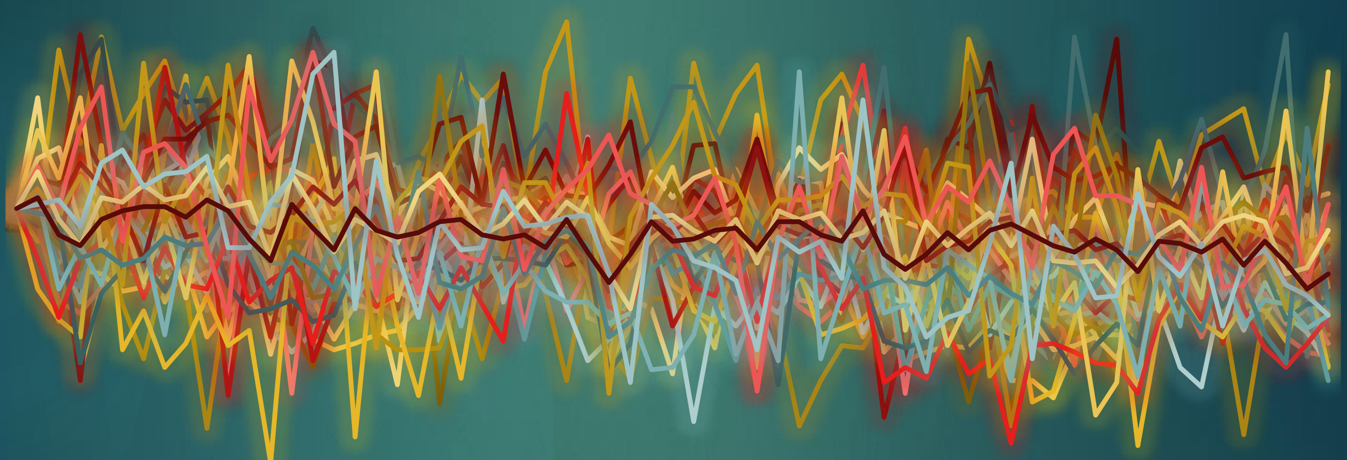
Giorgos Dimopoulos
Gabriel Garcia
Danny Marx
Ioanna Micha
Yixin Xu

Subsidence project

(Code Oranje)

DID-E5 Technical Report

Data analysis, processing and interpretation from different sources: satellites, ground sensor, citizens measurements and municipalities, to fight against building subsidence.



Supervisors: Tjeu Lemmens, Robert Voute, Peter Boelhouwer
Third parties: Dick de Jong (KCAF)

June 22, 2018
Geomatics Synthesis Project

DID-E5 Technical Report

Giorgos Dimopoulos	(4745590)
Francisco Gabriel Garcia Gonzalez	(4745892)
Daniel Benjamin Marx	(4624475)
Ioanna Micha	(4745610)
Yixin Xu	(4684710)

JUNE 21 2018

Delft University of Technology

Abstract

Every day, terabytes of information is generated, filling storage devices around the world. However, the human brain have limited capacities to read and understand raw data from a computer screen. That is why data specialists need to ingeniously create better ways to display, process and analyze massive amounts of data.

Our research project is not about avoiding subsidence, not even about cracks on buildings; it is purely data analysis and interpretation. This study will help professionals understand and fight against building subsidence. Our task was to create, manipulate and make sense of charts like the one below (a real line graph from InSAR data), then translate them into useful information for stakeholders in the local, national and global community.

The aim of the project was to understand if ground sensor technologies are comparable to other sources of information. In our analysis different strategies to analyze building subsidence were implemented, e.g. homogeneous subsidence, heterogeneous subsidence and for water levels, interpolation and cross correlation methods. In addition, other techniques like sensor fusing were implemented to compare data from different sources.

As a result from all these strategies, we can say that the water level sensors placed in our research building, have a high similarity with citizens and municipality data. In contrast, InSAR data is not comparable with the subsidence sensors placed in the building because they have different references and the period of study was too short to get accurate results from satellite data. Finally, an idea for future implementation strategies was proposed. On this idea, measurements of levels can be carried out taking as a reference the NAP level and comparing the subsidence between a healthy-foundations building and another one with wooden-piles foundation.

Acknowledgements

During these last 9 weeks we had an intensive time working on this Synthesis Project. We are a group of five students, with different background and personalities, and we managed to work all together and to cooperate in the most efficient way. We are grateful that we managed to complete the Subsidence project, and we are very pleased with what we accomplished.

Many people contributed to this Synthesis Project, with their support and guidance. As a team and individually we would like to thank them all. More specifically we would like firstly to thank our client, Mr Dick de Jong for providing us the datasets and being the intermediate person for the communication with the rest of the stakeholders (citizens, company that provide the sensors). He was always available whenever we needed him to help us understand the problem with the subsidence.

Secondly we would like to thank our supervisors Dr. Mathias Lemmens, Dr. Rober Voute, Dr Peter Boelhouwer for their guidance, for giving useful suggestions and remarks through the whole project and for offering us the opportunity to broaden our knowledge.

Lastly we would like to thank the citizens, for providing us the water datasets, and for being always willing to help us.

Reading Guide

This report is a detailed overview of the Subsidence project's work flow as a final technical report and is organized as follows. The first chapter encompasses the current situation, the research question that we set, and the methodology we follow in order to answer. The second chapter is a presentation of the technical background of the datasets that were provided to us and the third chapter is an overview of the dataset. The different analysis results are presented in the fourth and the fifth chapter, and at the sixth chapter we are gathering the conclusions that derived from this project and future recommendations. Details concerning the procedures and intermediate steps are presented in the Appendix.

Table of Contents

1 Introduction

1.1 Background information

For hundreds of years wooden foundations were used for constructions on weak soils around estuaries and near rivers in the Netherlands with the number of building standing on wooden foundations to be hundreds of thousands. As some of these buildings showed settlement or even collapsed in the last decades a discussion on the stability of the Dutch wooden foundations has started. Based on studies on different buildings in the Netherlands, three main factors have been identified which largely cause this subsidence: (1) a decline in ground-water level, (2) too high pile loads, (3) wood decay under water. These factors act independently, but often occur together.

To determine subsidence of buildings, accurate measuring techniques are required. These are essential for monitoring of the situation and to validate subsidence prediction models. So, in this part the field of Geomatics introduces the following observation methods to solve the problem: optical leveling, GPS surveys, LIDAR, InSAR, and Field Observations.

Recognizing the importance of this problem the KCAF foundation runs a pilot program called Code Orange. With this pilot program, foundations are monitored by means of sensors and the main aim is to predict in the most efficient way how long it takes for a foundation to require maintenance.

The present synthesis project is a part of the Code Oranje program. The goal of this project is to interpret and analyze different data sources related with the subsidence and its causes and try to find a relation between the information produced. More specifically, the data sources are related with satellite data (InSAR) and field observations (Sensors installed from KCAF, sensors from the municipality of Rotterdam and data collected from volunteers) and the aim is to assess the quality of the sensors in order to find the most efficient and economical way to monitor the subsidence.

1.1.1 Current Situation

The implementation phase of the Code Oranje pilot program started on February 2017 by placing sensors and connecting them with the server, in three blocks of Rotterdam: Orchideestraat, Almondestraat and Meerdervoortstraat. Three types of sensors were installed in different positions on the buildings (Figure 1-1):

1. sensors that registers the groundwater water levels
2. sensors that detects subsidence of the building
3. sensors that record deformation (distortions) of the building

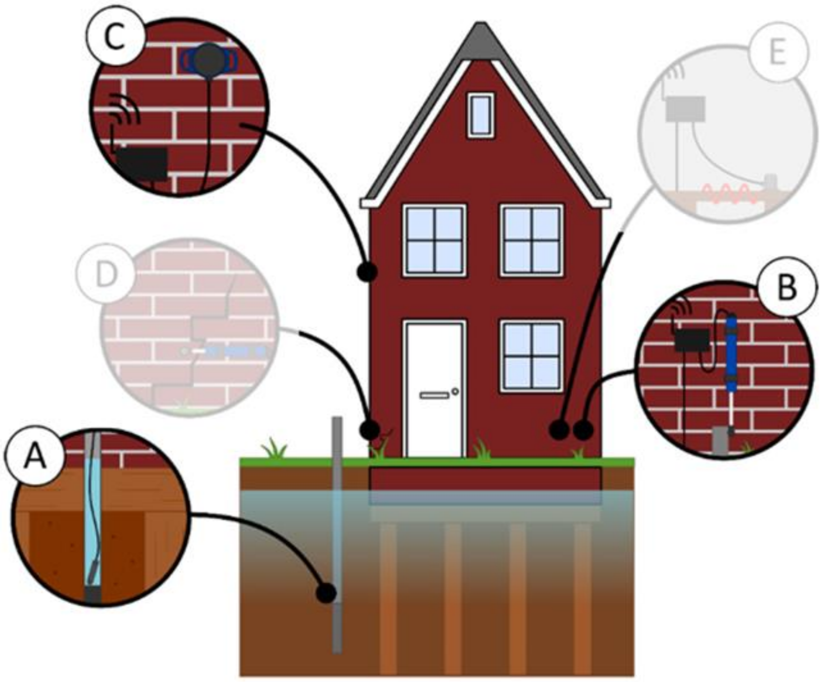


Figure 1.1 (A) Water level sensor, (B) Subsidence sensor (C) Deformation sensor

The main part of the program is to analyze and interpret the data from the sensors. For that reason the Code Orange has also a Science Council with experience in analysis of bid data concerning foundation issues and in that part our synthesis project is involved.

KCAF provided us with sensors data from the building block in Orchideestraat for the time period of 6 months in order to analyze them and check their quality. On that building block are placed 8 subsidence sensors, 3 ground water level sensors and 4 deformation sensors. The position of the sensors on the buildings is shown on the Figure 1-2. With blue are illustrated the ground water level sensors, with green the subsidence sensors and with red the sensors that measure the record the deformation.

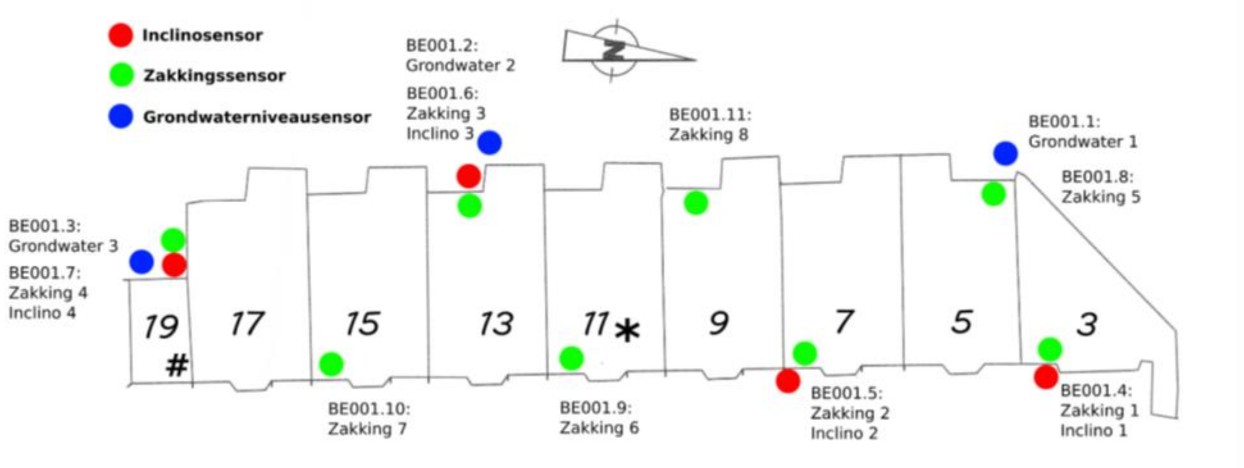


Figure 1.2 Sensors placed on buildings at Orchideestraat

Apart from the ground sensors data KCAF provided to us also with a pre-processed InSAR data of SkyGeo, ground water level measurements from the municipality, and ground water level measurements from the citizens (taken manually). Detailed specifications for all the provided datasets is presented on the Chapter 2.

1.1.2 Research question

The scope of the Subsidence synthesis project could be summarized in the form of a research question:

- Is comparable the use of subsidence sensors with InSAR data in order to detect movement on buildings?
- Related to water level in the soil, the sensors data is comparable with the data collected by the municipality or citizen's data?

1.1.3 Methodology

In order to reach our goal, we divided the project in two parts, where we analyze and interpret the ground water levels and the subsidence data separately.

1st part: Spatial and temporal comparison of the subsidence data from the ground sensors with the InSAR data of SkyGeo.

2nd part: Spatial and temporal comparison of the ground water level data from the sensors with the municipality data and the citizen's data.

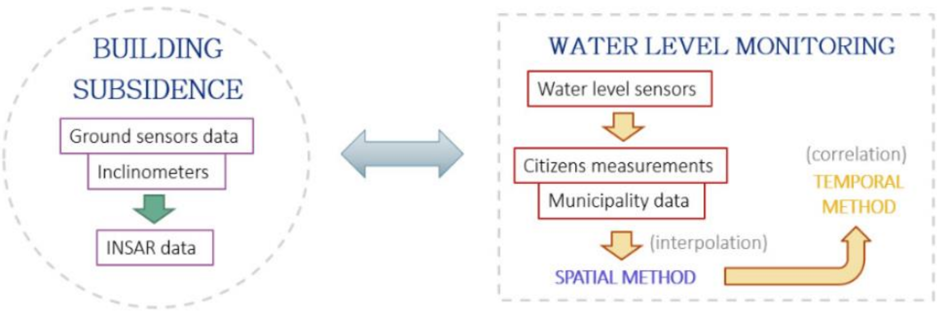


Figure 1.3 Two branches of the project

1.1.4 Requirements

After having defined the main objectives of the project, it is necessary to determine the conditions and needs that must be met by an end product based on the requirements of the involved stakeholders. The project is carried out in a team of five geomatics students and involves roles from both TU Delft and KCAF organization.

Although there are various types of requirements, the most important ones are the functional and non-functional. Functional requirements may be calculations, technical details, data manipulation and processing and other specific functionality that define what a system is supposed to accomplish, while non - functional requirement (NFR), is a requirement that specifies criteria that can be used to judge the operation of a system. Basically, Non-functional requirements describe how the system works, and usually are called as "quality attributes" of a system. (Wikipedia, n.d)

In the framework of our synthesis project the functional requirements could be listed as follows:

Table 1-1 Functional Requirements (Data processing)

Read datasets from different sources
Clean data
Spatial and Temporal analysis of the datasets
Compare datasets from different sources
Manipulate databases
Improve datasets
Visualize results

Table 1-2 Functional Requirements (Software tools)

Qgis	Spatial Analysis of the data
Python	Algorithm development
FME	Manipulation of Spatial data
SQL, Postgres, PostGIS	Database Management
Rhino-Grasshopper	3D analysis of the datasets

In the system of this synthesis project the most appropriate "quality attributes" to describe it could be the following:

Table 1-3 Non-Functional Requirements

Reliability	We ensure that our project provide reliable results.
Data Integrity	This synthesis project proved assurance of the accuracy and consistency of its data over the entire life-cycle of the project.
Usability	The results of this synthesis project are presented in a way that is easy understandable from all the stakeholders (client)

1.1.5 Work Breakdown Structure

All tasks for the project team are determined and organized in the Work Breakdown Structure, as shown in Figure 1-4. The project work is divided in six main tasks: background research, data collection, data preprocess, validation check, conclusion and final report. Research mainly focuses on subsidence background, object building, INSAR data etc. and it would be done throughout the project as it is needed in all phases as shown in Figure 1-3. Final report will illustrate findings, conclusions and recommendation among whole project about subsidence monitoring data in study area. The remaining tasks will be explained in more detail in the Work Package Description.

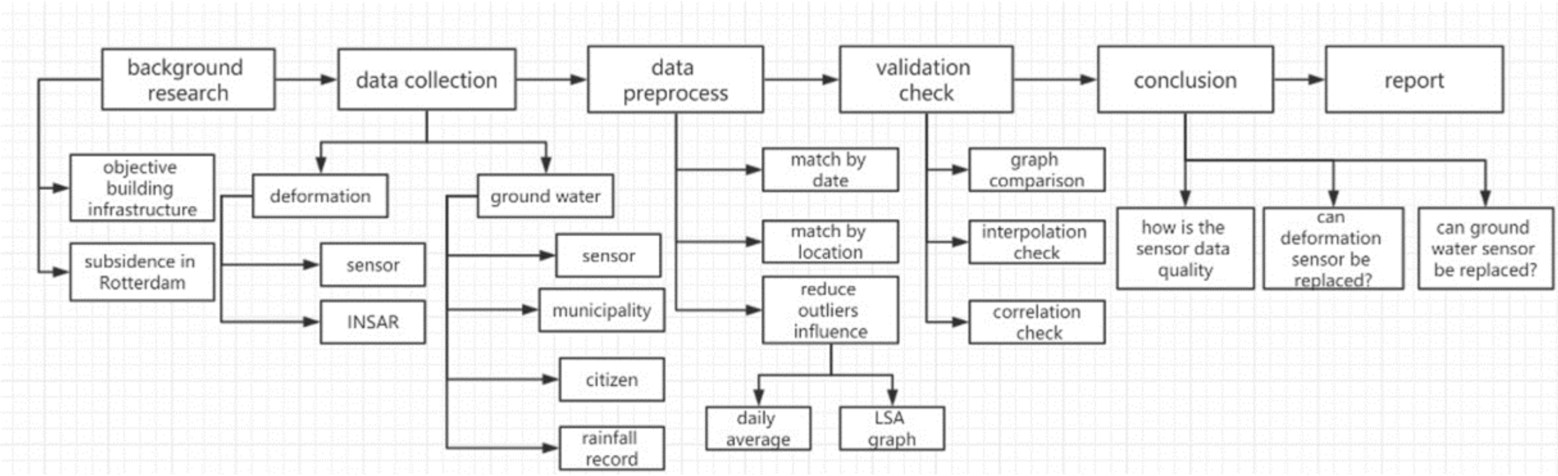


Figure 1.4 Work Breakdown Structure

2

Technical background of data

During the Subsidence Project we worked with datasets from different sources, and for that reason it was necessary to us to know the quality of each dataset and the technical specifications of the different equipment (ground sensors, Satellites). In the following sub-chapters is presented the technical background of each dataset.

2.1 Sensor data from “Code Orange”

2.1.1 Subsidence sensors

Subsidence is measured by linear position sensing technologies. The sensor reads the measurement in order to convert the encoded position into a digital signal. This position can then be decoded into position by a digital readout or a motion controller. Motion can be determined by change in position over time. It is a type of electrical transformer which is used for sensing and measuring linear displacement.

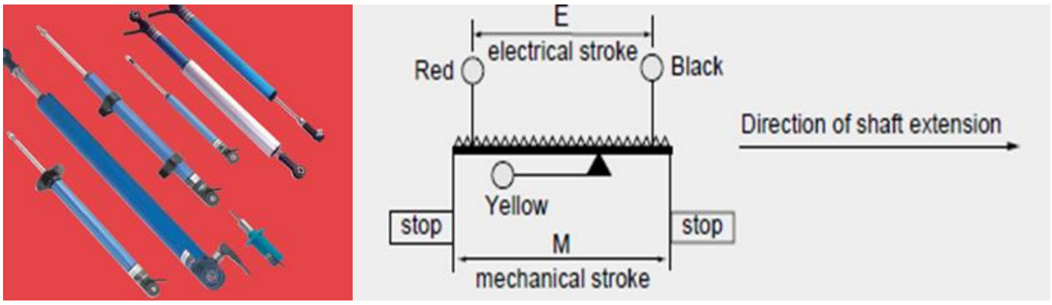


Figure 2.1 Linear position sensor and working principle

2.1.2 Inclinometer sensors

The sensors are based on an advanced “bulk micro machined” technology. The three dimensional structure of these sensors comprise a pendulum made of mono crystalline silicon. The pendulum is hermetically enclosed between two silicon discs. From this construction results a long term stable, high resolution and shock resistant sensor. A gas damping prevents overshooting and interfering resonance oscillation. An ASIC (Application-specific integrated circuit) measures the capacitive change caused by the movement of the pendulum.

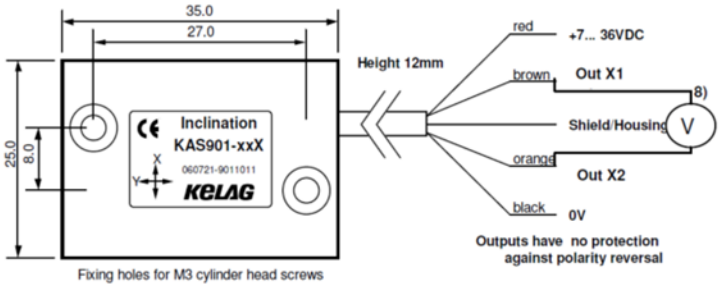


Figure 2.2 Inclinometer sensors

2.1.3 Water level sensors

The methods of measuring water level in wells is using the submersible pressure sensor. The use of micro machined silicon technology and analogue circuitry enables good performance for stability, low power and frequency response. At the heart of the sensor is a high stability pressure element manufactured from micro machined silicon. The silicon sensing element is fully isolated from the media by an isolation diaphragm. Surface mount electronics within the body tube minimize sensor size and improve reliability.

Figure 2.3 Submersible pressure sensor (model: UNIK 5000)

2.2 InSAR data from SkyGeo

The InSAR dataset that was delivered to us was already pre-process from SkyGeo. More specifically we were provided the InSAR data as point cloud datasets, with subsidence values in different times. The processing procedure to create the point cloud is unknown to us, but a general technical background of the satellites and the quality of the outcome is provided in a document attached to the datasets when they are downloaded.

2.2.1 InSAR in general

InSAR (Interferometric Synthetic Aperture Radar) is a technique for mapping ground deformation using radar images of the Earth's surface that are collected from orbiting satellites. Unlike visible or infrared light, radar waves penetrate most weather clouds and are equally effective in darkness. So with InSAR it is possible to track ground deformation even in bad weather and at night. (https://volcanoes.usgs.gov)

Two radar images of the same area that were collected at different times from similar vantage points in space can be compared against each other. Any movement of the ground surface toward or away from the satellite can be measured and portrayed as a "picture" – not of the surface itself but of how much the surface moved (deformed) during the time between images. Imagery is provided by space agencies in Italy, Germany, Canada, Japan, Korea, Europe, and the U.S. (https://volcanoes.usgs.gov)

To create this radar deformation "picture" a pulse of radar energy is emitted from a satellite, scattered by the Earth's surface, and recorded back at the satellite with two types of information: amplitude and phase. The amplitude is the strength of the signal recorded, and the phase is the fraction of a complete wave cycle that reaches the sensor. The phase measurement is extremely important for measuring deformation. A difference in phase between two sequential measurements means that something has changed. If the Earth's surface subsides, the emitted radar signal has to travel a further distance to reach the surface. This results in an extra fraction of the radar wave being reflected and recorded, known as the phase difference. The length of a complete wave cycle is in the order of centimeters and differs depending on the satellite. Because this length is known very precisely, the surface deformation can be determined with millimeter precision. (https://skygeo.com/)

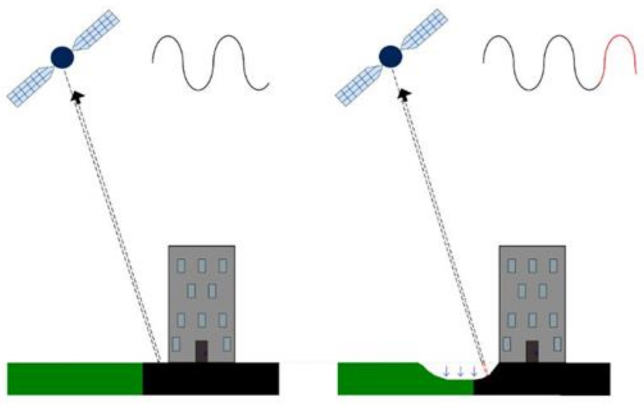


Figure 2.4 InSAR measurements before and after

Horizontal/ Vertical Deformations

Radar satellites orbit the earth at an altitude between 500-800 km with a velocity of approximately 7.5 km/s. They scan the whole earth in strips and because of their orbits and the rotation of the earth they will repeat the exact same cycle after a certain amount of days, depending on the satellite. Because of the orbit of the satellite, it passes a certain location both from south to north (the ascending orbit) as well as from north to south (the descending orbit). (https://skygeo.com/)

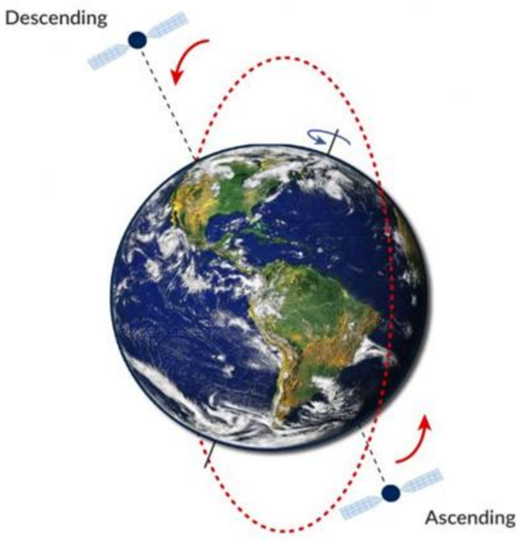


Figure 2.5 Ascending and descending orbit of the satellite, SkyGeo

The satellite is observing the earth under an angle with respect to the vertical, generally between 20 and 40 degrees. The deformations on the Earth's surface is measured in the viewing direction of the satellite, so the deformation measurement has both a vertical and a horizontal component.

Quality of satellite data

Quality is inherent to measuring; how precise and how reliable is the data; with InSAR it is measured the deformation at certain locations, but there is an uncertainty in the determined deformation as well as in the location where this deformation occurs. Measurements of the phase difference in InSAR images are very accurate, and this results in high accuracy deformation measurements. However, the measurement of the absolute location (X,Y,Z) in which the surface deformed is less accurate.

By combining a sequence a radar images, it is possible to analyze specific locations throughout time. One condition, however, is that these locations have to show a more or less consistent reflection in every image so they remain recognizable in the different recordings. This implies that changing objects, like vegetation, are not suitable for time-series analysis. Vegetation varies greatly between seasons and therefore becomes unrecognizable after a while. Buildings and other infrastructure, however, often do show consistent reflections throughout time. These objects (or parts of them) are called consistent reflectors and form the basis for accurate deformation measurements. But within one pixel, only one reflection value can be obtained, so the resolution of the satellite image, highly affects the accuracy in the measured location

The resolution of the satellite images differs according to the satellite. There are high or standard resolution satellites with the size of pixel to differ from cm to meter. As from one pixel, only one reflection can be measured, we cannot be sure for the exact location of that measurement inside the pixel. So the accuracy of the location of the measurement is highly connected with the resolution of the satellite.

2.2.2 SkyGeo Satellite Data

The SkyGeo's data that were provided to us, are referring to the time period between 9th of June 2015 to 28th of June 2017. (Table 2-1) The InSAR images were captured from the Terrasar- X satellites with the following specification. (Table 2-2 and Table 2-3).

Table 2-1 InSAR datasets

Dataset	Timespan	Images	Median Time Interval
TSX dsc DS - Hoge punten	2015-06-11 - 2017-06-28	63	11
TSX dsc DS - Lage punten	2015-06-11 - 2017-06-28	63	11
TSX dsc PS - Hoge punten	2015-06-11 - 2017-06-28	63	11
TSX dsc PS - Lage punten	2015-06-11 - 2017-06-28	63	11
TSX asc DS - Hoge punten	2015-06-09 - 2017-06-26	36	22
TSX asc DS - Lage punten	2015-06-09 - 2017-06-26	36	22
TSX asc PS - Hoge punten	2015-06-09 - 2017-06-26	36	22
TSX asc PS - Lage punten	2015-06-09 - 2017-06-26	36	22

Table 2-2 Satellite's information (Part 1)

Satellite	terraSAR-X
Pass direction	Ascending (350 [deg])
Incidence angle	39.3 [deg]
Resolution	3.0x2.8 m

Table 2-3 Satellite's information (Part 2)

Satellite	terraSAR-X
Pass direction	Descending (192[deg])
Incidence angle	24.1 [deg]
Resolution	3.0x3.1 [deg]

The different measured points provided deformation values in these two years and were accompanied by metadata information concerning for instance their quality, height, date. (Table 2-4).

Table 2-4 Metadata

Dem height	Height	Id	Lat-long	Linear	Quality	Rdx-Rdy	Date
Height according to SRTM [m]	Z-coordinate of observation [m] (+nap)	Unique code of point	WGS-84	Linear deformation [mm/year]	Relative quality of observation [no units]	X,Y coordinates [EPSG 28992]	The cumulative deformation at date [mm]

High and Low Points

SkyGeo divides the point cloud in two categories High Points and Low points. This separation is happening in order to distinguish points that are on building and those that fell on the ground. In order to separate the 'high' and 'low' points, the height obtained from SkyGEO's algorithms for each measurement is compared to a Digital Terrain Model (DTM) with relatively accurate continuous elevation values. If the height value obtained for a measured point is more than a set threshold of X m higher than the DTM value at the same location, the point is classified as a high point. If the height value obtained for a measurement point is below a second set threshold of Y m than the DTM value, the point is considered not trustworthy and is discarded. If the difference between the obtained height value and the DTM value falls within these two thresholds, the point is classified as a low point. This is visualized in the diagram below. The values for X = 3 and Y =10 for the Terrasar X satellite.

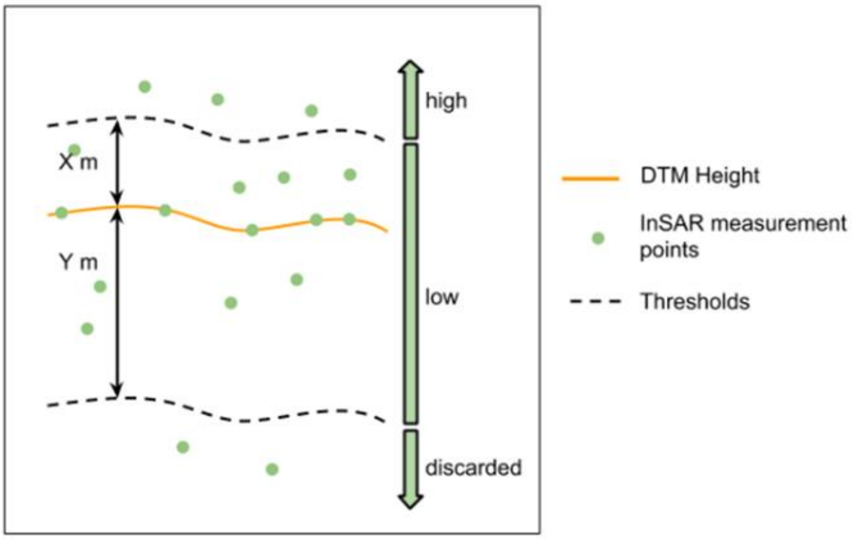


Figure 2.6 'High' and 'Low' Points separation

Precision

The precision of the measured points regarding the deformation value and the location, as is referred from SkyGEO technical report:

Table 2-5 Precision of measure points

Individual Measurement Precision	6-8 mm
Deformation Velocity Precision	1-2mm/yr
Location Precision	X,Y: 2-3m Z: 2-2.5m

Point Quality

SkyGeo provides in the datasets, a quality attribute for each point (Table 2-4). This value ranges from 0 to 1 and is relatively to the noise of the dataset. Generally, a lower quality value indicates a higher amount of noise in the time series.

2.3 Water level data from citizens

Since 2007, resident's group in Hillegersberg has realized the ground water level could be an issue to the building's foundation subsidence and the citizens themselves have been sampling several water walls about water level more than one year up to now. There are 58 sampling wells in total and the frequency of the sampling is about 15-20 times per month (this number might vary according to different wells and months). However, the wells are distributed in a way in order to cover an area much larger than our building's area, so only the 17 wells (shows in Figure 2-7) that are close to the block and the sampling time that matches the ground water sensor are selected to do the further analysis and calculation.

2.4 Water level data from municipality

Gemeente Rotterdam provides ground water level monitoring service that covers the whole city. The open data can be downloaded freely and are updated once per month. However, the municipality's data sampling spatial density is less than the corresponding one density of the citizen's water data. We used only 8 monitoring locations (also shows in Figure 2-7) that are close to the object building and data of 7 months that correspond to the research period of (March, 2017 till September, 2017).

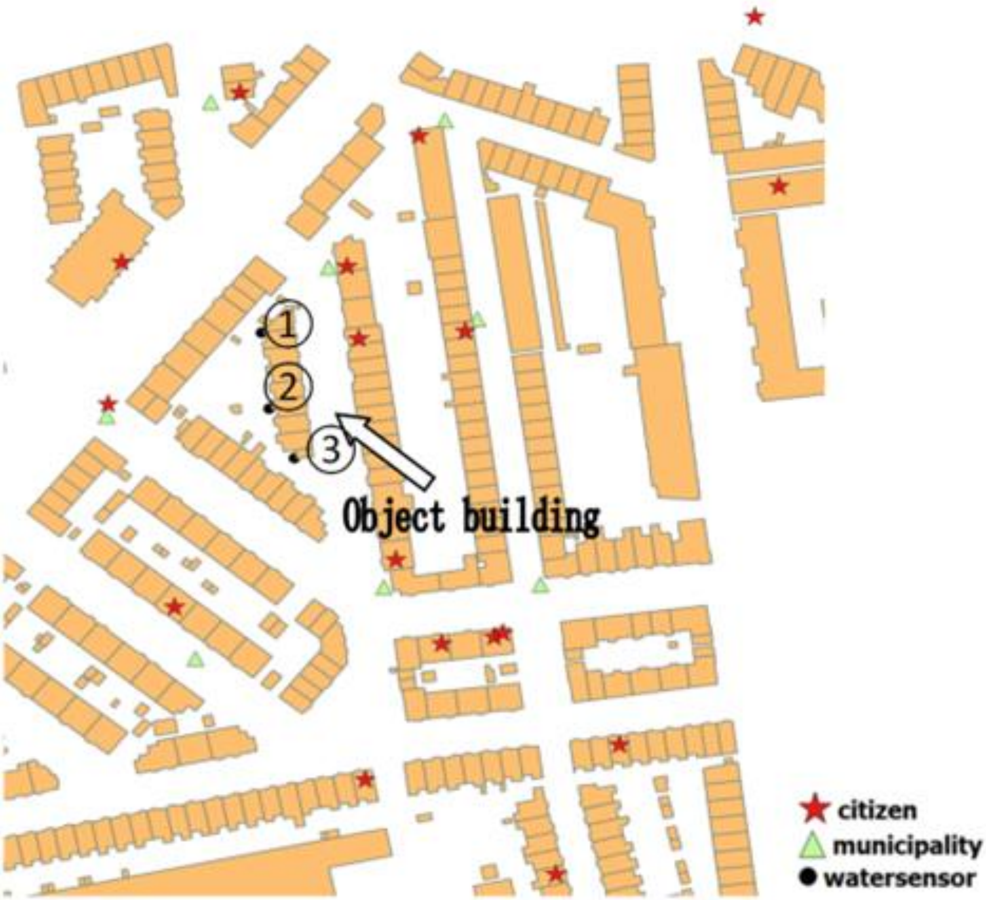


Figure 2.7 Citizen's data, municipality data and water sensor spatial distribution, the numbers indicates the sensor's ID in chapter 7

2.5 Precipitations data

Flow in the upper groundwater zone is primarily driven by rainfall-induced and changes of topographical structures, which could be referred to groundwater supplement and storage respectively. Considering topography is less likely to make a difference in the short-term research period, in this project we did not study this aspect. So, in the analysis of groundwater process, rainfall influence also is taken into consideration. According to Royal Netherlands Meteorology Institute website, weather data in Rotterdam e.g. daily precipitation amount and daily precipitation duration is provided. However, the specific position of observation station in unknown and the data documentation says 'the station relocations and changes in observation techniques'. This means that the precipitation data might not rightly represent the true weather situation around the block. As a result, the project will only give a simple correlation computation (table 2-6) instead of a detailed analysis.

In the second row of the table (2-6) are presented the correlation result when sensor data and rainfall data are observed in same day. These numbers indicate the weak correlation between rainfall and groundwater level that observed by the sensors. Sometime, because of the process of infiltration, groundwater level change will not reflect precipitation directly but need a time difference. Considering to this, we put rainfall data one day forward to offset this influence and calculate correlation again (row 3) but shows even weaker result. This confirms the discussion above, the precipitation cannot shows the real situation around the object building or there are some more strong factors that influence groundwater level.

Table 2-6 Correlation result of rainfall and groundwater sensor

sensor	1	2	3
same day	0.34	0.30	0.37
rainfall-1day	0.26	0.26	0.31

2.6 AHN 3

Three iterations of the country wide 'Actueel Hoogtebestand Nederland' exist, recorded over the last 20 years. Data was acquired via airborne LiDAR with the main purpose of creating a digital terrain model. Therefore coverage is focused on nadir measurements, rather than facades. The different properties of the versions/years are shown in Table 2-6.

Table 2-7 Properties of different iterations of the AHN product

	Error (vertical, 1σ)			
	Recording	**Systematic**	**Stohastic**	**Density**
AHN1	1996 – 2003	5 cm	15 cm	1 pt/16m^2
AHN2	2008 – 2012	5 cm	5 cm	6 – 10 pt/ m^2
AHN3	**2014 – 2018**	**5 cm**	**5 cm**	**~ 20 pt/ m^2**

Data is provided as tiled LAZ-files (5 km × 6.25 km) and is available for public download through PDOK (Publieke Dienstverlening op de Kaart). Coordinates are expressed as RD-NAP coordinates (EPSG:7415). For the purpose of this project we will use only the latest version of the AHN that is the AHN3 and the tile that covers our area is described with the code 37FZ1.

3

Overview of data

3.1 Sampling intervals

As the data was collected from different sources, the sampling intervals differ between each dataset. When the sampling resolution is too dense, it is possible to reduce the amount of samples using mean values every determinate period but when just a few samples are available it is not possible to increase the number of measurements. In the table 3-1, it is possible to see the different sample intervals of the available data for the project.

Table 3-1 Sampling interval for available data.

DATASET	SAMPLING INTERVAL
INSAR DATA	Around 1.5 samples per month
INCLINOMETER SENSORS	Around 110 samples per month
SUBSIDENCE SENSORS	Around 90 samples per month
GROUNDWATER LEVEL SENSORS	Around 600 samples per month
CITIZENS OVERLOOP	Around 13 samples per month
CITIZENS KLEIWEGKWARTIER	Around 10 samples per month
CITIZENS PLEIBUIZEN	Around 4 samples per month
MUNICIPALITY WATER LEVELS	1 sample per month
RAIN DATA (PRESIPITATIONS)	30 per month
LIDAR DATA (AHN3)	Only once
SOIL DATA	Only once

3.2 Timeline of data

Before confronting sensors data, it is important to understand what the sensors are measuring and in which manner. Subsidence sensors measure vertical movement of the building in millimeters, inclinometers measure angles of inclination of the facades and the water level sensors measure the level of water in meters, see Figure 3-1.

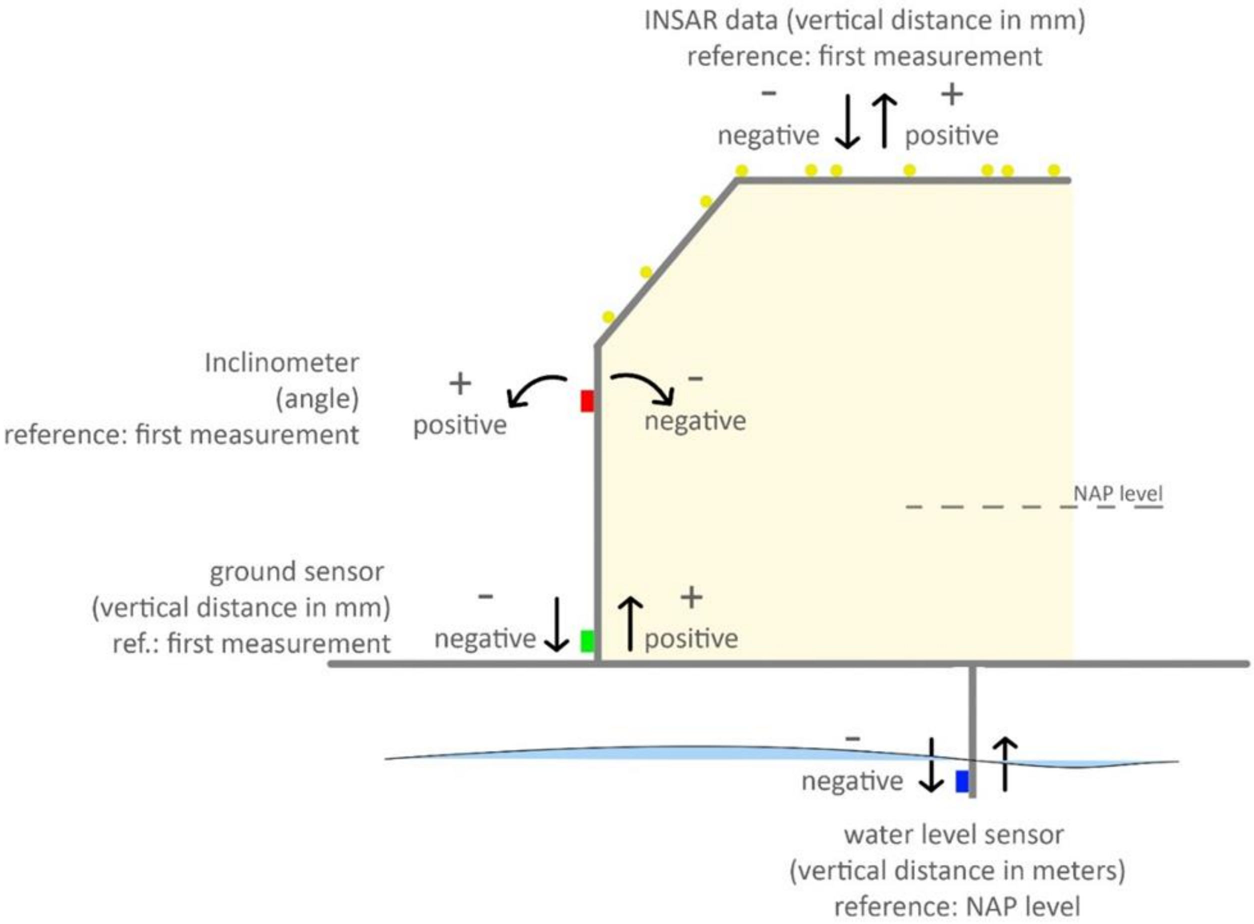


Figure 3.1 Sensors measuring units

During the “Code Oranje” project introduction by KCAF, it was explained that the subsidence of the buildings mainly happens when the water level in the soil goes down. According to this, we wanted to compare water levels with subsidence sensors (figures 3-2 and 3-3) and verify if the collected data reflect the explained theory.

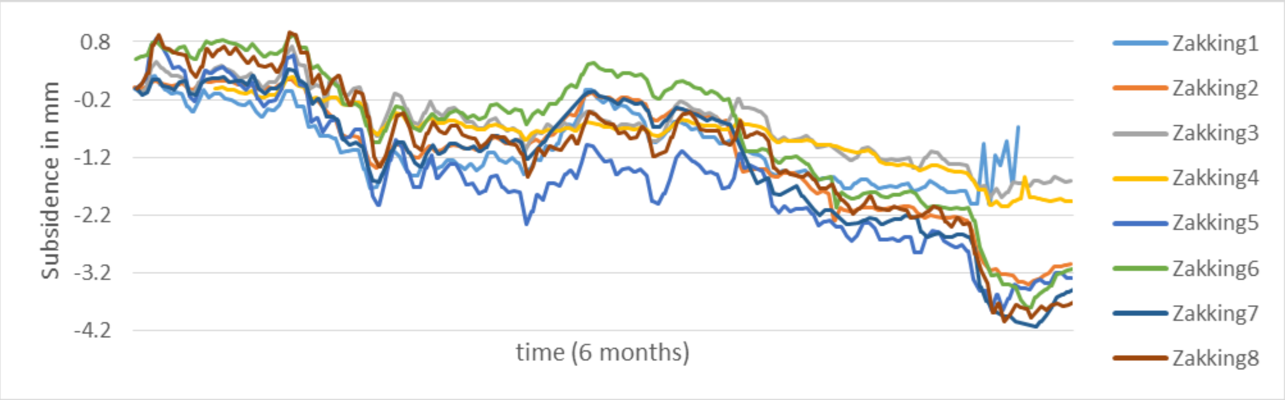


Figure 3.2 Subsidence monitoring sensors

Figure 3.3 Ground water level sensors

In the previous graphics, it is possible to see the opposite of the theory explained. According with the sensors, when the water in the soil increases, the buildings subside. It is clear that the data in the graphics is generally mirrored.

