/L and displacement reaching nearly -2 cm (Figures 11 & 12). This suggests a potential link between salinity stress and aquifer-related compaction, where saline intrusion or increased salinity may exacerbate subsidence, possibly due to changes in pore pressure and water density within the aquifer matrix. The similar patterning supports the hypothesis of a



common environmental stressor affecting both hydrochemistry and ground stability. During 2017 the lagoon salinity begins to rise around May and peaks mid-year, showing a moderate temporal alignment with subsidence events at Location 9 (Figure 13). In contrast, the lagoon exhibits a sustained increase in salinity (from ~20 to 55 g/L) from April to October associated with a steady subsidence trend reaching -4.5 cm at Location 23 (Figure 14).

From the correlation analysis the well location 23 during 2017 exhibits a stronger correlation ( $R^2 = 0.641$ ) compared to location 9 ( $R^2 = 0.202$ ), suggesting that the impact of subsidence on salinity is more pronounced at location 23 (Figure 16b). The coefficient of determination ( $R^2 = 0.202$ ) for well location 9 suggests a moderate but meaningful correlation, pointing to a possible physical linkage between vertical land movement and salinity dynamics. This particular extraction point is near to the main freshwater input of the region, Tyflomitis artesian springs, the freshwater flow is significantly constrained to  $5 \times 10^5 \text{ m}^3 \text{ yr}^{-1}$  due to upstream groundwater withdrawals (Maneas et al., 2019). According to the correlation analysis, the land subsidence of -1cm may correspond to an increase of approximately 4.8 g/L in lagoon salinity, however it is essential to account for other influencing factors. The land subsidence could alter the local hydrology in a way that facilitates increased saltwater intrusion or reduces subsurface freshwater flushing, contributing to elevated salinity in the deltaic and coastal regions (Ericson et al., 2006). These results align with broader studies that emphasize the compounding effect of land subsidence on salinization in low-lying coastal systems (e.g., Herrera-García et al., 2021).

## 6. CONCLUSION

This study confirms the occurrence of land subsidence in the Gialova catchment, Greece, through the application of InSAR techniques using Sentinel-1 data (2016–2017) and processing tools such as OpenSARLab, MintPy, and Python-based workflows. The southwestern coastal zone, particularly near the lagoon, was identified as the most subsidence-prone area. Subsidence was also detected across agricultural lands, including olive groves. The final cumulative displacement map generated after the stacking of displacement maps with time series information enabled the classification the whole catchment into 5 zones of land displacement. The zone of uplift or rebound observed is very less in the whole catchment. It's interpreted that a significant increase in the area affected by subsidence greater than -2 cm covers an area of  $0.14\text{km}^2$  during 2016 and it increased to  $5.69\text{km}^2$  during 2017. The southwestern part of the catchment covering the coastal belt and near to the lagoon falls under the high prone zone of subsidence during 2017. While the vast agricultural lands of olive groves and common irrigated forage crops land, both in the coastal region and western tract, show the signal of subsidence during both years.

A detailed time series analysis at two well locations in the coastal belt demonstrated a moderate to strong correlation between land subsidence and lagoon salinity, with location 23 showing a particularly clear trend: a 1 cm drop in land elevation was associated with a 4.8 g/L increase in salinity. This influence is likely due to the hydrogeological connectivity between the aquifer and the lagoon, which may reduce freshwater buffering capacity as land subsides. While

multiple factors (e.g., rainfall, evaporation, temperature) influence lagoon salinity, the spatial and statistical relationship with land subsidence indicates that subsidence should be considered a contributing factor to hyper salinity. It is important to carryout multi-linear regression analysis by including land subsidence and other salinity influencing variables.

Furthermore, the weak correlation between rainfall and subsidence suggests a delayed aquifer recharge response, reinforcing the complexity of groundwater dynamics in the region. The short-lived uplifts/rebounds in the time series plot reflects the trend of land surface lowering likely driven by groundwater extraction in a geologically sensitive zone. This aligns with findings from other Greek regions, where subsidence and rebound phases followed the changes in groundwater extraction.

Overall, the study highlights the observed increase in lagoon salinity in 2017 and its correlation with land subsidence should be recognized as a key factor influencing lagoon health and freshwater balance. This study clearly shows the importance of continuous monitoring of land subsidence and to improve the current condition of groundwater resources for a long-term sustainable management of the Gialova lagoon and the catchment.

