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PAPER TITLE:**DInSAR data assimilation for settlement prediction: case study of a railway embankment in The Netherlands**

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Abstract

Secondary settlements in soft soils represent a significant fraction of the total settlement induced by external loads. Consequently, these settlements can play a key role on performance, serviceability and safety of engineering works such as buildings, roads, embankments, pipelines. This paper addresses the setting up of a predictive settlement model for a railway embankment built on soft clayey-peaty soils by following an original procedure consisting of three cascading steps: i) preliminary detection of the most settlement-affected portions of the infrastructure; ii) development of an equivalent subsoil model to study secondary settlements; iii) back-calculation of the parameters of a predictive settlement model (design subsoil model) via a variational data assimilation scheme that exploits ground displacement measurements derived from differential interferometric synthetic aperture radar (DInSAR) data. The main achievement relies on the retrieval of a stochastic prediction of secondary settlements that can contribute to rationalize both conventional monitoring campaigns and management of key infrastructure.

Keywords: settlement prediction; data assimilation; DInSAR; embankment; soft soils.

Introduction

Settlements associated with secondary compression (or creep) in soft soils like peat and organic clays develop within a time dependent process, which typically occurs after the full dissipation of the excess pore pressure (Huat et al. 2014; Den Haan 1996) and which can be so severe that cannot be easily ignored as often done with firmer inorganic soils (Huat et al. 2014; Edil 1997). Consequently, buildings and infrastructure (e.g. pipelines, roads or embankments) resting on these soils may suffer in time from settlement-induced damages of various levels of severity, as testified by a number of case histories resulting in economic losses of billions of dollars per year (Bucx et al. 2015). As for infrastructure, it is well known that even small deformations must be prevented. Indeed, slow creep settlements may affect the performance of structures and infrastructure and cause high maintenance and repair costs. Moreover, partial closures of infrastructure networks during the repair work have significant economic and social impact as well.

For these reasons, the use of an adequate subsoil settlement model that accounts for creeping behavior of soils turns out to be extremely important under the infrastructure management perspective. The key parameters of this model in turn can be calibrated via back-calculations in order to tackle both the intrinsic uncertainties related to soil properties derived from in-situ or laboratory tests and their frequent limited availability over large areas. For this purpose, settlement monitoring data can be used as testified by various case studies on back-analyses for soil model calibration such as Huat et al. (2014), Kempfert and Gebreselassie (2006), Wu et al. (2007), Zhang et al. (2009), Juang et al. (2013), among the others. The novel approach in this paper follows this line and it is employed for secondary settlement prediction to a simplified case study of a railway embankment resting on soft soils in order to easily test the procedure. The core idea is the combination of typical geotechnical aspects regarding both subsoil and settlement modelling with the information gathered on ground displacements via the interferometric elaboration of images, which are acquired by spaceborne synthetic aperture radar (DInSAR), as shown by first examples of DInSAR data use in geotechnical modelling (Castaldo et al. 2015; Modoni et al.

2013). To this aim, an equivalent geotechnical subsoil model resulting from the elaboration of both geotechnical in-situ tests (e.g. Cone Penetration Tests, CPT) and DInSAR-derived settlement measurements is developed. Then, the aforementioned subsoil model is used for settlement prediction following both a deterministic and a stochastic approach. This latter allows calibrating soil parameters (i.e. thickness and secondary compression index) to minimize the difference between predicted and DInSAR-derived settlement trends. Via a Monte Carlo based stochastic approach the calibrated subsoil model (design subsoil model) can be used for a stochastic settlement prediction accounting for uncertainties related to the variability of both properties and thicknesses of soil layers.

Methods

Reliable prediction and control of settlements are key issues in design, construction and maintenance of railway lines. Within this, displacement monitoring data can play a two-fold role consisting of: *i*) the calibration of soil parameters within a settlement prediction model aimed at predicting the response of the investigated physical system; *ii*) a check on the efficiency of the corrective measures undertaken to mitigate the related effects. This section provides a background in displacement monitoring dataset derived from the interferometric processing of images acquired by spaceborne Synthetic Aperture Radar sensors (DInSAR) and the outline of the proposed procedure for DInSAR data assimilation within a predictive settlement model (design subsoil model).