To have a reference about the water level sensors are working correctly, we compared the water measurements with rain data from the municipality. In the figures 3-4 and 3-5, it is possible to verify that the data from the water level sensors is directly related with the amount of rain in Rotterdam.

Figure 3.4 Ground water level sensors

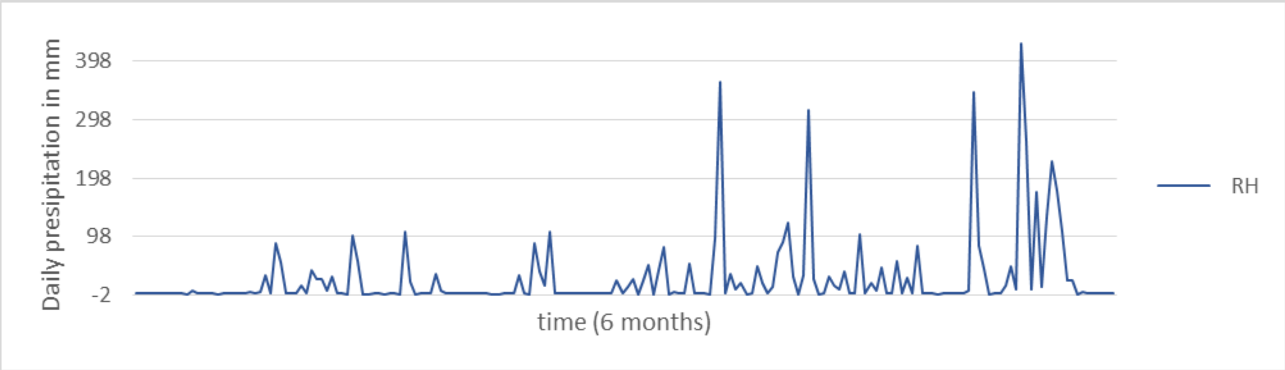


Figure 3.5 : Precipitation data

Finally, in order to show the clearer change pattern of subsidence and groundwater level and the relationship of them, we take the mean measurements of each two data and compute the correlation of the averages. The result is **-0.91** which indicates a strong negative correlation, and it means in the research period, regardless time delay, the object building will drop vertically when the groundwater beneath is risen.

Figure 3.6 Correlation between subsidence data and water level data.

3.3 Inclinometer Data Sensor

Other than the subsidence monitoring sensors and the water level sensors we also have datasets derived from the Inclinometer Sensors. On the block of buildings that we examine we have four of this kind of sensors mounted on the three out of the four side of the block with two of them being on the front façade of the block, one on the back façade and the last one is on the south side of the block. In Figure 1-2 we can see the position of the sensors in red color.

As it is depicted in Figure 3-1 the inclinometer are measuring positive and negative angles in only one direction. Positive values we have when the sensor is moving outwards (relative to the buildings) and negative when it is moving inwards.

With simple trigonometric equations we were able to transform the measured angles in horizontal deformations. The resulted diagrams for all four sensors are presented in the Figure 3-6 to Figure 3-9.

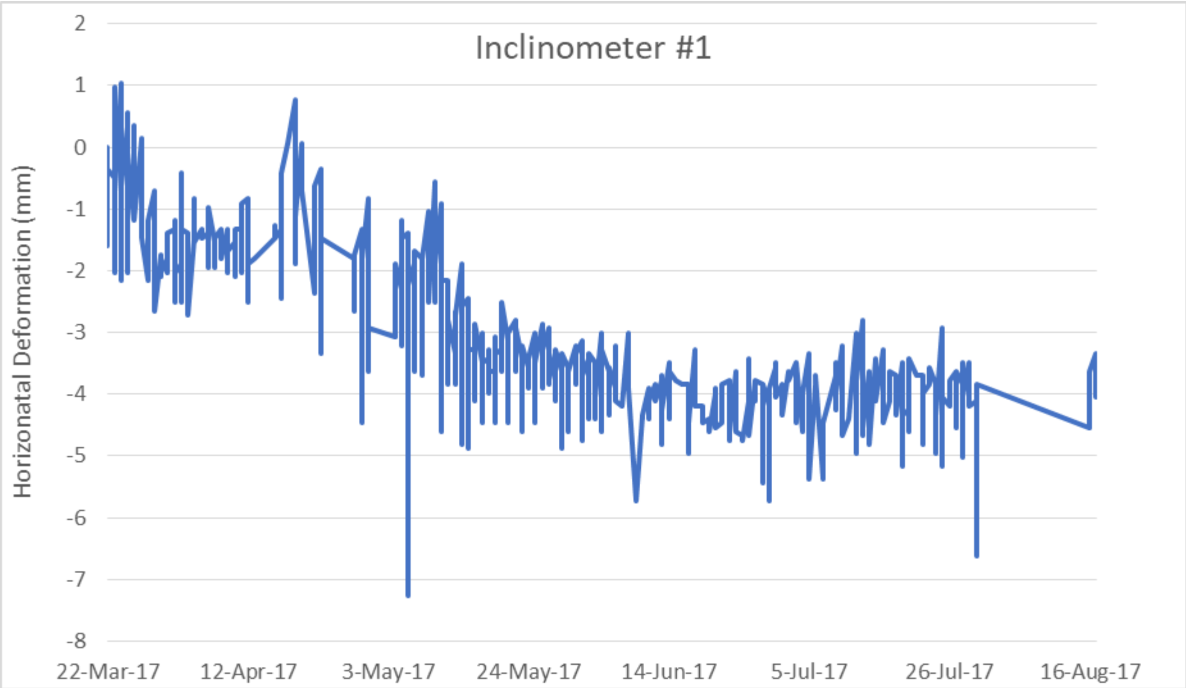


Figure 3.7 Horizontal deformations of sensor 1

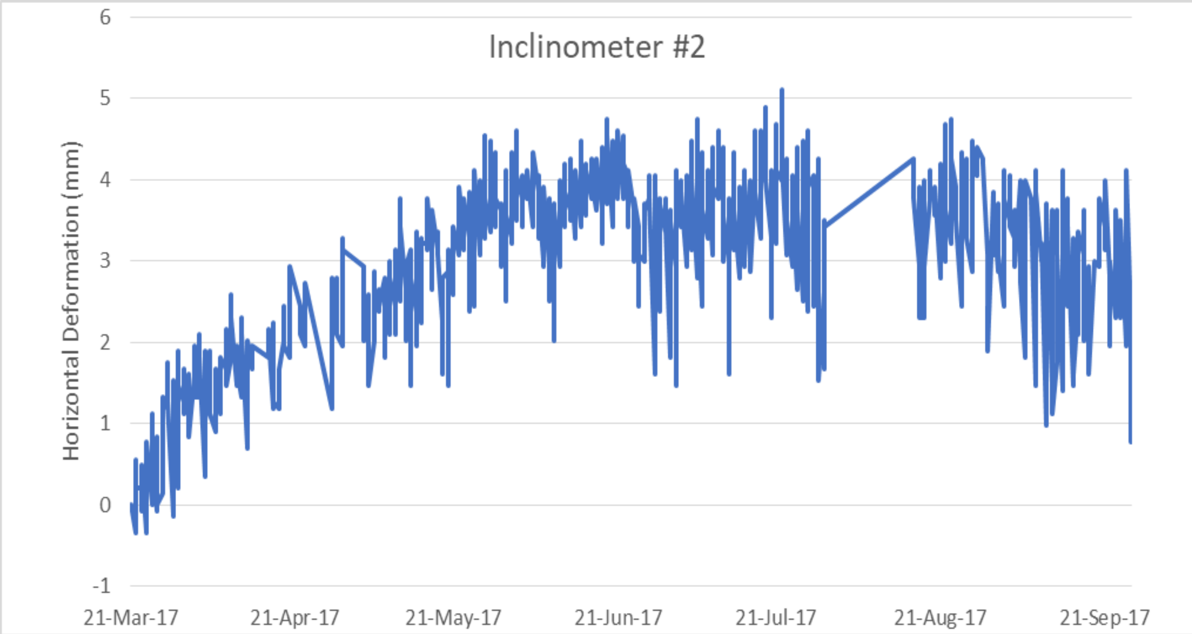


Figure 3.8 Horizontal deformations of sensor 2

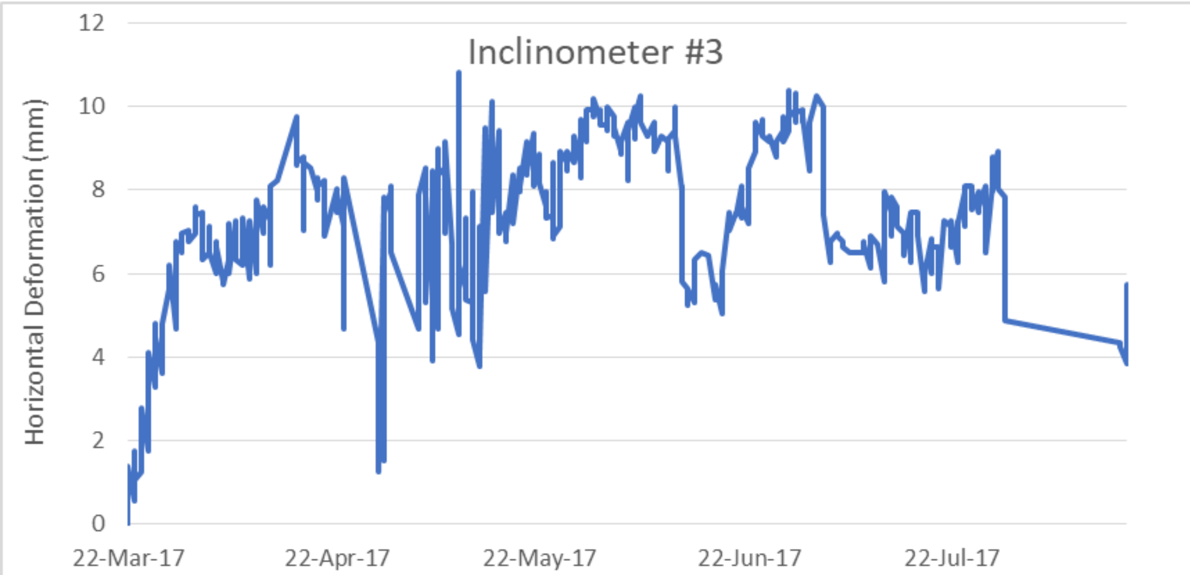


Figure 3.9 Horizontal deformations of sensor 3

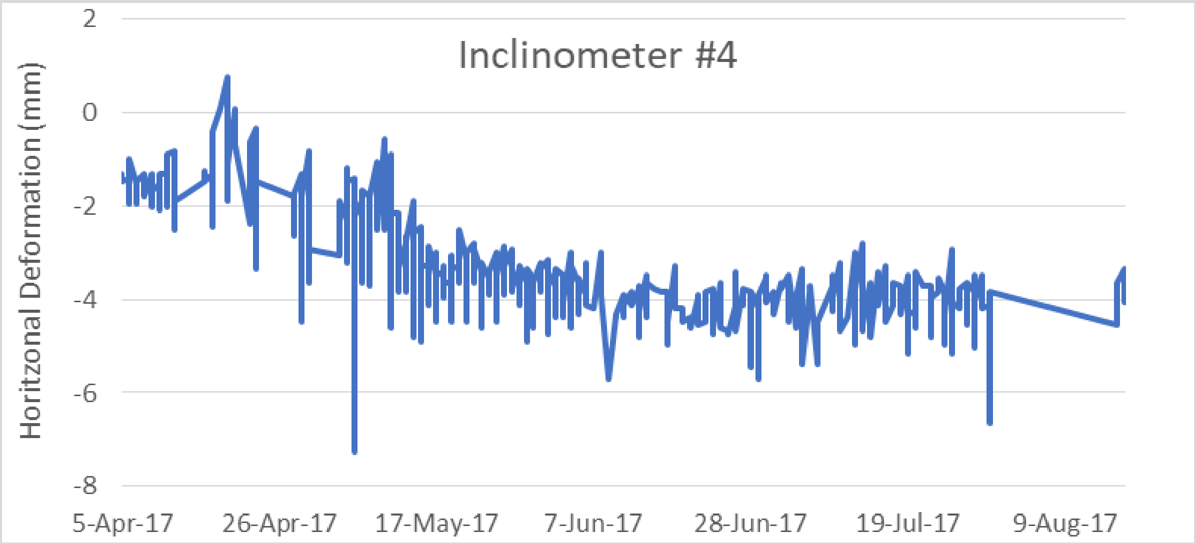


Figure 3.10 Horizontal deformations of sensor 4

From the Figures 3-6 to 3-9 we can notice that two of the sensors have positive values (outwards) and the other two have negative values (inwards). As it is also clear from the Figure 3-10 we have two really close together sensors in the front façade that are resulting in opposite direction of deformation while in the middle part of the block we notice two opposite direction deformations for each façade. The side sensor is depicting a minor deformation leading to the conclusion that the block is mainly moving around the North – South axe of the block.

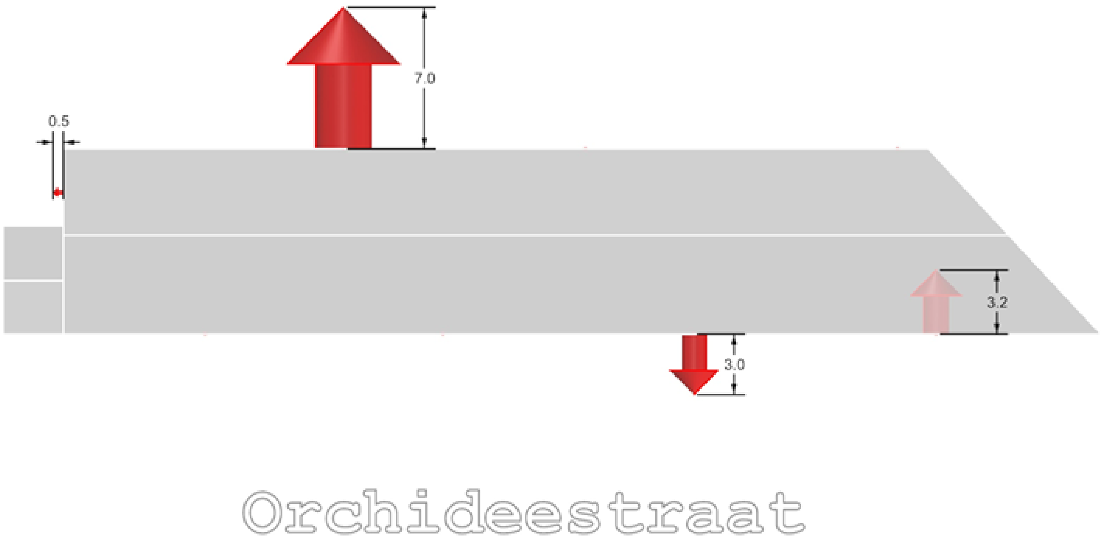


Figure 3.11 Mean inclination at four sensor locations, two along the back and two along front façade of the Block, can be seen in millimeters.

Since we have rather contradicting results from our four sensors it would have been optimal to have more sensors around the block in order to be able to determine the movement of each building of the block separately and more accurately.

4
Building movement

In order to understand if the sensors are working in the correct way, we compared the sensors measurements with InSAR data. The aim of this comparison is to understand if it is possible to detect millimeter subsidence using InSAR data, and if possible, how accurate it is.

For this purpose, different analysis were carried out. The building movement was analyzed from different perspectives, punctually, locally and generally to identify possible ways of movement. In some cases, we used only 5 months of data (the overlapping period) and in other cases the whole 2-year period of InSAR measurements, see Figure 4-1 with the timeline of buildings data.

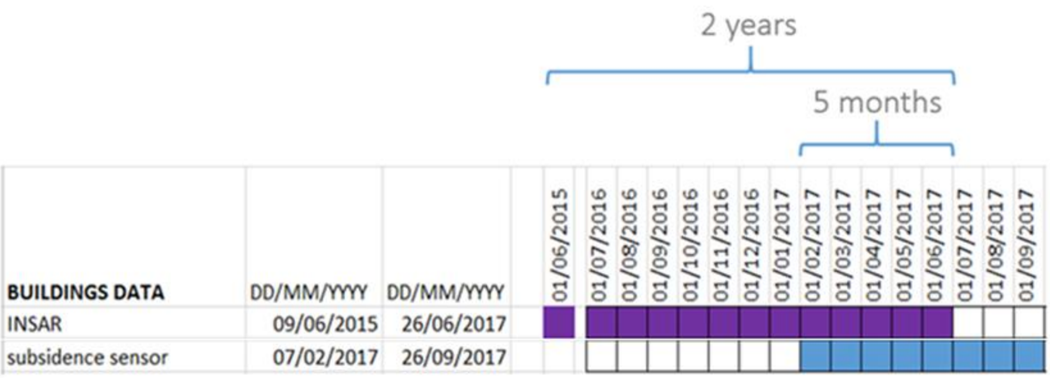


Figure 4.1 Timeline of data with study periods

4.1 InSAR height map in relation with NAP

Every InSAR point have a different height with an error of 1.5 meters. For this first study, the data was filtered using 5 height intervals depending on the analysis to carry on (Figure 4-2). In this case, we are interested only in the points related with the structure of the house, 3 meters above the NAP level.

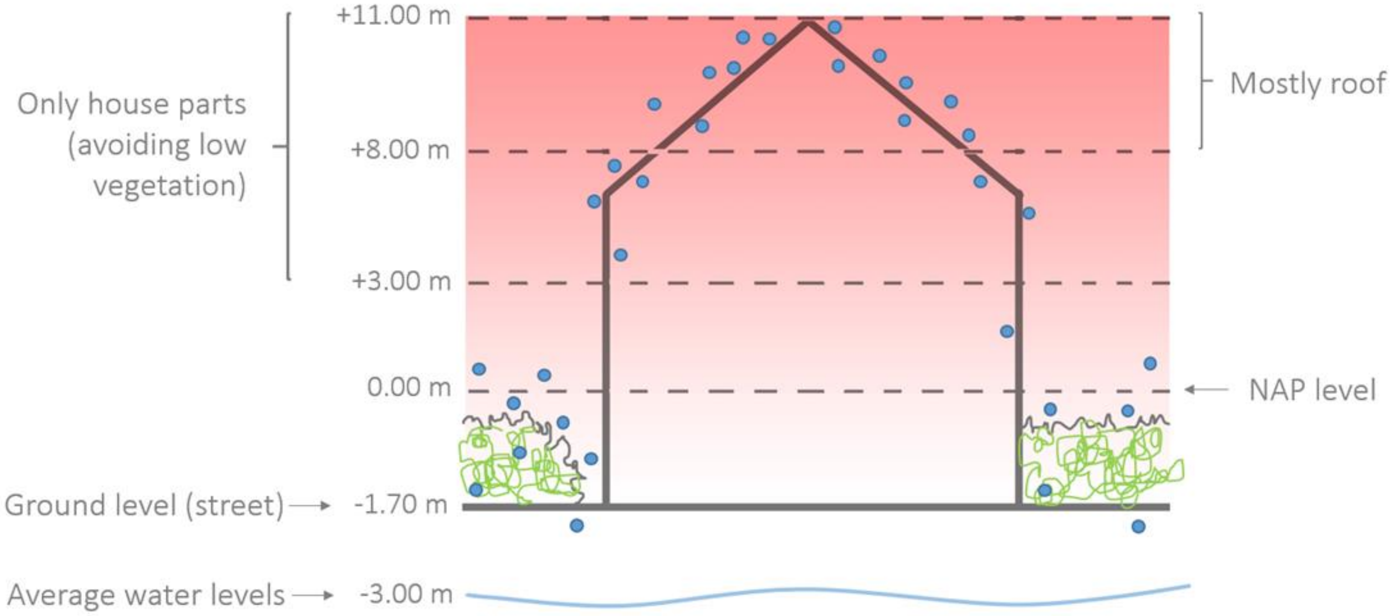


Figure 4.2 Interval heights used to filter InSAR data

4.2 “Linear” comparison between sensors and InSAR

To understand the movement of the building, we have created a vector plot using the sensor measurements and connecting lines between highest values in the 7-month period of sensors data (Figures 4-3, 4-4).

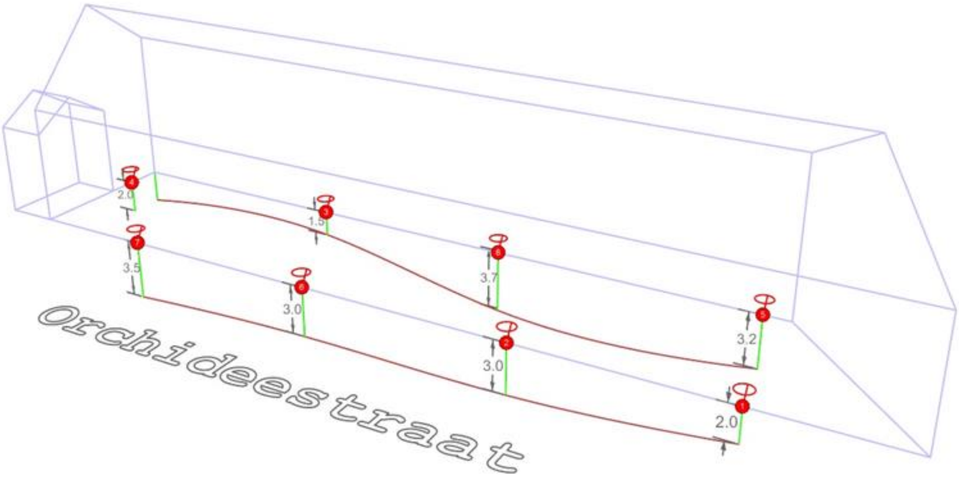


Figure 4.3 Perspective of the vector plot

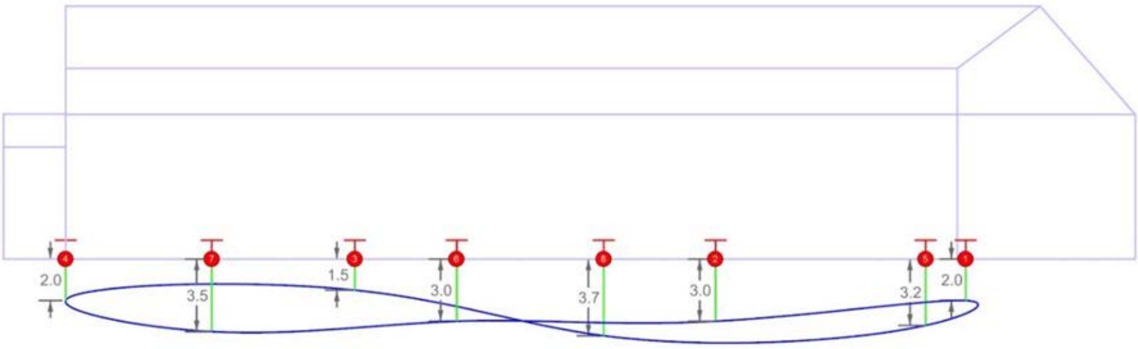


Figure 4.4 Front view. Sensors data

Once we know the different subsidence’s of the building according with sensor data, we compared the lines of the vector plot with a similar line created using with InSAR data. We picked 4 random points with a height between 10 and 11 meters from one InSAR dataset, assuming that the position of the points was on the roof of the building (Figure 4-5).

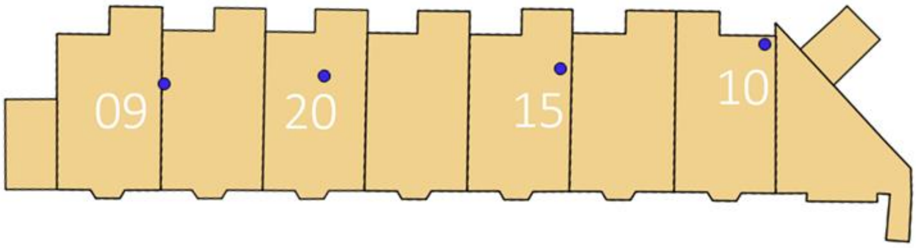


Figure 4.5 Position of the picked points. InSAR data.

Once we selected the points, we filter the data to get only the 5 months of overlapping data (Figure 4-6) and created linear graphics and fitted a straight line through the measurements to find the trend of the data over time (Figure 4-7). One of the main findings was the big fluctuation of the values.

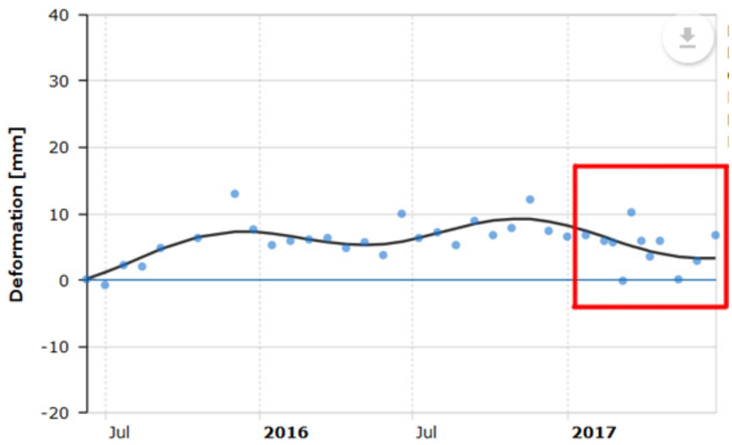


Figure 4.6 In red, 5 months of InSAR data (overlapping period)

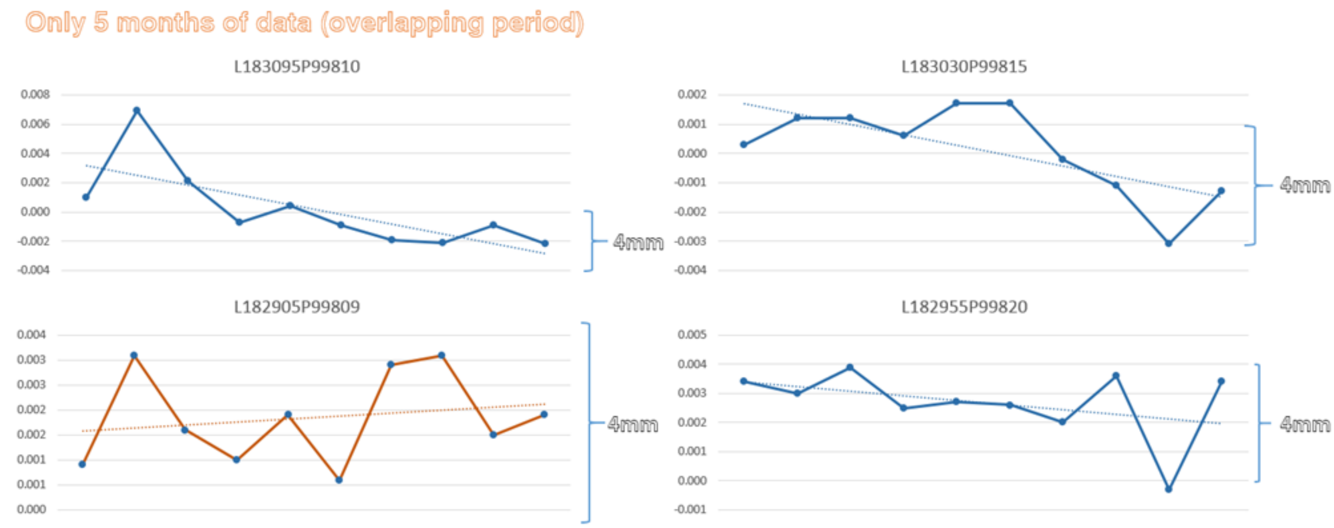


Figure 4.7 Graphics from the 4 points. X-axis, 5 months of measurements. Y-axis, deformation in meters.

The resulting graphics were unexpected. The peaks in the measurements influence the trend of the graph and one of the points detect elevation instead of subsidence. Using the initial and final value of the trend line, we obtained a deformation value to create a vector plot and compare with the sensors data (Figure 4-8, 4-9).

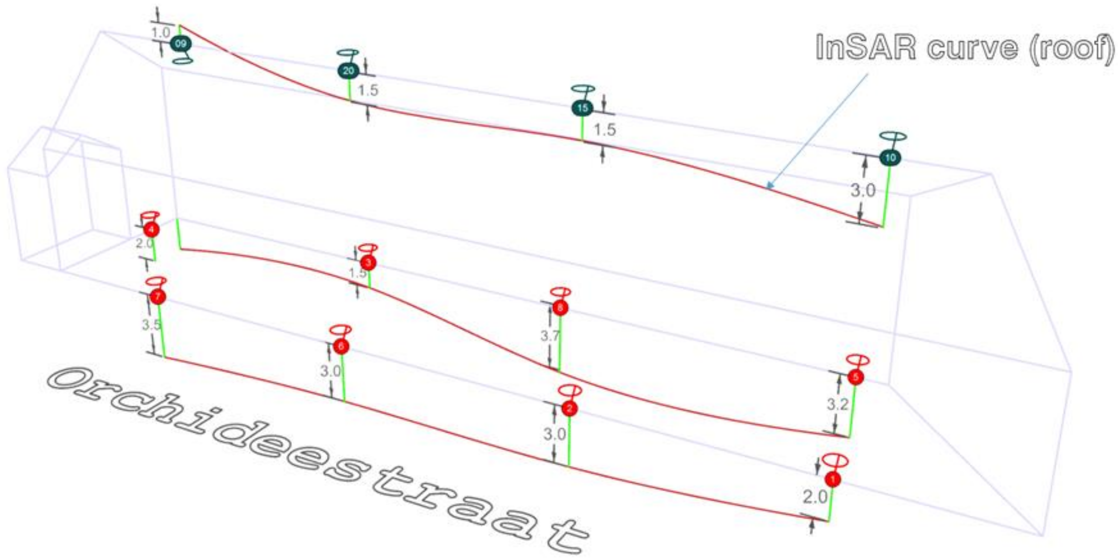


Figure 4.8 Perspective view of the vector plots

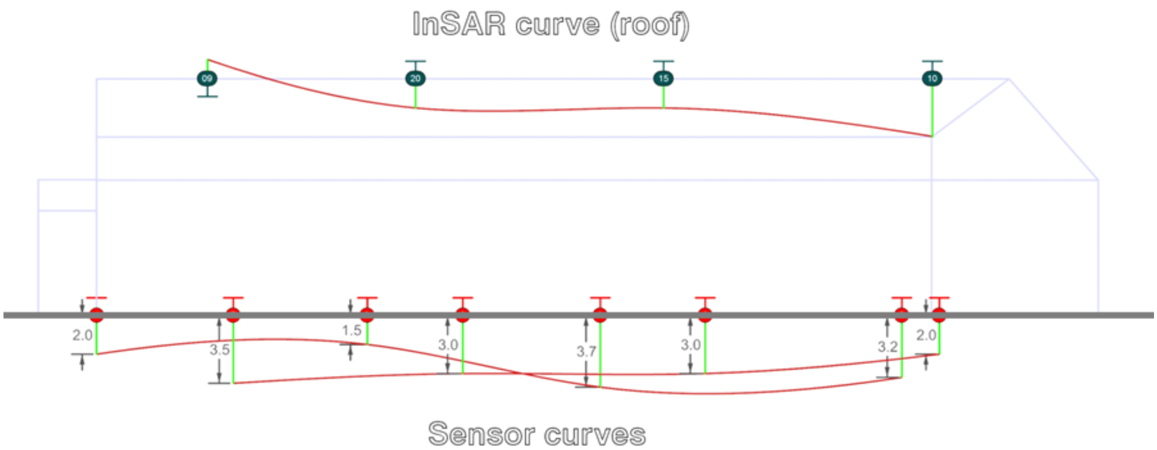


Figure 4.9 Front view. InSAR +sensors

By analyzing the results we realized that it is not possible to use and compare InSAR data using only single points and we introduce more data to the analysis.

4.3 Positive and negative values on InSAR points (5 months of data)

After analyzing 4 points of InSAR data and getting positive and negative values we decided to analyze more data and detect how many positive and negative values result from a bigger study.

For this research, we considered points between 8 and 11 meters of height within the 5-month period of overlapping data aimed to select only the points touching the roof of the houses (see Figure 4-10).

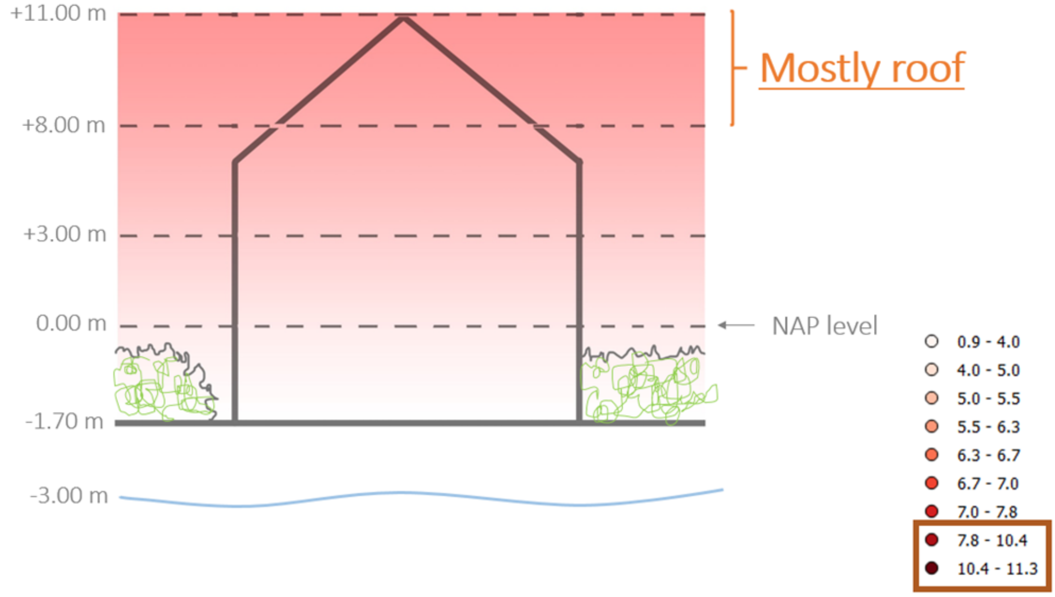


Figure 4.10 Height between 8 and 11 meters

For this method, two of the four InSAR data satellites with the maximum number of points were analyzed. The graphics were created in the same way as the previous analysis using trending lines. For the first satellite, 11 points were studied detecting elevation on 3 points and in the second one 2 points from 7 detect elevation (see the graphics in the figures 4-11 and 4-12).

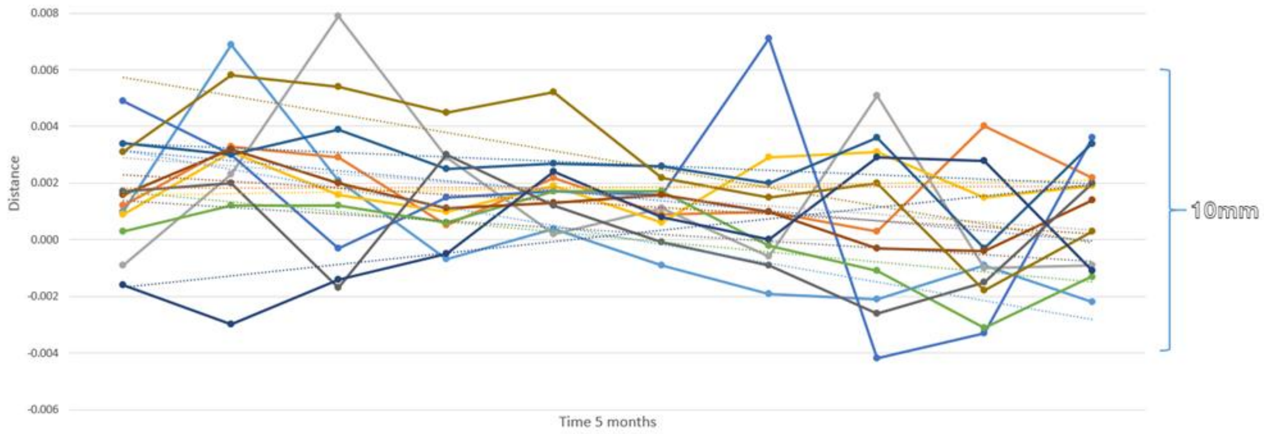


Figure 4.11 From the first satellite, 11 points

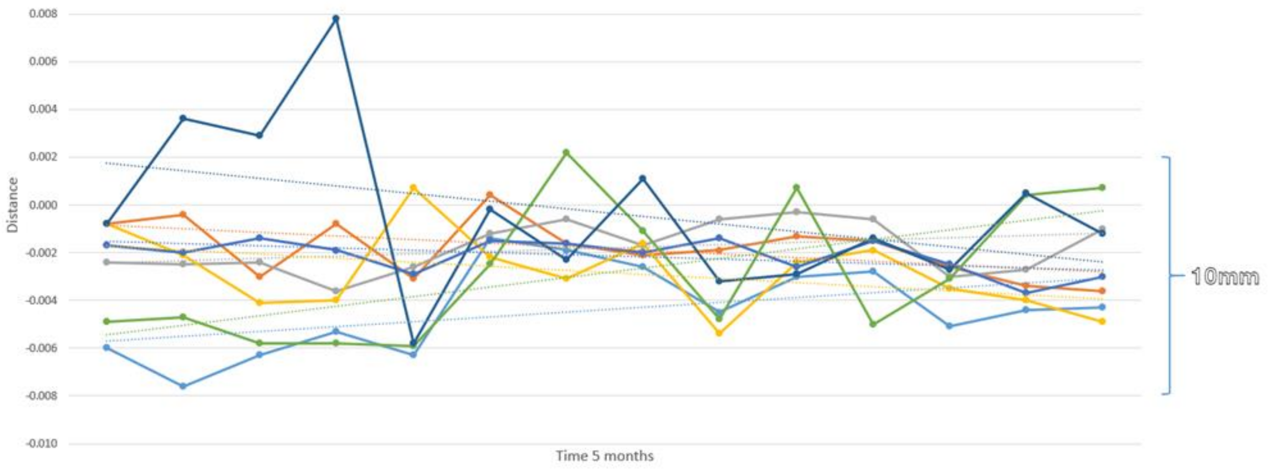


Figure 4.12 from the second satellite, 7 points

As we found again a high fluctuation in the measurements, we realized that is not possible to analyze InSAR data using only a 5 months of data.

4.4 Homogeneous subsidence InSAR and sensors

For this analysis, we introduced the whole period of InSAR data (2 years) and the points higher bigger than 3 meters were considered, using all the points theoretically touching the house structure. On this way, we will avoid vegetation close to the ground and possible outliers higher than 11 meters (see Figure 4-13).

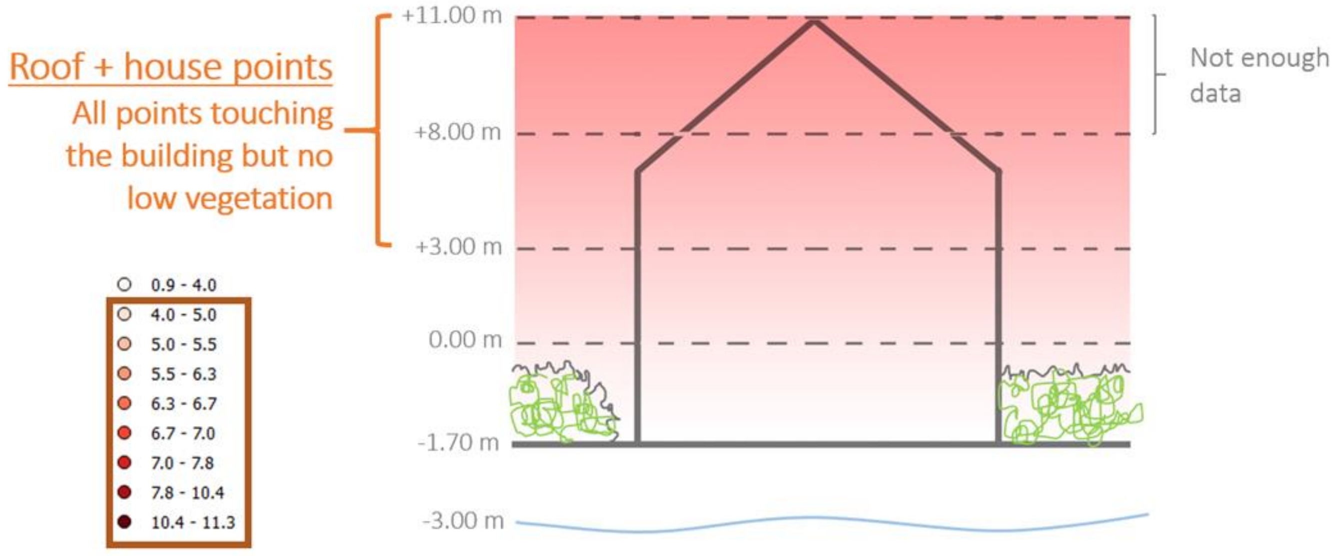


Figure 4.13 Threshold between 3 and 11 meters.

If we calculate the mean of the sensors subsidence we have an homogeneous subsidence of 2.7mm in 7 months. On this chapter, we will try to detect homogeneous subsidence from InSAR data by using the measurements of a group of points from one satellite at the time.

In our methodology, the first step to calculate homogeneous subsidence is to create a graph with all the available data (Figure 4-14), 2 years of measurements and all measurements in millimeters of the considered points.

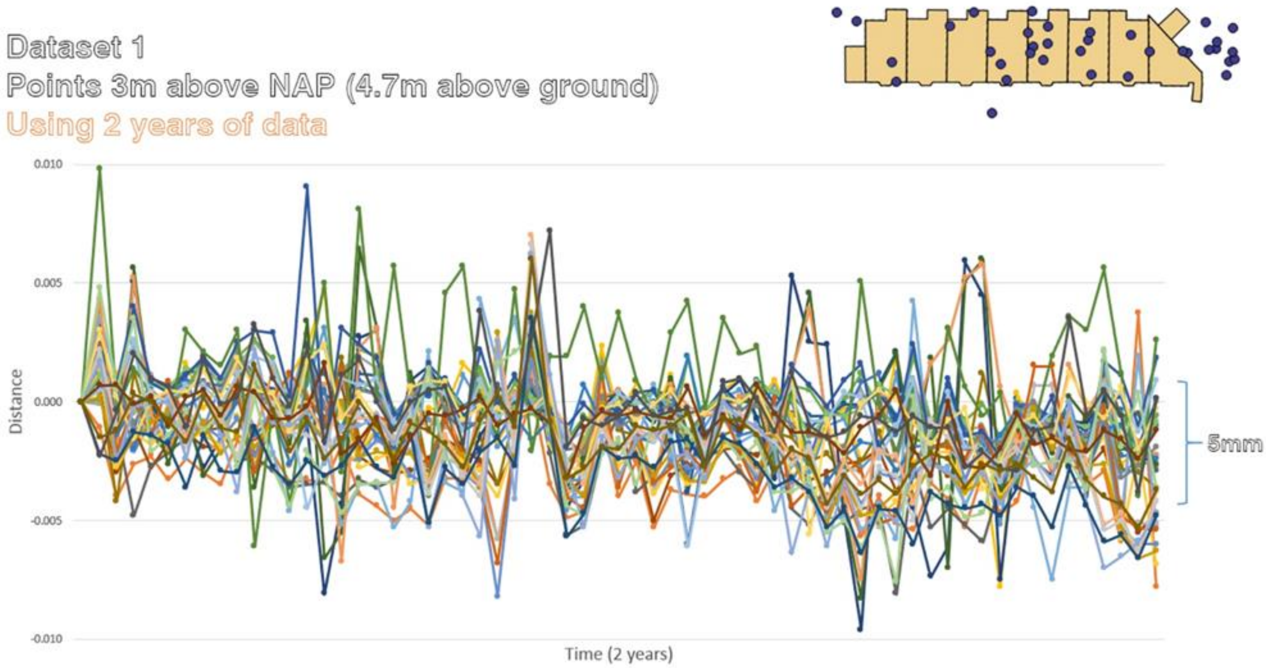


Figure 4.14 Graph with all the measurements of InSAR points in 2 years (Satellite1).

Depending of the satellite, it is possible to have from 36 to 42 measurements in 2 years. The next step in our methodology is to calculate the mean for each of these 36/42 measurements using all the considered points (Figure 4-15).