## **LIMITATIONS OF STUDY**

This study presents a remote sensing-based assessment of land deformation in the Gialova catchment, with a particular focus on potential groundwater–land surface interactions. However, several limitations affect the scope and interpretation of the findings. No direct measurements of groundwater levels were available from well observations. As such, interpretations of subsurface hydrological processes were inferred indirectly through remote sensing data, limiting the ability to validate deformation mechanisms with in-situ hydrogeological data. No field visits were conducted. This restricted the ability to ground-truth satellite-derived observations and to collect additional contextual or geological information on site. Lack of data on groundwater salinity, chemistry, hindering a robust assessment of potential saltwater intrusion or subsurface groundwater–lagoon interactions. Information on irrigation practices, groundwater extraction rates, and other anthropogenic pressures on water resources in the catchment was limited or unavailable, which constrains causal attributions of observed deformation.

## **FUTURE RECOMMENDATIONS**

- The observed correlation between salinity and land displacement highlights the importance of further investigating surface–groundwater interactions.
- To deepen the understanding of subsidence mechanisms, it is recommended to evaluate the relationship between groundwater depletion and land subsidence through long-term monitoring, hydrogeological modelling, and integration with InSAR-derived deformation time series.

## **AI TOOLS**

During the preparation of this thesis, AI-assisted tools were used to refine academic writing, improve grammatical accuracy, and clarify technical explanations. The tool was also consulted for guidance on Python scripting. All AI-generated content was critically reviewed and edited to ensure alignment with scientific standards and personal understanding

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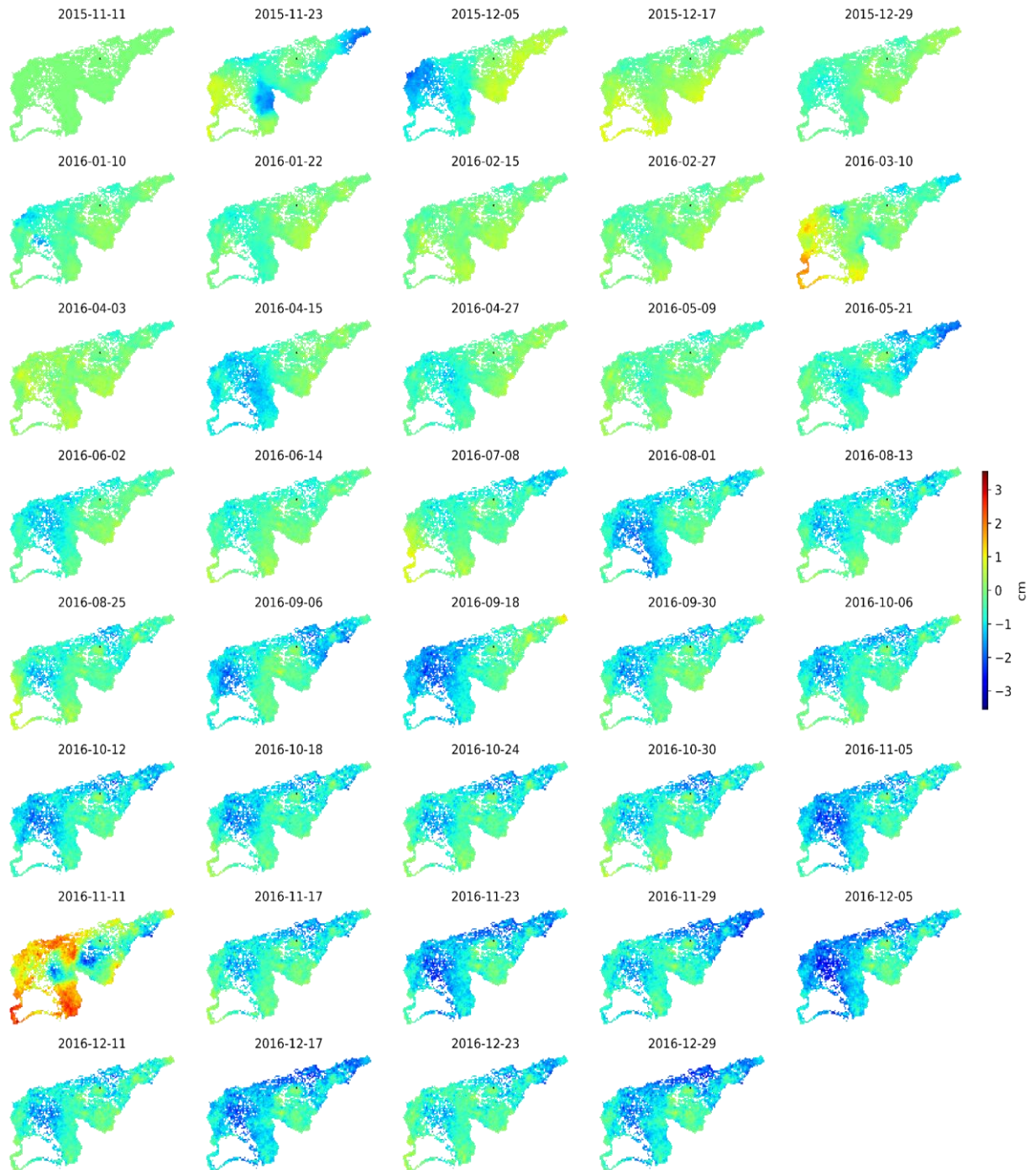
**Appendix IA: Rainfall and Salinity data of 2016 with displacement observed at well location9**