DInSAR Techniques

DInSAR techniques represent a well-established tool to measure ground displacements induced by many natural or anthropogenic phenomena in different fields. These latter range from earthquake engineering (Reale et al. 2011), volcanology (Lee et al. 2013), mining (Herrera et al. 2010), water extraction (Cascini et al. 2006; Sanabria et al. 2014; Peduto et al. 2015), underground construction works (Bandini et al. 2015), slow-moving landslides (Cascini et al. 2013a; Wasowski and Bovenga

2014; Gullà et al. 2016; Calvello et al. 2016), and monitoring of structures and infrastructure (Arangio et al. 2013; Cascini et al. 2013 b; Peduto et al. 2015, 2016 a, 2016 b).

The available techniques for the analysis of phase signals in interferometric stacks can be grouped in two main classes: Persistent Scatterers Interferometry (PSI) (Costantini et al. 2008; Ferretti et al. 2001; Crosetto et al. 2008) and Small-Baseline (SBAS) approaches (Berardino et al. 2002; Fornaro et al. 2009). PSI techniques operate at full spatial resolution and identify reliable scatterers by measuring their multitemporal coherence related to the phase stability; monitored scatterers (i.e. persistent scatterers, PS) correspond to man-made structures (buildings, roads, bridges) or bare rocks, whose size is smaller compared to the system resolution. Conversely, the SBAS techniques are tailored to detect scatterers that may be distributed in the resolution cell or characterized by slow temporal change of scattering properties and to measure ground deformations over large areas (Fornaro et al. 2009).

Algorithms have been recently developed to apply the same technique to both traditional point targets, i.e. targets captured by a single pixel that contains one dominant scatterer, as well as extended targets, i.e. targets that spread over a collection of pixels, each of which contains multiple nondominant scatterers, usually referred to as distributed scatterers (DS). Examples of DS are homogeneous ground patches in deserts and in non-cultivated lands (Fornaro et al. 2015).

The PS-derived velocity is acquired along the radar line of sight (LOS) with reference to a fixed point on the ground (reference point) and with a sub-millimeter accuracy on the average velocity and sub-centimeter accuracy on the single displacement measure (Colesanti et al. 2003; Hanssen 2003). An experimental evidence of the possibility to achieve an accuracy up to the order of 1 mm on a single displacement measurement is provided in Fornaro et al. (2013). Each PS is associated with a coherence value ranging from 0 up to 1, which indicates the model fitting for measured displacements. Recently, the monitoring of ground displacements in built-up urban areas at detailed scale ($>1:5000$) was significantly enhanced by the last generation X-Band high resolution SAR sensors TerraSAR-X/TanDEM-X (TSX/TDX) mission of the German Aerospace Center (DLR) and the COSMO-SkyMed

(CSK) constellation of the Italian Space Agency (ASI) (Peduto et al. 2015, 2016 b). For instance, in the case of CSK the use of a constellation of satellites with revisiting time down to 4 days (on average) allows the collection of data stacks useful for interferometric analysis (about 30 SAR images) in few months. Furthermore, the resolution improvement allows more details of single facilities to be observed and hence their precise monitoring (Zhu and Bamler 2010). The Sentinel mission of the European Space Agency launched in April 2014 is providing continuity of ERS-1/2 and ENVISAT data archives with reduced revisiting times and larger coverage swath.

The feasibility of monitoring railway infrastructure using dedicated satellite radar observations was demonstrated by Chang et al. (2014) with reference to a ballasted embankment in The Netherlands using a TerraSAR-X image dataset. Further examples in the scientific literature deal with DInSAR applications to the monitoring of high-speed railways in China and Taiwan. As highlighted by Galve et al. (2015), in these countries railway and highway infrastructure are experiencing rapid development and they traverse numerous areas affected by ground instability phenomena (Chen et al. 2012; Ge et al. 2013; Hung et al. 2010; Shi et al. 2010; Tan et al. 2010; Zhang et al. 2010). Among these authors, Chen et al. (2012) carried out a comparison of the PSI-observations against the spirit leveling data for a railway embankment in Tibet demonstrating both consistent displacement rates and trends.

The image dataset used in the present study consists of 125 images acquired from April 2009 to May 2013 by TerraSAR-X satellite (revisiting time of 11 days) on descending orbit (incidence angle of 24.1° ; ground resolution of 3.0×3.0 m) that were processed by the company SkyGeo via a PSI-like algorithm.

Proposed Procedure

The flowchart in Fig. 1 schematically summarizes the procedure, which consists of two phases preceded by a preliminary one.