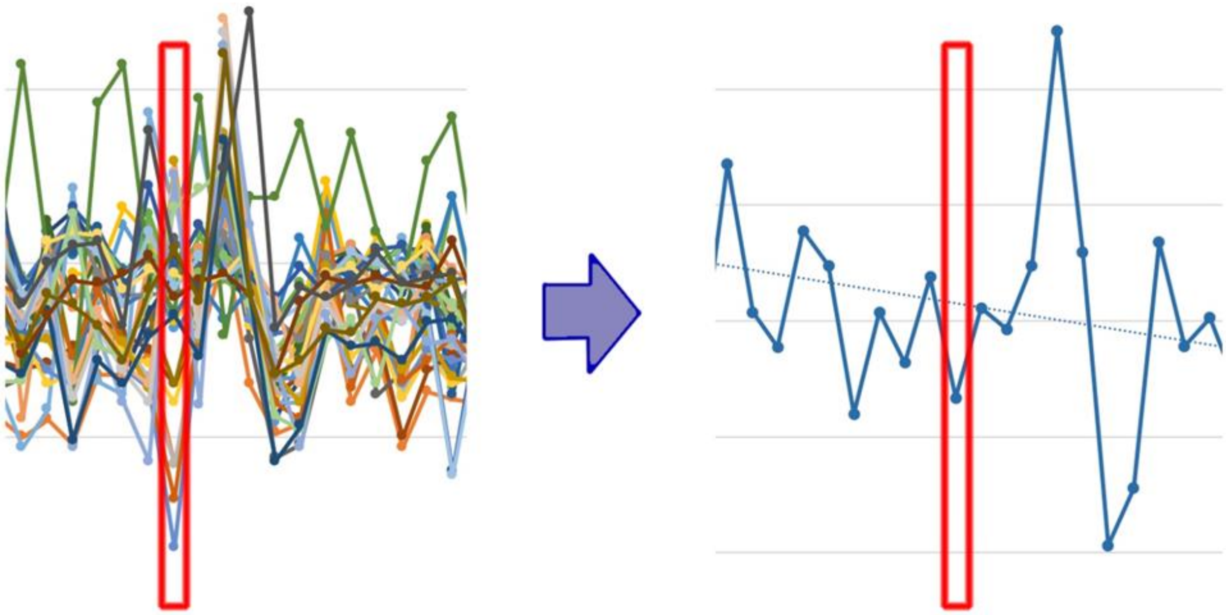


Figure 4.15 Mean of the values for every measurement in the whole dataset.

The resulting graph provides an overview of the vertical building movement according with the studied satellite. By using the mean on every step of the sampling interval for all the points it is possible to consider the result as homogeneous subsidence.

Finally, to give a numerical value to the results, again we fitted a straight line to the resulting graph and considered the interval between the start and the end of the line as the homogeneous subsidence see Figure 4-16.

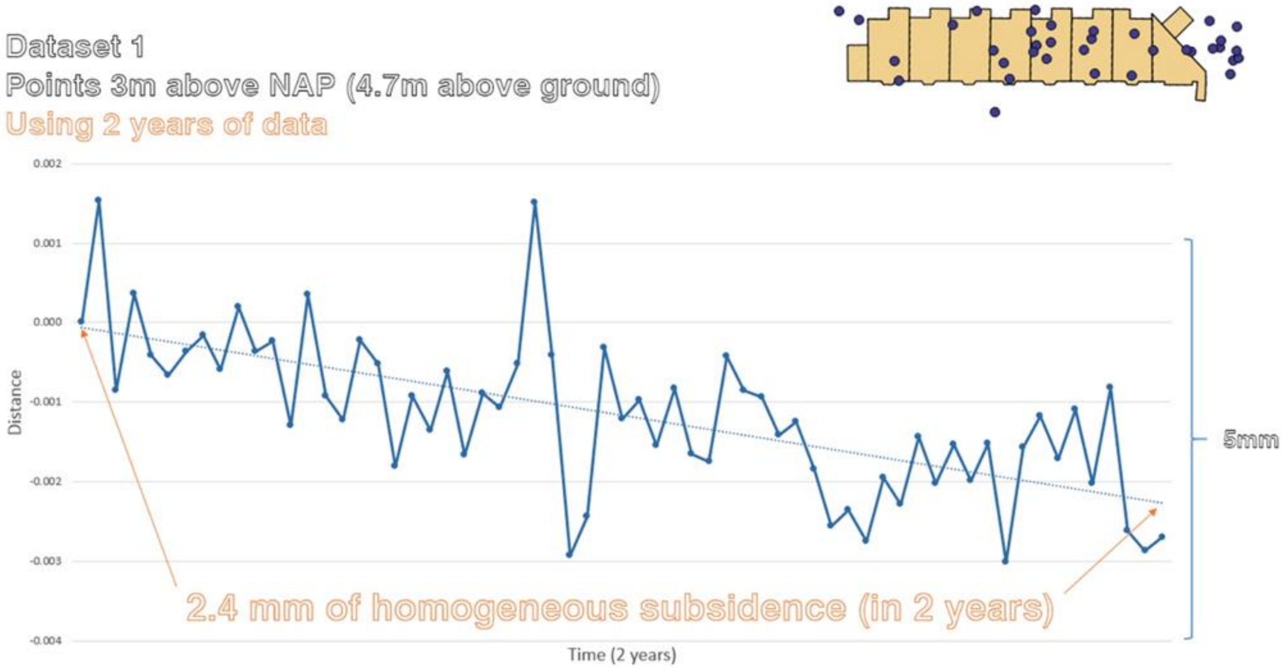


Figure 4.16 Resulting graph. Homogeneous subsidence according with satellite 1.

In order to analyze satellites separately we repeat the whole process for every dataset (4 times). The results of this analysis detect an homogeneous subsidence in three of the four satellites between 2.2mm and 3.4mm and the fourth satellite detected 1mm of elevation, see Figure 4-17.

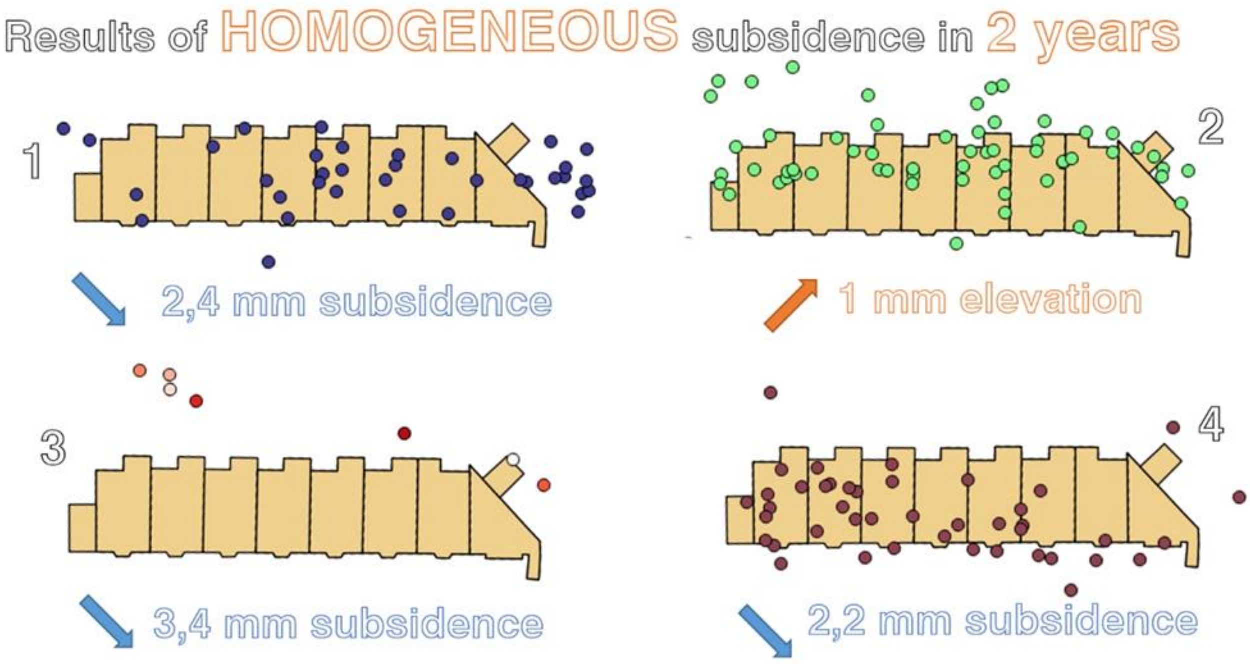


Figure 4.17 Results. Homogeneous subsidence according with satellites 1-4.

If we compare the mean of these results with the mean of sensors data, with the four InSAR satellites we have a homogeneous subsidence of 1.75mm in 2 years or 0.51mm in 7 months, definitely not comparable with the 2.7mm of sensors in 7 months.

4.5 Quality of InSAR data

One of the attributes of InSAR data is a quality value, a number between 0 and 1 assessing the quality of the measurements, when this value is bigger the measurement should be most accurate.

In the dataset number 4 we have 43 points of which 20 have a value higher than 0.8. If we compare the homogeneous subsidence of the 43-point dataset and the 20-point dataset, the results show a difference of 0.2mm. All quality values = 2.2mm of homogeneous subsidence, quality higher than 0.8 = 2.0mm.

Because of these results, we decided to not taking into consideration the quality attribute.

4.6 Local analysis of InSAR data according with sensors to detect non heterogeneous subsidence

As the results of homogeneous subsidence were not what we expected, we decided to use another approach to compare InSAR data with sensors data.

When the subsidence in buildings is not homogeneous, positive and negative values can neutralize the subsidence detecting no movement (Figure 4-18). If the subsidence is heterogeneous, InSAR data should be analyzed punctually based on the position of the sensors.

Figure 4.18 Positive and negative values affect the homogeneous subsidence results.

For the punctual analysis of InSAR data, we took the positions of the sensors and created buffer areas of 6 meter radius to overlap the biggest amount of points on every satellite (Figure 4-19).

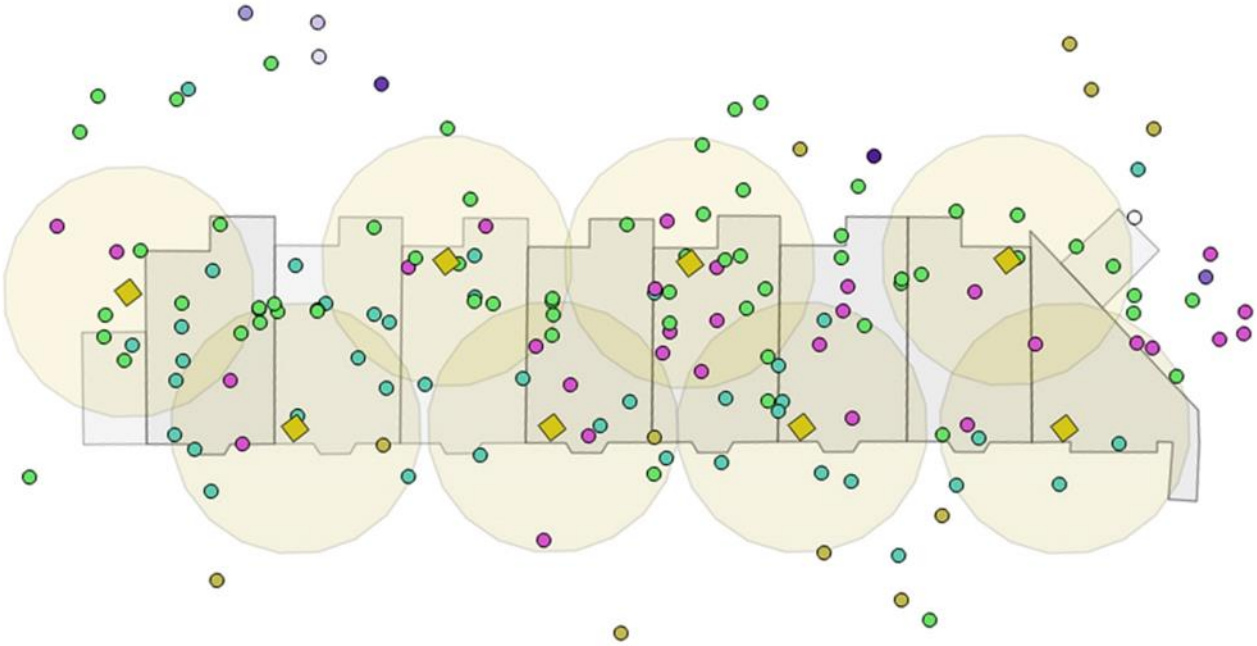


Figure 4.19 Buffer areas with InSAR points between 3 and 11 meters (4 satellites).

Every single buffer area was studied individually for every satellite repeating the whole methodology as the previous analysis 20 times (satellite number 3 and in some cases satellite number 2 and 4 had no points inside the buffers).

The results of the punctual analysis compared with sensors data are shown in the Figure 4-20. It is important to remark that the values in the results for sensors data are from 7 months and for InSAR data from 2 years. These results on every satellite are different; the satellite number 2 detected always elevation and in one case nothing, the 1 and 4 detected always subsidence with values between 1.5mm and 3.5mm of subsidence in 2 years.

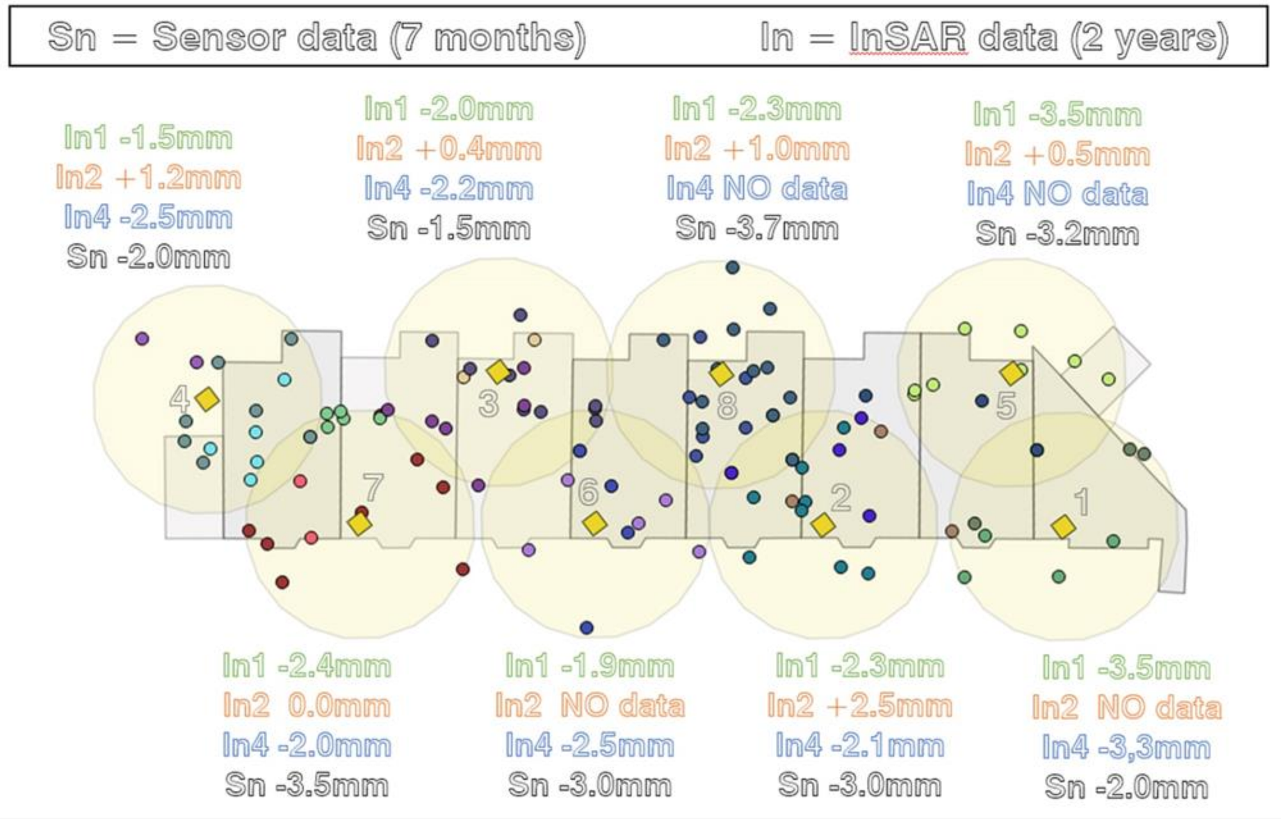


Figure 4.20 Results of punctual analysis.

4.7 Low points on InSAR data (street levels)

So far, we have not taken into consideration the subsidence of the ground or the streets. On InSAR data we had 4 datasets related with the points below the NAP level. On this chapter we will analyze the movement of the ground in two different ways: close to the building and the whole neighborhood.

As we had 4 satellites, two ascending and two descending, we mixed the procedures; one of the ascending satellites analyze the points close to the building and the other ascending one, the whole neighborhood. The same procedure for the descending satellite (Figure 4.21).

For this analysis the points were also filtered, using only the points higher than -3meter in relation with the NAP because the error in height for InSAR data is 1.5, so all the points considered could be at the ground level (-1.7meter below NAP).

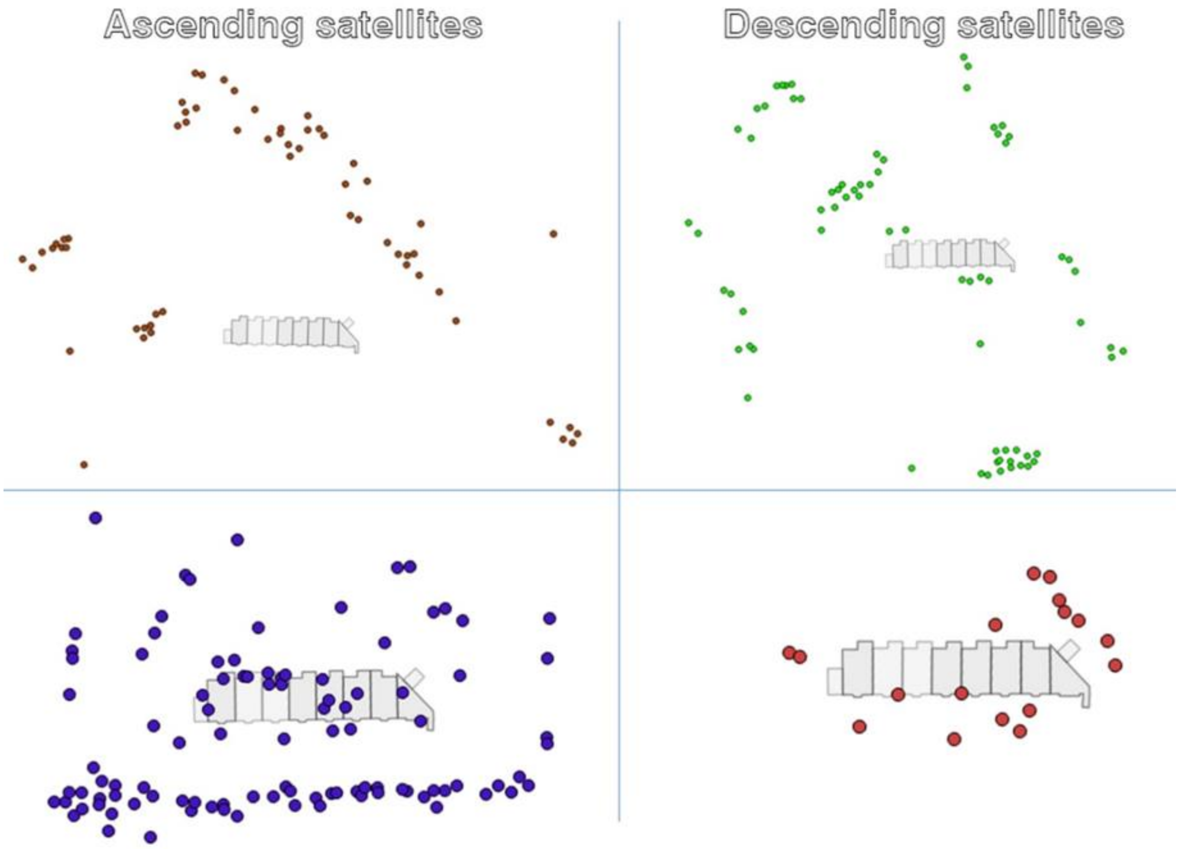


Figure 4.21 Distribution of the points in the ground according with the different satellites.

The methodology to analyze this data was the same as in the previous analysis and the results detect a homogeneous subsidence in all the cases between 8.5mm and 11mm in 2 years. The table 4-1, show the results for every satellite. These results demonstrate that the ground is subsiding faster than the buildings according with InSAR data.

Table 4-1 Results of homogeneous subsidence in ground point analysis

	Ascending Satellite	**Descending satellite**
Neighborhood area	11mm	8.5mm
Local area	10mm	11mm

4.8 Improving InSAR data accuracy with Lidar data (AHN3)

When measurements are done with radar, it is hard to find what is being measured, because a radar observes entities so different from us that we cannot easily use our imagination to track down the point. To be able to find the real location of an observed Persistent Scatterer (PS), we must first understand what a persistent scatterer is, and how its location is defined.

A persistent scatterer is an object that is much larger than the radar wavelength, in order to reflect the electromagnetic waves, but small enough to not be influenced by geometric decorrelation. The geometric decorrelation is related with change in look angle and to non-parallel satellite orbits (Piyush Agram, 2015). In practice, the size of a persistent scatterer can vary from a few decimeters up to a few meters. In some cases the scatterers are big enough that can be seen in aerial images or in maps and these objects can be straight corners , like corners of walls and ground, and surfaces that are pointed towards the radar, for example rooftops.

The location of these scatterers has three coordinates the azimuth, range and a perpendicular offset, also referred to as height. The ratio between the errors of the above mentioned coordinates is 1/3/213 according to the paper "high-precision positioning or radar scatterers" by P. Dheenathayalan et al. This approximate location is then converted to a reference system for the Netherlands this reference system can be the global WGS84 or the local RD. The coordinates in azimuth and range direction are estimated from the known orbit and timing information, whose perpendicular offset is estimated during the InSAR process.

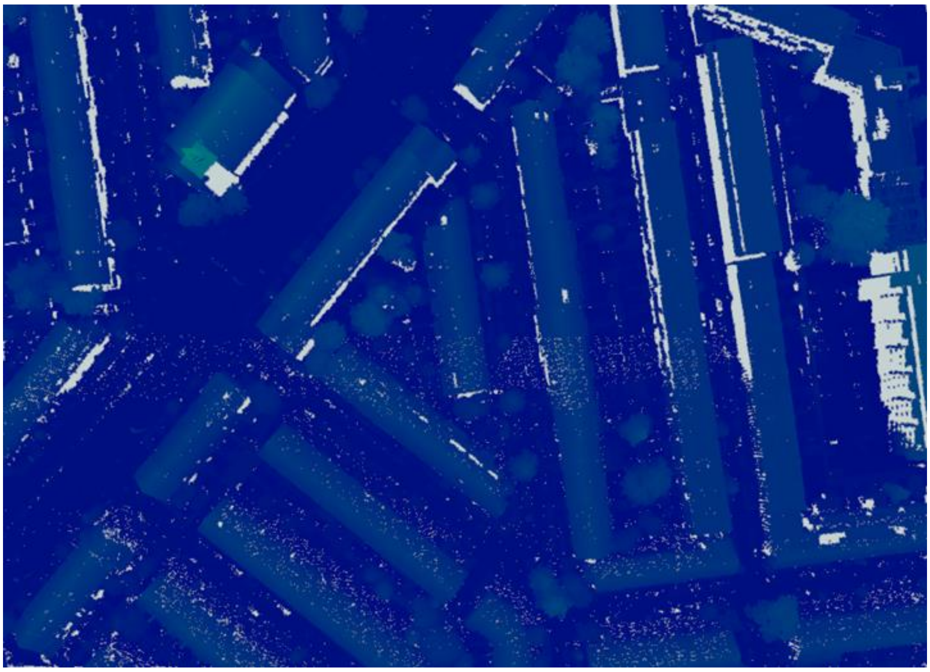


Figure 4.22 AHN3 of the research area

To relate the PS points to real objects, the points are loaded in a 3D visualization system (Rhinoceros) and compared to reference data. For this we will use the AHN3, an accurate height model of the Netherlands, and BGT, the Dutch big scale base map. The AHN3 is a Lidar point cloud created for our area in 2017 and has accuracy of 5cm and a density of approximately 20 points per m2.

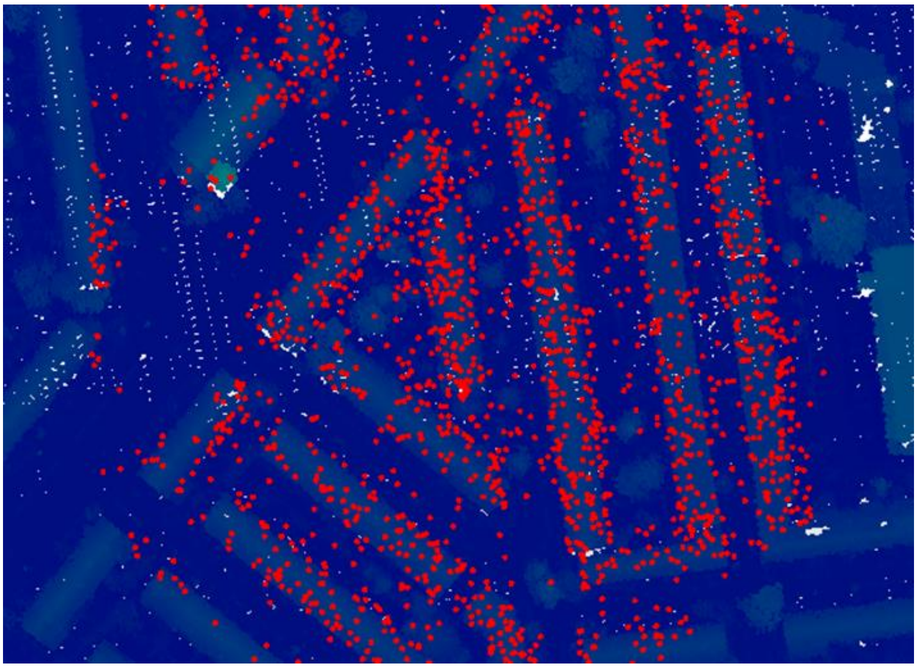


Figure 4.23 AHN3 with the InSAR point cloud overlaid

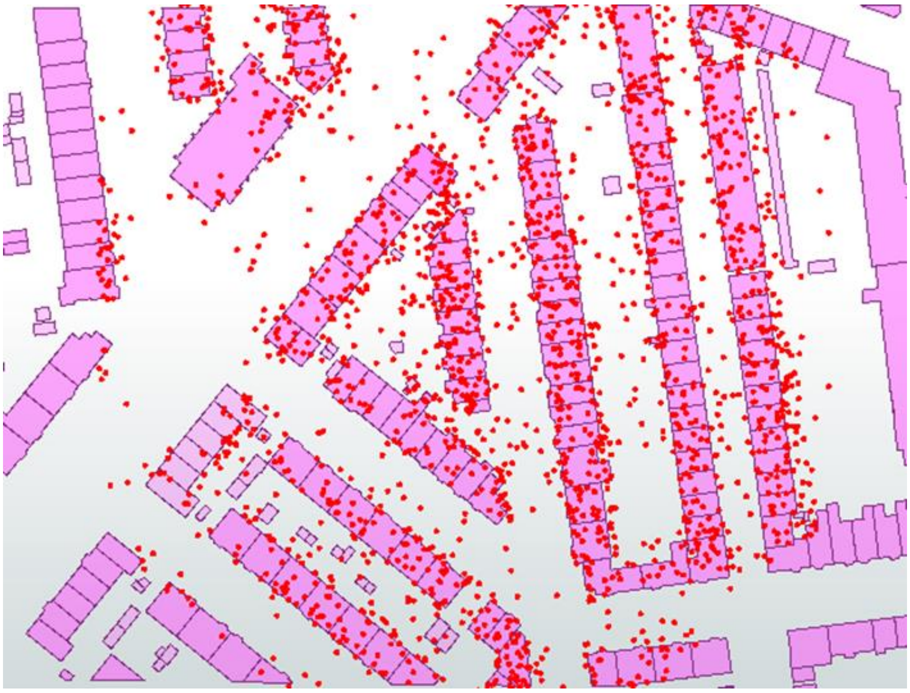


Figure 4.24 BGT with the InSAR point cloud overlayed

4.8.1 Creating the datasets

This project is referring to only one block of buildings so the first step that we had to make was to keep for both dataset (InSAR, Lidar) only the area in question. Then, we had to transform the shapefiles (InSAR) into a point cloud. The two most common formats are the LAS (Lidar) and .XYZ. Since we needed all the attributes of the shapefile for our further analysis the LAS format was the first choice, but since the Rhinoceros does not read this kind of format the only solution we had was the .XYZ. Also, it was important to keep only the buildings from the whole area since the trees that are present around our block can give as wrong results for our analysis. All the above analysis occurred in FME software. The point clouds that we are going to use for this analysis will be the ones that can be seen in the Figure 4-25. For InSAR we used only one point cloud that is the one with code "asc025ps".

Figure 4.25 Lidar point cloud (Black) with InSAR pointcloud overlaid (Red)

4.8.2 General approach

In order to try to improve the position of the persistent scatterer we had to find some patterns that may help us to improve the accuracy. These patterns should have been detected in X,Y and Z coordinates but since our area of analysis is really small unfortunately this kind patterns is really hard to be observed. Nevertheless, we divided the analysis into two parts:

- X, Y comparison for similar height
- Height comparison for similar X, Y

4.8.3 X, Y Comparison

The first part of this analysis is related with the X,Y comparison. In order to achieve this kind of comparison we created a python code in Grasshopper (Rhinoceros). In this code we were reading the InSAR points and we filtered out all the points with height bigger than 14m since the highest point of the buildings is around 11.5m and the maximum given height error (SkyGeos documentation) is 2.5m. After the filtering we read the Lidar points and we tried to find all the points that belongs in an area of 3m × 3m × 2.5m (Case 1). These thresholds are related with the maximum given errors (SkyGeos documentation) for our InSAR dataset. A second analysis were made using the estimated errors for the InSAR data in which the ratio between the errors, standard deviations, in range, cross-range and azimuth direction was taken from the paper "high-precision positioning or radar scatterers" by P. Dheenathayalan et al. and was estimated to be 1/3/213 in range/azimuth/cross-range. So since our block of buildings and as a result the point cloud is directed from North to South we can assume that the azimuth is parallel with the Y axes and the thresholds that they were used were 3m × 0.05m × 2.5m (Case 2) in order to match the above mentioned ratio.

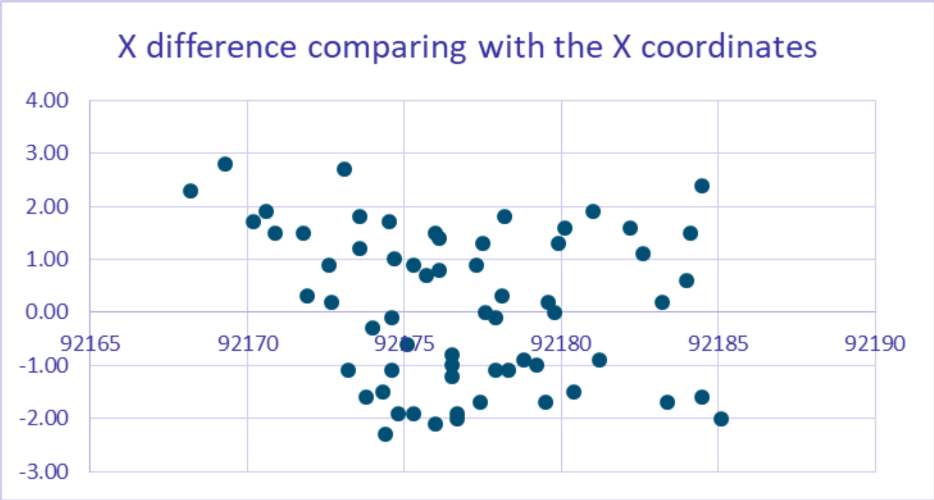


Figure 4.26 The X differences for the first case (of 3m × 3m × 2.5m)

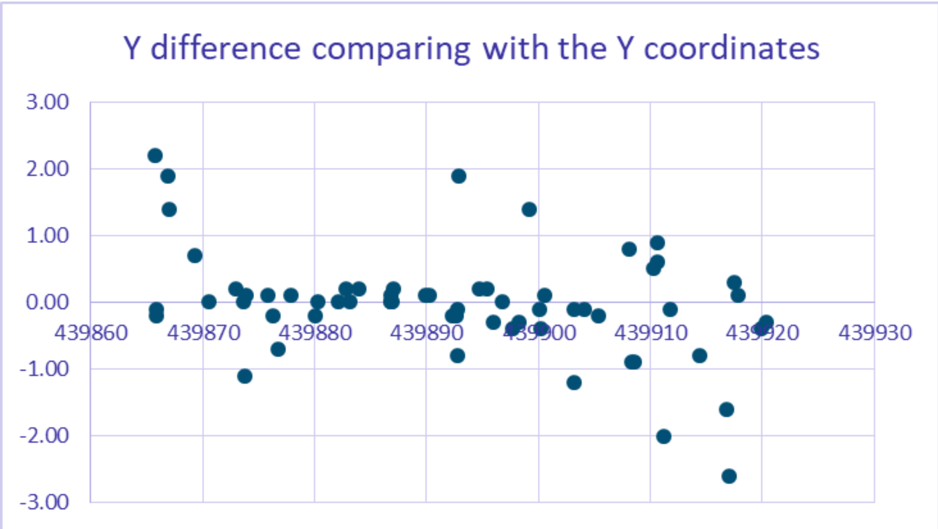


Figure 4.27 The Y differences for the first case (of 3m × 3m × 2.5m)

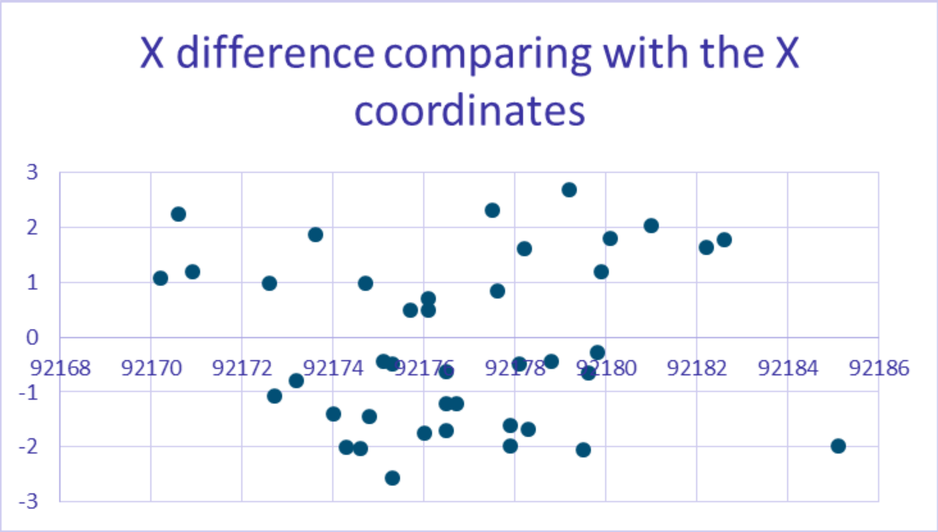


Figure 4.28 The X differences for the second case (of 3m × 0.05m × 2.5m)

For the Case 2 we visualized only the X difference since the Y coordinate is limited in such degree that the resulted scatter plot is of no significance.

What we can observe from the diagrams 4-26 to 4-28 is the fact that for the X coordinate there are no trend that can be considered as significant as well as the fact that even though we minimized the Y coordinate the scatter plot in both cases are similar. For the Y coordinate as we expected the accuracy is higher and most of the points are gathered around 0.

It is important to be mentioned the fact that from the total 78 points in the InSAR point cloud in the Case 1 we had 15 points considered as outliers and at the second case this number was 27. Overall, even though the number of outliers in the second case is almost double than that of the first case we need to consider the fact that the Y threshold is reduce by 70 times indicating the higher precision of the Y coordinate.

4.8.4 H comparison

In this second part we used threshold only for the X and Y coordinate and our aim was to identify the average height difference for all the points with similar position. The thresholds that were used was the 3m × 3m.The results of this analysis is demonstrated in the diagrams 4-29 and 4-30.

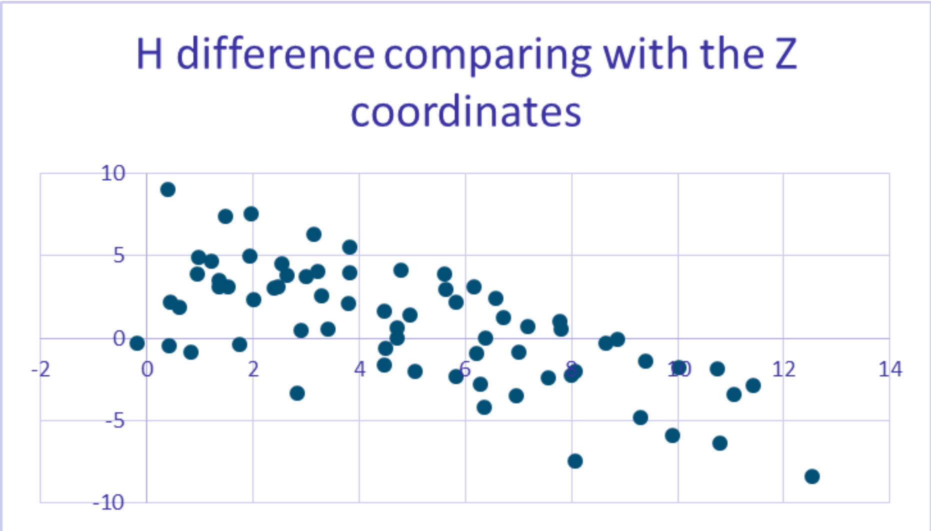


Figure 4.29 The H difference (3m × 3m).

In diagram 4-29 a pattern is visible in which the lowest points have the biggest positive difference and the high points have the biggest negative difference. Either way the most important finding is the fact that the H differences are between -8m to +9m more than three times bigger error than the error given from SkyGeos.

In this part, two more analysis were made. In the first one we used smaller thresholds for the X and Y coordinates (as small as 1m) and the results were similar with the only difference is having more outliers.

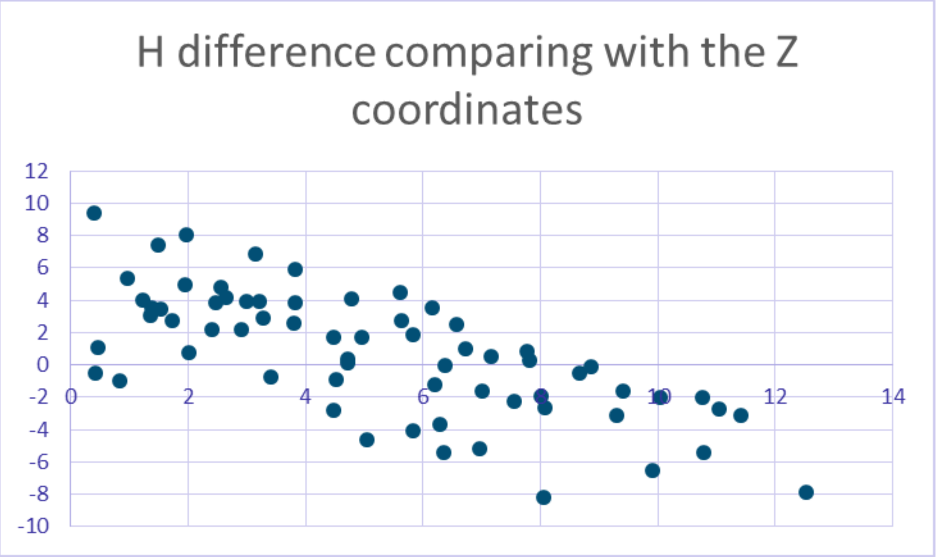


Figure 4.30 The H difference (1m × 1m).

The last analysis was made using new coordinates that were an output of the X, Y analysis. The new coordinates were the old ones with the difference of the X and Y coordinate added to them. The same calculations were made and the results were still similar(Figure 4-31).

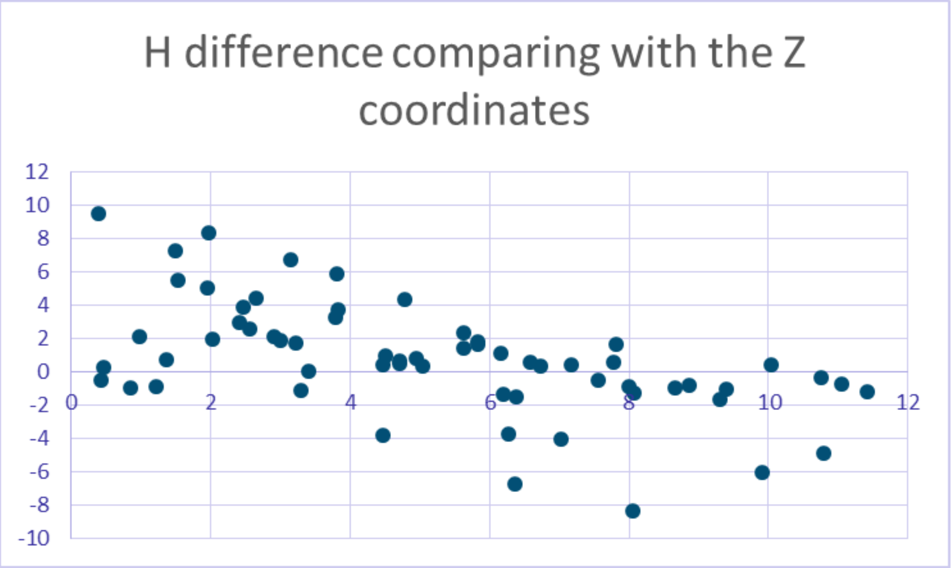


Figure 4.31 The H difference (1m × 1m) computed with the new coordinates

4.8.5 Comparing The Subsidence Using The New Coordinates.

In this part of the analysis we used the newly computed coordinates (X + DX, Y + DY) in order to repeat the subsidence calculations that were published in the previous paragraphs. For the purpose of this analysis we had to transform back the .XYZ into a shapefile and to add to the coordinates the attributes that had been removed during the first transformation (from shapefile to .XYZ).

Since we had the shapefile we imported it in the QGIS and we used the buffer operation (6m) in order to keep only the points related with a certain ground sensor. After that, the process was similar with what have already been described. For our tests we used only one sensor (Zakking 8) and two different set of coordinates that were products of the Case 1 and Case 2 analysis from the "X, Y Comparison" paragraph. The results of the spatial analysis are demonstrated in the Figure 4-32.

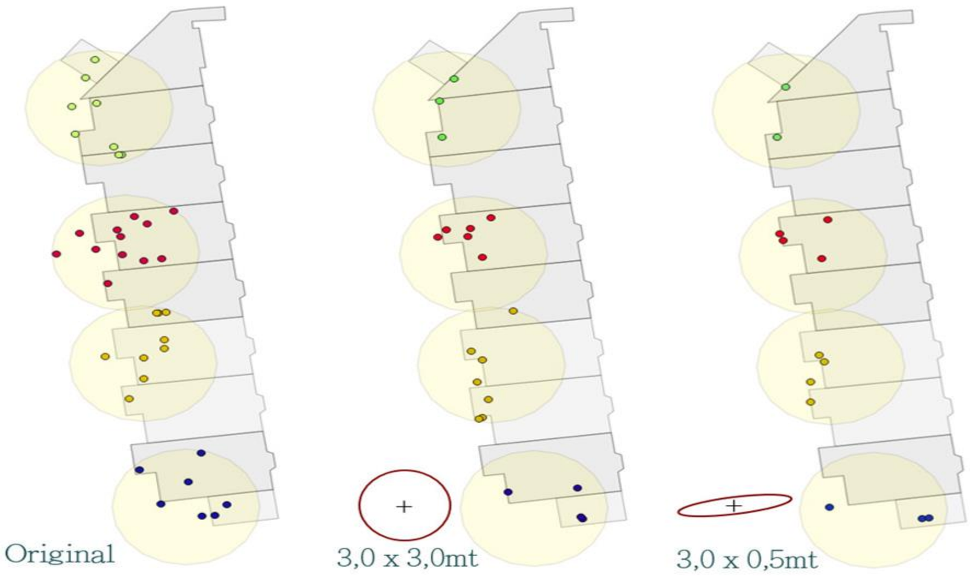


Figure 4.32 The spatial comparison between the original and the two new point clouds.

The position of the points in the new datasets can be described as improved since almost all the points belongs on the buildings which is the most probable location of the persistent scaterrers. Also the points are fewer because the algorithm excluded all he points that could not find Lidar points in the area defined by the thresholds.

For the average total deformation, in this case elevation, the results were, in all three cases, between **0.9mm** and **1.2mm** something that indicates that the improved location of the scatters does not affect the final results.