| Date       | Displacement (cm)    | Rainfall (mm) | Salinity (g/L) |
|------------|----------------------|---------------|----------------|
| 2015-11-28 | 0.0                  | 4.98          | 0.0            |
| 2015-12-08 | -0.4155673086643219  | 10.97         | 0.0            |
| 2015-12-18 | -0.7946945428848267  | 70.8          | 0.0            |
| 2015-12-28 | 0.3893371820449829   | 12.75         | 0.0            |
| 2016-01-07 | -0.4688440263271332  | 0.0           | 0.0            |
| 2016-01-17 | -0.380077600479126   | 72.0          | 0.0            |
| 2016-01-27 | -0.7844138741493225  | 61.57         | 0.0            |
| 2016-02-06 | 0.0705500915646553   | 31.0          | 0.0            |
| 2016-02-16 | -0.35836270451545715 | 5.78          | 0.0            |
| 2016-02-26 | 0.14394554495811462  | 38.0          | 0.0            |
| 2016-03-07 | -0.15841498970985413 | 32.8          | 25.2           |
| 2016-03-17 | -1.645839810371399   | 17.4          | 27.3           |
| 2016-03-27 | -1.0417006015777588  | 2.2           | 28.9           |
| 2016-04-06 | -0.45596611499786377 | 63.2          | 27.8           |
| 2016-04-16 | -0.8301751017570496  | 8.4           | 29.6           |
| 2016-04-26 | -1.2565845251083374  | 2.6           | 32.3           |
| 2016-05-06 | -0.6965382099151611  | 8.4           | 34.6           |
| 2016-05-16 | -0.7343199849128723  | 0.4           | 38.5           |
| 2016-05-26 | -1.988574504852295   | 0.2           | 40.4           |
| 2016-06-05 | -1.0428639650344849  | 0.2           | 41.1           |
| 2016-06-15 | -0.7344199419021606  | 22.8          | 38.9           |
| 2016-06-25 | -0.6560142636299133  | 93.0          | 29.7           |
| 2016-07-05 | -1.4581022262573242  | 47.2          | 24.3           |
| 2016-07-15 | -1.0479716062545776  | 40.2          | 24.9           |
| 2016-07-25 | -0.7839388847351074  | 0.2           | 25.6           |
| 2016-08-04 | -1.2949098348617554  | 12.4          | 26.4           |
| 2016-08-14 | -0.8447211980819702  | 0.2           | 27.8           |
| 2016-08-24 | -0.8351736664772034  | 26.4          | 36.1           |
| 2016-09-03 | -0.6706238985061646  | 64.0          | 33.6           |
| 2016-09-13 | -1.5337001085281372  | 85.5          | 31.7           |
| 2016-09-23 | 1.5467746257781982   | 21.6          | 31.5           |
| 2016-10-03 | -0.9597145915031433  | 12.8          | 30.6           |
| 2016-10-13 | -1.7108467817306519  | 0.0           | 28.5           |
| 2016-10-23 | -0.9928696155548096  | 91.4          | 27.7           |
| 2016-11-02 | -1.9788315296173096  | 12.8          | 25.9           |
| 2016-11-12 | -1.2004413604736328  | 14.4          | 25.3           |
| 2016-11-22 | -1.6815162897109985  | 7.0           | 26.1           |
| 2016-12-02 | -0.8769088387489319  | 0.0           | 26.5           |
| 2016-12-12 | -1.5864454507827759  | 1.4           | 27.0           |