- In the *Preliminary Phase*, DInSAR data are analysed in order to detect the portions of the railway embankment that need detailed investigations since therein the highest settlements are recorded.
- In *Phase I*, the results of geotechnical investigations and DInSAR data are jointly used to build the subsoil model of some specific sections within homogeneous sub-areas. These sections are within a portion of the railway embankment selected in the *Preliminary Phase*. For each sub area, the available geotechnical information (e.g. borehole data, CPT measurements, laboratory tests, etc.) are analysed. Due to sparse information, geostatistical methods for the spatial data interpolation are applied in order to derive an equivalent subsoil model.
- In *Phase II*, the aforementioned subsoil model allows settlement prediction following two approaches. A deterministic approach, which uses viscoplastic creep Isotache model (Den Haan 1996), is implemented into a commercial geotechnical software (D-Settlement) (Visschedijk et al. 2016) and a stochastic approach uses variational data assimilation for the calibration of soil parameters (thickness and secondary compression index) also to take into account the limited availability of both in-situ and laboratory tests. As described in Huber (2016) amongst others, variational data assimilation minimizes the difference between the predicted and measured (from DInSAR data) settlement trends. Finally, the calibrated subsoil model (i.e. design subsoil model) allows predicting settlements over different time intervals. These predictions are provided with uncertainty assessment resulting from the application of the Monte Carlo probabilistic method on the variability of geotechnical parameters.

The case study

Highly compressible layers of soft soils occur in large parts of the Western and Northern Netherlands (CUR 1996) as shown in Fig. 2a. This region consists of recently sedimented clayey and peaty layers, extending to depths of 10-20 m below ground level, mainly deposited by rivers or the sea. In this region,

the ground water level is high and in many cases comes almost up to ground level. These soft soils have a large influence on infrastructure and buildings. Figure 2 b shows that in the delta of the *Nieuwe Maas* River the cumulative thickness of soft soils is the largest in The Netherlands. In particular, cumulative thickness of peat layers reaches 10 m. This area is crossed by the railway embankments of the *Hoekse Line* connecting Schiedam Centrum and Hoek van Holland Strand in the Zuid Holland province (the track is highlighted with red dotted lines in Fig. 2 b). The *Hookse Line* is 24 km long and consists of two rails positioned at the top of a single embankment. The line was built as a branch of the existing Rotterdam - The Hague line between the end of the 19th century and the beginning of the 20th century. This embankment has an average height of 2.0-2.5 m and an average width ranging between 13 m and 15 m at the top and about 20 m at the level of the ground. The ground water level is half a meter below the ground surface and it is kept constant in order to avoid settlements and the related risks for infrastructure and buildings. In this study, it is assumed to be constant due to the absence of continuous groundwater measurement data.

In addition to the geometry of the railway embankment, the results of geotechnical in-situ and laboratory tests as well as the GeoTOP model (www.dinoloket.nl/en) are used in the present study. The GeoTOP model is provided by the Geological Survey of The Netherlands (Stafleu et al. 2011) and consists of a 3-D subsoil model extending to a depth of 50 m. Within this, the subsoil is discretized into cells (so-called voxels) of 100 m x 100 m in the horizontal direction and 0.50 m in the vertical direction with constant subsoil characteristics. The GeoTOP model takes advantages of the availability of over 430,000 boreholes over the Dutch territory that have been supplemented with data from cone-penetration tests and digitized geological maps (www.dinoloket.nl/en). In particular, it results from a three-step procedure consisting of: interpretation of boreholes, modelling of interfaces and stochastic interpolation techniques to assign a lithoclass to the voxels. As shown in the longitudinal sections of Figs. 3 (a, b, c), which are indicated between the two red squares in Fig. 2 b, GeoTOP allows estimating the spatial distribution of soil types (Fig. 3 a) and the corresponding probability of occurrence, as given

for clayey and peaty layers in Figs. 3 b and 3 c. Owing to its resolution, GeoTOP offers limited insights for analyses at detailed scale. Therefore, in the present study available data of 20 CPT and core borings are exploited to set up a conceptual geological-geotechnical model. For this purpose, taking into account that secondary settlement modelling, as shown hereafter, is performed along a 550-meter long portion of the railway track, standard empirical correlations from Robertson (1990, 2009) are employed to convert CPT measurement data into different soil types. Figure 4 compares results from GeoTOP with the empirical CPT interpretation, which give different results. In particular, the CPT interpretations highlight thicker peat layers in the top part of the investigated subsoil. However, both approaches show a top layer of anthropogenic soil in a similar way. Due to the absence of suitable data, no transformation error and no statistical model error are considered within the CPT interpretations.