4.8.6 Conclusions

The aim of this analysis were to improve the position of the persistent scaterrers. We can conclude that this attempt was quite successful since, as we can see from the Figure 4-32, we were able to keep only the points related with the buildings (mainly with the roof) removing all the ambiguous points as outliers.

Even though the improving of the location can be considered as a success the deformation results were not improved. This is mainly because the threshold that were used were at maximum 3m and the buffer zones around the ground sensors were 6m so most of the points were referring to the same sensor in all three different cases and subsequently the results could not change drastically.

5

Water level analysis

5.1 Methodology

The second branch of this project is referring to the comparison of the three ground water level datasets. The three datasets are the KCAF sensor data, municipality sensor data and citizen data while a rainfall dataset was used only for reference. All the groundwater data is measured base on NAP (Normaal Amsterdams Peil). The aim of this analysis is to check the comparability of the three groundwater datasets and we are only interested in groundwater level in the KCAF sensors position. Due to fact that the three datasets have different sampling locations, an interpolation method should be used in order to find the the values in the KCAF sensors locations. Since we don’t know the technical specifications or accuracy of each dataset, in the beginning we couldn’t assume that one of groundwater dataset is more accurate than the others. Therefore, instead of setting one as a reference among groundwater datasets, each two of datasets were compared.

In order to check the comparability of datasets, we calculated the correlations for every pair of the three datasets and also computed the best fitting equations for each scatter plot. Even though the correlation can describe a broad class of statistical relationships involving dependence, the most common usage is referred to how close two variables are to having a linear relationship with each other. Correlations are useful because they can indicate a predictive relationship that can be exploited in practice.

Among the best fitting equations, R2 represents the coefficient of determination, which is the proportion of the variance in the dependent variable that is predictable from the independent variables, the value of R2 varies from 0(independent) to 1(dependent). R2 provides a measure of how well observed outcomes are replicated by the model, which is based on the proportion of total variation of outcomes explained by the model.

Below is the detailed implementation of data preprocess and the interpolation concept.

5.1.1 Data preprocess

KCAF sensors raw data is recorded every hour while others are not, so the pre-process of sensor data is calculating a daily average value (Figure 5-1, 5-2) and this is also helpful to reduce the impact of potential outliers. This step is achieved by a Python code that can be seen in the appendix.

at	dvcBE001G	dvcBE001G	dvcBE001Gw3Disp4Tilt4.gw
3/21/2017 14:42	1.14		
3/21/2017 15:42	1.138		
3/21/2017 16:42	1.137		
3/21/2017 17:42	1.137		
3/21/2017 18:43	1.137		
3/21/2017 19:43	1.136		
3/21/2017 20:43	1.137		
3/21/2017 21:43	1.137		
3/21/2017 22:43	1.137		
3/21/2017 23:44	1.138		
3/22/2017 0:44	1.138		
3/22/2017 1:44	1.139		
3/22/2017 2:44	1.14		
3/22/2017 3:44	1.14		
3/22/2017 4:44	1.142		
3/22/2017 5:45	1.143		
3/22/2017 6:45	1.143		
3/22/2017 7:45	1.143		
3/22/2017 8:45	1.144		
3/22/2017 9:40		-3.099	
3/22/2017 9:45	1.144		
3/22/2017 10:40		-3.097	
3/22/2017 10:45	1.145		
3/22/2017 11:40		-3.096	
3/22/2017 11:46	1.145		
3/22/2017 11:59			-3.054
3/22/2017 12:40		-3.095	
3/22/2017 12:46	1.147		

Figure 5.1 Sensor raw data

	dvcBE001Gw1Disp5.gw	dvcBE001Gw2Disp3Tilt3.	dvcBE001Gw3Disp4Tilt4.gw
3/21/2017	1.1374		
3/22/2017	1.145583333	-3.094066667	-3.053333333
3/23/2017	1.149047619	-3.0938	-3.0563
3/24/2017	1.138	-3.103130435	-3.065
3/25/2017	1.142826087	-3.095869565	-3.05875
3/26/2017	1.150954545	-3.087333333	-3.050565217
3/27/2017	1.151782609	-3.085952381	-3.050681818
3/28/2017	1.152869565	-3.091652174	-3.060375
3/29/2017	1.145708333	-3.104625	-3.07073913
3/30/2017	1.147391304	-3.105565217	-3.078782609
3/31/2017	1.163583333	-3.090791667	-3.067041667
4/1/2017	1.166304348	-3.089304348	-3.069
4/2/2017	1.1535	-3.102391304	-3.082458333
4/3/2017	1.144826087	-3.111875	-3.09575
4/4/2017	1.152130435	-3.105333333	-3.09025
4/5/2017	1.150208333	-3.108	-3.093916667
4/6/2017	1.1495	-3.10825	-3.094791667
4/7/2017	1.15615	-3.101619048	-3.0879
4/8/2017	1.158565217	-3.098782609	-3.084782609
4/9/2017	1.164458333	-3.092666667	-3.078916667
4/10/2017	1.165208333	-3.093625	-3.07925
4/11/2017	1.16025	-3.098909091	-3.084916667
4/12/2017	1.174869565	-3.08273913	-3.068125
4/13/2017	1.1775625	-3.080647059	-3.066625
4/16/2017	1.173764706	-3.0855625	-3.0731875
4/17/2017	1.185458333	-3.07375	-3.061208333
4/18/2017	1.176090909	-3.0808	-3.067833333
4/19/2017	1.166347826	-3.092380952	-3.079695652
4/20/2017	1.166	-3.092714286	-3.08
4/22/2017	1.185	-3.074	-3.061333333
4/23/2017	1.186681818	-3.075181818	-3.059636364
4/28/2017	1.219863636	-3.0473	-3.027736842
4/29/2017	1.215173913	-3.045125	-3.032875

Figure 5.2 daily average data

5.1.2 Interpolation concept

For the purpose of this synthesis project we had to interpolate the water values, in order to extract information. We investigate two interpolation methods the IDW (inverse distance weighted and Kriging interpolation method.

The Inverse distance weighted (IDW) interpolation is referred to as deterministic interpolation method since it is directly based on the surrounding measured values or on specified mathematical formulas that determine the smoothness of the resulting surface. More specifically the IDW explicitly makes the assumption that things that are close to one another are more alike than those that are farther apart. To predict a value for any unmeasured location, IDW uses the measured values surrounding the prediction location. The measured values closest to the prediction location have more influence on the predicted value than those farther away.

The kriging method belongs to a second family of interpolation methods which are based on statistical models that include autocorrelation—that is, the statistical relationships among the measured points. Because of this, geostatistical techniques not only have the capability of producing a prediction surface but also provide some measure of the certainty or accuracy of the predictions.

<u>The Kriging and IDW formula</u>

The kriging method is similar to IDW in that it weights the surrounding measured values to derive a prediction for an unmeasured location. The general formula for both interpolations is formed as a weighted sum of the data:

$$Z(S_0) = \sum_{i=1}^{N} \lambda_i Z(s_i)$$

Where:

Z(si) = the measured value at the ith location

λi = an unknown weight for the measured value at the ith location

s0 = the prediction location

N = the number of measured values

In IDW, the weight, λi, depends solely on the distance to the prediction location. However, with the kriging method, the weights are based not only on the distance between the measured points and the prediction location but also on the overall spatial arrangement of the measured points. To use the spatial arrangement in the weights, the spatial autocorrelation must be quantified. Thus, in ordinary kriging, the weight, λi, depends on a fitted model to the measured points, the distance to the prediction location, and the spatial relationships among the measured values around the prediction location.

To make a prediction with the kriging interpolation method, two tasks are necessary:

a. Uncover the dependency rules.

b. Make the predictions.

Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface. The Kriging tool fits a mathematical function to a specified number of points, or all points within a specified radius, to determine the output value for each location. Kriging is a multistep process; it includes exploratory statistical analysis of the data, variogram modeling, creating the surface, and (optionally) exploring a variance surface. Kriging is most appropriate when you know there is a spatially correlated distance or directional bias in the data. It is often used in soil science, geology and hydrology.

Kriging in our synthesis project

The best interpolation for the water level analysis is the kriging method. However, in order to conduct the geostatistical analysis the minimum number of samples measurements is 50 or more. In our case we have only three sample points and the calculation of the variograms is not feasible.

For this reason we selected the IDW interpolation method, which is based only on the distance for the prediction of the water level values.

5.2 Interpolation results

As discussed above, IDW interpolation is applied to simulate citizen and municipality data in the sensors location. Here two interpolation tools are used, and one is Qgis while the other is the Python programming language. Qgis is for creating the interpolation maps and for visualizing them. Because there are more than 60 interpolations that had to be computed and the target coordinates are known, developing a Python code for the calculations of the IDW formula is more efficient. In the Qgis part, the major parameters of IDW are set by default (inverse power = 2, search distance = 100). In order to output better raster maps, cell size is adjusted to 2. One example of interpolation map is created and presented in Figure 5-3 (darker blue means deeper ground water level). The created Python code can be found in appendix.

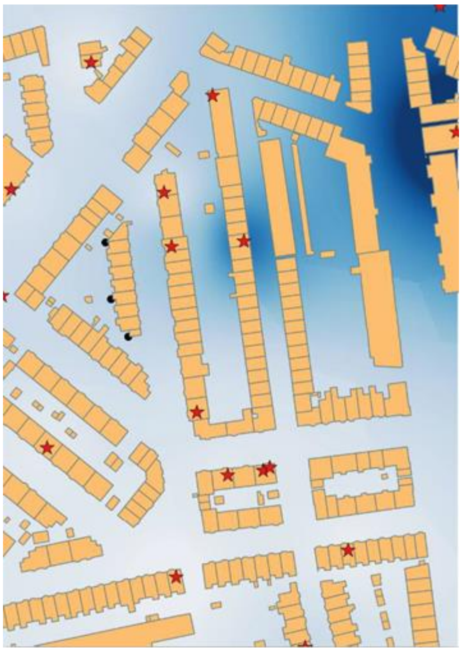


Figure 5.3 Interpolation layer of citizen data in September 13th

5.3 Comparison between municipality, citizens and sensors data

The three groundwater level datasets are compared in this sub-chapter. Due to the fact that municipality dataset has lower sampling frequency (once per month), we tried to find the corresponding sampling time on the other two datasets. So the data comparison for this analysis will be held only once per month during the seven research months. It is worth mentioning that not all corresponding time could be found in citizen data because its frequency is around 15-20 times per month. In this case, linear estimation is applied into find the citizen value. For example, if ground water in 9th September is -20cm while 12th September is -23cm and we want to know the value in 11th September. It should be estimated from the following formula:

$$Value_{11th} = Value_{12th} - (12-11) \times \frac{Value_{12th} - Value_{9th}}{12-9} = -22cm$$

The correlation result (Figure 5-4) shows that the data sources are highly dependent or associated in a statistical relationship. In the fitting function, y-axis is equal to the latter part of the picture title and x-axis is the front part, e.g. x = citizen1 and y = sensor 1 in the left-top picture. Among 9 comparisons, 6 correlations have values higher than 0.9 and the lowest correlation reaches as low as 0.78. Also, the fitting functions show that 6 of them have good linear relationships, which can be approved by R2 (all these values are higher than 0.8), and the remaining 3 comparisons also could be fitting precisely by a second order polynomial. Although three datasets value do not share completely same result in the 3 sensors location, they still show the similar trends and high correlations of them. Generally, the average correlation among nine comparison is 0.91.

More specifically, each row represents one pair of data comparison, e.g. in the first row is the result of citizen-sensor and sensor and each column is each sensor’s location. Citizen-sensor shows 0.91 average correlation and municipality-sensor shows 0.94 and citizen-municipality shows 0.88. All of three datasets have strong correlation so they are comparable according to monthly data. Regardless the sampling frequency, municipality data simulates the sensor’s observations the best.

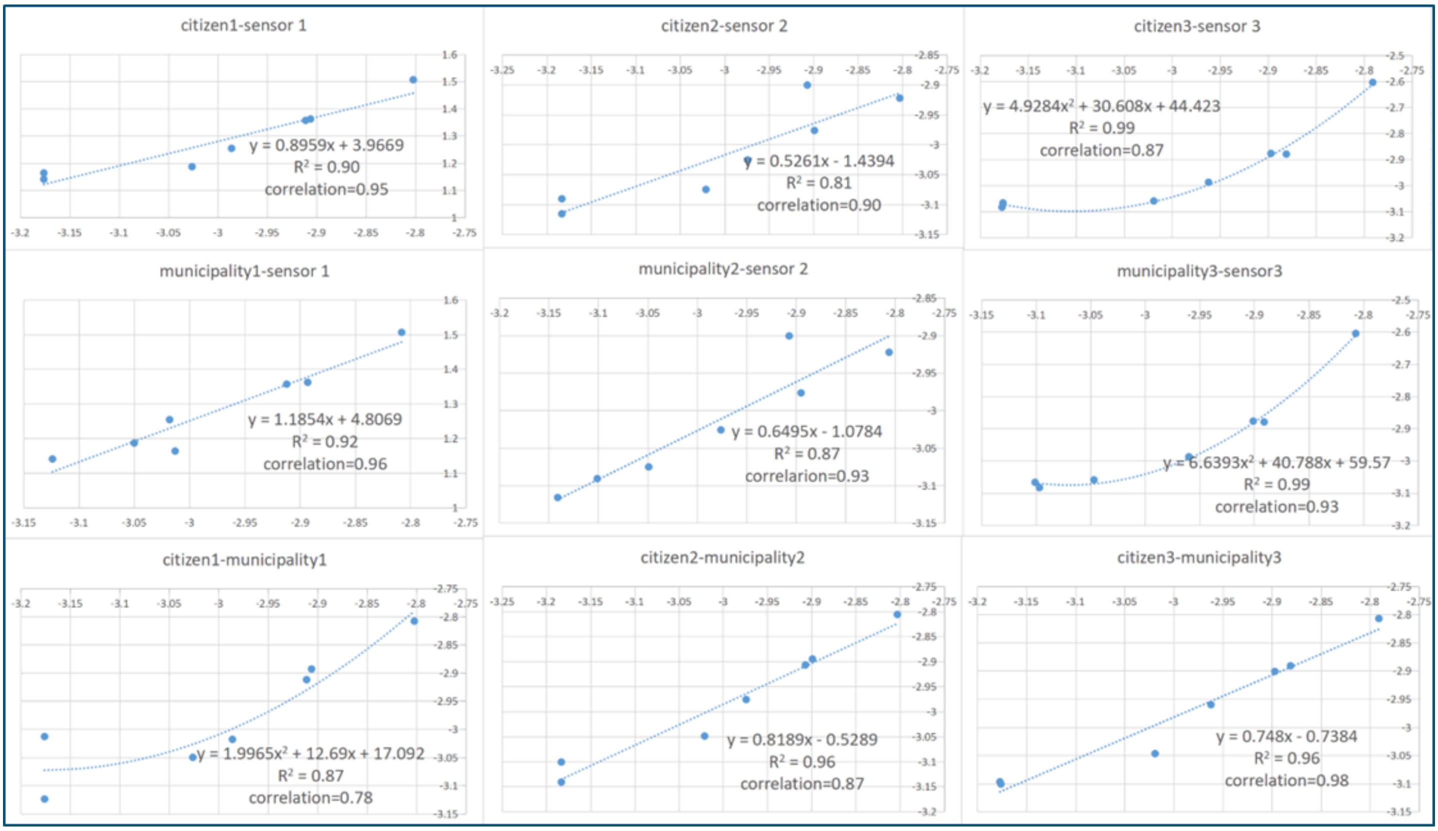


Figure 5.4 Correlation and fitting function of three data sources

5.4 Deeper comparison between citizens and sensors

The data comparisons discussed in the last sub-chapter are only based on monthly basis. However, citizen and KCAF sensors data do provide more dense (temporally) datasets and in this analysis every data which share same sampling time is compared. Due to the increased number of the comparing data, the interpolation in this step is carried by Python programming while the IDW parameters are the same as in the case that the interpolations occurred via Qgis.

As Figure 5-5 shows that the citizen data can best fit the sensor1's observations where it has the highest correlation (0.95) and R2 (0.90) among the three comparisons. Although the second comparison also shows a very high correlation, the residuals between the scatter points and the fitting function are higher than the first one. These numbers can go up to 10 cm around 7 times. In the third comparison, the fitting function can simulate the sensor3 accurately when the groundwater level is below -2.9m and as the level goes up, the points become more discrete, accordingly the correlation and R2 also is the lowest. Overall, the average correlation is 0.91 which shows a very strong relationship between the two data sources while the average residual is 1.74cm.

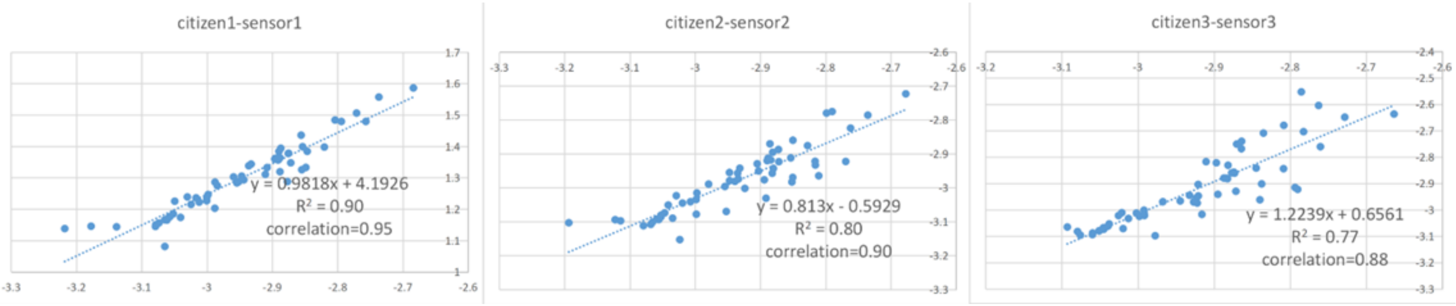


Figure 5.5 Correlation and fitting function of citizens and sensor data

6

Conclusions and recommendations

One of the main goals of this project was to understand if sensors data could be comparable with other sources of information, and partially it can be. For water level measurements, we obtained a good correlation, an average of 0.9 or 90% of similarity, between sensors data, citizen's measurements and municipality records. For building movement, the ground sensors detect in general 5 times more subsidence than InSAR data and in some cases elevation.

However, on this research, we understand that subsidence in buildings is more than just measurements with sensors or satellites because of the time factor, always present in the analysis. When several measurements related with time are present, a measure of reference is needed to compare the rest, and this should be completely static. But, what happen when your reference is not static and all your new measurements are related with it? This is the problem we had with sensors and InSAR data.

The subsidence sensors are fixed to the house (which have wooden piles) and these are measuring in reference to the ground (which does not have deep foundations) but according with InSAR data, the ground is subsiding faster than the building so how can we trust on sensors if "maybe" the reference is moving too?

The same for InSAR data, when the values were calculated, according with SkyGeo, they took a reference point to relate the rest of the measurements during the 2-year period. However, as we saw on this research project, the satellite number 2 was always detecting elevation, "maybe" because the reference point was subsiding faster than the rest of the points in the dataset.

Having said that, for this project, all is about references and to compare oranges with oranges (similar objects). InSAR data is not comparable with sensors data because they have different references. Furthermore, InSAR is suited to detect deformation in long periods, 3/4 years and with a minimum of one centimeter and in our case, we are talking about 3 millimeter in ground sensors data. Finally building subsidence cannot be compared with streets subsidence because they have different foundations.

According to this, for future implementations, we propose to get the difference of movement between a healthy building and an unstable one in relation with a reliable reference, the NAP levels. The NAP level, is the national height reference for the Netherlands and the network of references is quite dense that near to our research building we have 3 reference points to use to calculate levels (see figure 6-1). These references are updated every 10 years but is the most reliable level source in the Netherlands.

Figure 6.1 The red dots are the NAP reference levels close to our building. In the oval our research building. (Source: https://geoservices.rijkswaterstaat.nl/geoweb51/index.html?viewer=NAPinfo)

The idea of our proposal is to measure the level of our building (with wooden piles) according with the NAP reference level and then another sane building (maybe one with concrete piles) according with the same NAP reference. Then the difference of measurements will be calculated to get the effective subsidence (see figure 6-2). If there is no difference, that means both buildings are having a natural subsidence.

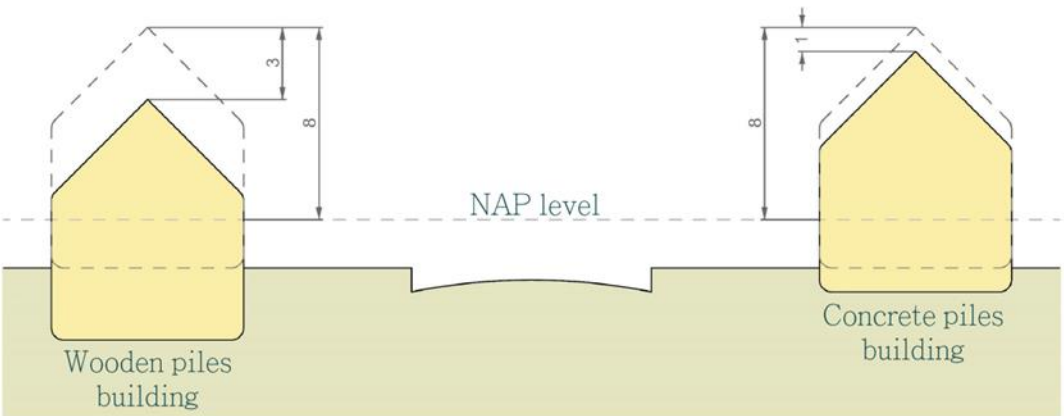


Figure 6.2 Example of subsidence calculation between two buildings

Of course all these calculations should be made physically on site by an expert in surveys. The method that will be used to calculate the height values of our building is the levelling. The instrument to be used is the level (see figure 6-3), since it is the most precise of all the surveying instruments. The level has sub-millimeter precision (0.5mm) in a distance of a kilometer. Since the subsidence of our building according with the sensors is of sub-millimeter per month, we can assume, that if the leveling is taking place once per month then the precision is high enough to be comparable with ground sensors.

Figure 6.3 Instrument (level) and level staff(Source: http://www.surveyingequipment.com/product/leica-jogger-32-automatic-level-package/)

This measuring method (leveling) for small distances (like in our case) is the best possible solution. An electronic level (it is called level because it gives a true horizontal line) with a barcode leveling staff.

According with water level sensors, in general, all three sources of data show high similarities and comparability based on the correlation computation (see Table 6-1).

Table 6-1 Result of the water levels analysis.

Comparison	Similarity
Sensors Vs. Citizens	91,0 %
Sensors Vs. Municipality	94,1 %
Citizens Vs. Municipality	87,9 %

If we try to find substitutability of groundwater sensor by creating interpolation and fitting functions, the municipality-sensor model has higher R2 (how well observed outcomes are replicated by the model); we still believe that the citizen data is more reasonable as alternative. The R2 of citizen-sensor model also reaches to 0.82, which means they are 82% dependent, and the average residual between sensor observation and predicted model is 1.74cm. Considering the observation error and interpolation method, we think these numbers are better than expected. More importantly, the sampling temporal density of citizen data is much higher than that of municipality data so this enables the research monitors groundwater more frequently.

Finally, for inclinometers, we couldn't find any data to compare them. However, we can say that the higher inclination is always happening in the short axis of the building (see figure 6-4), so for future implementations it is recommendable to use them only in the long facades.

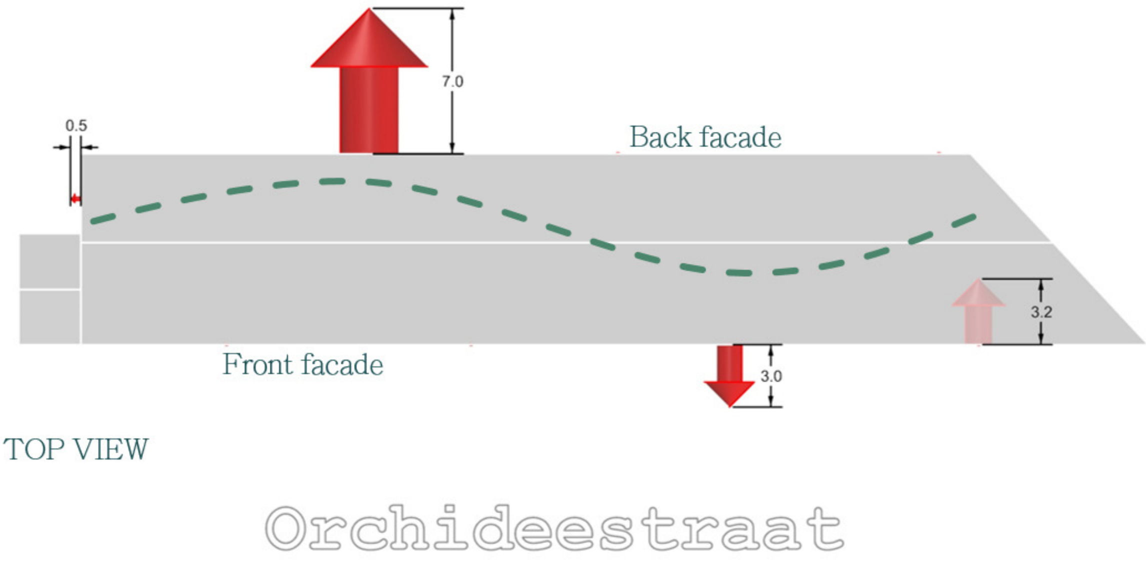


Figure 6.4 Top view of our research building with vector plot of horizontal movement in millimeters according with inclinometers data.

References

- Adriaan van Natijne (n.d), MSc Thesis, Web based visualization of 3D radar and LiDAR data

- Burrough, P. A. (1986) Principles of Geographical Information Systems for Land Resources Assessment.

- Deltares-Taskforce Subsidence (2013) Sinking Cities

- K. Arroyo,P. Bhattacharya, F. Biljecki, D. Kalpoe, Á. Muñoz, P. van der Torren, S. Verlaar and H. Yu. (2009) Satellite radar observation feasibility study for large infrastructural public works.

- McBratney, A. B., and R. Webster. (n.d.) Choosing Functions for Semi-variograms of Soil Properties and Fitting Them to Sampling Estimates. Journal of Soil Science 37: 617–639. 1986.

- Piyush Agram, Jet Propulsion Laboratory (2015) InSAR time-series a quick introduction

- Rene K.W. Klaasen (2015) Life expectation of wooden foundations- a Non- Destructive Approach

- ArcMap(Esri)- How IDW works available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-idw-works.htm

- ArcMap(Esri)-How Kriging works available at: http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/how-kriging-works.htm

- Gemente Rotterdam- Funderingskaart- Available at: https://rotterdam.maps.arcgis.com/apps/MapSeries/index.html?appid=e0ff1f373bca4574a751529c7bc536d7%20

- KCAF- Pilot Orange Program available at: https://www.kcaf.nl/pilot-code-oranje/

- Rijkswaterstaat-GeoWeb-Nap Available at: https://geoservices.rijkswaterstaat.nl/geoweb51 index.html?viewer=NAPinfo

- RNMI- Climatology Daily weather data for the Netherlands, available at: http://www.sciamachy-validation.org/climatology/daily_data/selection.cgi

- USGS-InSAR – Satellite- based technique captures overall deformation “picture”, available at: https://volcanoes.usgs.gov/vhp/insar.html

- V.B.H. (Gini) Ketelaar (2009), Satellite Radar Interferometry- Subsidence Monitoring Techniques

- Penny+Giles, (n.d.), SLS & MLS series Linear Position Sensor

- KELAG Kunzli Elektronik AG, (n.d.) Single Axis Precision Differential Inclination Sensor, available at www.inclinometer.ch/en

- GE, (n.d.) UNIC 5000 Pressure Sensing Platform

Appendix A
Rich Picture

The Rich Picture provides a visual overview of all actors and stakeholders, from different perspectives on the project. It provides an insight in the approach chosen by the team and the way the project is framed.

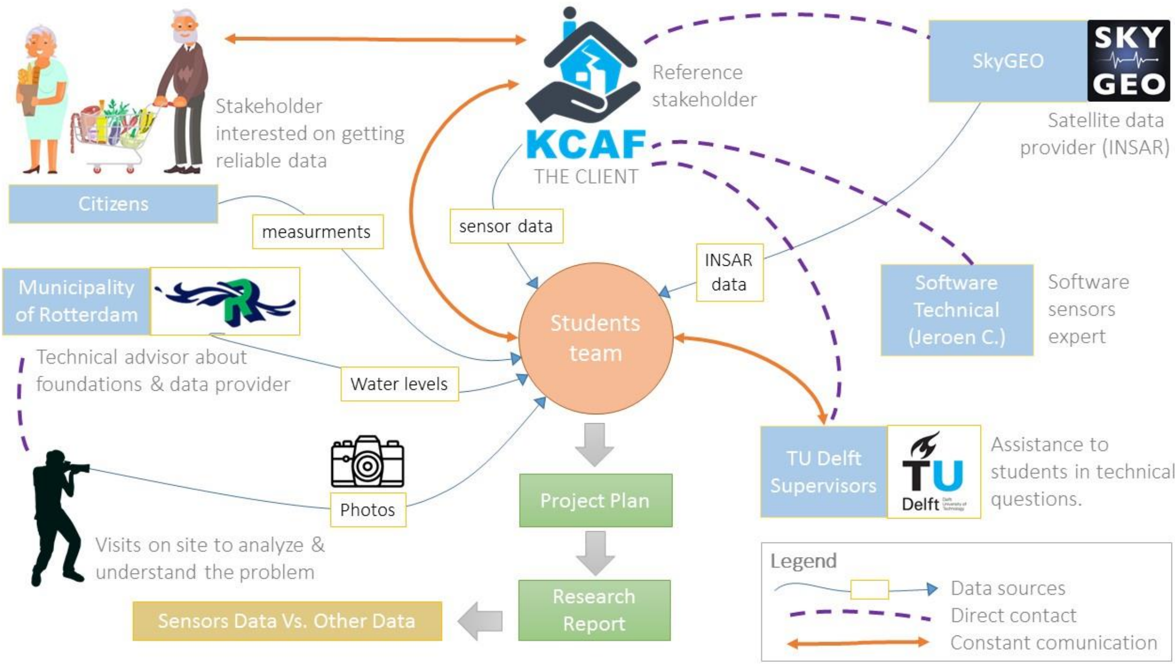


Figure A -0.1 Rich picture subsidence project.

Appendix B
Geodetic Measurements

The main problem we faced during this project was the lack of reference measurements for comparison with the ground sensors and the InSAR data. So one of the idea we had but we couldn't apply, was to use geodetic measurements (measurements with total station) as our ground truth measurement which are very accurate in mm level.

A total station (TS) is an electronic/optical instrument used for surveying and building construction (Figure B-2). The total station is an electronic theodolite (transit) integrated with an electronic distance measurement (EDM) to read slope distances from the instrument to a particular point, and an on-board computer to collect data and perform advanced coordinate based calculations.

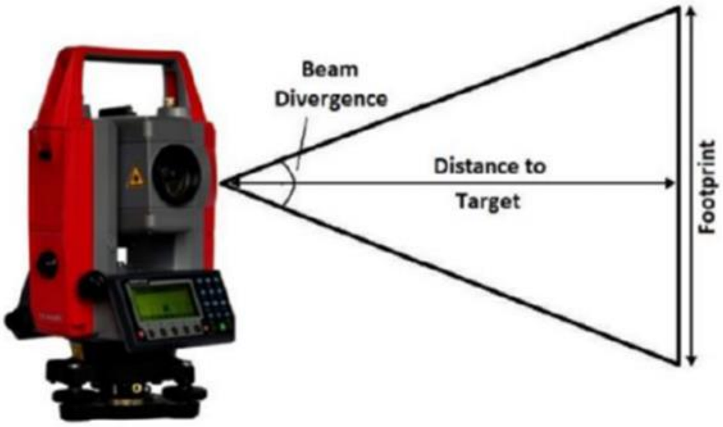


Figure B. -0.1 Working principle of the total station

Our idea for the geodetic measurements was to create two networks, one network on the ground and one on the buildings. The first would be an independent network with fixed points on stable spots on the roads around the building block, and the second would be created from fixed point on the buildings. The points on the buildings would have been place near the sensors and on the roof. (Figure B-2)

Figure B -0.2 Example of how the geodetic networks would have been established.

The measurements would be repeated every week, in order for us to had 1 month comparable results with the sensors and the InSAR. But as it was mentioned before the measurement were not applied us we had difficulty to find total station in the narrow time period we had.

Appendix C
Evolution of Research Question

“Due to the nature of this project the research question changed a lot through the past two months. At the beginning we had as a goal to firstly analyze the data and after this analysis to try and create a prediction model about the subsidence. This idea was dropped early on during the first weeks of the projects, since we did not had the required technical knowledge for completing this task. Furthermore our MSc program is related with Information Technologies and as a result we are only responsible the analyzing data.

The second research question was modified to reflect more our information analysis background and knowledge.

“Our role on this project is to analyze different sources of data and try to find a relation between the information produced by the sensors and other reliable sources of data”

• Check the reliability of the sensors

For the subsidence monitoring our main comparing data set was the InSAR one that through our first analysis did not provided reliable enough Data in order to determine the reliability of the sensors data. As a result, we had to change one more time the research question and to and up to our final one. This final change is not as drastic as the first one but mainly helps to clarify the aim of this project.

• Is comparable the use of subsidence sensors with InSAR data in order to detect movement on buildings?

If yes, what is the procedure to follow and how similar are the results?

If not, is there another data source to compare sensors data? How reliable is this new source?

• Related to water level in the soil, the sensors data is comparable with the data collected by the municipality or citizen’s data?

If yes, is it possible to determine if the sensors data are reliable?

If not, which alternative methods can be used to get the correct water level in the soil?”

Appendix D
Calculations-Codes

During this synthesis project we had to automate some of the calculations. In this appendix we are attaching

1. the python code that we developed in order to interpolate the citizen's and the KCAF sensor's data (see 5.4 Deeper comparison between citizens and sensors)
2. the python code we developed in order to improve the location of InSAR data with Lidar (AHN3) (see 4.3 Improving InSAR data accuracy with Lidar data (AHN3)

```
import math
#import spatial data
muni_loca=[[92198,439932,],[92213.5,439829.3],[92122.31,439883.8],[92235.4,439909.3],[92164,439993],[92220.7,439977.8],
[92327.1,440019.6],[92334.7,439960.2],[92201.7,439906.75],[92244.52,439802.23],[92227.9,439799.91],[92247.4,439803.5],[92126.7,439933.5],
[92284.2,439764.5],[92203.8,439752.1],[92143.4,439812.7],[92264.1,439719.0]]
sensor_loca=[[92170.8,439908.85],[92173.3,439882.2],[92181.3,439864.85]]
def idw(munidata,m,s):
    #set 0 if no data
    a = munidata.split(',')
    timestamp=a[0]
    # c=[[1 or 0,value,[distance1,distance2,distance3]].......]
    c=[]
    for i in range(1,len(a)):
        # b=[1 or 0,value,[distance1,distance2,distance3]]
        b = []
        if a[i] == "" or a[i]=="0":
            b.append(0)
            b.append(0)
        elif a[i]!= "" and a[i]!=0:
            a[i] = float(a[i])
            b.append(1)
            b.append(a[i])
        #get distance
        x1 = m[i-1][0]
        y1 = m[i-1][1]
        distance=[]
        for k in s:
            x2 = k[0]
            y2 = k[1]
            d = math.sqrt((x1 - x2) ** 2 + (y1 - y2) ** 2)
            distance.append(d)
        b.append(distance)
        c.append(b)

    accu_vd1 = 0
    accu_vd2 = 0
    accu_vd3 = 0

    accu_d1 = 0
    accu_d2 = 0
    accu_d3 = 0

    for i in c:
        vd1=i[1]/(i[2][0])**2
        vd2=i[1]/(i[2][1])**2
        vd3=i[1]/(i[2][2])**2
        d1=i[0]/(i[2][0])**2
        d2=i[0]/(i[2][1])**2
        d3=i[0]/(i[2][2])**2
        accu_vd1=accu_vd1+vd1
        accu_vd2=accu_vd2+vd2
        accu_vd3=accu_vd3+vd3
        accu_d1 = accu_d1 + d1
        accu_d2 = accu_d2 + d2
        accu_d3 = accu_d3 + d3
    sensor1= accu_vd1/accu_d1
    sensor2= accu_vd2/accu_d2
    sensor3= accu_vd3/accu_d3
    print timestamp,",",sensor1,",",sensor2,",",sensor3
f=open('01.csv','r')
for line in f.readlines():
    idw(line,muni_loca,sensor_loca)
```

```python

# Code for improving the InSAR point cloud's location (X, Y) using a Lidar Point cloud (AHN3)


import Rhino.Geometry as rg
import math
import scriptcontext
import System.Guid

Hdiff=[]#a list with the height differences
XYdiff=[]#a list with the X,Y differences
XYdiff2=[]

for vertex in Pi:
    Pin=[]
    PsX=[]
    PsY=[]
    PsX2=[]
    PsY2=[]

    if vertex.Z>14:#removal of really high points that can be considered as outliers (2.5m above the highest lidar point)
        Pi.remove(vertex)
    else:#check if there are lidar points within 3m in x direction, 3m in y direction and 2.5m in Z direction of the insar point that can be considered that have similar height but wrong position
        for point in Pl:
            if abs(point.X-vertex.X)< 3 and abs(point.Y-vertex.Y)<3 and abs(point.Z-vertex.Z)<2.5:

                PsX.append(point.X-vertex.X)
                PsY.append(point.Y-vertex.Y)


            if abs(point.X-vertex.X)<3 and abs(point.Y-vertex.Y)<0.05 and abs(point.Z-vertex.Z)<2.5:#check if there are lidar points within 3m in x direction, 0.05m in y direction and 2.5m in Z

                PsX2.append(point.X-vertex.X)
                PsY2.append(point.Y-vertex.Y)

        if len(PsX)==0: # assigning values for the empty lists
            meanX=9999

        elif len(PsY)==0:
            meanY=9999
        else:
            meanX=(sum(PsX)/len(PsX))
            meanY=(sum(PsY)/len(PsY))

        if len(PsX2)==0:
            meanX2=9999

        elif len(PsY2)==0:
            meanY2=9999
        else:
            meanX2=(sum(PsX2)/len(PsX2))
            meanY2=(sum(PsY2)/len(PsY2))

        if meanX!=9999 and meanY!=9999: #removing outliers
            X=(vertex.X+meanX, vertex.Y + meanY, vertex.Z)
        elif meanX==9999:
            X=(vertex.X, vertex.Y + meanY, vertex.Z)
        elif meanY==9999:
            X=(vertex.X+meanX, vertex.Y, vertex.Z)

```

```
        if meanX2!=9999 and meanY2!=9999:
            X2=(vertex.X + meanX2, vertex.Y + meanY2,vertex.Z)
        elif meanX2==9999:
            X2=(vertex.X, vertex.Y + meanY2, vertex.Z)
        elif meanY2==9999:
            X2=(vertex.X+meanX2, vertex.Y, vertex.Z)

        XYdiff.append(X)
        XYdiff2.append(X2)

for vertex in XYdiff2:
    Pin=[]
    for point in Pl: # chech the heigh differense between the insar point and lidar points that have aproximately similar location

        if abs(point.X - vertex[0]) < 0.5 and abs(point.Y - vertex[1])< 0.5:
            Pin.append((point.Z - vertex[2]))

    if len(Pin)==0:
        mean=9999

    else:
        mean=(sum(Pin)/len(Pin))

    Zcomp=(vertex[2], mean)
    Hdiff.append(Zcomp)

fileName = open(FileAddressH, 'w')#save the result in a csv file
fileName.write('InSAR_H' + ',' + 'DH' + '\n')
for item in Hdiff:
    fileName.write(`item[0]` + ',' + `item[1]` + '\n')

fileName.close()

fileName2 = open(FileAddressXY, 'w')#save the result in a csv file
fileName2.write('New_InSAR_X' + ',' + 'New_InSAR_Y' + ',' + 'InSAR_H' +'\n')
for item in XYdiff:
    fileName2.write(`item[0]` + ',' + `item[1]` + ',' + `item[2]` + '\n')

fileName2.close()

fileName3 = open(FileAddressXY2, 'w')#save the result in a csv file
fileName3.write('New_InSAR_X' + ',' + 'New_InSAR_Y' + ',' + 'InSAR_H' +'\n')
for item in XYdiff2:
    fileName3.write(`item[0]` + ',' + `item[1]` + ',' + `item[2]` + '\n')

fileName3.close()
```

Apendix E – Graphics & charts

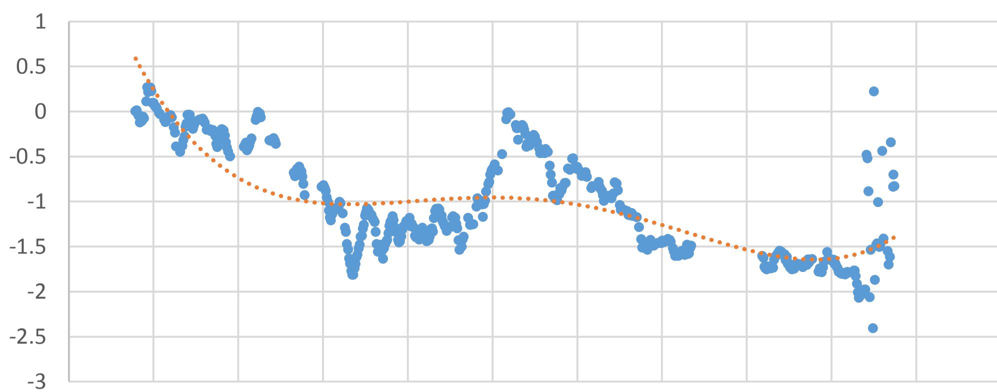
1. Subsidence sensors
2. Comparison between subsidence and water levels
3. InSAR Data
   a) 4 random points in the roof (linear comparison)
   b) How many points detect elevation (2 datasets)
   c) Homogeneous subsidence
   d) Heterogeneous subsidence
   e) Comparison with better position according with Lidar
   f) Streets and ground points
4. Water level sensors
5. Correlation results - water levels
6. Comparison between water levels and rain data

1
Subsidence sensors data

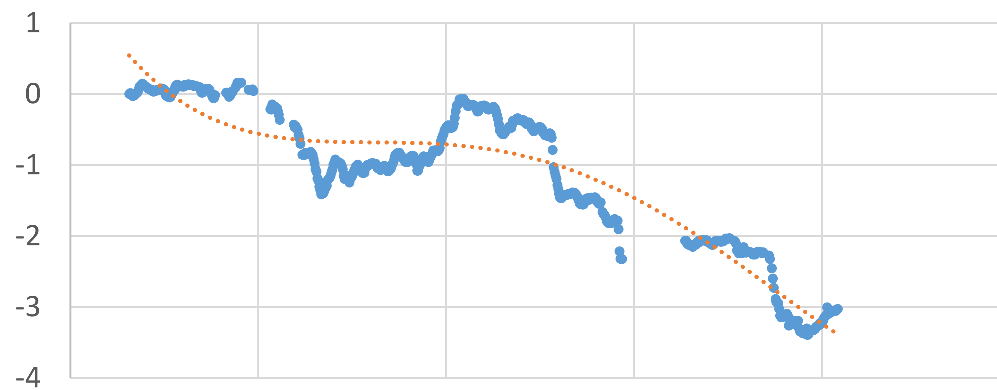
Subsidence sensors

Sensors 1-4 (data cleaned)