**Appendix IB: Rainfall and Salinity data of 2017 with displacement observed at well location23**

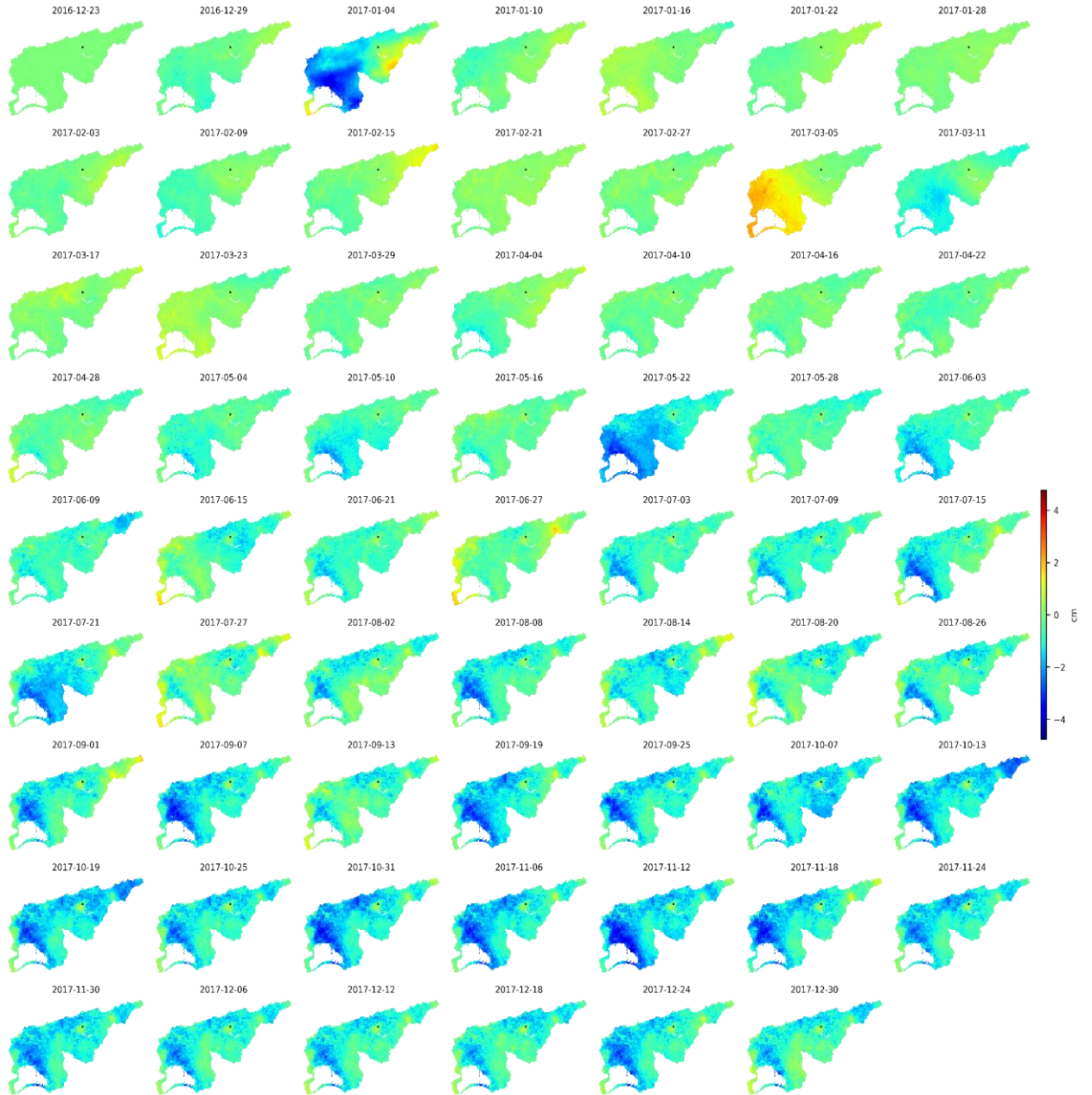
| Date       | Displacement (cm)    | Rainfall (mm) | Salinity (g/L) |
|------------|----------------------|---------------|----------------|
| 2016-12-30 | 0.0                  | 1.4           | 27.0           |
| 2017-01-05 | -0.6404272317886353  | 31.2          | 26.6           |
| 2017-01-11 | -3.512070655822754   | 16.4          | 26.4           |
| 2017-01-17 | -0.46199890971183777 | 38.0          | 24.6           |
| 2017-01-23 | 0.5054785013198853   | 2.4           | 22.0           |
| 2017-01-29 | -0.09466379135847092 | 57.6          | 20.0           |
| 2017-02-04 | 0.21424251794815063  | 21.0          | 17.8           |
| 2017-02-10 | -0.26005080342292786 | 28.0          | 18.2           |
| 2017-02-16 | -0.3527231812477112  | 9.6           | 18.9           |
| 2017-02-22 | -0.1568222939968109  | 11.4          | 17.8           |
| 2017-02-28 | 0.30861711502075195  | 1.2           | 18.8           |
| 2017-03-06 | 0.07733628153800964  | 8.4           | 20.5           |
| 2017-03-12 | 1.8718622922897339   | 43.2          | 23.1           |
| 2017-03-18 | -0.7985836863517761  | 0.0           | 22.6           |
| 2017-03-24 | 0.14321103692054749  | 0.8           | 21.3           |
| 2017-03-30 | 0.7245373129844666   | 1.2           | 24.3           |
| 2017-04-05 | -0.273860901594162   | 1.4           | 25.9           |
| 2017-04-11 | -0.6323727965354919  | 1.4           | 26.5           |
| 2017-04-17 | -0.3151974380016327  | 0.8           | 28.1           |
| 2017-04-23 | -0.392668217420578   | 1.6           | 29.0           |
| 2017-04-29 | -0.6403471827507019  | 0.0           | 25.7           |
| 2017-05-05 | -1.1352819204330444  | 0.2           | 28.6           |
| 2017-05-11 | -1.1180601119995117  | 0.8           | 32.1           |
| 2017-05-17 | -1.9128520488739014  | 16.2          | 28.5           |
| 2017-05-23 | -1.2084510326385498  | 8.4           | 33.5           |
| 2017-05-29 | -3.0886287689208984  | 41.8          | 32.5           |
| 2017-06-04 | -1.5241094827651978  | 1.7           | 30.9           |
| 2017-06-10 | -2.6627840995788574  | 4.2           | 34.7           |
| 2017-06-16 | -1.8414126634597778  | 0.4           | 37.7           |