Results

In order to detect the most settlement-affected portion of the infrastructure track, a geostatistical analysis of DInSAR data is carried out in the *Preliminary Phase*. To this aim, firstly 10,488 PS located on the railway embankment are selected. Their average settlement velocity and their cumulative settlements over the period of acquisition (i.e. 08-04-2009 / 05-13-2013) are shown in Figs. 5 a and 5 b.

Note that DInSAR-measured velocities provide the deformation velocity along the LOS and it is necessary to have images acquired on both ascending and descending orbits over the same area in order to retrieve the vertical and horizontal components of displacement (Peduto et al. 2015). However, since for the case study at hand only a descending orbit dataset is available, vertical displacements are considered as a projection from the LOS direction and possible horizontal displacements affecting the embankment are disregarded. Then, using the inverse distance weighted method (IDW) for squared cells of 100 m and a radius of influence of 100 m allows the identification in Fig. 5 b of those sections of the railway embankment, where cumulative settlements exceeding 50 mm in the period between 2009 and 2013 are recorded.

Phase I

In order to achieve the equivalent stratigraphic sections a geostatistical analysis of DInSAR data is first carried out with reference to the portion of the embankment exhibiting the highest settlements. Accordingly, the mean and the standard deviation of the DInSAR-derived settlement rates are derived for 25-meter analysis domains (given in Fig. 6 a as circles). In particular, the size of these domains coincides with the maximum width at the bottom of the typical embankment section. In Fig. 6 b the settlement trends of PS falling within the red framed domain are shown.

Under the key assumption that similar DInSAR settlement rates correspond to similar thickness of soft soil layers, as a result of the computation of mean values and standard deviations of DInSAR-derived settlement rates, seven quasi-homogeneous subareas (labelled in Figs. 6 a and 7 with Roman numbers) are identified. The number of the available CPT measurements is also indicated in Fig. 7 at the bottom of each subarea.

For the seven sub-areas the variability of soil layer cumulative thicknesses derived from CPT is analyzed. The mean value and the standard deviation of the thicknesses of peat, clay and sand are obtained in Figs. 8 (a, b and c). In the following, these data are employed to derive the equivalent stratigraphic sections for creep settlement modelling.

Phase II

In *Phase II* the creep-related settlements after six, ten and twenty years are analyzed using a deterministic and a stochastic approach. Both of them use the equivalent stratigraphic sections obtained for the seven analyzed sub-areas.

At first, deterministic settlement predictions are carried out and then the stochastic approach is applied. This latter consists of: *i*) updating of the subsoil model through the data assimilation approach. Herein, DInSAR data and the subsoil uncertainty related to both the thicknesses of soil layers and their

secondary compression indexes are combined in order to derive a design cross section; *ii*) a Monte Carlo-based approach is employed for the stochastic settlement prediction.

It is assumed in the sequel case study that the embankment is rigid and the watertable is constant, as described earlier in this paper. Within this, the Isotache model (Den Haan 1996; Suklje 1957) is used to simulate the settlements based on a rate formulation, where all inelastic compression is assumed to result from visco-plastic creep. In the Isotache model creep settlements are independent of the stress and are linearly related to the time on a logarithmic scale, as described by Den Haan (1996) in detail. Note that, in order to apply the Isotache model, the secondary compression index C_{α} is converted into the corresponding model parameters for creep within both approaches employed in the present case study.

Deterministic approach

The equivalent stratigraphic sections (Fig. 9), whose soil parameters derive from available laboratory tests (see Table 1), are used for the analysis and the prediction of settlements. Each cross section is modelled according to the homogeneous sub-areas defined in *Phase 1* (assuming thickness values of each strata corresponding to their mean values) via D-Settlement software.

In the present analysis, the primary consolidation is not taken into account and only creep settlements are addressed. Indeed, as previously said, the railway embankment was built between the end of the 19th century and the beginning of the 20th century; thus, it can be expected that the construction of the railway embankment initiated a consolidation process that, however, nearly 100 years later the consolidation process can be assumed to be over and, if not, has only minor influences. Assuming that the creep is independent of the stress level, it is possible to derive linear creep-settlement trends on logarithmic time scale based on the deterministic subsoil models for seven sub-areas analyzed, as given in Fig. 10. This implies that all initial and primary consolidation settlements are over.

For each cross section of the homogeneous sub-areas the settlement predictions after six, ten and twenty years are calculated as given in Fig. 11.