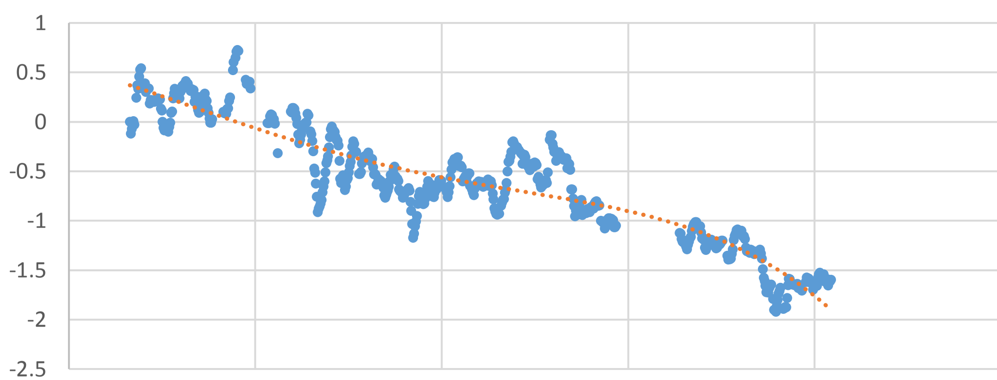
SENSOR 1



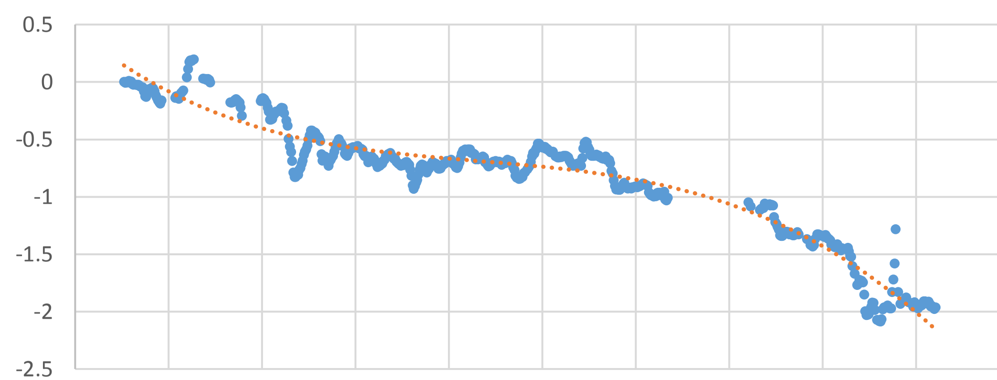
SENSOR 2



SENSOR 3



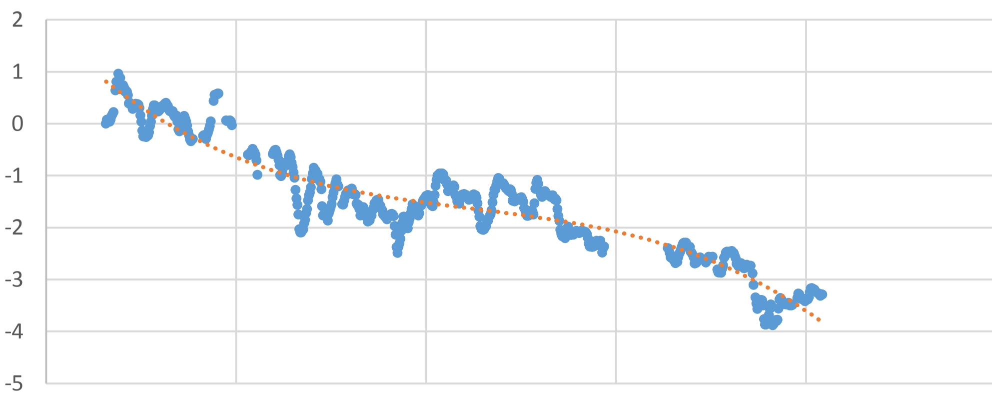
SENSOR 4



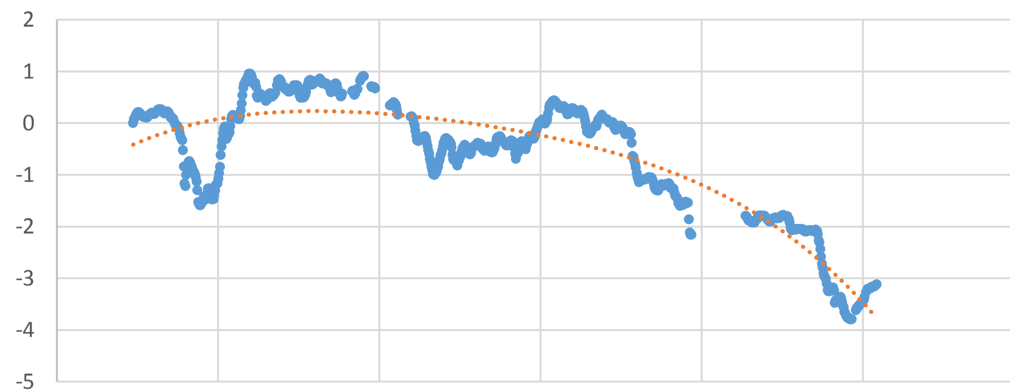
Subsidence sensors

Sensors 5-8 (data cleaned)

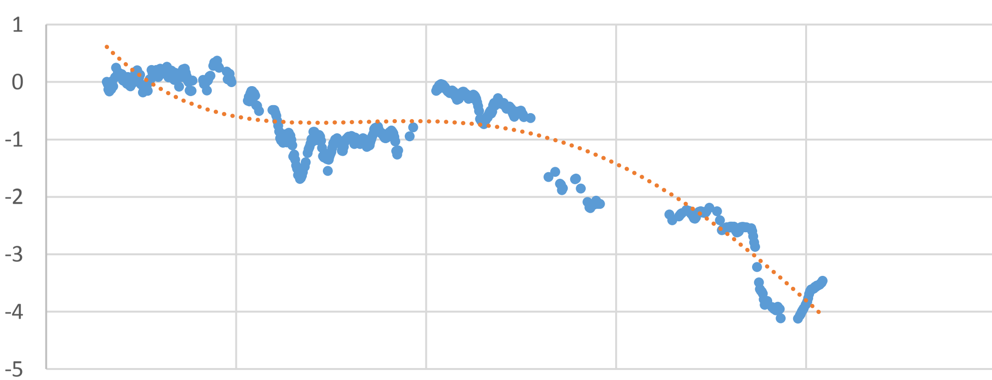
SENSOR 5



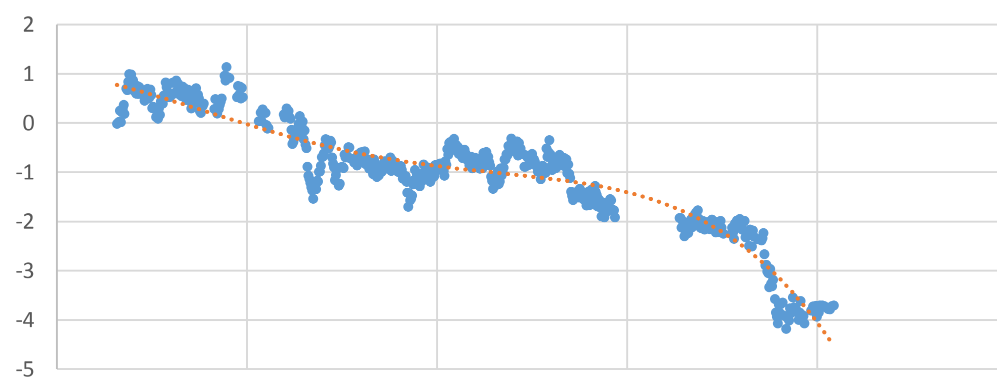
SENSOR 6



SENSOR 7



SENSOR 8



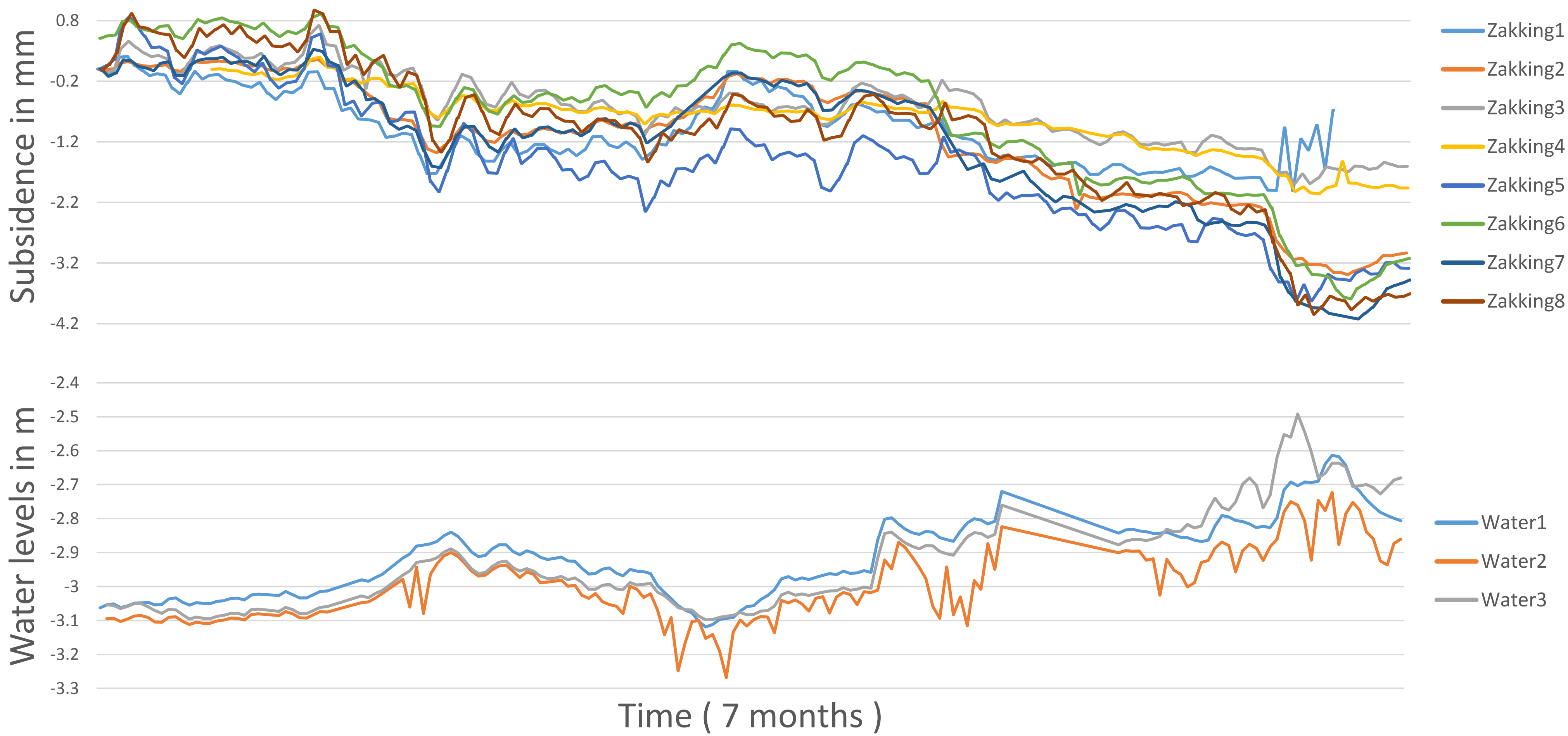
2

Comparison between subsidence sensors and water level sensors

Relation between subsidence and water levels

- According with sensors data -

Negative correlation
-0,91



3.a

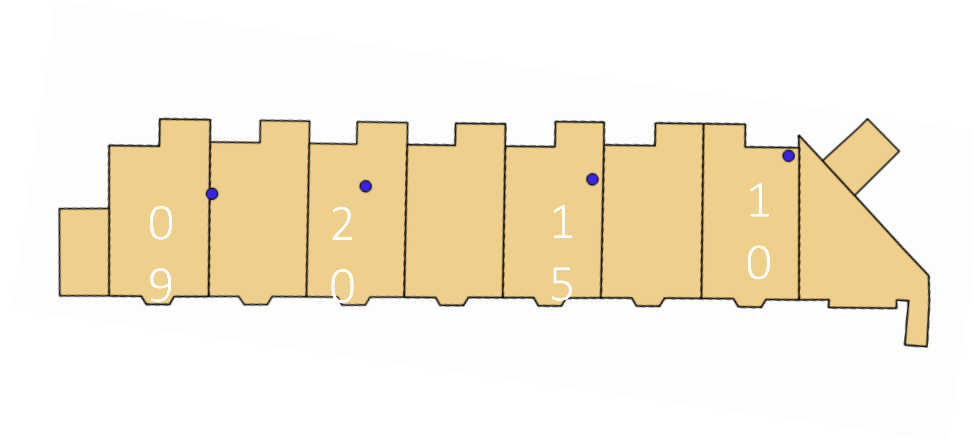
InSAR data

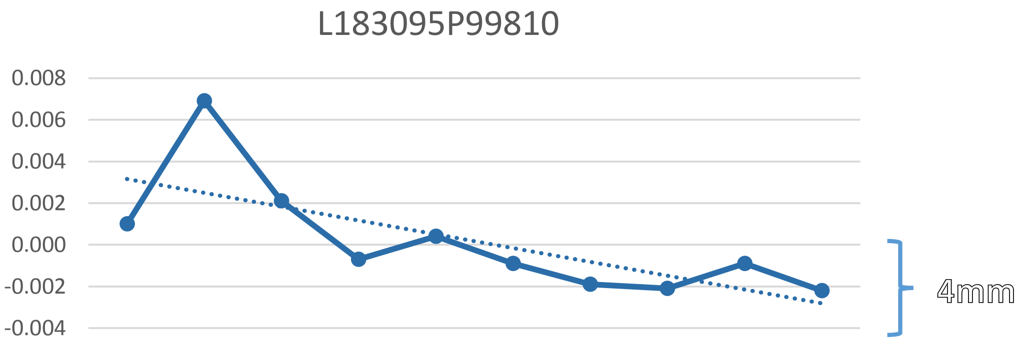
4 random points in the roof (linear comparison)

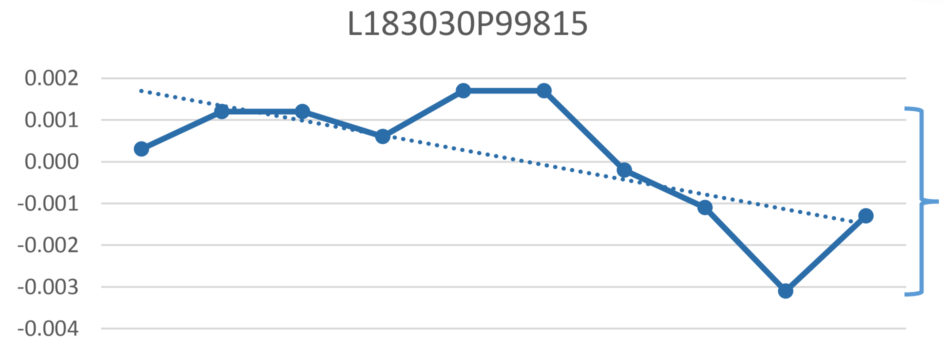
Building subsidence – InSAR data

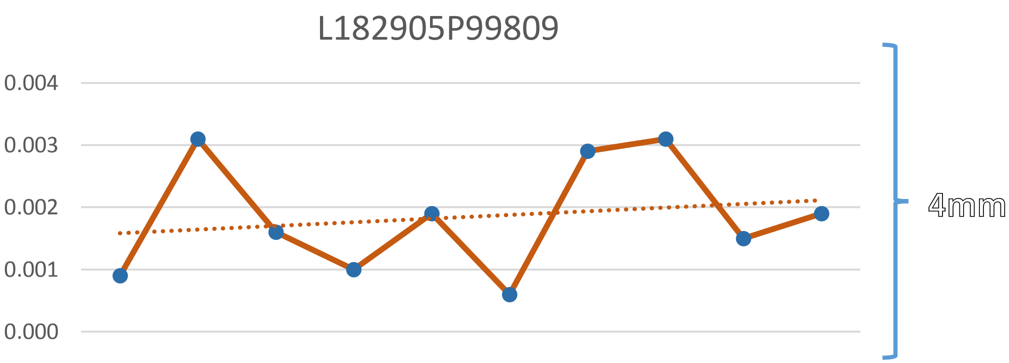
4 high points (+8mt) along the roof to create a level curve to compare with sensors

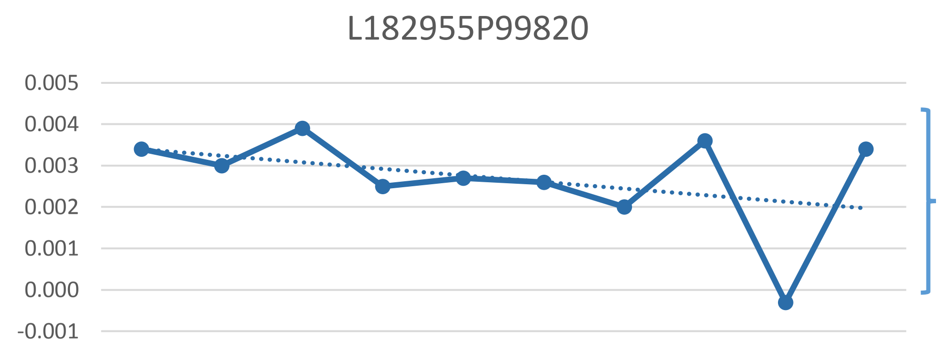
Only 5 months of data (overlapping period)











3.b

InSAR data

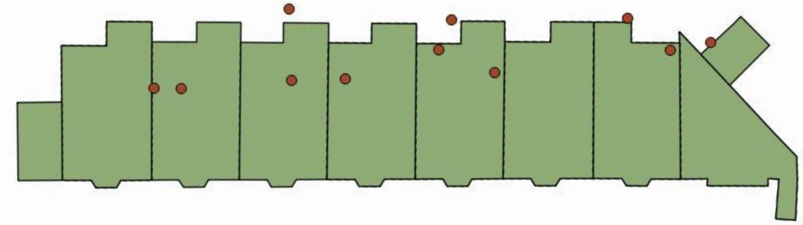
How many points detect elevation (2 datasets)

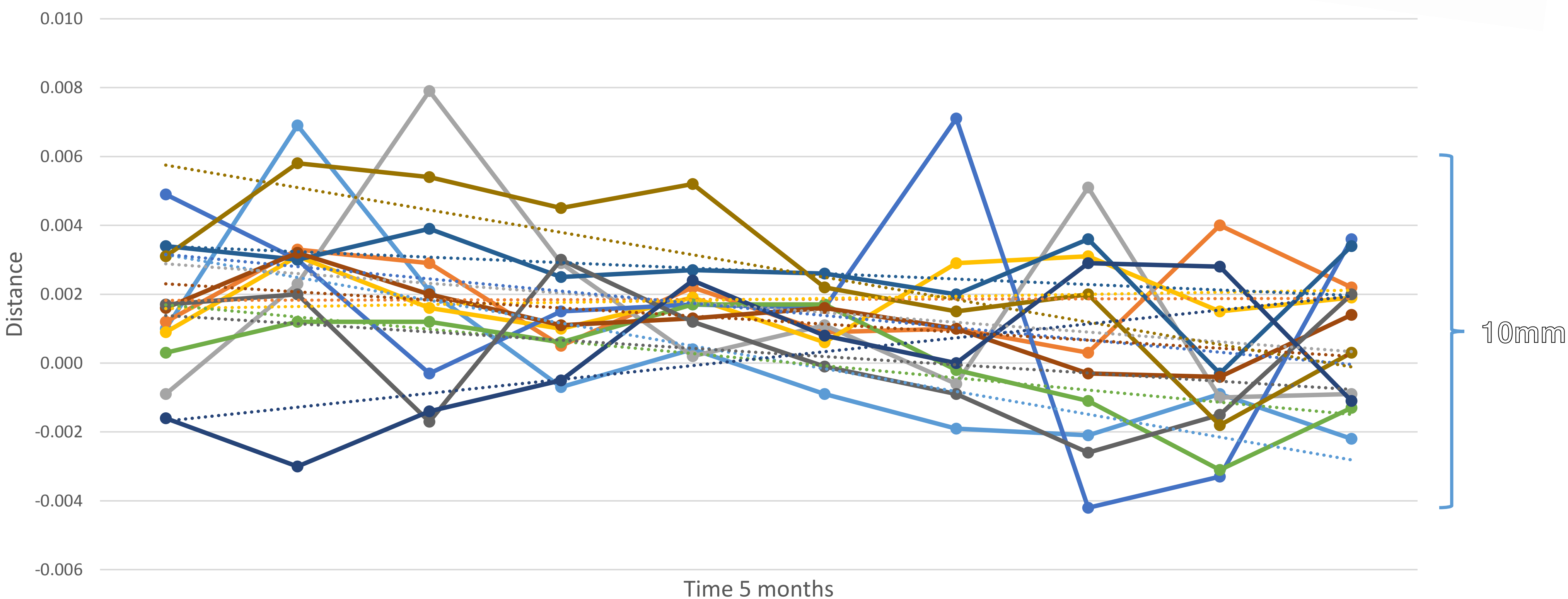
Building subsidence – InSAR data

8 from 11 points detected subsidence

3 points detect ELEVATION

Using 5 months of data



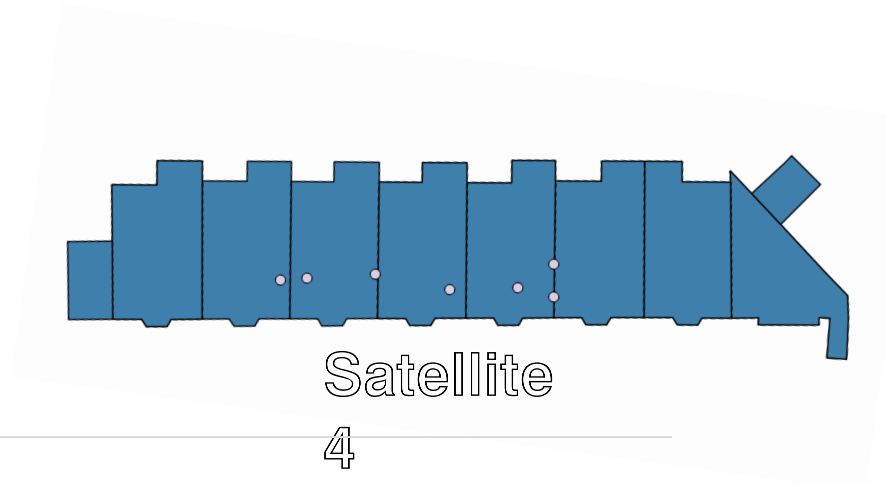


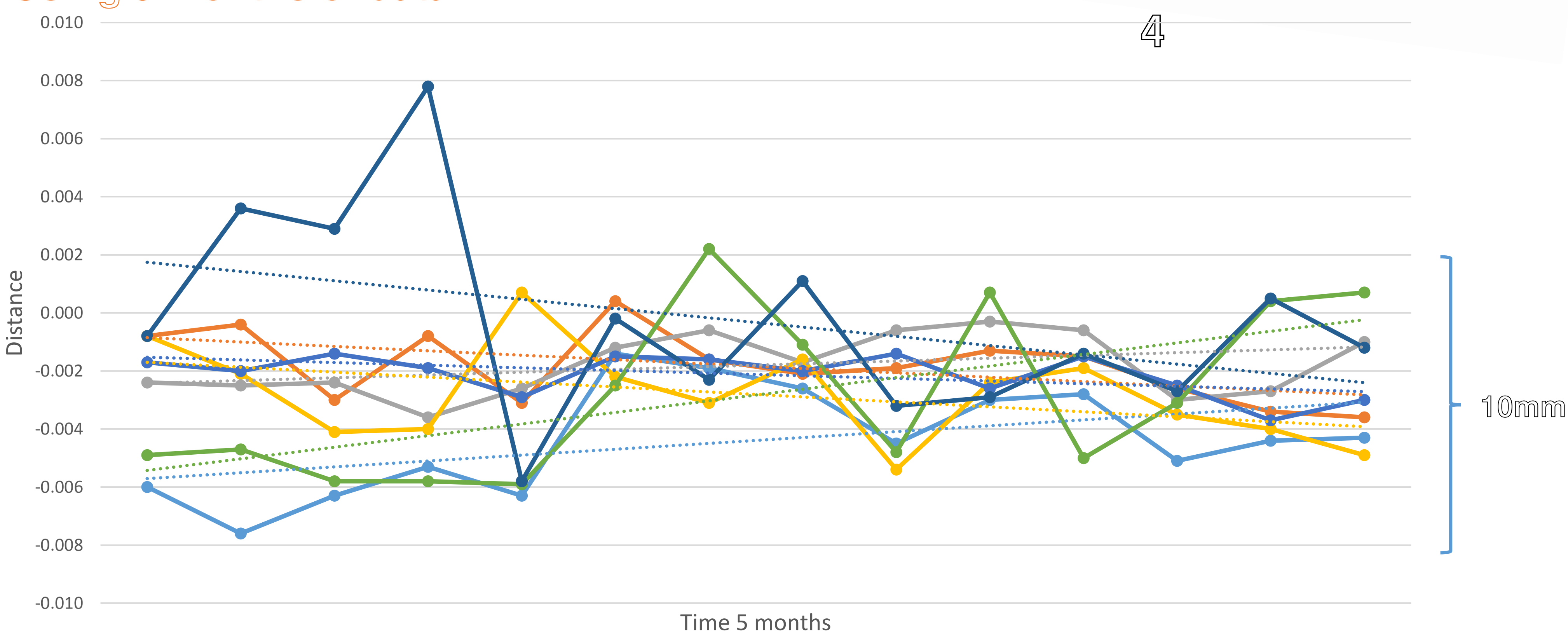
Building subsidence – InSAR data

5 from 7 points detected subsidence

2 Points detect ELEVATION

Using 5 months of data





3.c

InSAR data

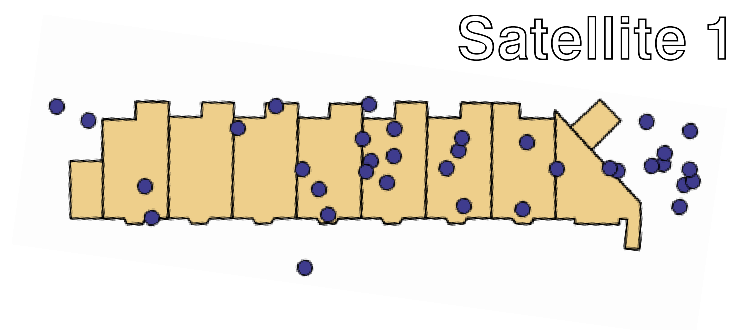
Homogeneous subsidnence

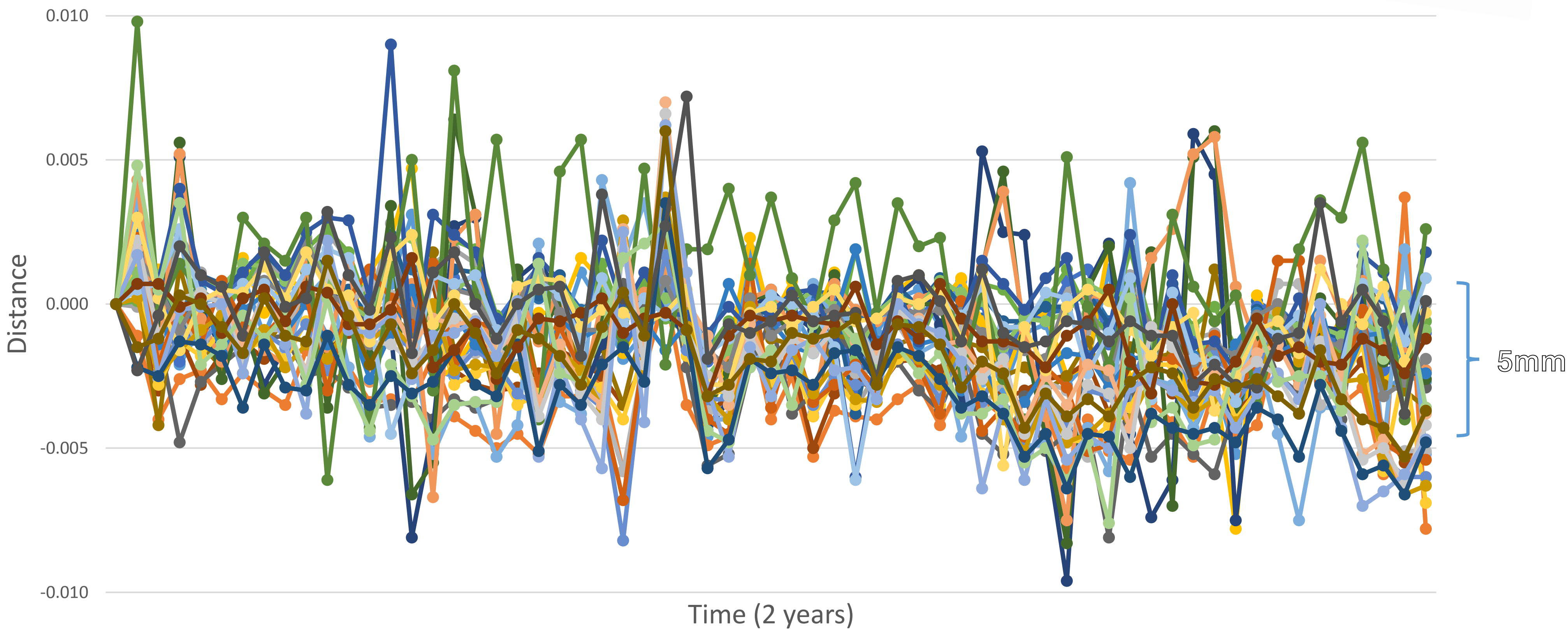
Building subsidence – InSAR data

Dataset 1

Points 3m above NAP (4.7m above ground)

Using 2 years of data



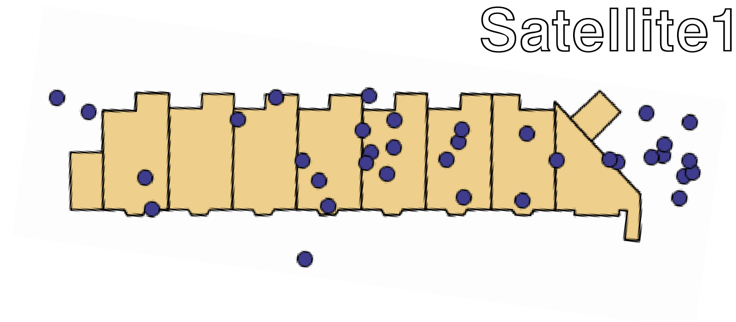


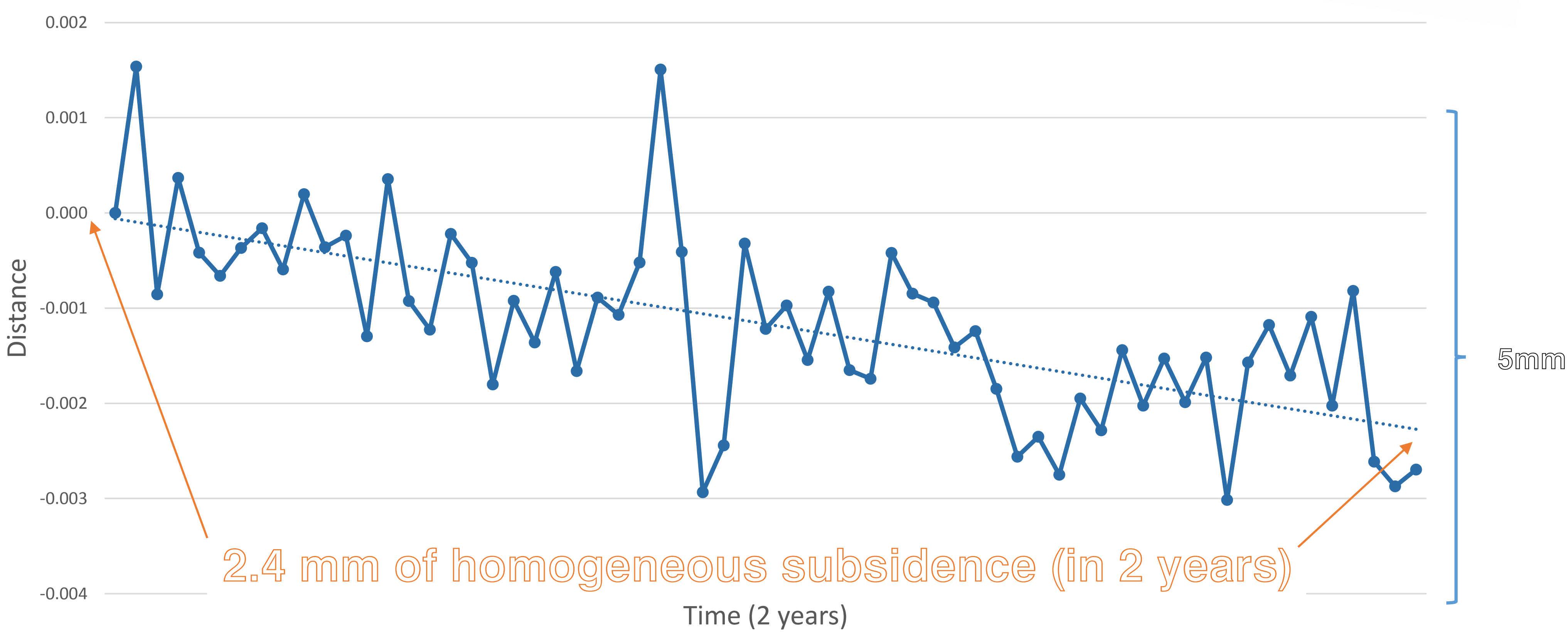
Building subsidence – InSAR data

Dataset 1

Points 3m above NAP (4.7m above ground)

Using 2 years of data



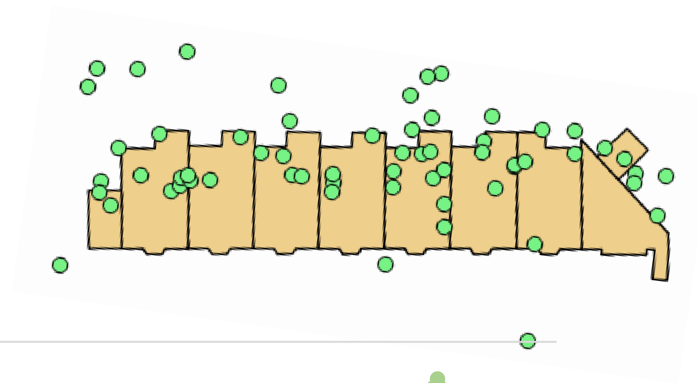


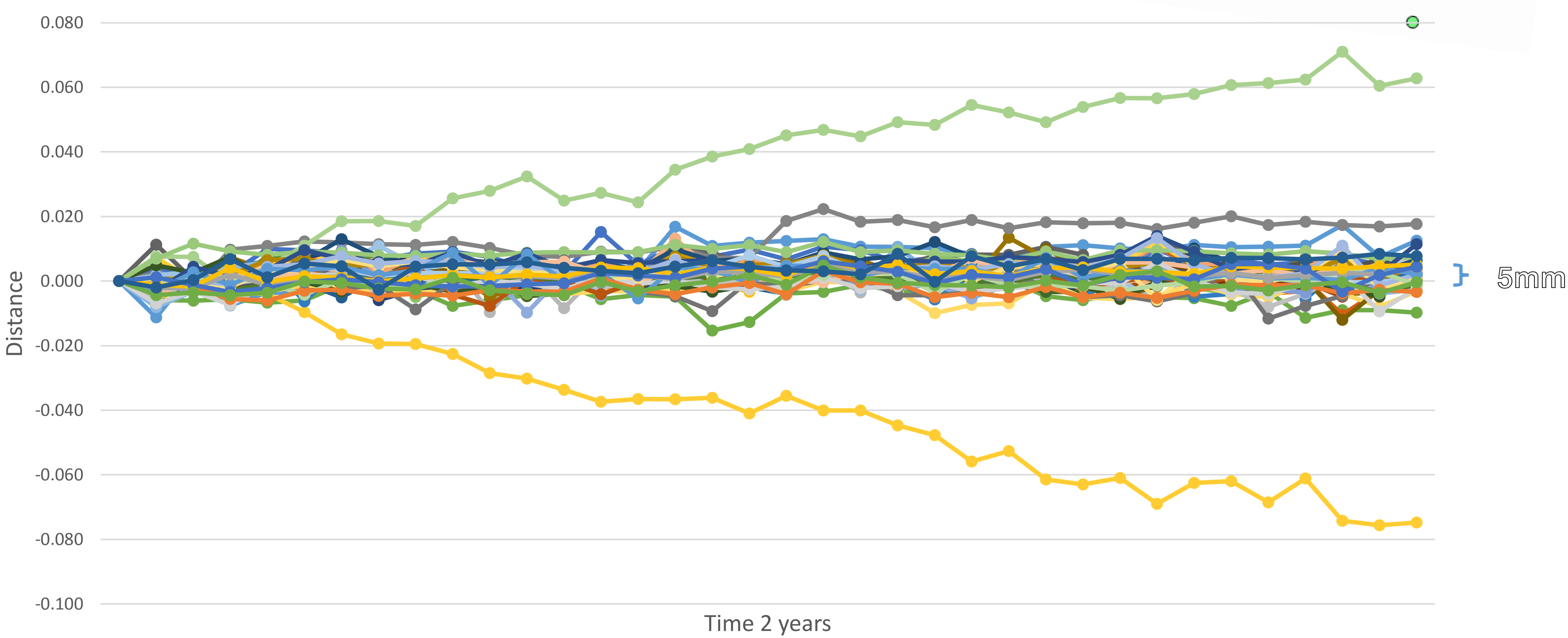
Building subsidence – InSAR data

Dataset 2

Points 3m above NAP (4.7m above ground)

Using 2 years of data



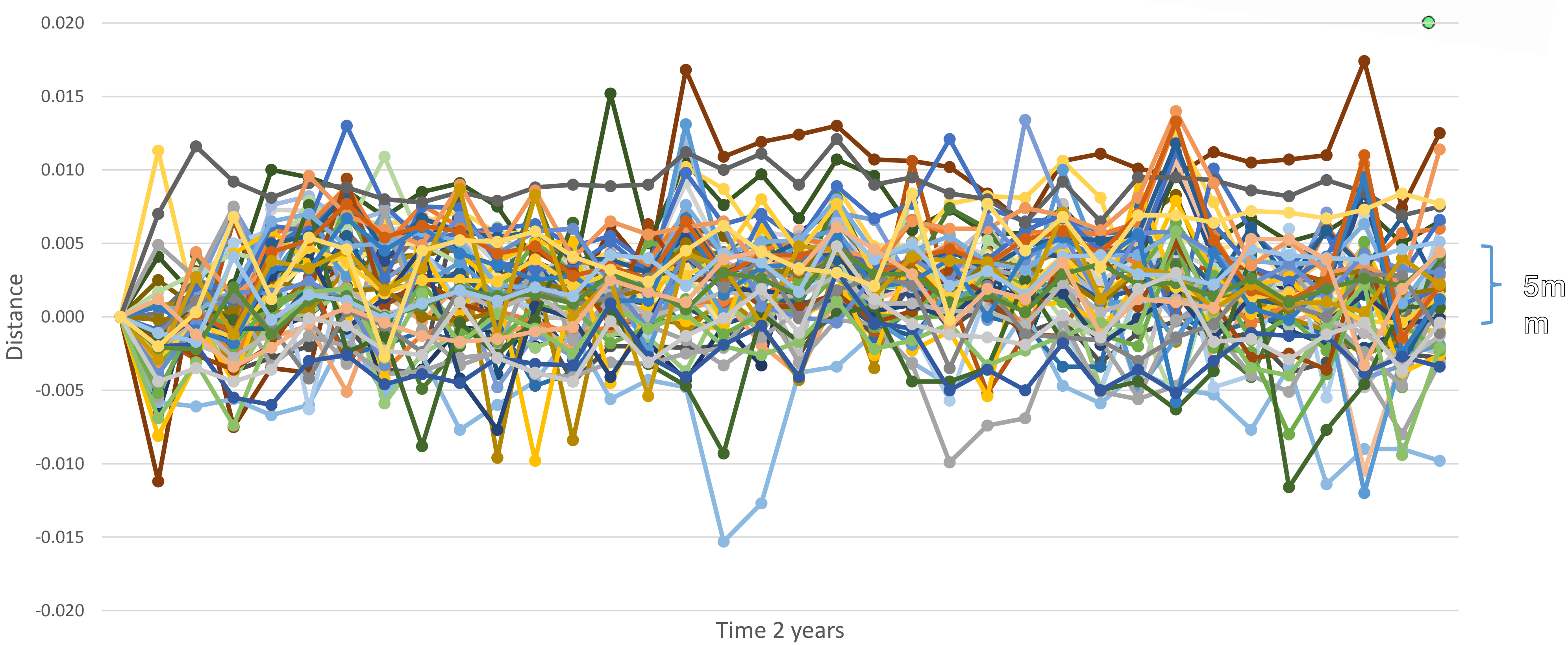


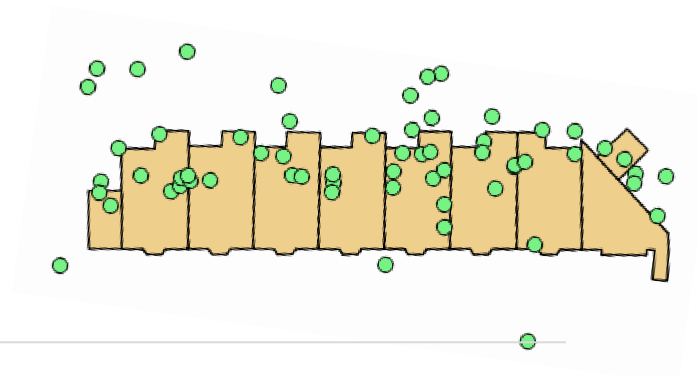
Building subsidence – InSAR data

Dataset 2

Points 3m above NAP (4.7m above ground)

Using 2 years of data (after eliminating outliers)





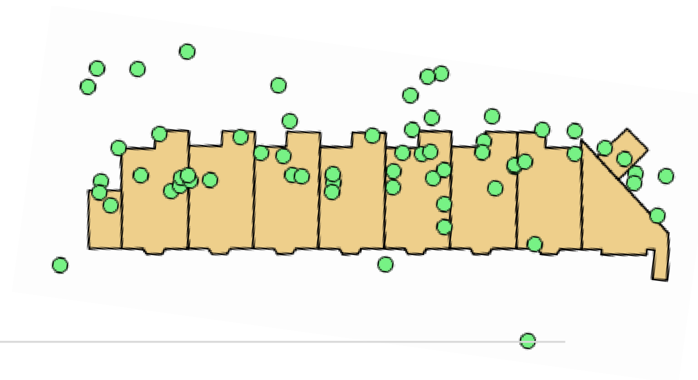
2

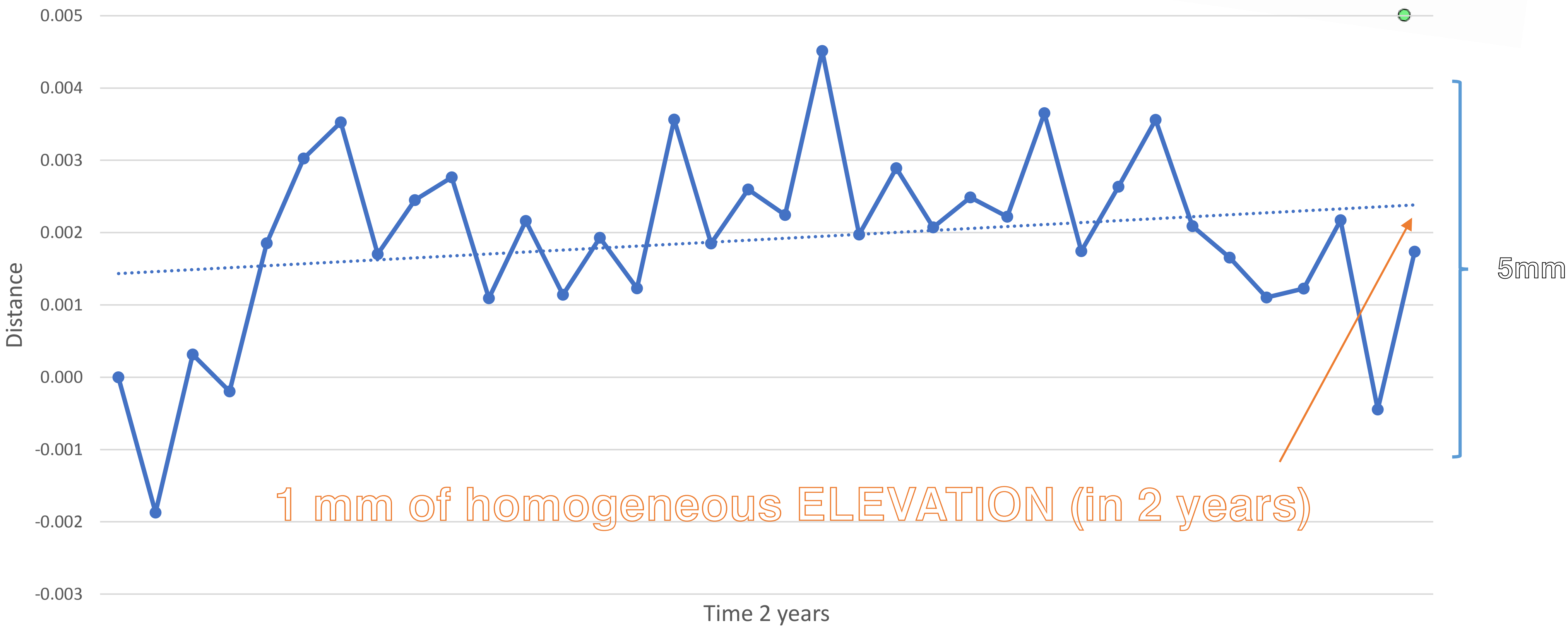
Building subsidence – InSAR data

Dataset 2

Points 3m above NAP (4.7m above ground)