| 2017-06-22 | -1.3235118389129639  | 0.8           | 39.2           |
| 2017-06-28 | -2.241150379180908   | 0.8           | 41.3           |
| 2017-07-04 | -1.189267635345459   | 0.8           | 42.4           |
| 2017-07-10 | -2.755267381668091   | 0.0           | 43.9           |
| 2017-07-16 | -2.3702824115753174  | 0.2           | 45.4           |
| 2017-07-22 | -3.322878360748291   | 12.8          | 43.8           |
| 2017-07-28 | -3.2035019397735596  | 1.8           | 45.3           |
| 2017-08-03 | -2.096522092819214   | 0.0           | 47.3           |
| 2017-08-09 | -2.9067952632904053  | 0.0           | 45.8           |
| 2017-08-15 | -3.491048574447632   | 0.0           | 46.2           |
| 2017-08-21 | -2.5138580799102783  | 0.0           | 48.0           |
| 2017-08-27 | -2.621453285217285   | 0.0           | 48.4           |
| 2017-09-02 | -3.0063397884368896  | 17.8          | 44.9           |
| 2017-09-08 | -3.765599012374878   | 0.2           | 46.1           |
| 2017-09-14 | -4.296868801116943   | 0.2           | 47.9           |
| 2017-09-20 | -2.8056139945983887  | 0.0           | 47.6           |
| 2017-09-26 | -4.09604549407959    | 0.4           | 47.6           |
| 2017-10-02 | -3.8956732749938965  | 7.0           | 47.7           |
| 2017-10-08 | -4.006961822509766   | 2.4           | 46.9           |
| 2017-10-14 | -4.36248779296875    | 0.2           | 46.2           |
| 2017-10-20 | -3.862492322921753   | 0.2           | 46.6           |
| 2017-10-26 | -3.6760311126708984  | 26.4          | 44.1           |
| 2017-11-01 | -4.325733661651611   | 9.0           | 44.8           |
| 2017-11-07 | -4.187749862670898   | 13.0          | 44.6           |
| 2017-11-13 | -4.610263347625732   | 5.4           | 45.2           |
| 2017-11-19 | -4.322211265563965   | 90.0          | 37.8           |
| 2017-11-25 | -3.848445415496826   | 9.6           | 39.9           |
| 2017-12-01 | -3.808488607406616   | 43.2          | 37.1           |
| 2017-12-07 | -3.649740695953369   | 3.0           | 37.3           |
| 2017-12-13 | -3.557131767272949   | 39.2          | 37.4           |
| 2017-12-19 | -3.270641326904297   | 40.6          | 35.1           |
| 2017-12-25 | -4.002434253692627   | 83.6          | 32.9           |
| 2017-12-31 | -3.190497398376465   | 101.0         | 28.0           |