Stochastic approach

The stochastic approach consists of two steps. At first, data assimilation is used for back-calculation of the soil properties and soil layer thicknesses incorporating both uncertainties and DInSAR measurements. This is followed by a stochastic settlement prediction that is based on a Monte-Carlo approach.

Amongst others, Evensen (2007) and Huber (2016) describe that the basic idea of variational data assimilation is to find the initial conditions of a model to minimize some scalar quantity J . The cost function $J[\mathbf{x}]$ is a function of the state vector $\mathbf{x}$, which is a vector of all variables describing the conditions of the system like model parameters and/or deformations. In the case study at hand, the vector $\mathbf{x} = [\mathbf{s}_{\text{peat}}, \mathbf{s}_{\text{clay}}, \mathbf{d}_{\text{peat}}, \mathbf{d}_{\text{clay}}, \mathbf{C}_{\alpha, \text{peat}}, \mathbf{C}_{\alpha, \text{clay}}]^T$ consists of the settlements of the cumulative peat layer $\mathbf{s}_{\text{peat}}$, the settlements of the cumulative clay layer $\mathbf{s}_{\text{clay}}$, the cumulative thicknesses of the peat layer $\mathbf{d}_{\text{peat}}$, the cumulative thickness of the clay layer $\mathbf{d}_{\text{clay}}$, the secondary compression index for peat $\mathbf{C}_{\alpha, \text{peat}}$, and the secondary compression index for clay $\mathbf{C}_{\alpha, \text{clay}}$. The cost function $J[\mathbf{x}]$ defines a global measure of the simultaneous misfit between $\mathbf{x}$, the current guess of the model state, and the observations $\mathbf{y}$. The cost function $J[\mathbf{x}]$ simultaneously penalizes a bad fit between the model state $\mathbf{x}$ and the background, and the model state and the predicted observations, given in equation (1).

$$J[\mathbf{x}] = \frac{1}{2} (\mathbf{x}^f - \mathbf{x})^T \mathbf{B}^{-1} (\mathbf{x}^f - \mathbf{x}) + (\mathbf{y} - \mathbf{H} \cdot \mathbf{x})^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H} \cdot \mathbf{x}) \quad (1)$$

$\mathbf{B}$ is the background error covariance matrix, $\mathbf{y}$ is the set of observations made at time t and $\mathbf{R}$ is the observational error covariance matrix. The vector $\mathbf{y} - \mathbf{H} \cdot \mathbf{x}$ is the residual. The covariance matrix $\mathbf{P}$, which contains the variances and covariances of the resulting state vector $\mathbf{x}$, is equal to the inverse of the Hessian matrix of the objective function evaluated at $\mathbf{x}$. Note that one assumes that within the variational data assimilation approach the errors are unbiased and standard normally distributed. Additionally, the model is assumed to represent the system behaviour perfectly. This implies that the model uncertainty of

the mechanical model is assumed to be perfect. Evensen (2007) reports that the drawback of the variational approaches is the limited applicability since it is very difficult to implement and solve the equations of non-linear systems. Additionally, a large number of state variables, which are stored in the state vector $\mathbf{x}$, lead to a very large error covariance matrix $\mathbf{B}$ that implies a huge computational effort (Huber 2016).

The input data for the variational data assimilation are given in Table 2, where μ indicates the mean values, σ the standard deviation and $COV=\sigma/\mu$ the coefficient of variation of log-normally distributed DInSAR settlement rates and the log-normally distributed secondary compression index C_{α} , peat thickness and clay thickness (Huang et al. 2010). The iterative procedure of variational data assimilation consists of variation of the secondary compression indexes and the thicknesses of peat and clay until the difference between the values of predicted settlements and DInSAR-measured ones goes to minimum value. As for the mean values of the peat and clay thickness, Figs. 12 a and 13 a show the difference before and after the back analysis. The standard deviation of thickness values for peat and clay are highlighted in Figs. 12 b and 13 b. Comparing the input data and results of the variational data approach one can see that, on average, the variational data assimilation approach is reducing the uncertainty of the simulated variables. Note that the results in Table 3 represent the combination of the uncertainty of observed settlement measurement, the estimated uncertainty of the soil parameters and the uncertainty of the cumulated soil layer thicknesses.

In Figs. 14 a and 14 b, the values of the secondary compression index of the analyzed peat and clay layers, after variational data analysis for each 25m-domain, are compared to the value of the compression index derived from the available geotechnical laboratory tests (Fig. 14 b).