Using 2 years of data



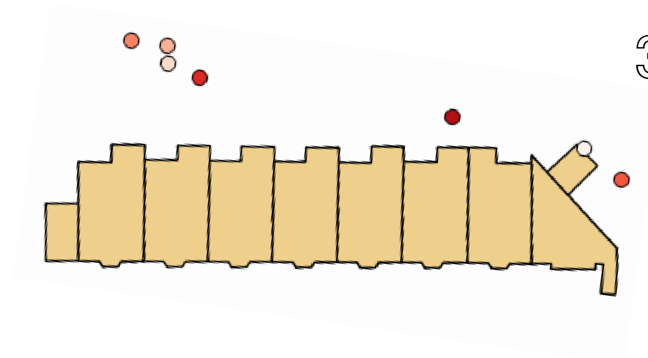


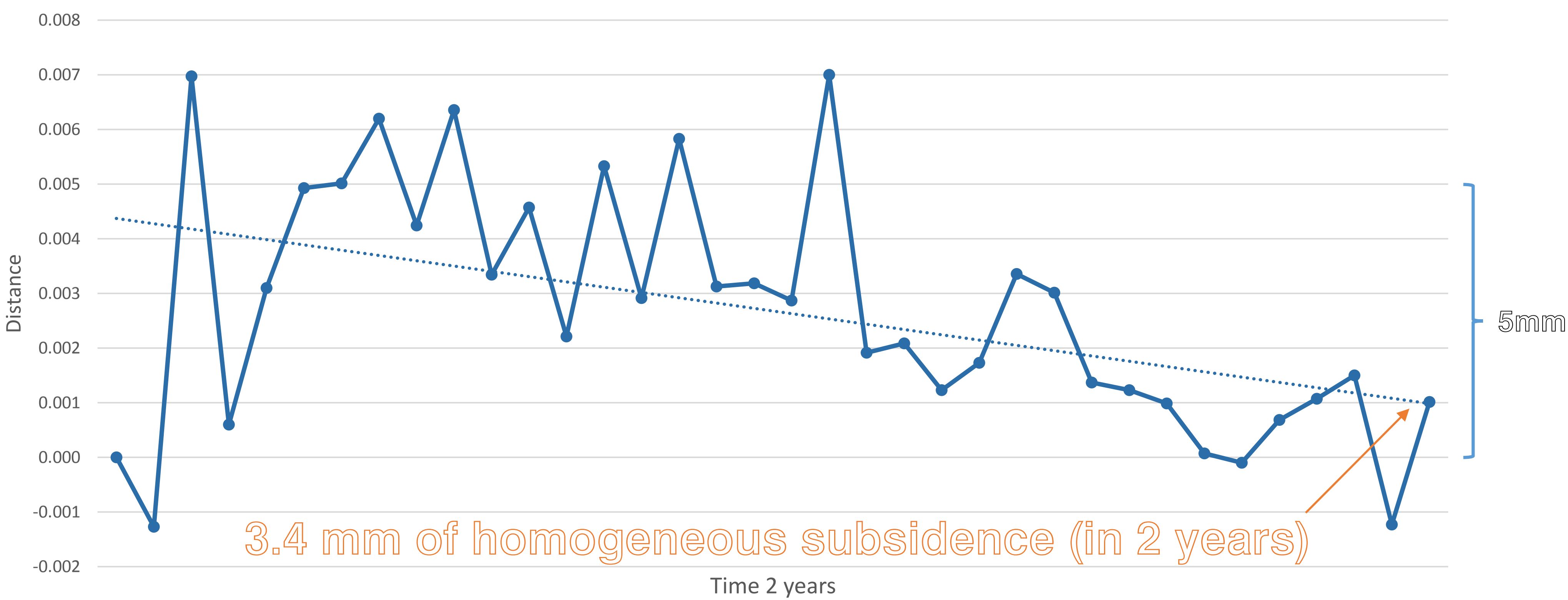
Building subsidence – InSAR data

Dataset 3

Points 3m above NAP (4.7m above ground)

Using 2 years of data



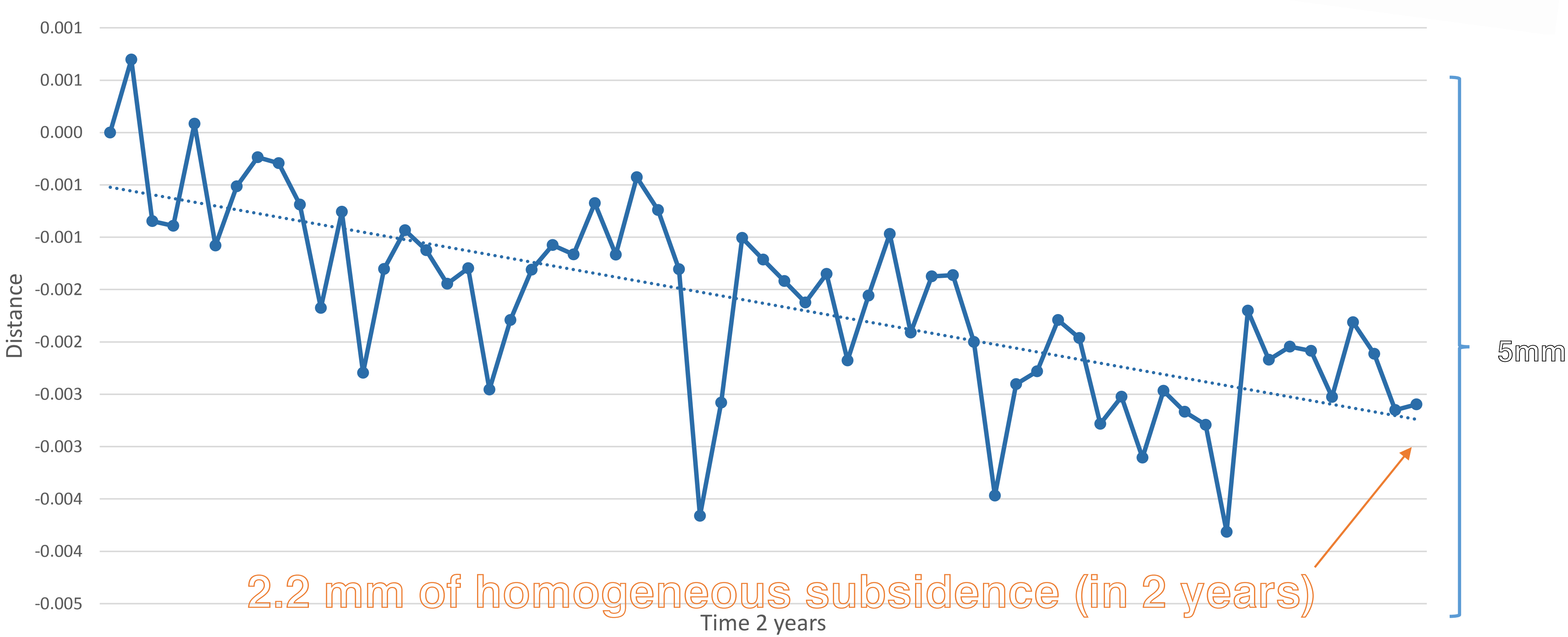


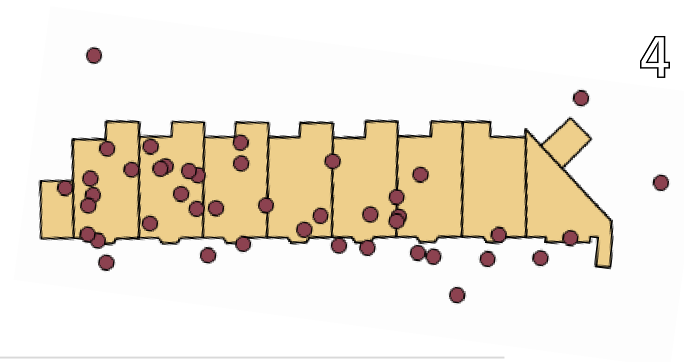
Building subsidence – InSAR data

Dataset 4

Points 3m above NAP (4.7m above ground)

Using 2 years of data



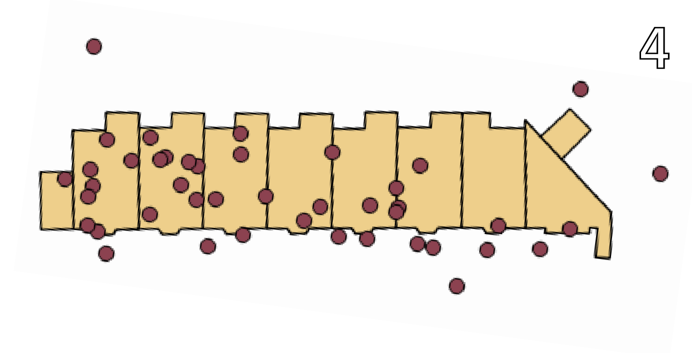


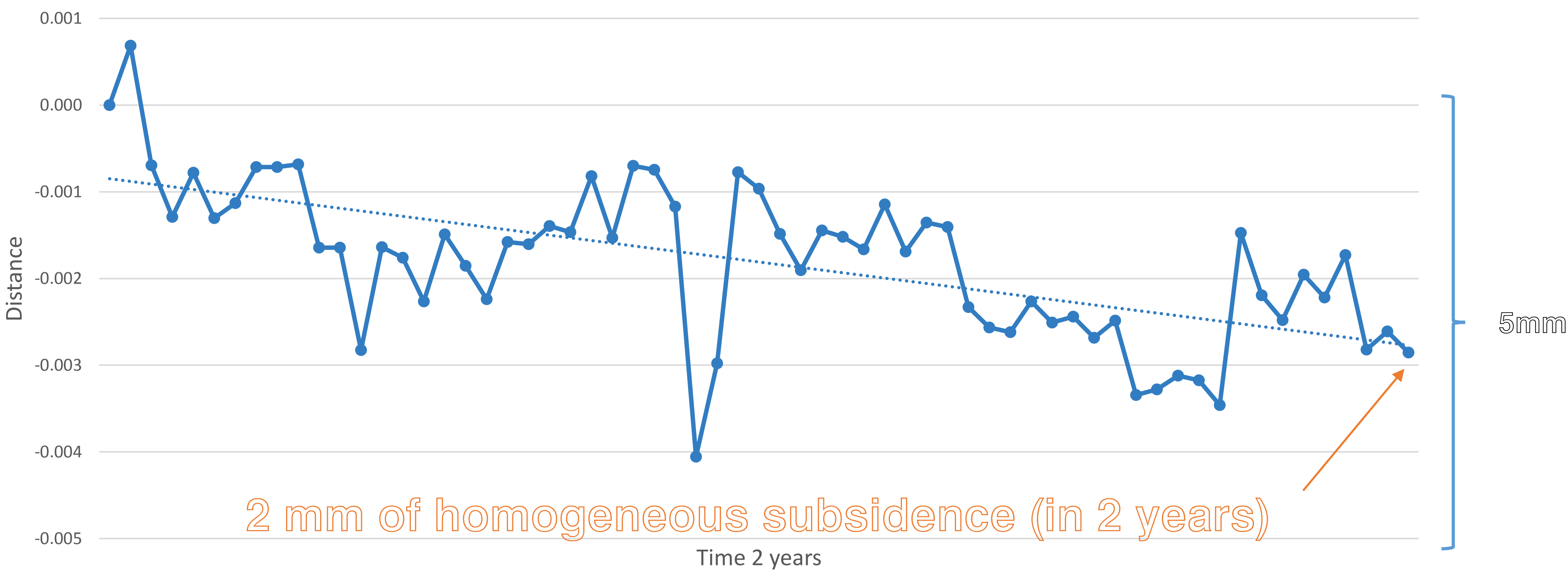
Building subsidence – InSAR data

Dataset 4

Points 3m above NAP (4.7m above ground)

Using 2 years of data (QUALITY + 0.8)





3.d

InSAR data

Heterogeneous subsidnence

Building subsidence – InSAR data

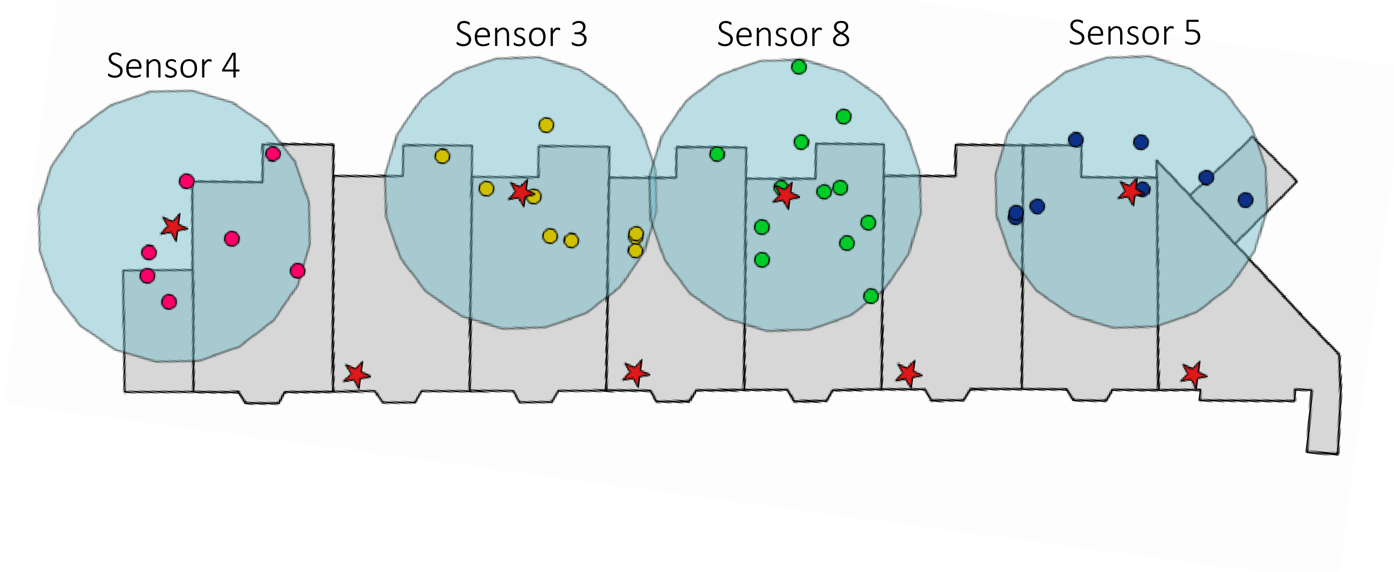
Dataset 2 (best suited)

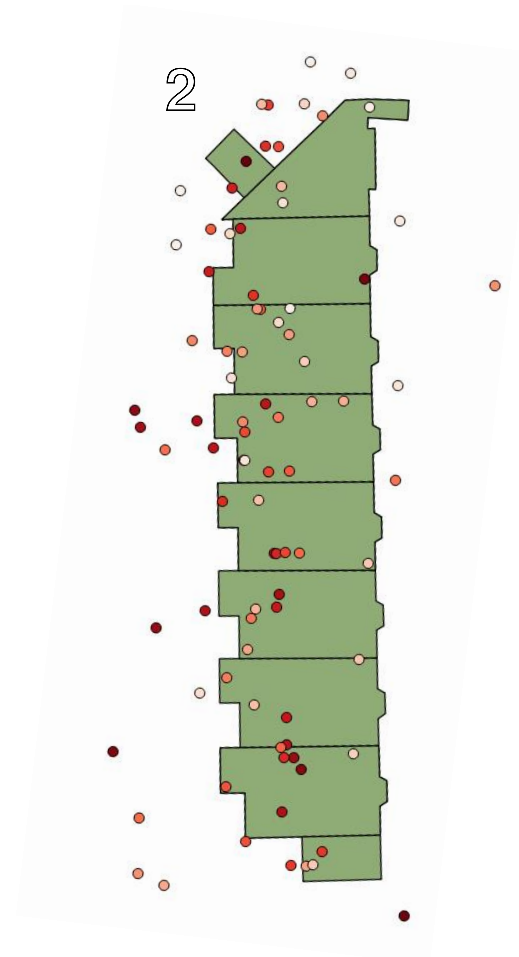
Points 3m above NAP (4.7m above ground)

Using 2 years of data

BACK FAÇADE

Buffer 6m radius



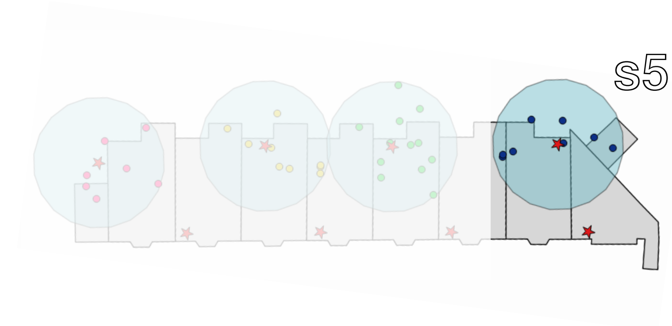


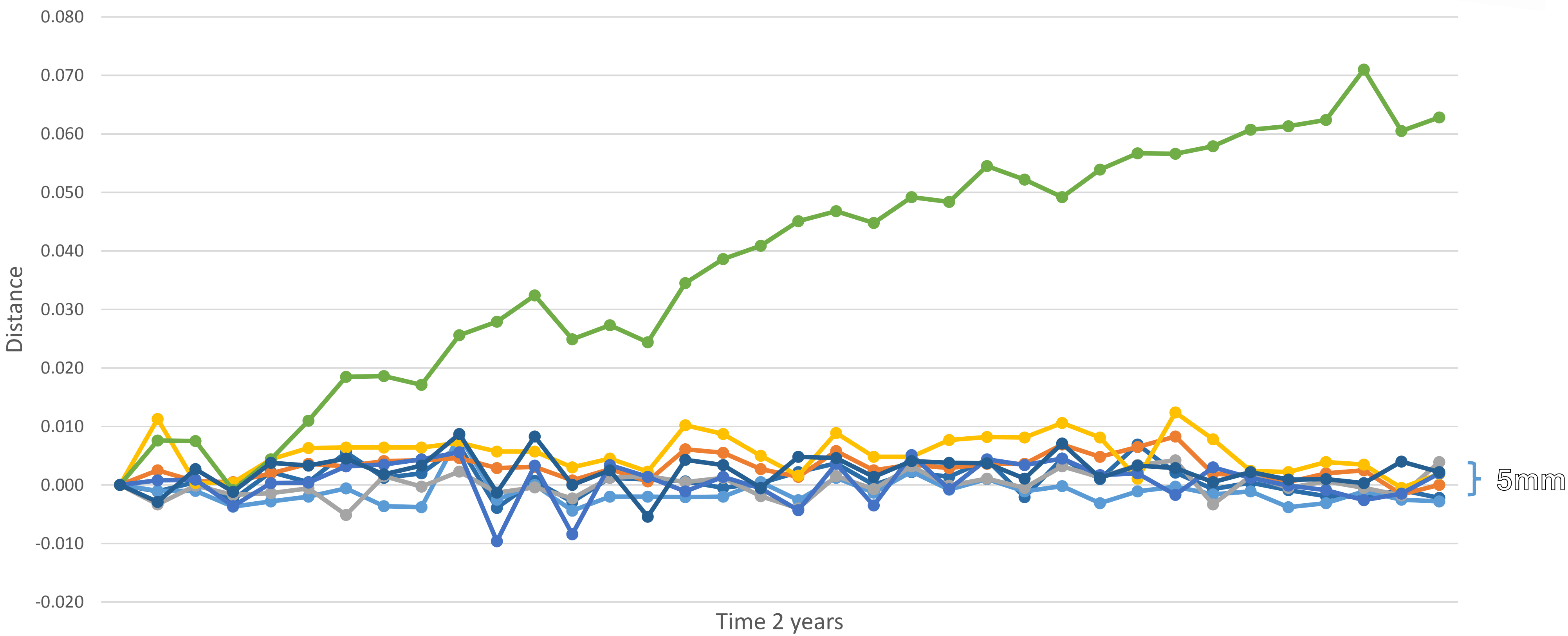
Building subsidence – InSAR data

Dataset 2 (best suited)

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



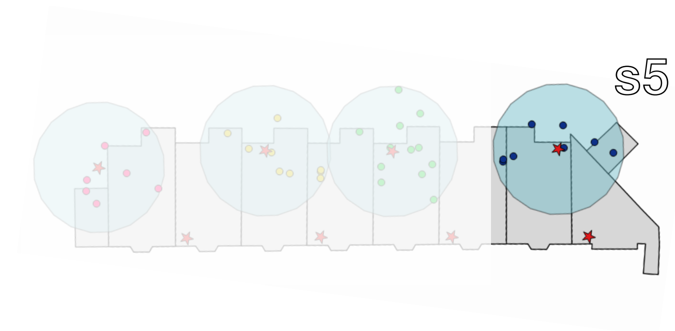


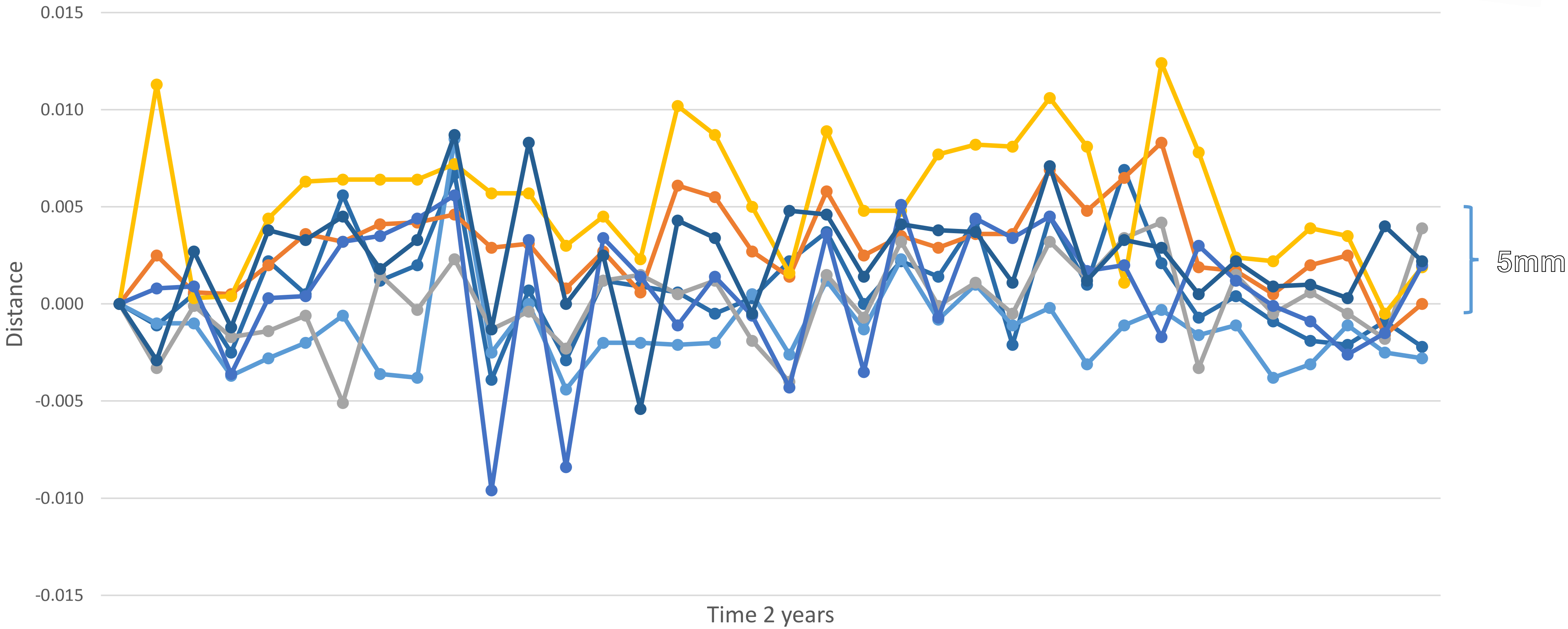
Building subsidence – InSAR data

Dataset 2 (best suited)

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius (No outlier)

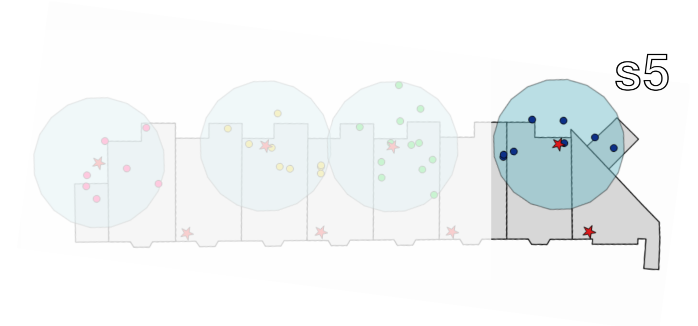


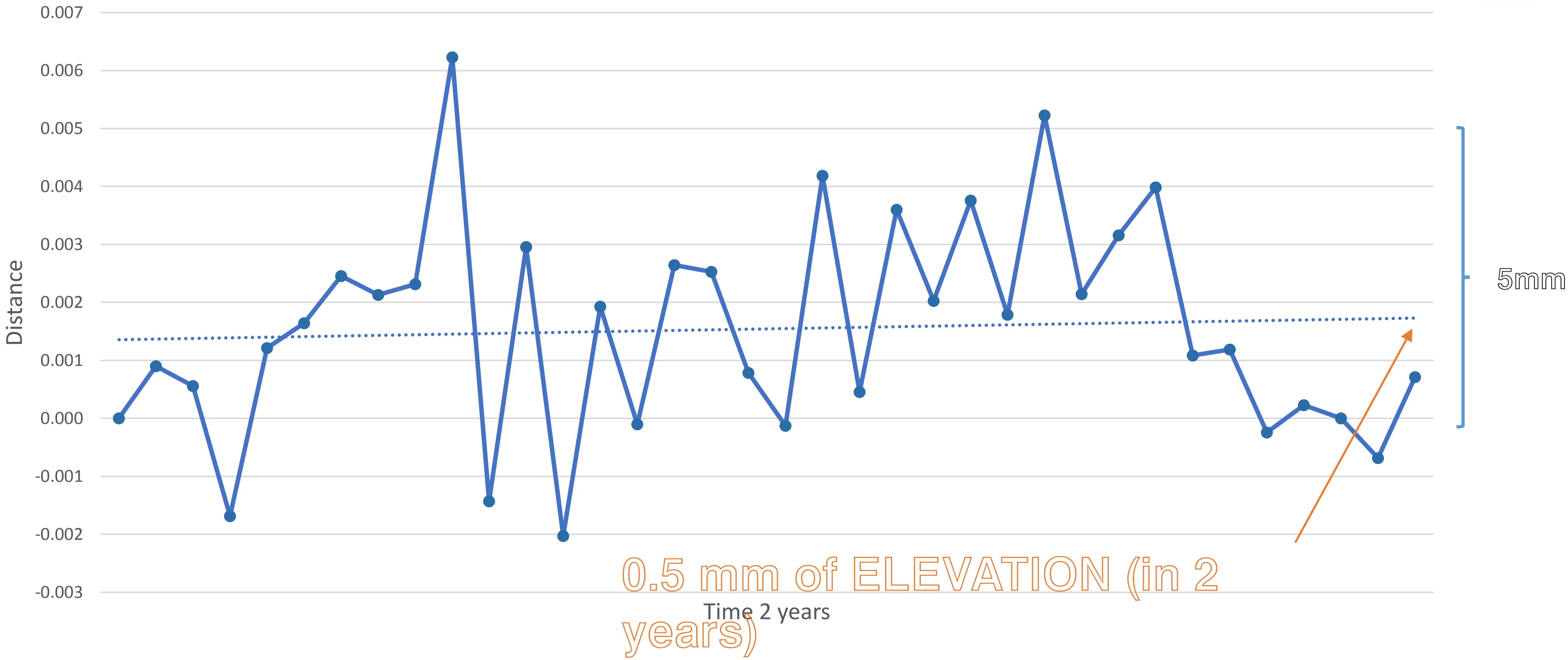


Building subsidence – InSAR data

Dataset 2 (best suited)
Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



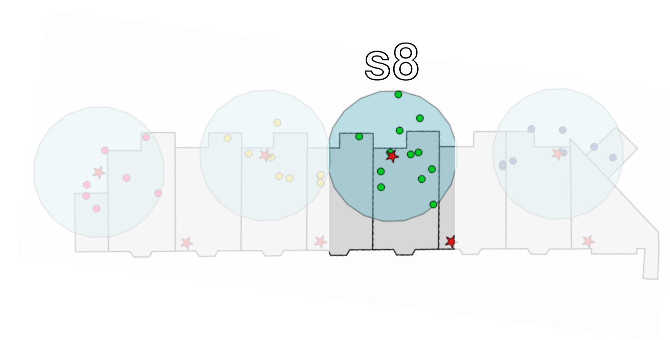


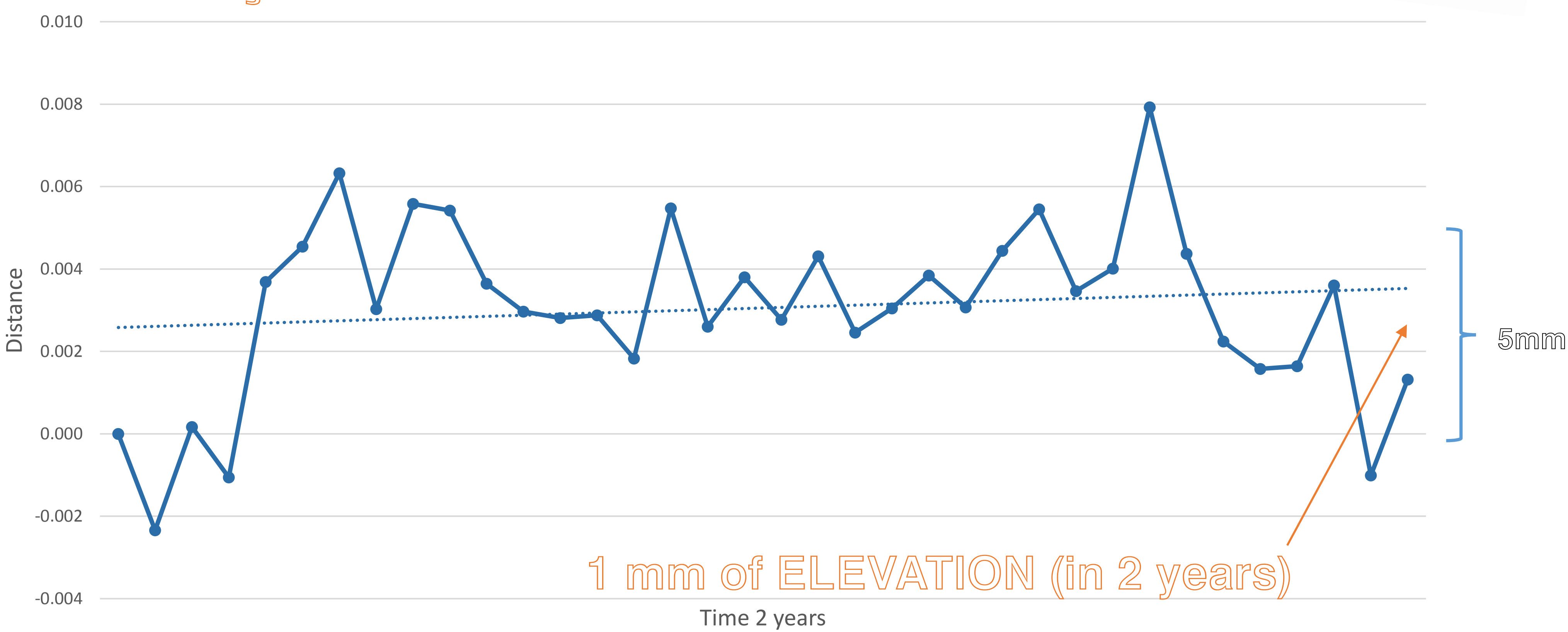
Building subsidence – InSAR data

Dataset 2 (best suited)

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



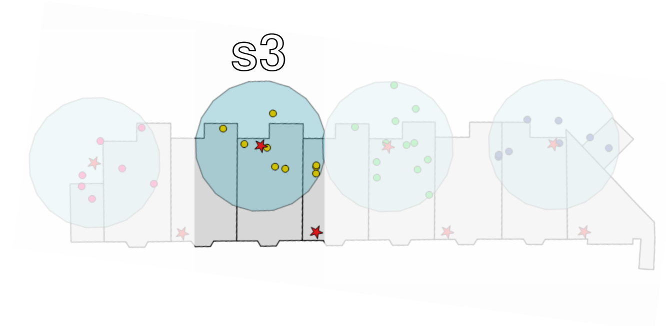


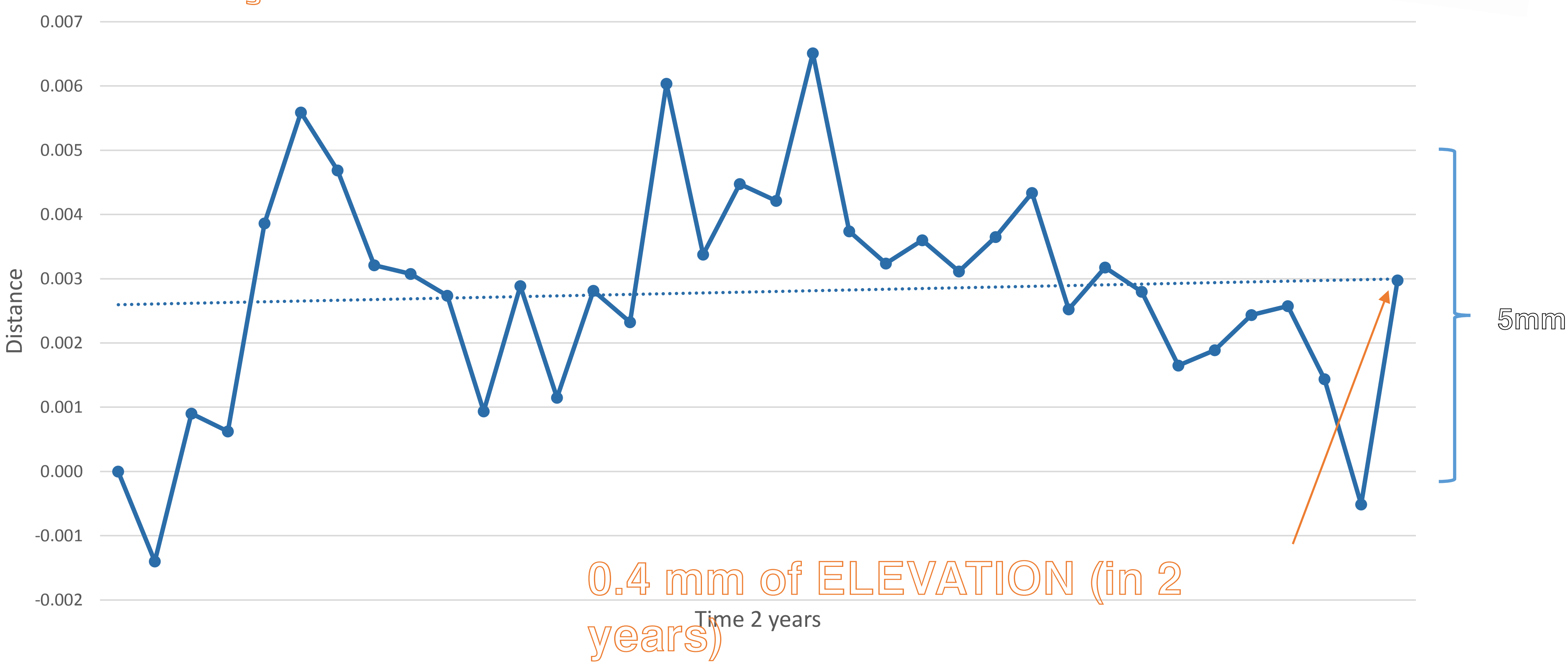
Building subsidence – InSAR data

Dataset 2 (best suited)

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



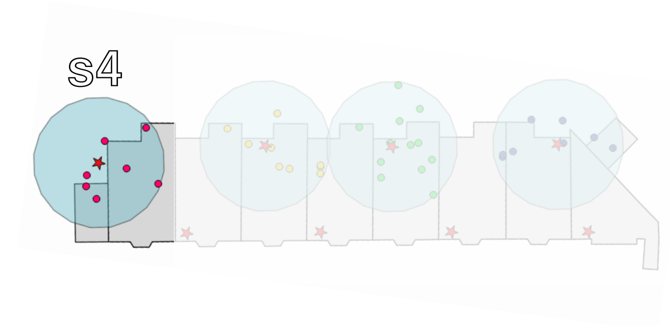


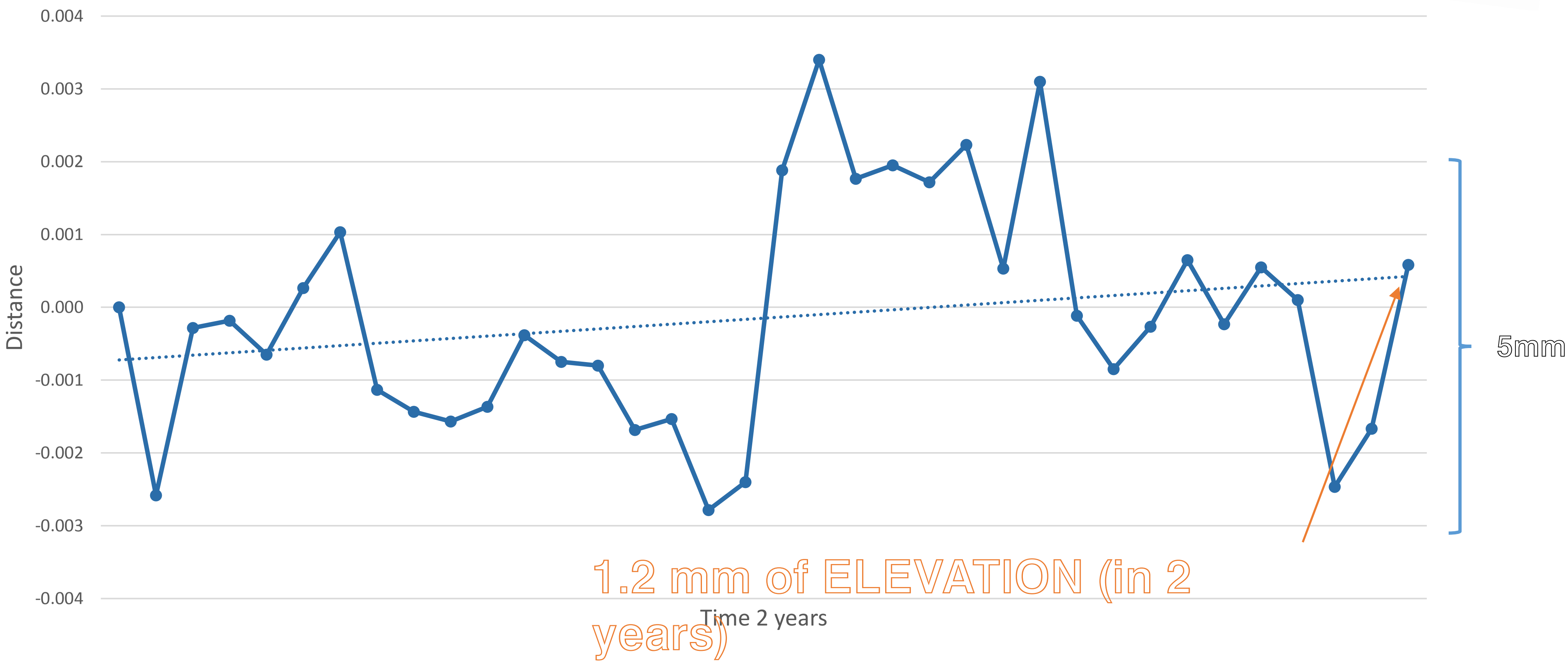
Building subsidence – InSAR data

Dataset 2 (best suited)

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



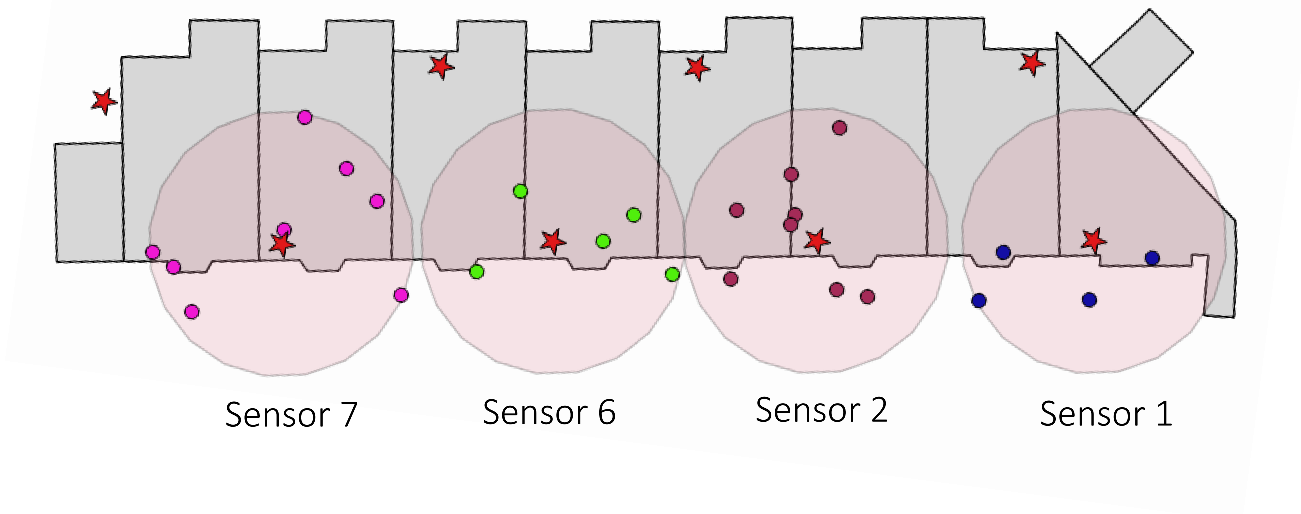


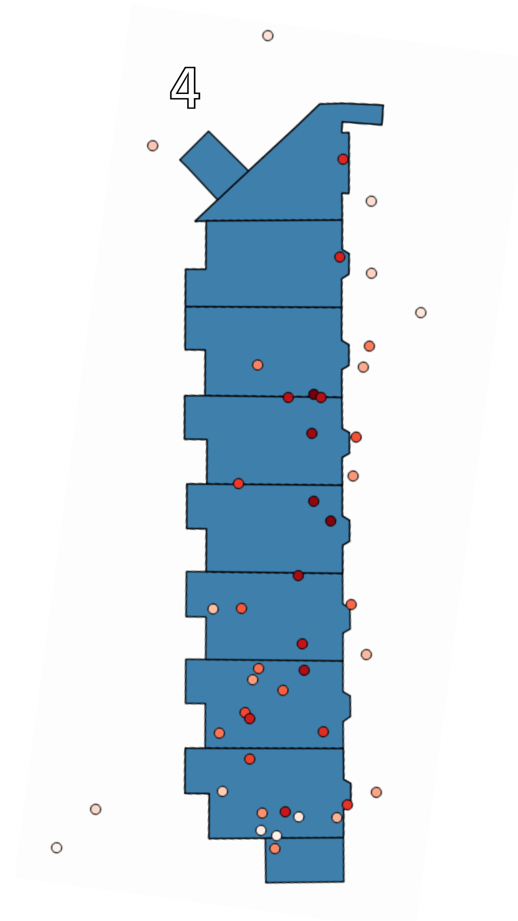
Building subsidence – InSAR data

Dataset 4 (best suited)
Points 3m above NAP (4.7m above ground)
Using 2 years of data