**Appendix II:** Time series displacement maps from InSAR analysis showing cumulative surface deformation for 39 acquisition dates during 2016





**Appendix III:** Time series displacement maps from InSAR analysis showing cumulative surface deformation for 62 acquisition dates during 2017



## Appendix IV: Python scripts used for final plottings

### • Displacement map with well locations

```
import geopandas as gpd
import rasterio
import matplotlib.pyplot as plt
from rasterio.plot import show
from rasterio.warp import calculate_default_transform, reproject

# Path to the stacked GeoTIFF (displacement map)
stacked_tif = "/mnt/e/Swetha/2017BurstGialova/MintPy/Cumu_displacement_centimeters.tif"

# Path to the shapefile containing well locations
shapefile_path = "/mnt/e/Swetha/Shapefilegialova/groundwater
wells/reprojected_shapefile.shp"

# Specify the band number (e.g., Band 39)
band_number = 52 # Change this to the desired band number (1 to 39)

# Load the shapefile with GeoPandas
shapefile_data = gpd.read_file(shapefile_path)

# Check the CRS of the shapefile
print (f"Shapefile CRS: {shapefile_data.crs}")

# Reproject shapefile to EPSG:4326 (lat/lon) if necessary
if shapefile_data.crs != 'EPSG:4326':
    shapefile_data = shapefile_data.to_crs(epsg=4326)
    print (f"Reprojected Shapefile CRS: {shapefile_data.crs}")

# Extract coordinates for plotting
x_coordinates = shapefile_data.geometry.x
y_coordinates = shapefile_data.geometry.y

# Open the raster file
with rasterio.open(stacked_tif) as src:
    # Get the CRS of the raster
    raster_crs = src.crs
    print (f"Raster CRS: {raster_crs}")
    # Reproject raster to EPSG:4326 (latitude/longitude)
    if raster_crs != 'EPSG:4326':
        # Get the transform and dimensions for the new CRS
        transform, width, height = calculate_default_transform(
            src.crs, 'EPSG:4326', src.width, src.height, *src.bounds)

        # Create a new file for the reprojected raster
        reprojected_raster =
'/mnt/e/Swetha/2017BurstGialova/MintPy/Geotiffs/displacement_maps/unwrapped/Centimeters/repr
ojected_cumu_displacement1.tif'
        with rasterio.open(reprojected_raster, 'w', driver='GTiff', count=1,
            dtype=src.dtypes[0], crs='EPSG:4326', width=width, height=height,
            transform=transform) as dst:
            reproject (
                source=rasterio.band(src, band_number),
                destination=rasterio.band(dst, 1),
                src_transform=src.transform,
                src_crs=src.crs,
                dst_transform=transform,
                dst_crs='EPSG:4326',
                resampling=rasterio.enums.Resampling.nearest
            )

    print (f"Reprojected raster saved to: {reprojected_raster}")
else:
    print ("Raster is already in EPSG:4326")

# Read the reprojected raster
with rasterio.open(reprojected_raster) as reprojected_src:
    reprojected_band_data = reprojected_src.read(1) # Read the first band of the
```



```

reprojected raster

# Plotting the shapefile and the reprojected raster on the same plot
fig, ax = plt.subplots(figsize= (10, 8))

# Plot the reprojected raster
show (reprojected_band_data, ax=ax, cmap='RdYlBu',
transform=reprojected_src.transform, title="Displacement Map with Well Locations")

# Plot the shapefile data (well locations)
ax.scatter(x_coordinates, y_coordinates, color='red', label='Well Locations', s=20)

# Add title and legend
ax.set_title ("Displacement Map with Well Locations")
ax.legend()

# Add axis labels
ax.set_xlabel ('Longitude (degrees)')
ax.set_ylabel ('Latitude (degrees)')

# Show the plot
plt.show()