The results in Table 3 are then used in the second step of *Phase II* in order to predict settlements and assess related uncertainty. Herein, the mean values and standard deviations of the log-normally distributed soil parameters (thickness and secondary compression index) are used to generate the random numbers, which are used as input parameters for settlement calculation. These results quantify

the mean and standard deviation of predicted settlements. This simple approach allows the uncertainty of both DInSAR data and soil parameters to be merged in the prediction uncertainty. The results of these Monte Carlo simulations are given in the Table 4 and Figs. 15 a and 15 b for different forecast times (6, 10 and 20 years).

Analyzing the results in Table 4 and Fig. 15 b, one can see that the standard deviation of the predicted settlements increases over time. However, the coefficient of variation $COV=\sigma/\mu$ is staying constant for each investigated section. This can be related to the linearity of the model that is employed for creep settlements.

Discussion

The deterministic approach followed used mean values of key parameters without accounting for uncertainties or referring to any type of in-situ settlement measurement.

In the stochastic approach, the first result was an updated equivalent model of subsoil (design cross section) and its standard deviation. As for the domain of analysis, for both peat and clay layers the lines of cumulative thickness (before and after fitting) are very close with a reduction of standard deviation in the second case.

For the purpose of creep analysis, a complete design cross section required the identification of the secondary compression indexes. The available laboratory tests for the clay layer allowed a comparison with clay layer properties. In particular, starting from a random value, calculation results close to laboratory test values (i.e. to the lower bound of standard deviation) are achieved for the secondary compression indexes. This comparison is not possible for peat since only one test is available.

The comparison between the after-6-year predicted settlements and the updated model of subsoil (with DInSAR data) highlights the strong dependence of the phenomena on the peat thickness (Fig. 16). Indeed, settlements increase with increasing of peat thickness. This is closely related to the secondary compression index of peat that is fairly higher than that of clay.

Comparing the deterministic approach with the stochastic one (Fig. 17), it can be derived that the former underestimates the predicted settlements in the center and on the east side of the analyzed track. In the western portion the two approaches provide similar creep settlement predictions. Apart from this, one can see in Fig. 17 that the results of the deterministic creep settlement prediction approach fall inside the confidence bound of the stochastic settlement predictions with a lower settlement bound ($\mu-\sigma$) and an upper settlement bound ($\mu+\sigma$).

Conclusions

Compared to other modes of transport, railways have the big drawback of high costs of construction and maintenance. According to Zhai et al. (2004) maintenance represents between 40% and 75 % of the total operational costs. Within maintenance, a great share is spent to preserve safety and riding quality up to high standards. This problem is amplified by the existence of soft soil conditions like, for instance, in The Netherlands, where it is estimated that 40% of the maintenance costs are associated with preserving geometry of the railway track (Hölscher and Meijers 2007).

Therefore, it is necessary to develop procedures to improve track maintenance, monitoring and settlement predictions, especially for railways built on soft soils, which contribute to a reduction of the total life costs, with major benefits for railway system owners, operators, and users.

This paper aims to provide a contribution to this issue by proposing a procedure for secondary settlement prediction via data assimilation of densely distributed DInSAR-derived ground displacement data.

The novel procedure, which is applied to a simplified case study of a 550-meter portion of a railway embankment in The Netherlands resting on soft soils, consists of two main steps. In *Phase I*, via the joint use of the results of geotechnical investigations and DInSAR data a preliminary equivalent subsoil model is derived. The preliminary character of the abovementioned model allows the use of empirical interpretations (Robertson 1990, 2009) as well as relying on a limited number of CPT measurements.

Note that other correlations for the transformation from CPT data to subsoil properties can be employed for this purpose as well. In *Phase II* deterministic and stochastic models are used for settlement prediction.

The design subsoil model, which is used for settlement prediction, is calibrated using the parameters of the equivalent subsoil model in Phase II and DInSAR-settlement time series. The results show that the stochastic approach provides confidence bounds ($\mu \pm \sigma$) for settlement prediction, whereas the deterministic approach results in only one set of predicted settlements. It can be derived from the given results that the deterministic settlement predictions are located in the confidence bounds ($\mu \pm \sigma$) of the stochastic settlement predictions.

The innovative aspect of the presented analysis relies on the pioneering attempt to exploit the information derived from DInSAR data for the definition of the geotechnical subsoil model used for embankment settlement prediction.

The results highlighted the potential of DInSAR techniques for back analyses on classical geotechnical problems, also complementing with geotechnical data when these are scarce (e.g. CPT and laboratory test in the presented case study). This is in line with previous research in the field of geotechnical back analysis (Ledesma et al. 1996; Knabe et al. 2012).