FRONT FAÇADE

Buffer 6m radius



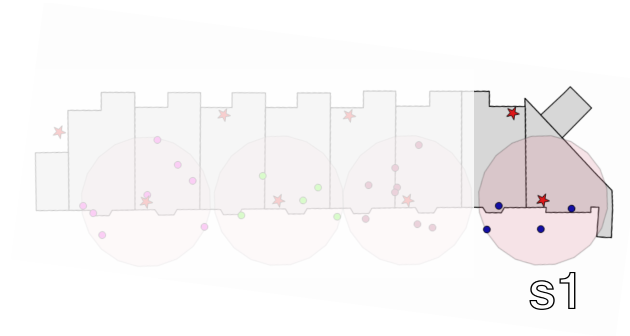


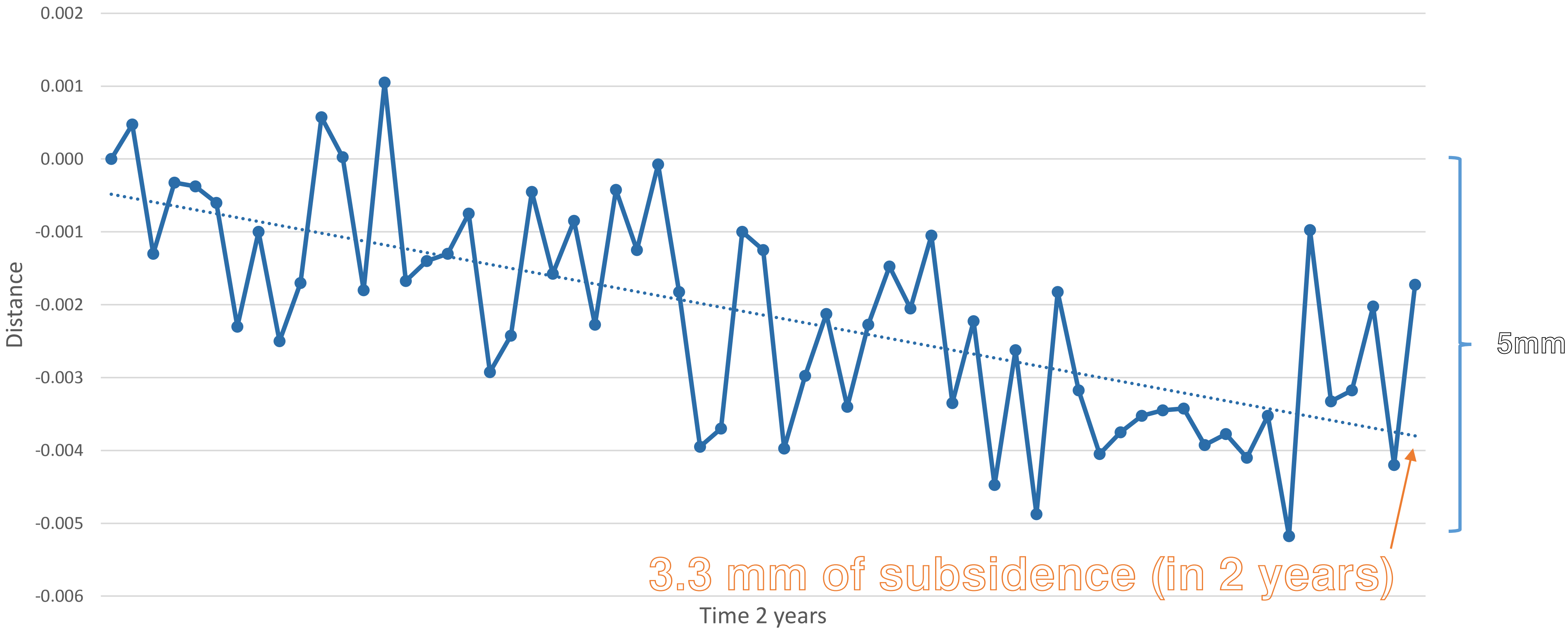
Building subsidence – InSAR data

Dataset 4 (best suited)

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



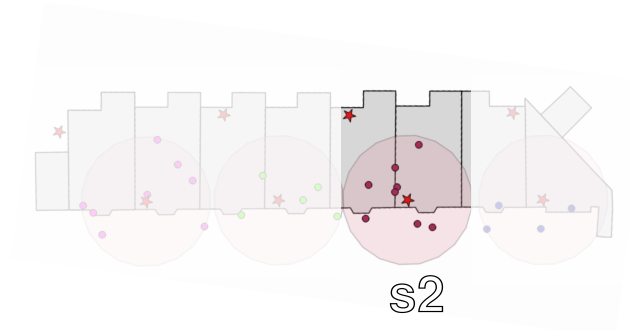


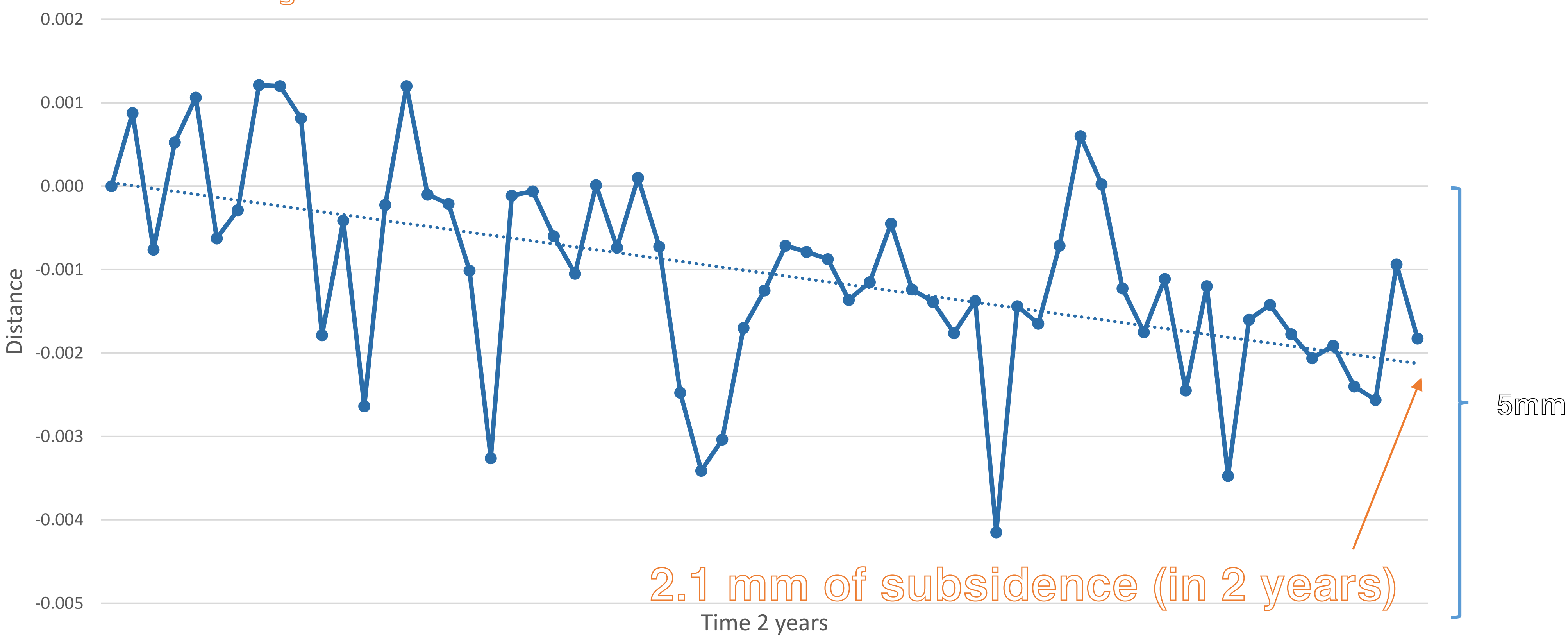
Building subsidence – InSAR data

Dataset 4 (best suited)

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



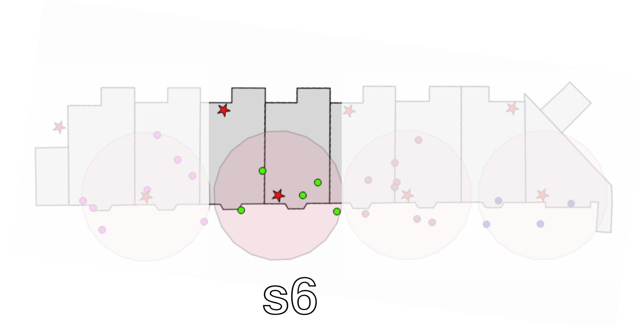


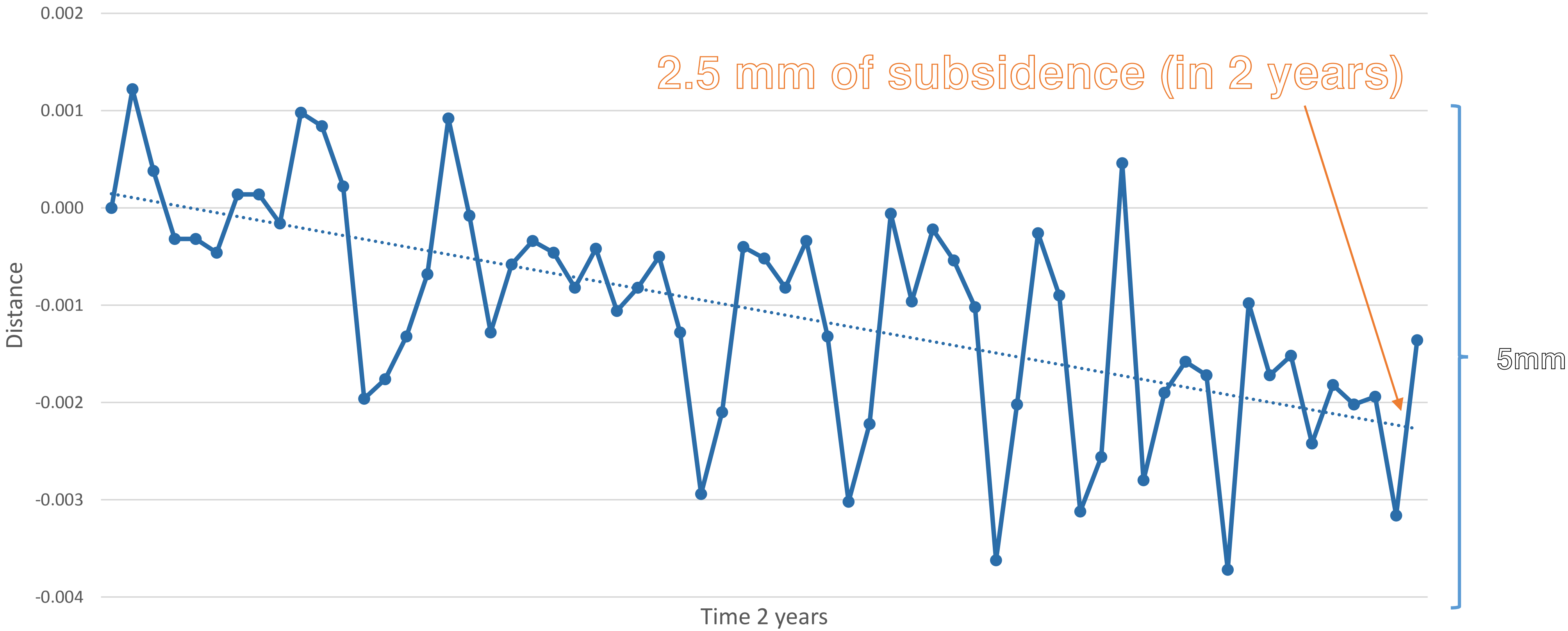
Building subsidence – InSAR data

Dataset 4 (best suited)

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



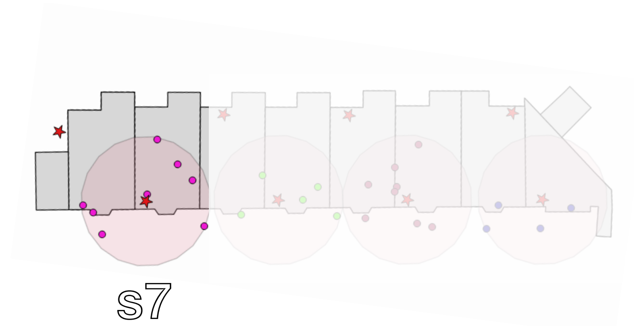


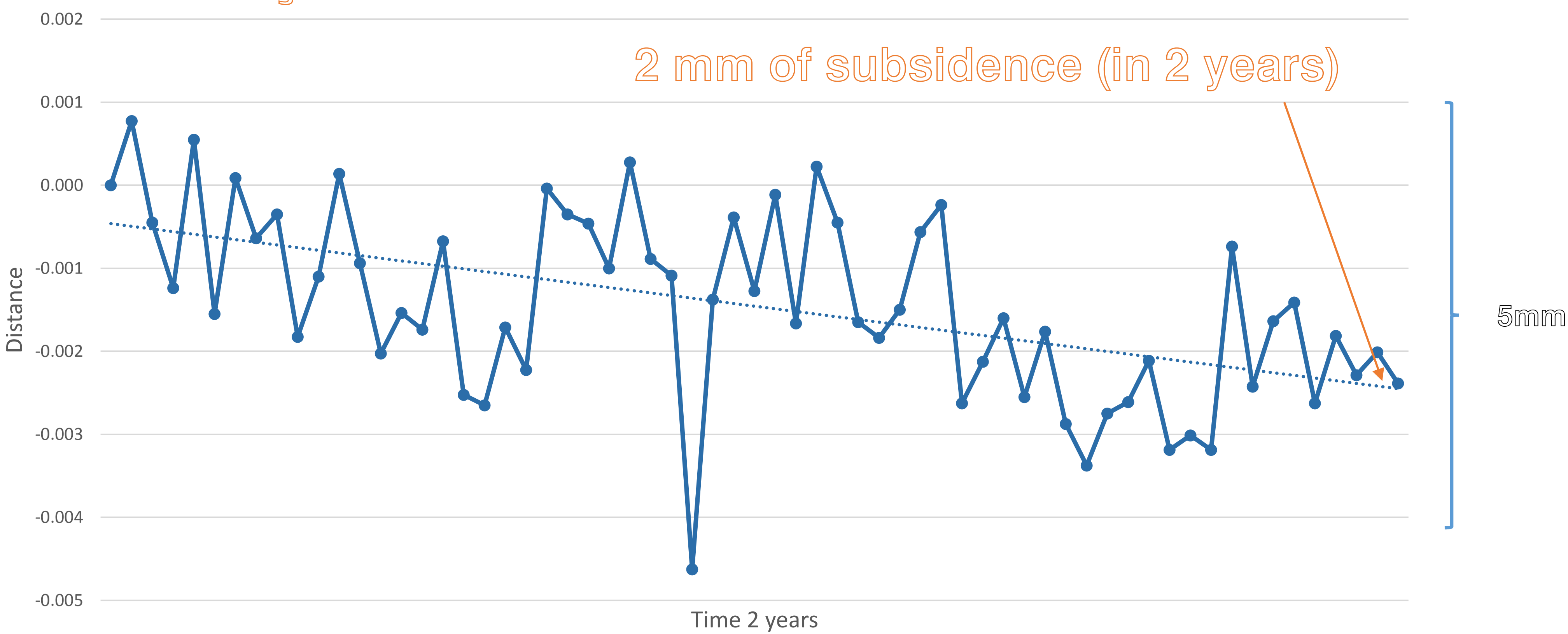
Building subsidence – InSAR data

Dataset 4 (best suited)

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



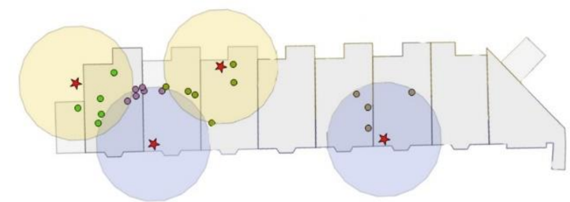


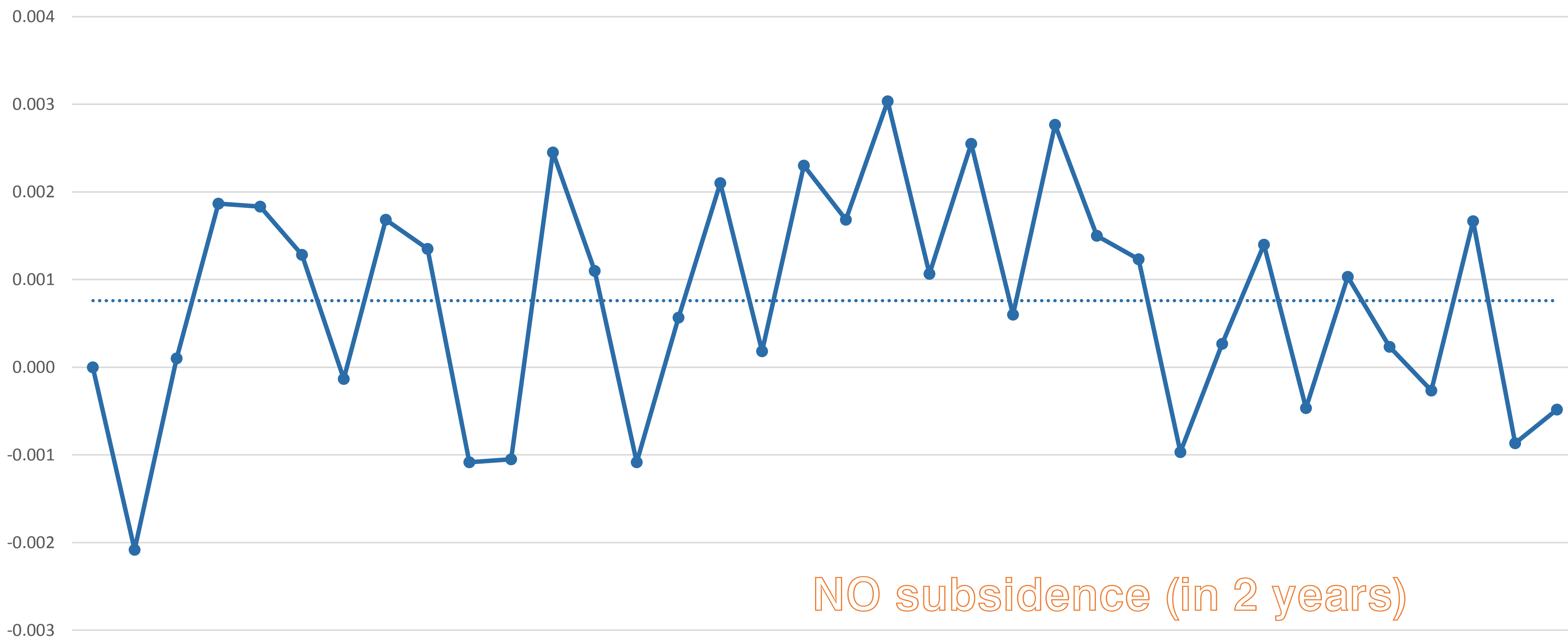
Building subsidence – InSAR data

Dataset 2

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



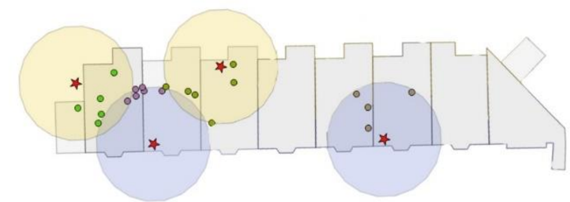


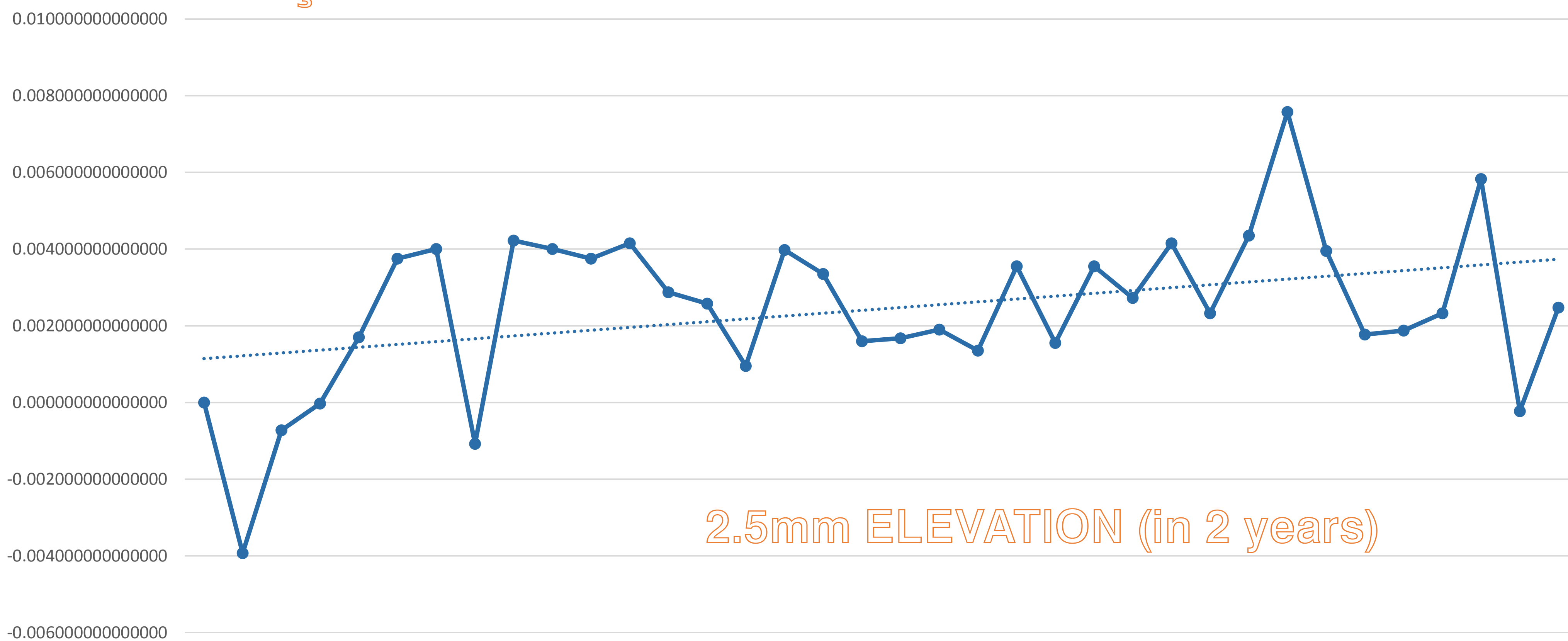
Building subsidence – InSAR data

Dataset 2

Points 3m above NAP (4.7m above ground)

FRONT FAÇADE Buffer 6m radius



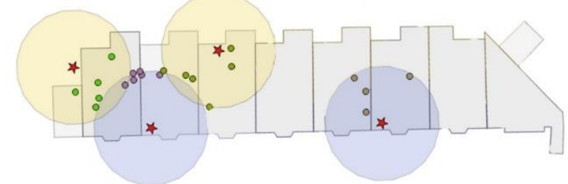


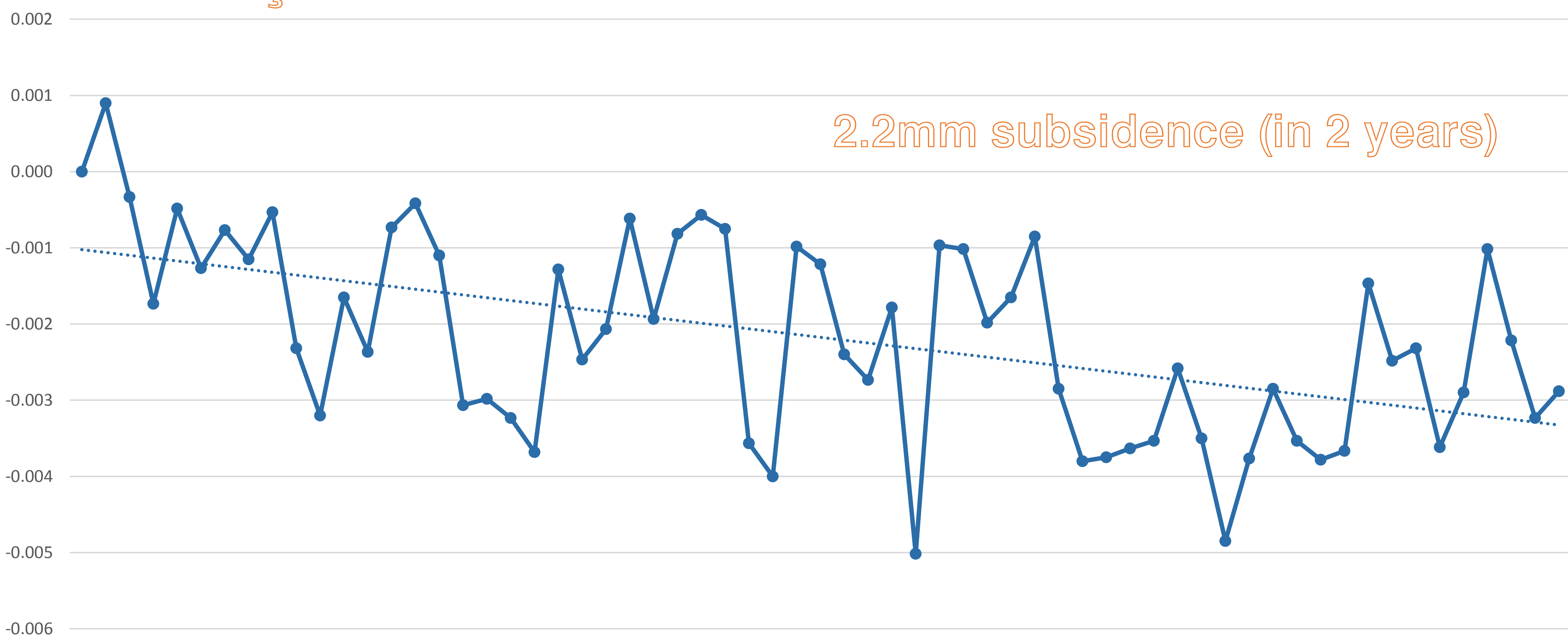
Building subsidence – InSAR data

Dataset 4

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius



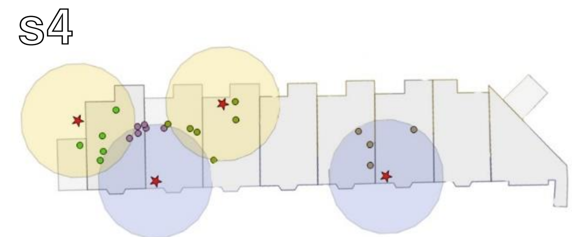


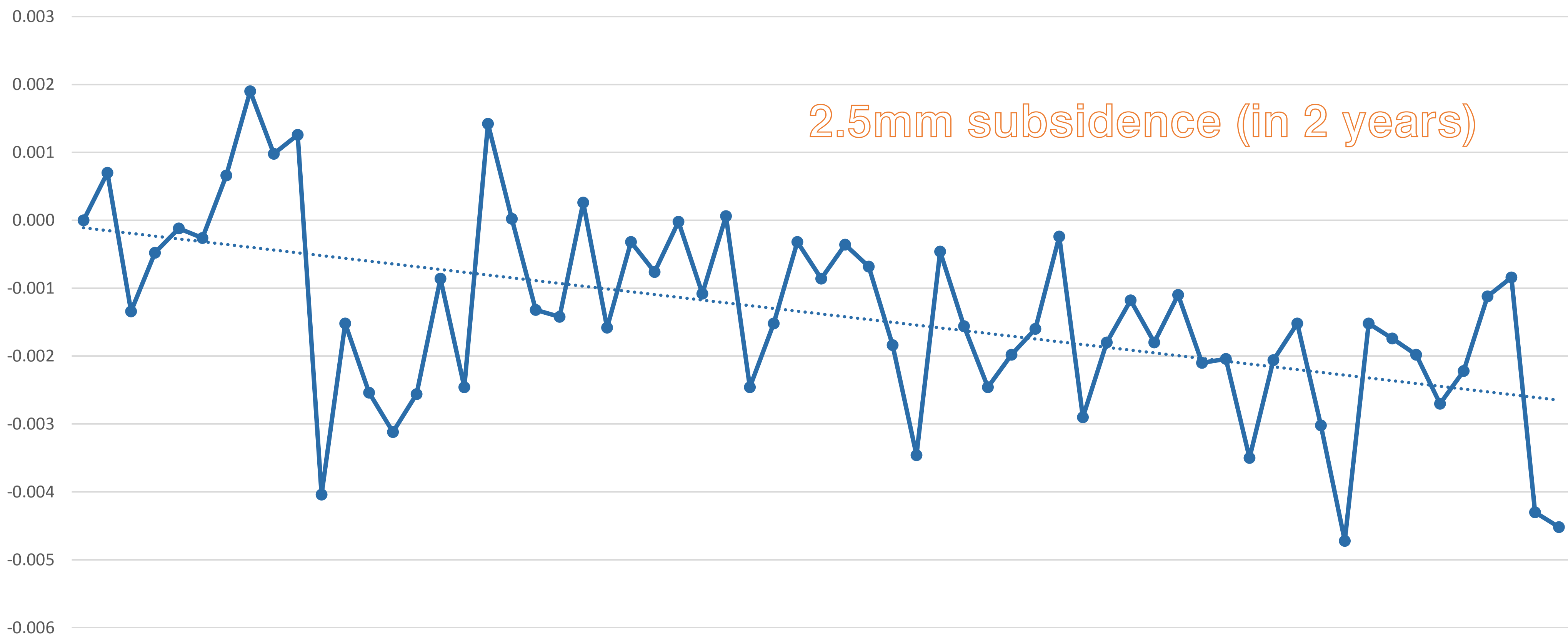
Building subsidence – InSAR data

Dataset 4

Points 3m above NAP (4.7m above ground)

BACK FAÇADE Buffer 6m radius





3.e

InSAR Data

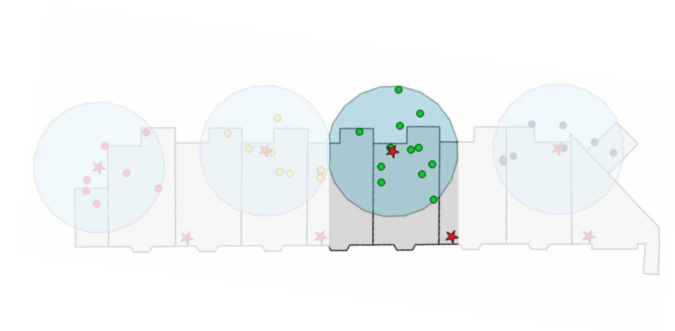
Comparison between InSAR and InSAR + LiDAR