```

#### • Classified displacement map

```

import numpy as np
# Read the reprojected raster
with rasterio.open(reprojected_raster) as reprojected_src:
    reprojected_band_data = reprojected_src.read(1) # Read the first band of the reprojected
raster

# Mask out 0 values
masked_data = np.ma.masked_where(reprojected_band_data == 0, reprojected_band_data)

# Plotting the shapefile and the reprojected raster on the same plot
fig, ax = plt.subplots(figsize= (10, 8))

# Show the masked raster using imshow
img = ax.imshow(masked_data, cmap='RdYlBu',
extent=rasterio.plot.plotting_extent(reprojected_src),
origin='upper')

# Plot the shapefile data (well locations)
ax.scatter(x_coordinates, y_coordinates, color='red', label='Well Locations', s=20)

# Add colorbar for subsidence scale
cbar = plt.colorbar(img, ax=ax, shrink=0.7, label="Cumulative displacement (cm)")

# Add title and legend
ax.set title ("Displacement Map with Well Locations (2017)")
ax.legend()

# Add axis labels
ax.set_xlabel ('Longitude (degrees)')
ax.set_ylabel ('Latitude (degrees)')

# Show the plot
output_path = '/mnt/e/Swetha/2017BurstGialova/velocitydisplacement_map_with_wells.jpg' #
Change path/format as needed
plt.savefig(output_path, dpi=600, bbox_inches='tight') # High resolution and tight lay
plt.tight_layout ()
plt.show()

```

#### • Time series of displacement, Rainfall and Salinity

```

import matplotlib.pyplot as plt
import numpy as np
import rasterio
import datetime
import pandas as pd
import matplotlib.dates as mdates

```

```

# --- Rainfall data (62 values) ---
rainfall_ts = [
    1.4, 31.2, 16.4, 38.0, 2.4, 57.6, 21, 28, 9.6, 11.4, 1.2, 8.4,
    43.2, 0, 0.8, 1.2, 1.4, 1.4, 0.8, 1.6, 0, 0.2, 0.8, 16.2,
    8.4, 41.8, 1.7, 4.2, 0.4, 0.8, 0.8, 0.8, 0, 0.2, 12.8, 1.8,
    0, 0, 0, 0, 0, 17.8, 0.2, 0.2, 0, 0.4, 7, 2.4, 0.2, 0.2,
    26.4, 9, 13, 5.4, 90, 9.6, 43.2, 3, 39.2, 40.6, 83.6, 101
]

# --- Salinity data (62 values, in g/L) ---
salinity_ts = [
    27, 26.6, 26.4, 24.6, 22, 20, 17.8, 18.2, 18.9, 17.8,
    18.8, 20.5, 23.1, 22.6, 21.3, 24.3, 25.9, 26.5, 28.1, 29,
    25.7, 28.6, 32.1, 28.5, 33.5, 32.5, 30.9, 34.7, 37.7, 39.2,
    41.3, 42.4, 43.9, 45.4, 43.8, 45.3, 47.3, 45.8, 46.2, 48,
    48.4, 44.9, 46.1, 47.9, 47.6, 47.6, 47.7, 46.9, 46.2, 46.6,
    44.1, 44.8, 44.6, 45.2, 37.8, 39.9, 37.1, 37.3, 37.4, 35.1,
    32.9, 28
]

# --- Load displacement time series from raster ---
with rasterio:
    open("/mnt/e/Swetha/2017BurstGialova/MintPy/Geotiffs/displacement_maps/unwrapped/Centimeters
    /Cumulativedisplacement_with_rainfall.tif") as src:
        displacement_data = src.read(list(range(1, 63))) # Bands 1-62
        pixel_row, pixel_col = 54, 23 # Choose a valid pixel inside the raster
        displacement_ts = displacement_data[: pixel_row, pixel_col]

# --- Generate time axis (62 x 6-day intervals) ---
start_date = datetime.datetime(2016, 12, 23)
dates = [start_date + datetime.timedelta(days=6*i) for i in range(62)]

# --- Plotting ---
fig, ax1 = plt.subplots(figsize=(12, 6))

# Displacement line + markers
ax1.plot(dates, displacement_ts, 'b-o', label='Displacement (cm)', linewidth=2)
ax1.set_ylabel("Cumulative displacement (cm)", color='b')
ax1.tick_params(axis='y', labelcolor='b')

# Set monthly x-axis ticks for 2017
monthly_ticks = pd.date_range(start="2016-12-23", end="2018-01-01", freq="MS")
ax1.set_xticks(monthly_ticks)
ax1.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.setp(ax1.get_xticklabels(), rotation=45)

# Rainfall line + scatter dots on second y-axis
ax2 = ax1.twinx()
ax2.plot(dates, rainfall_ts, 'g--', alpha=0.7, label="Rainfall (mm)", linewidth=2)
ax2.scatter(dates, rainfall_ts, color='g', marker='x')
ax2.set_ylabel("Rainfall (mm)", color='g')
ax2.tick_params(axis='y', labelcolor='g')

# Salinity on third y-axis (improved)
ax3 = ax1.twinx()
ax3.spines["right"].set_position(("outward", 60)) # Offset right
ax3.plot(dates, salinity_ts, 'r-.', label='Salinity (g/L)', linewidth=2)
ax3.set_ylabel("Salinity (g/L)", color='r')
ax3.tick_params(axis='y', labelcolor='r')
ax3.set_ylim(15, 65) # Manually adjust limits to better fit salinity values

# Make sure the third axis is drawn on top
ax3.spines["right"].set_zorder(10)
ax3.yaxis.set_zorder(10)

# Combine legends
lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
lines3, labels3 = ax3.get_legend_handles_labels()
ax1.legend(lines1 + lines2 + lines3, labels1 + labels2 + labels3, loc='upper left')

# Final touches
plt.title("Time Series of Displacement, Rainfall, and Salinity (2017) - Well Location 23")