As it was shown for the case study at hand, employing the presented approach within an infrastructure management context in The Netherlands, where a rich database on subsoil stratigraphy and properties is available, can clear the way towards a rationalization of further geotechnical investigations as well as more expensive conventional monitoring just in those sections, where the highest uncertainties are recorded. Secondly, the results of the predictive settlement model would contribute to prioritize maintenance works just in the most settlement-affected sections.

Finally, the achieved results strongly encourage further deepening and validation of the proposed procedure in view of the upcoming improvements, in terms of resolution and frequency, of SAR data

acquisition, thus holding the promise of possible full-integration of DInSAR data in geotechnical modelling in the near future. The presented workflow can be easily extended to account for different and/or multiple mechanisms in order to improve the incorporation of DInSAR data assimilation in settlement prediction, which, as a result, goes in one line with a high computational effort and more complex simulation models.

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Table 1. Soil parameters adopted for modeling.

Sub Area	Thickness [m]			Secondary compression index C_a			weight		
	Peat	Clay	Sand	Peat	Clay	Sand	Peat	Clay	Sand
(a)	7.65	5.24	17.12						
(b)	5.02	6.72	16.85						
(c)	6.68	4.59	14.96						
(d)	6.03	7.10	16.30	2.33E-02	7.25E-03	(-)	10.40	16.02	20.00
(e)	5.19	8.95	15.05						
(f)	4.28	9.79	11.10						
(g)	4.68	8.82	16.46						

Table 2. Log-normally distributed input data for variational data assimilation approach in Phase II.

Sub area	location	Secondary compression index C_a of peat			Secondary compression index C_a of clay			DInSAR settlement measurements			Peat layer thickness			Clay layer thickness		
		μ_{C_a}	σ_{C_a}	COV	μ_{C_a}	σ_{C_a}	COV	μ	σ	COV	μ_{peat}	σ_{peat}	COV	μ_{clay}	σ_{clay}	COV
		[1/ year]	[1/ year]	[%]	[1/ year]	[1/ year]	[%]	DInSAR [mm/ year]	DInSAR [mm/ year]	[%]	[m]	[m]	[%]	[m]	[m]	[%]
(a)	0	0.01	0.01	100	0.003	0.003	100	-6.19	2.28	37	7.65	1.73	23	5.24	2.2	42
	25	0.01	0.01	100	0.003	0.003	100	-4.38	1.24	28	7.65	1.73	23	5.24	2.2	42
	50	0.01	0.01	100	0.003	0.003	100	-2.21	1.8	81	7.65	1.73	23	5.24	2.2	42
	75	0.01	0.01	100	0.003	0.003	100	-3.86	0.72	19	7.65	1.73	23	5.24	2.2	42
(b)	100	0.01	0.01	100	0.003	0.003	100	-2.69	0.5	19	5.02	0.65	13	6.72	1.42	21
	125	0.01	0.01	100	0.003	0.003	100	-2.63	0.29	11	5.02	0.65	13	6.72	1.42	21
	150	0.01	0.01	100	0.003	0.003	100	-2.57	0.08	3	5.02	0.65	13	6.72	1.42	21
	175	0.01	0.01	100	0.003	0.003	100	-2.59	2.93	113	5.02	0.65	13	6.72	1.42	21
(c)	200	0.01	0.01	100	0.003	0.003	100	-4.27	0.22	5	6.68	1.78	27	4.59	1.42	31
	225	0.01	0.01	100	0.003	0.003	100	-4.14	1.55	37	6.68	1.78	27	4.59	1.42	31
	250	0.01	0.01	100	0.003	0.003	100	-3.79	1.48	39	6.68	1.78	27	4.59	1.42	31
	275	0.01	0.01	100	0.003	0.003	100	-3.68	0.78	21	6.68	1.78	27	4.59	1.42	31
(d)	300	0.01	0.01	100	0.003	0.003	100	-4.89	1.2	25	6.03	2.19	36	7.1	2.11	30
	325	0.01	0.01	100	0.003	0.003	100	-4.95	1.47	30	6.03	2.19	36	7.1	2.11	30
	350	0.01	0.01	100	0.003	0.003	100	-5.07	2.31	46	6.03	2.19	36	7.1	2.11	30
(e)	375	0.01	0.01	100	0.003	0.003	100	-6.19	0.8	13	5.19	1.18	23	8.95	1.67	19
	400	0.01	0.01	100	0.003	0.003	100	-6.07	1.02	17	5.19	1.18	23	8.95	1.67	19
(f)	425	0.01	0.01	100	0.003	0.003	100	-4.45	0.86	19	4.28	1.73	40	9.79	2.2	22
	450	0.01	0.01	100	0.003	0.003	100	-3.37	0.3	9	4.28	1.73	40	9.79	2.2	22
	475	0.01	0.01	100	0.003	0.003	100	-4.07	2.19	54	4.28	1.73	40	9.79	2.2	22
	500	0.01	0.01	100	0.003	0.003	100	-3.6	1.27	35	4.28	1.73	40	9.79	2.2	22
(g)	525	0.01	0.01	100	0.003	0.003	100	-5.39	1.93	36	4.68	1.73	37	8.82	2.2	25
	550	0.01	0.01	100	0.003	0.003	100	-3.58	1.54	43	4.68	1.73	37	8.82	2.2	25