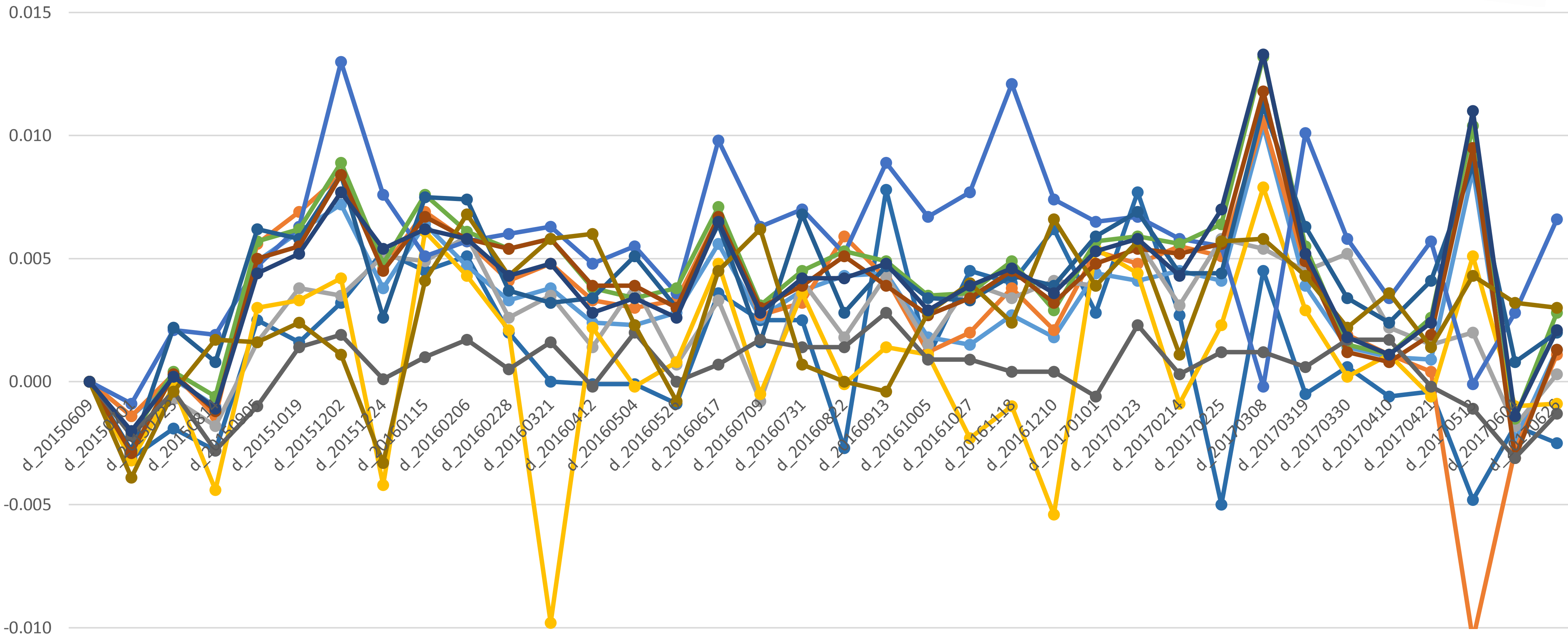
Sensor 8 - comparison LiDAR

No filter

Dataset 2 – Backyard facade

Buffer area 6mt



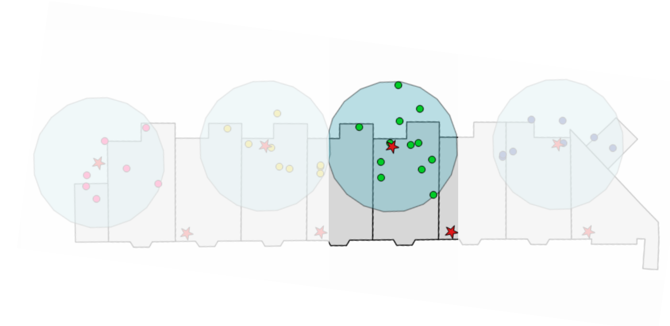


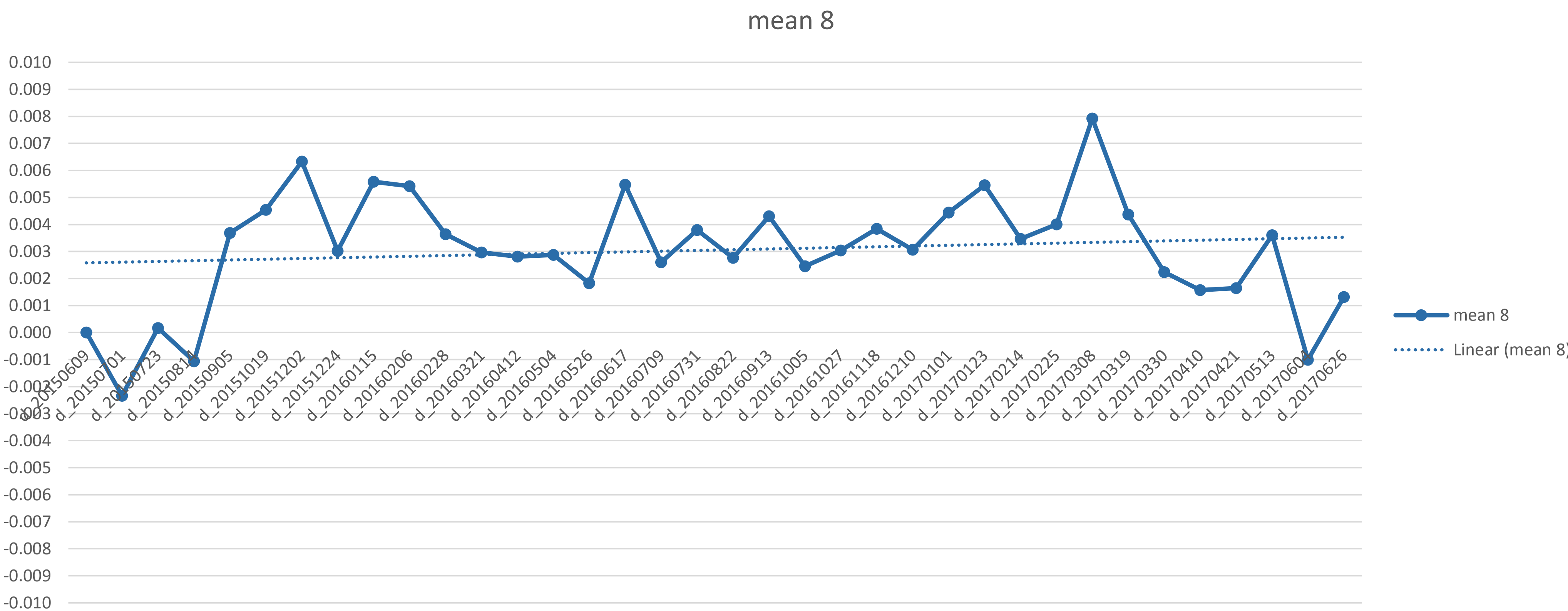
Sensor 8 - comparison LiDAR

No filter

Dataset 2 – Backyard facade

Buffer area 6mt



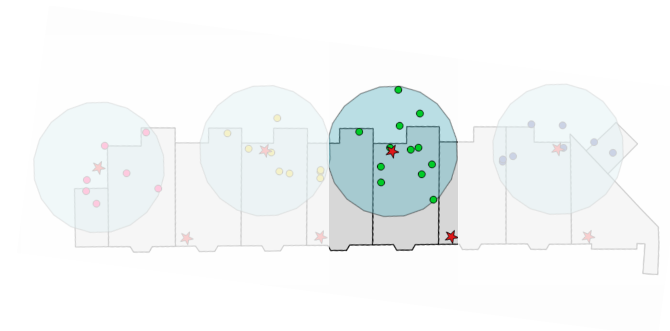


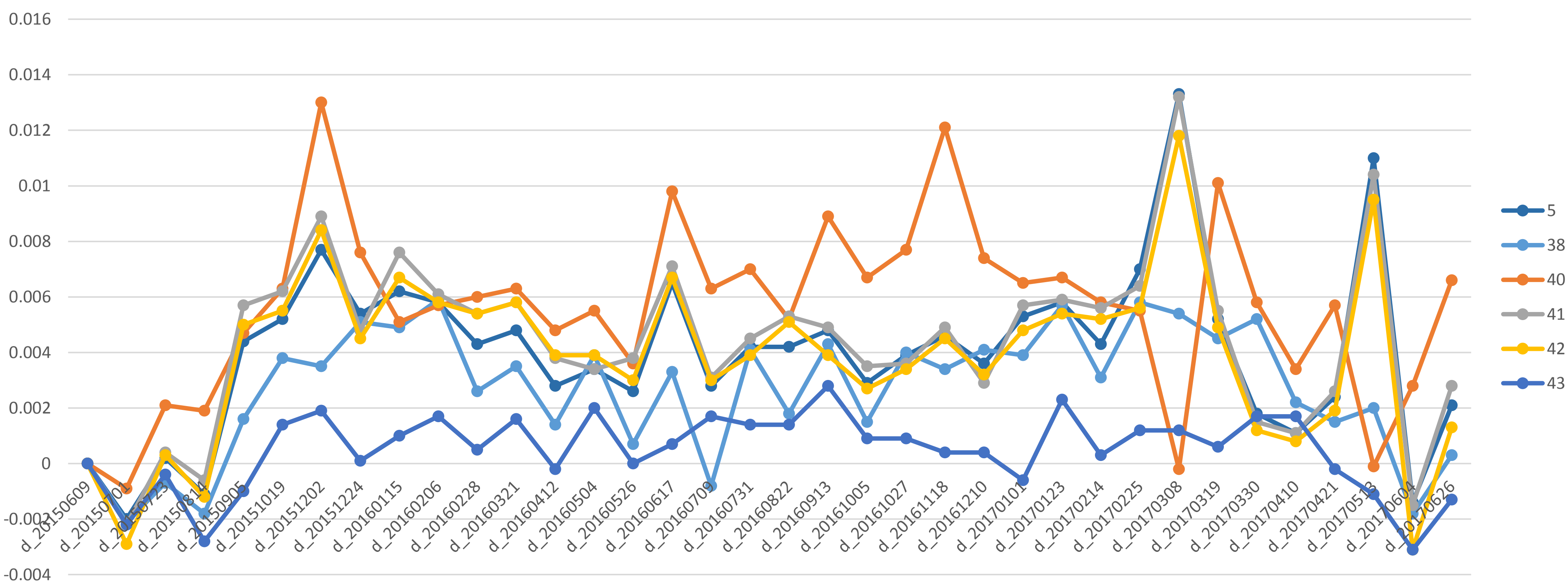
Sensor 8 - comparison LiDAR

Search in 3mt x 3mt

Dataset 2 – Backyard facade

Buffer area 6mt



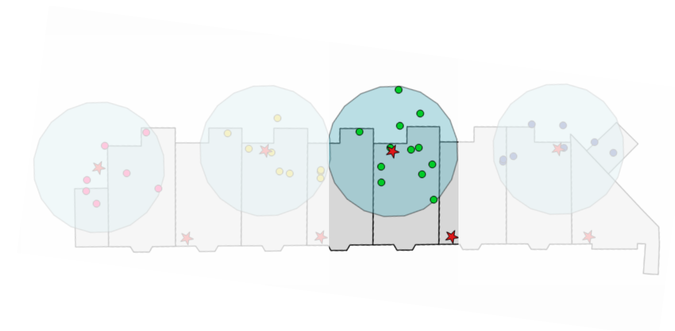


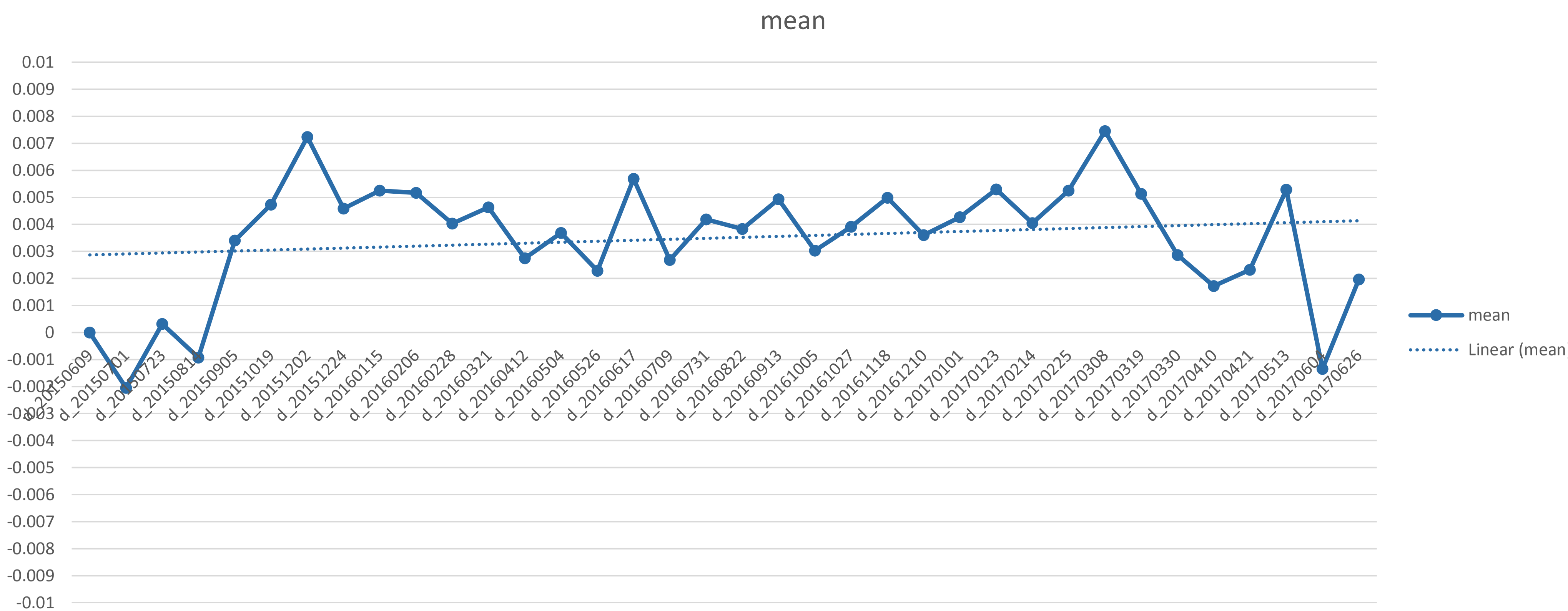
Sensor 8 - comparison LiDAR

Search in 3mt x 3mt

Dataset 2 – Backyard facade

Buffer area 6mt



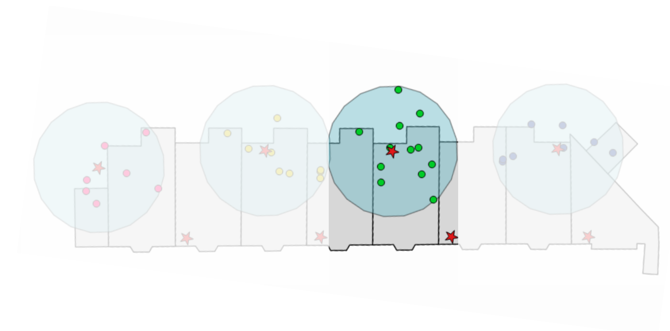


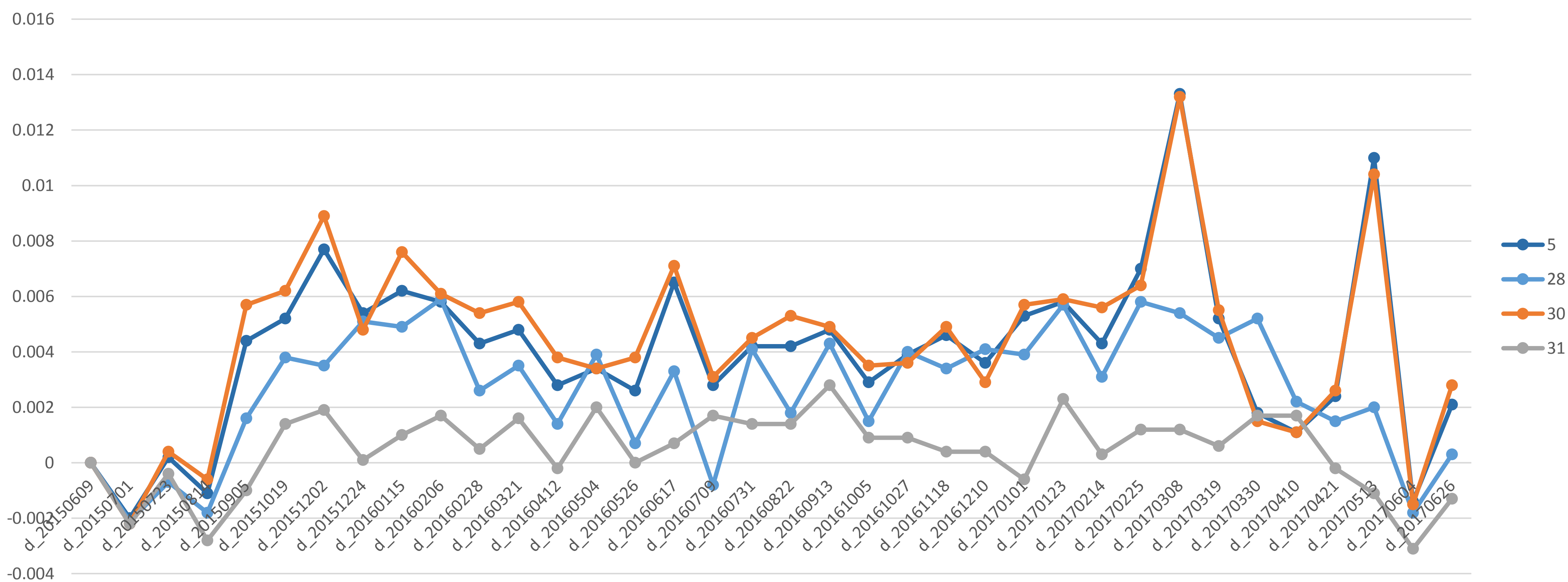
Sensor 8 - comparison LiDAR

Search in 3mt x 0,5mt

Dataset 2 – Backyard facade

Buffer area 6mt



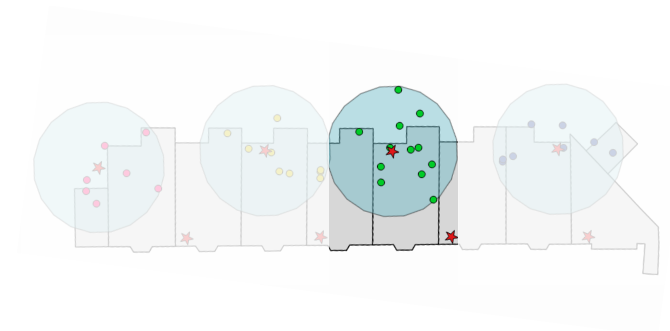


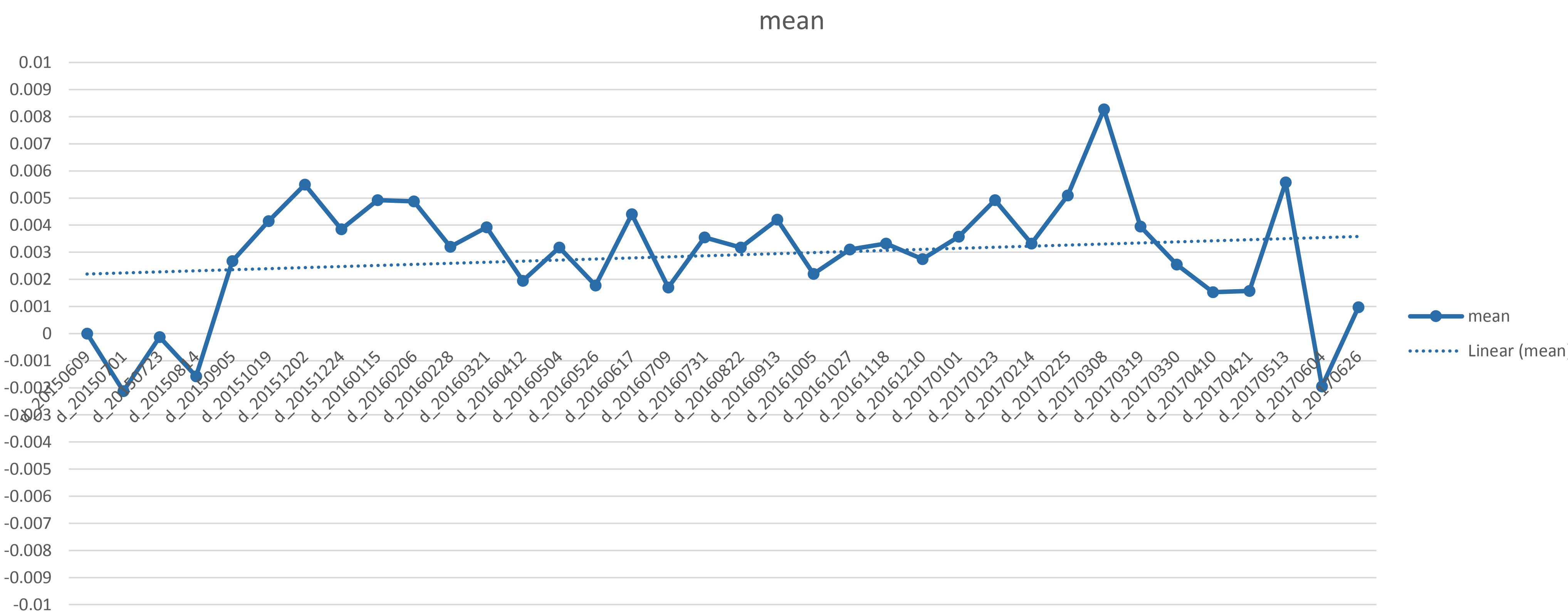
Sensor 8 - comparison LiDAR

Search in 3mt x 0,5mt

Dataset 2 – Backyard facade

Buffer area 6mt





3.f

InSAR data

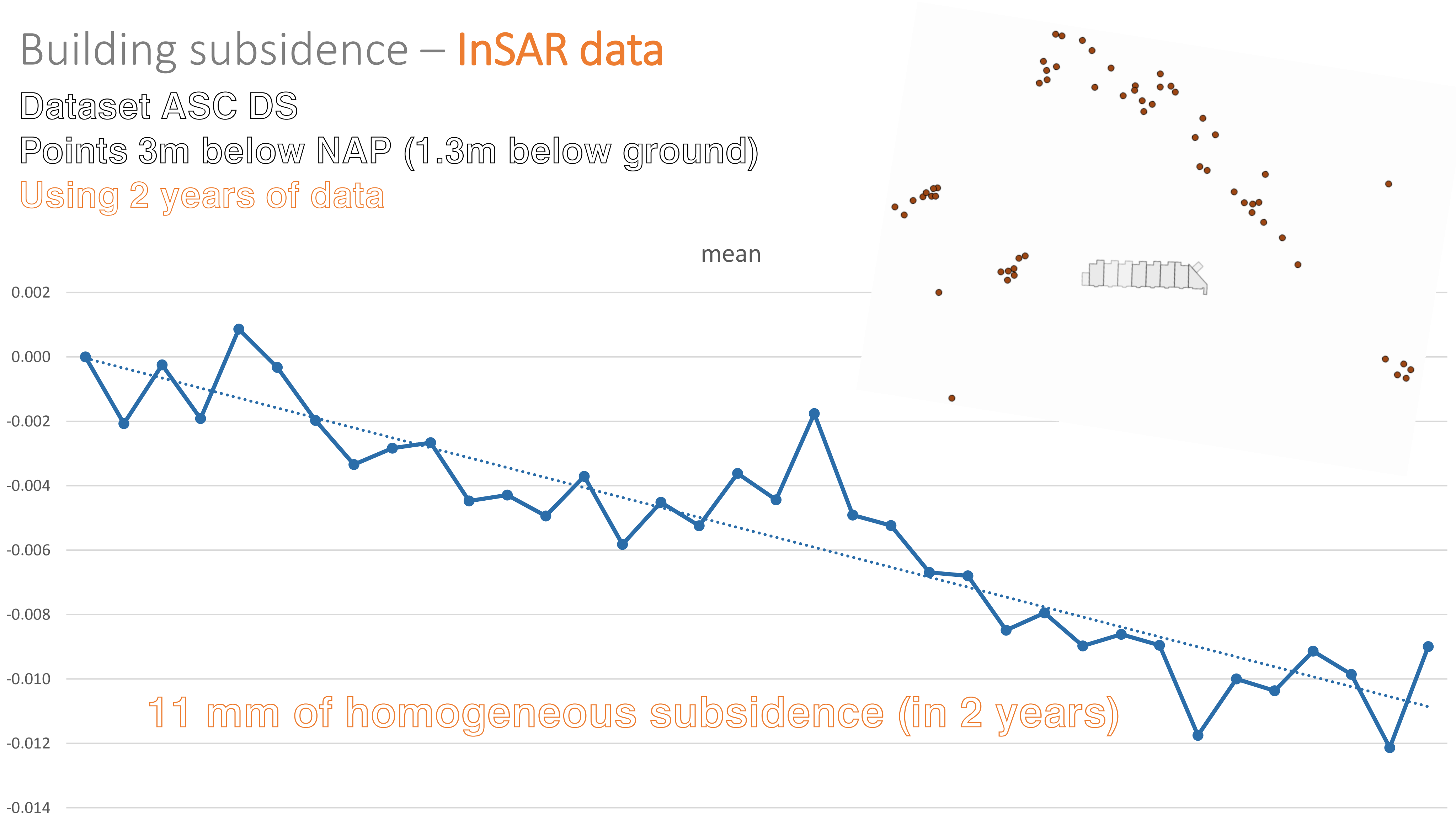
Streets and ground points

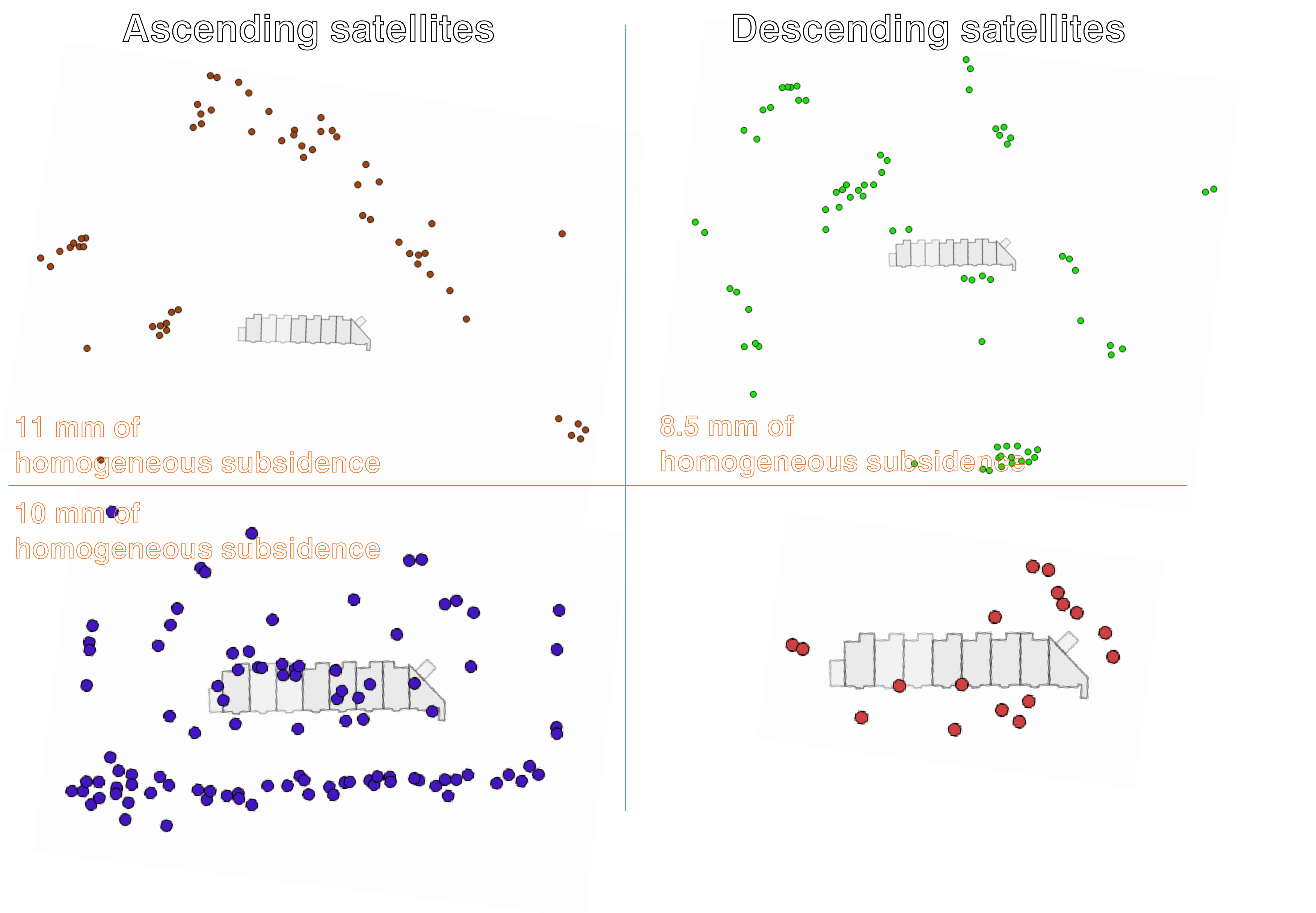
Building subsidence – InSAR data

Dataset ASC DS

Points 3m below NAP (1.3m below ground)

Using 2 years of data



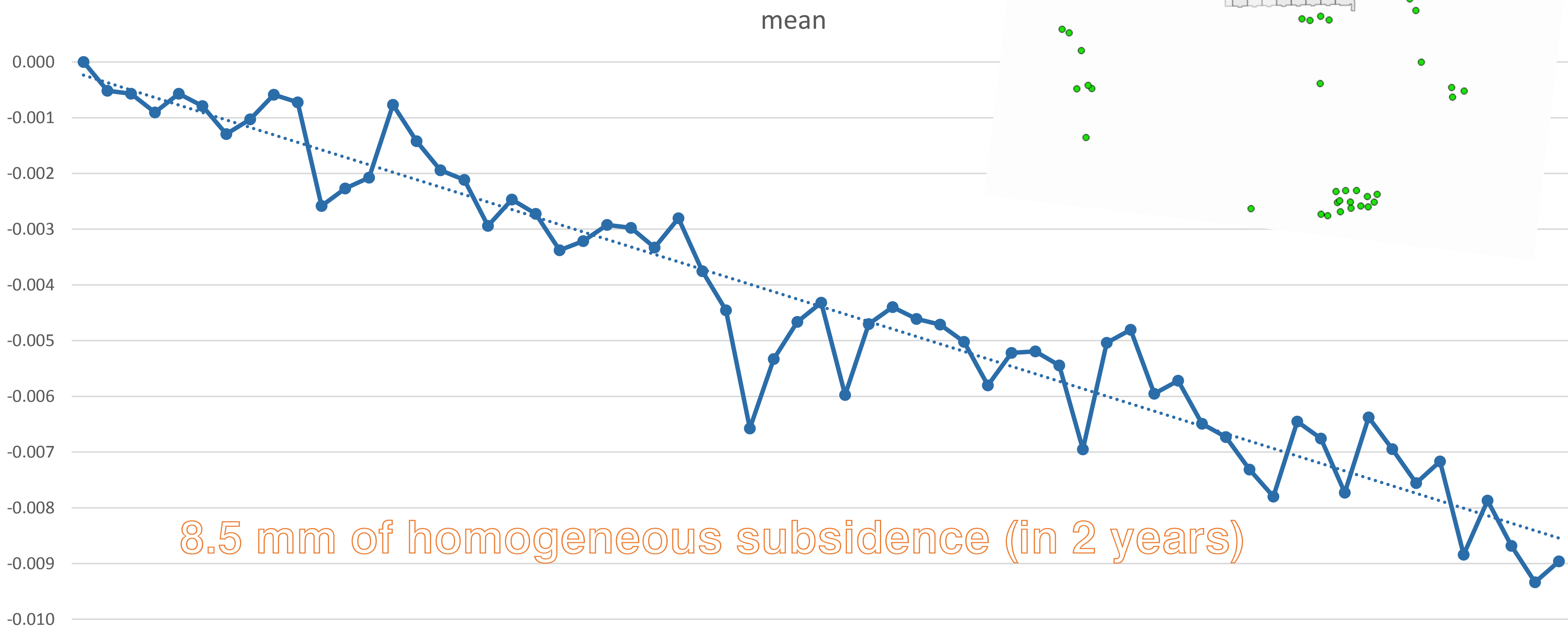

Ascending satellites
Descending satellites
11 mm of
homogeneous subsidence
8.5 mm of
homogeneous subsidence
10 mm of
homogeneous subsidence

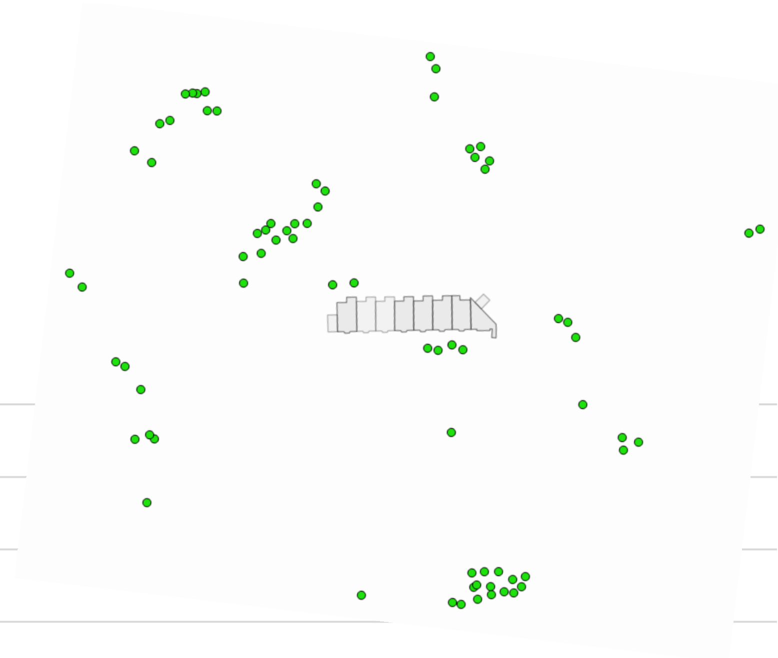
Building subsidence – InSAR data

Dataset DSC DS

Points 3m below NAP (1.3m below ground)

Using 2 years of data



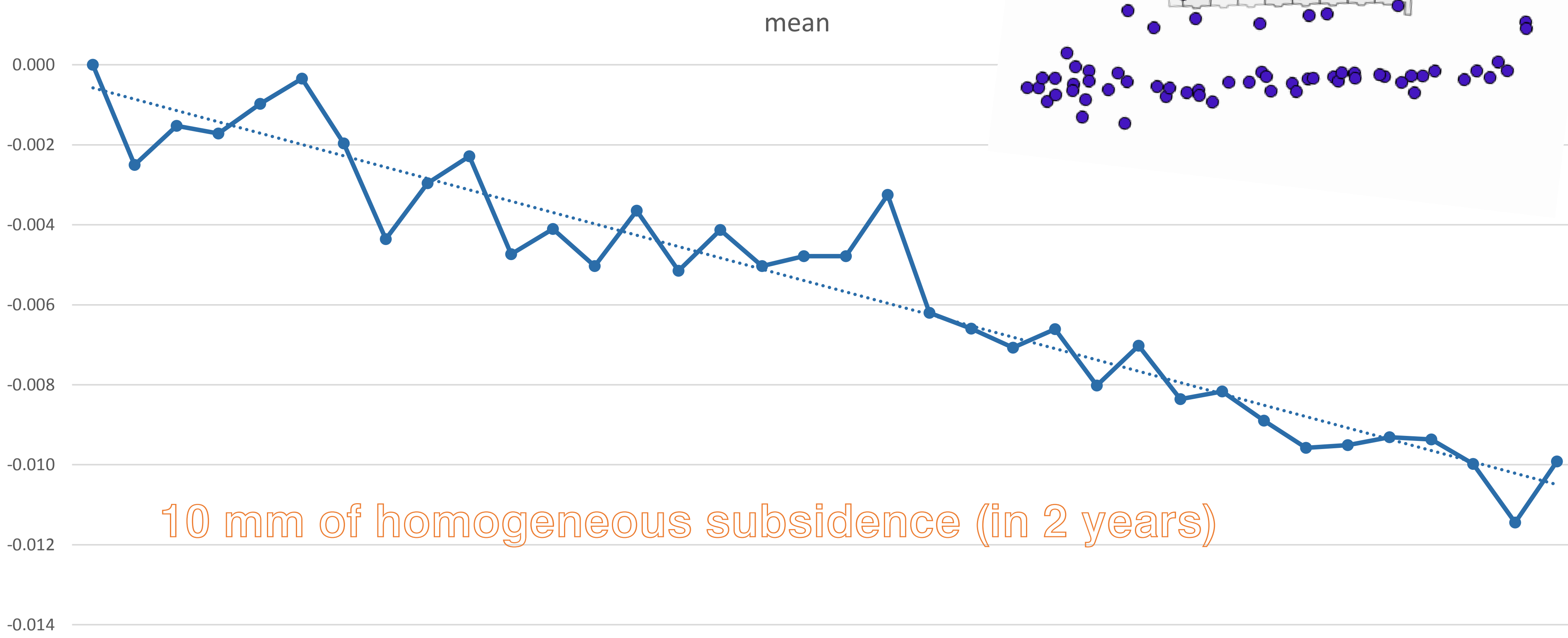


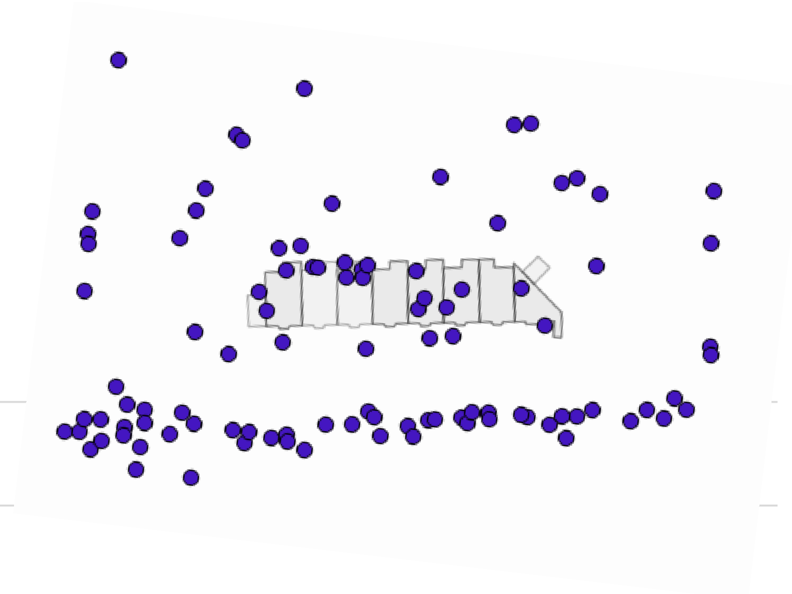
Building subsidence – InSAR data

Dataset ASC PS

Points 3m below NAP (1.3m below ground)

Using 2 years of data



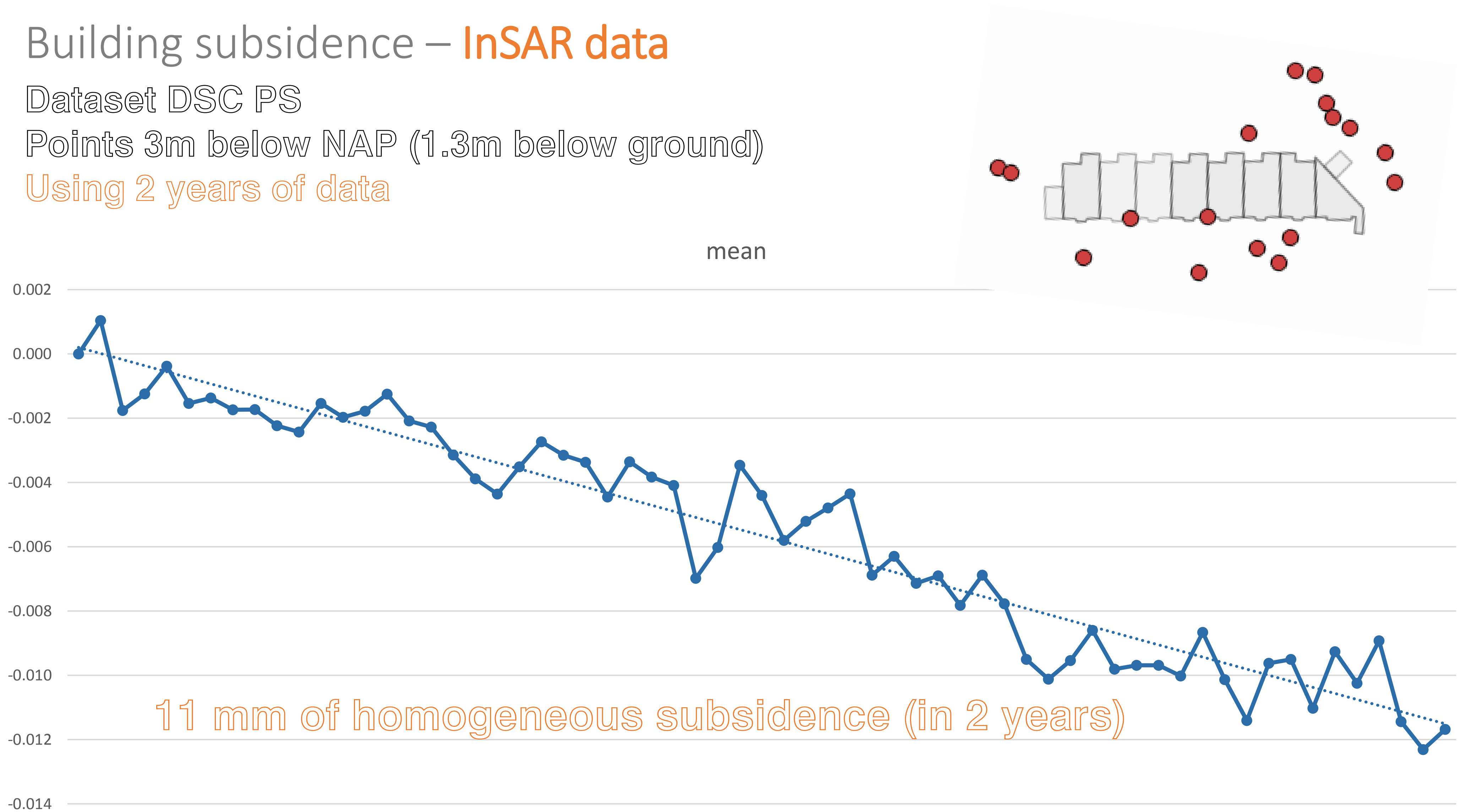


Building subsidence – InSAR data

Dataset DSC PS

Points 3m below NAP (1.3m below ground)

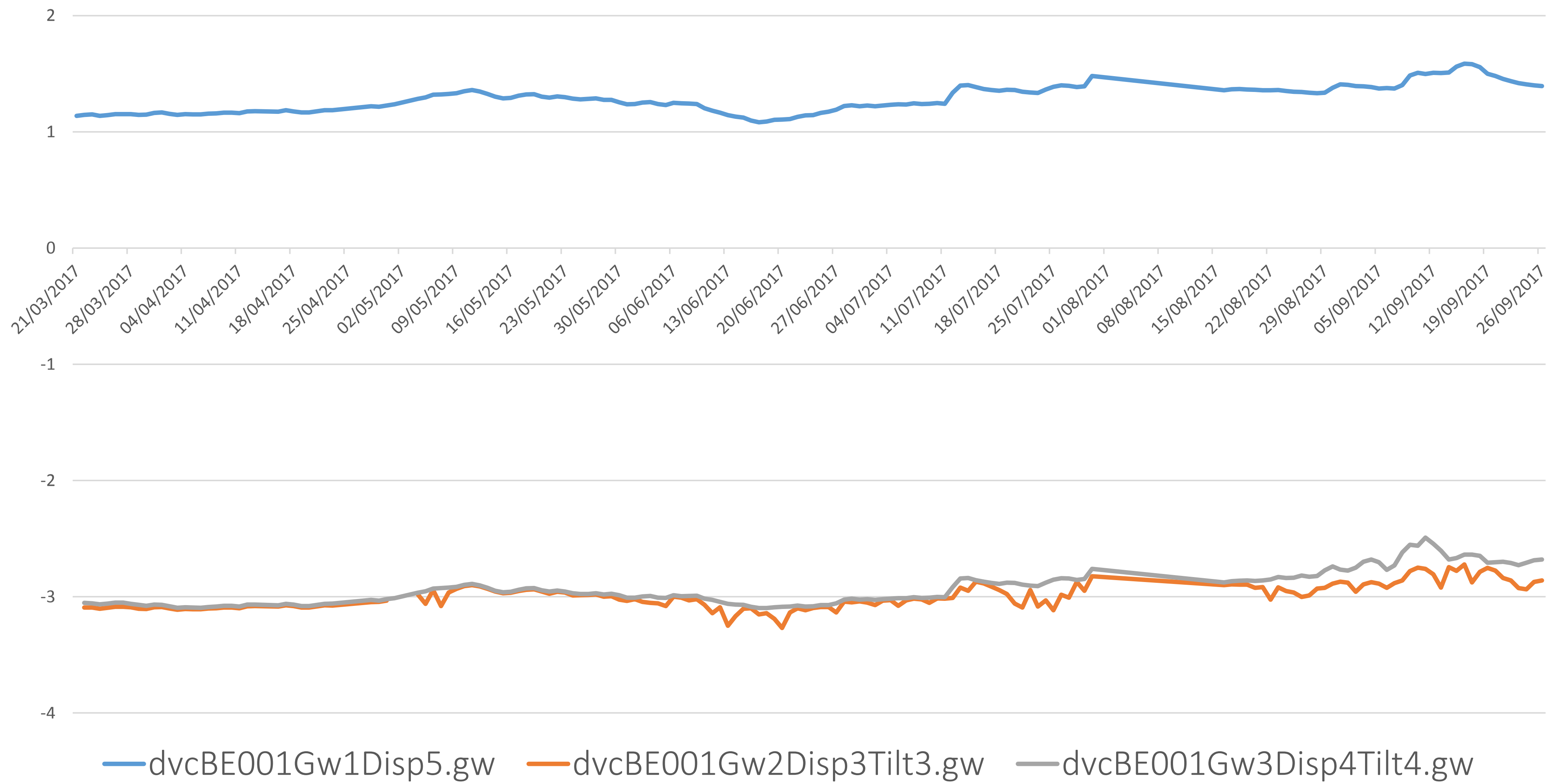
Using 2 years of data

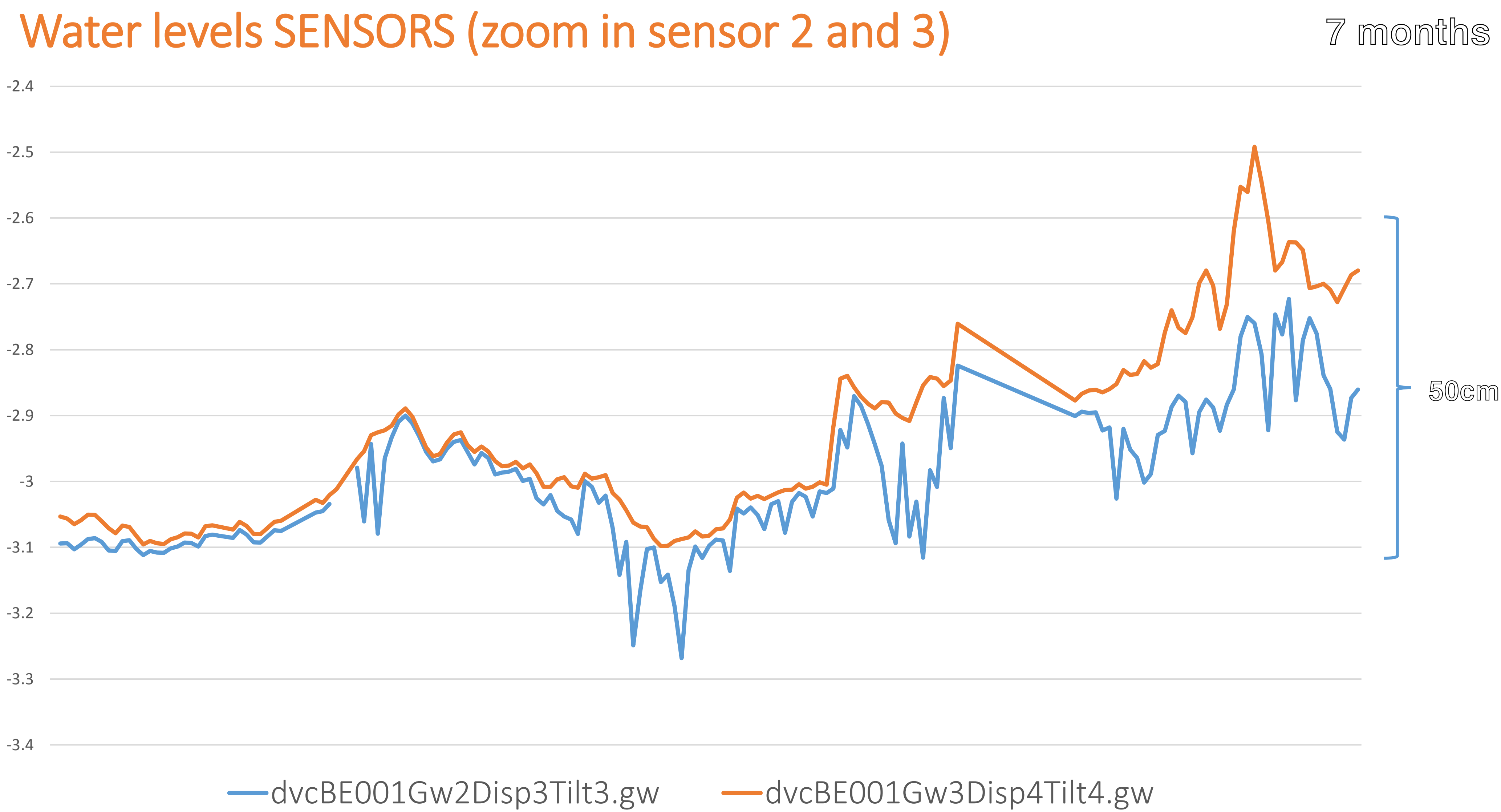


4
Water level sensors data

Water levels SENSORS – (RAW data)

7 months

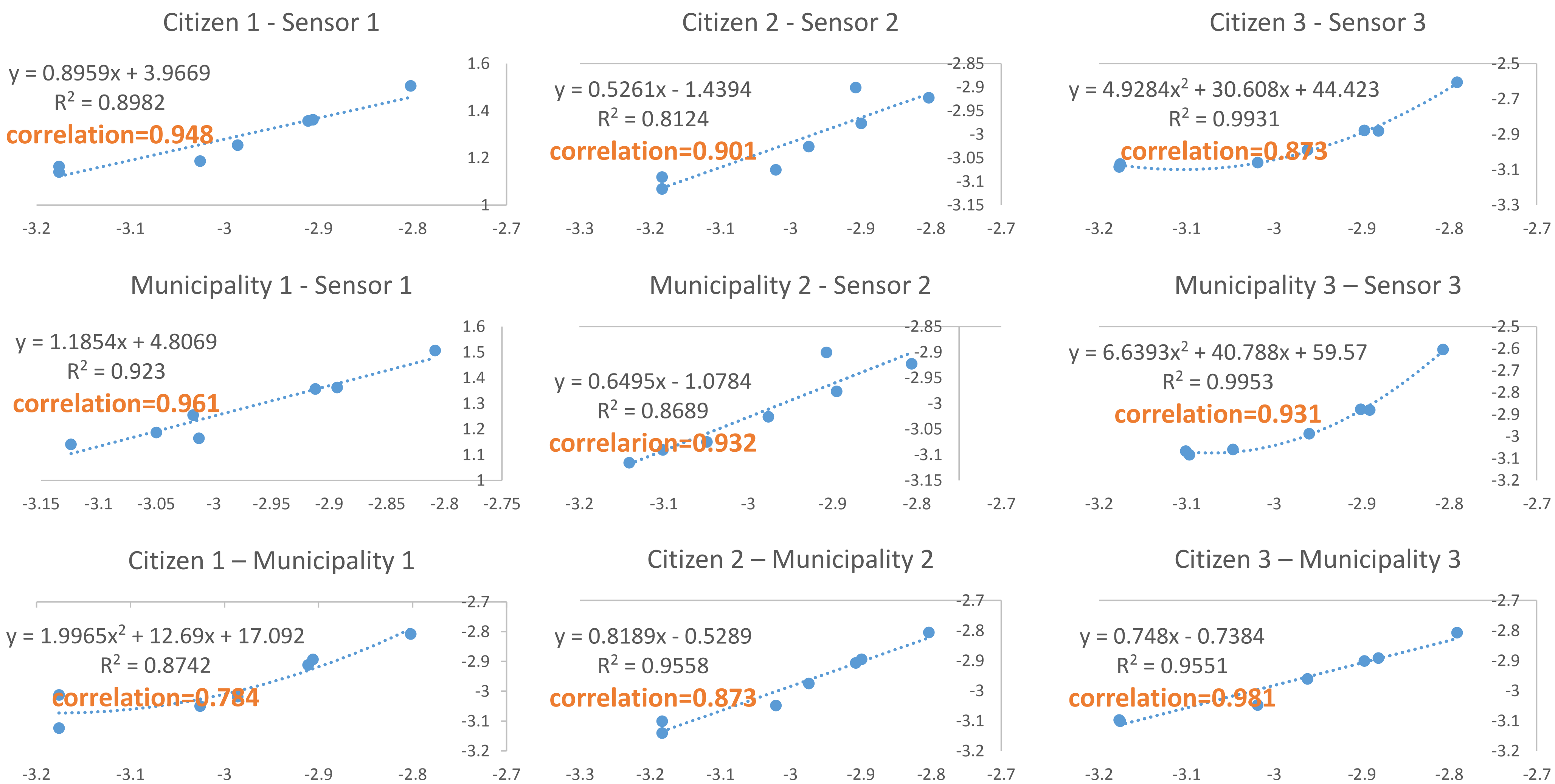



Water levels SENSORS (zoom in sensor 2 and 3)
7 months
-2.4
-2.5
-2.6
-2.7
-2.8
-2.9
-3
-3.1
-3.2
-3.3
-3.4
50cm
dvcBE001Gw2Disp3Tilt3.gw
dvcBE001Gw3Disp4Tilt4.gw

5

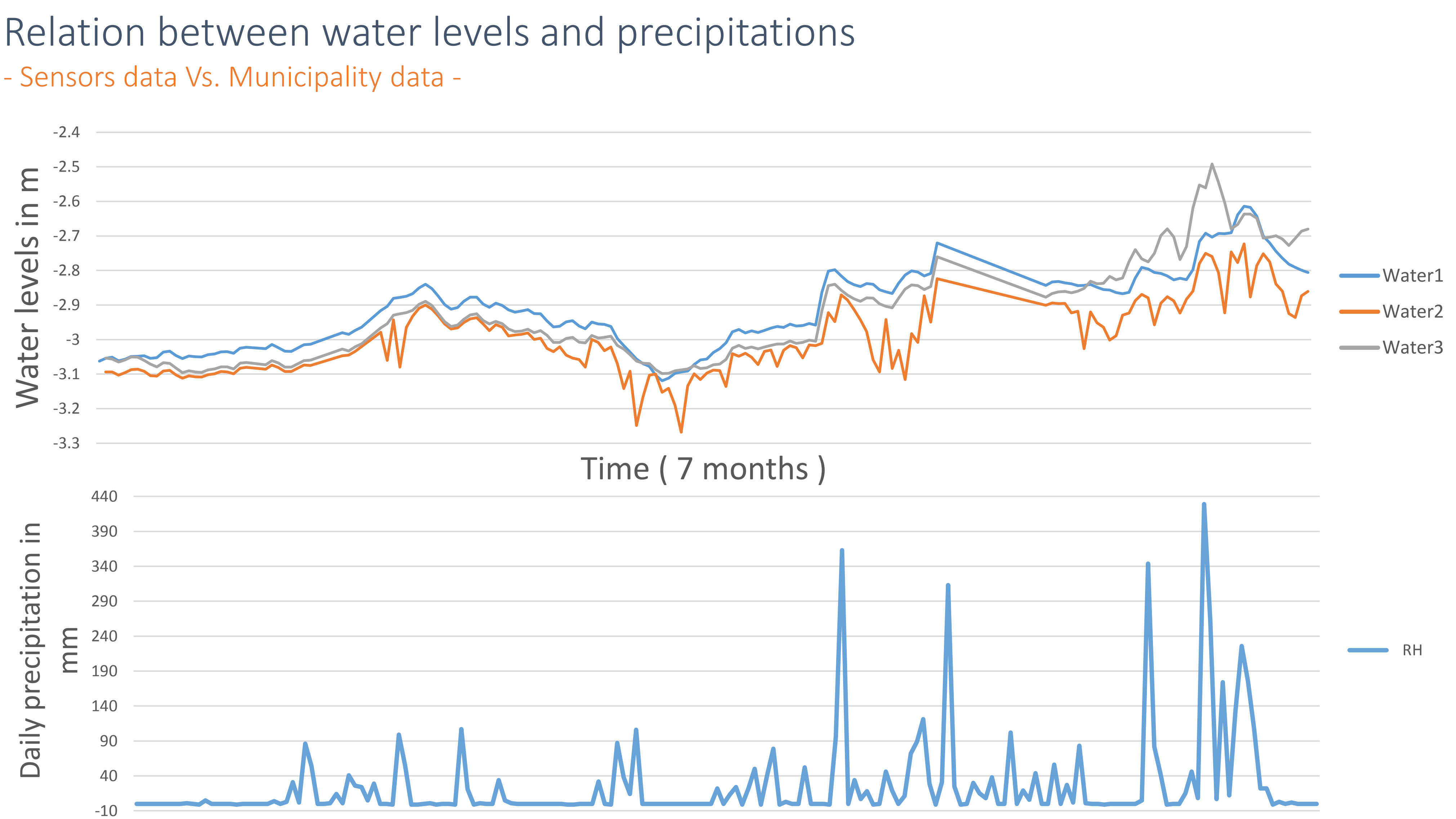
Correlation results water levels

Building subsidence – Water levels COMPARISON



6

Comparison between water level sensors and rain data


Relation between water levels and precipitations
- Sensors data Vs. Municipality data -
Water levels in m
-2.4
-2.5
-2.6
-2.7
-2.8
-2.9
-3
-3.1
-3.2
-3.3
Water1
Water2
Water3
Time (7 months)
Daily precipitation in mm
440
390
340
290
240
190
140
90
40
-10
RH