```

```

ax1.set_xlabel("Date")
plt.grid(True)
fig.tight_layout ()
plt.savefig
('/mnt/e/Swetha/2017BurstGialova/MintPy/plots/2017Rain_displaceWell_23_Salinity.png',
dpi=600, bbox_inches='tight')
plt.show()

```

#### • Regression Analysis

```

import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from statsmodels.api import OLS, add_constant
import pandas as pd
import numpy as np

def plot_regression(x, y, xlabel, ylabel, title):
    x_vals = x.values.reshape(-1, 1)
    model = LinearRegression (). fit (x_vals, y.values)
    y_pred = model.predict(x_vals)
    slope = model.coef_ [0]
    intercept = model.intercept_
    r2 = model.score(x_vals, y.values)

    plt.figure(figsize= (7,5))
    sns.scatterplot(x=x, y=y)
    plt.plot(x, y_pred, color='red')
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title)
    plt.text (0.5, 0.95,
              f'Slope: {slope:.3f} \nIntercept: {intercept:.3f} \n$R^2$: {r2:.3f}',
              transform=plt.gca (). transAxes,
              verticalalignment='top',
              bbox=dict(boxstyle='round,pad=0.5', facecolor='white', alpha=0.7))
    plt.show()

# 1) Salinity vs Displacement plot
plot_regression(df['Displacement'], df['Salinity'],
               'Displacement (cm)', 'Salinity (g/L)',
               'Salinity vs Displacement')

# 2) Displacement vs Rainfall plot
plot_regression(df['Rainfall'], df['Displacement'],
               'Rainfall (mm)', 'Displacement (cm)',
               'Displacement vs Rainfall')

# 3) Multiple regression: Salinity ~ Displacement + Rainfall
X = df[['Displacement', 'Rainfall']]
X = add_constant(X)
y = df['Salinity']

model = OLS (y, X). fit ()

# Format regression results table
results_df = pd.DataFrame({
    'Coefficient': model.params,
    'Std Error': model.bse,
    't-value': model.tvalues,
    'P>|t|': model.pvalues
})

# Add R-squared as a separate row for clarity
results_df.loc['R-squared'] = [model.rsquared, np.nan, np.nan, np.nan]

print ("\nMultiple Regression Results: Salinity ~ Displacement + Rainfall\n")
print(results_df.round(4))

```