Table 3: Log-normally distributed results of the variational data assimilation approach in Phase II (used as input data in the Monte Carlo approach).

Sub area	dista nce	compression index C_a						thickness					
		mean	clay standard deviation	COV	mean	peat standard deviation	COV	mean	clay standard deviation	COV	mean	peat standard deviation	COV
[-]	[m]	[1/year]	[1/year]	[%]	[1/year]	[1/year]	[%]	[m]	[m]	[%]	[m]	[m]	[%]
(a)	0	1.00E-03	6.28E-04	63	2.40E-03	2.18E-04	9	5.12E+00	1.36E+00	27	7.65E+00	1.25E+00	16
	25	1.00E-03	6.28E-04	63	1.66E-03	2.18E-04	13	5.24E+00	2.20E+00	42	7.65E+00	1.73E+00	23
	50	3.10E-04	1.78E-05	6	9.10E-04	2.18E-04	24	5.19E+00	1.38E+00	27	7.88E+00	1.23E+00	16
	75	1.00E-03	6.20E-04	62	1.36E-03	2.18E-04	16	5.24E+00	1.38E+00	26	7.63E+00	1.23E+00	16
(b)	100	2.21E-04	9.68E-05	44	1.45E-03	2.12E-04	15	7.12E+00	6.10E-01	9	5.02E+00	6.00E-01	12
	125	1.00E-03	3.76E-04	38	9.30E-04	2.18E-04	23	6.72E+00	7.50E-01	11	5.02E+00	6.35E-01	13
	150	2.32E-04	1.27E-04	55	1.25E-03	2.18E-04	17	6.20E+00	6.15E-01	9	5.85E+00	6.35E-01	11
	175	2.41E-04	6.28E-05	26	1.00E-03	2.08E-04	21	6.22E+00	6.21E-01	10	5.52E+00	6.45E-01	12
(c)	200	2.34E-04	9.06E-05	39	2.34E-03	2.18E-04	9	4.88E+00	1.15E+00	24	6.04E+00	1.18E+00	20
	225	2.36E-04	6.28E-05	27	1.20E-03	2.09E-04	17	4.24E+00	1.14E+00	27	6.68E+00	1.20E+00	18
	250	1.01E-03	6.28E-04	62	1.81E-03	2.18E-04	12	4.59E+00	1.42E+00	31	6.58E+00	1.00E-01	2
	275	1.02E-03	6.28E-04	61	1.63E-03	2.18E-04	13	4.59E+00	1.41E+00	31	6.58E+00	1.20E-01	2
(d)	300	1.04E-03	6.28E-04	60	1.99E-03	2.18E-04	11	7.10E+00	1.52E+00	21	6.02E+00	1.51E+00	25
	325	1.02E-03	6.28E-04	61	2.21E-03	2.18E-04	10	7.10E+00	2.12E+00	30	6.02E+00	2.25E+00	37
	350	3.22E-04	2.28E-04	71	2.02E-03	2.02E-04	10	7.63E+00	1.51E+00	20	5.61E+00	1.52E+00	27
	375	1.04E-03	6.28E-04	60	2.88E-03	1.22E-04	4	8.95E+00	8.00E-01	9	5.19E+00	1.02E+00	20
	400	2.34E-04	1.28E-04	55	2.78E-03	2.18E-04	8	8.95E+00	9.40E-01	10	5.51E+00	9.70E-01	18
	425	2.54E-04	6.28E-05	25	2.34E-03	7.22E-05	3	9.81E+00	1.35E+00	14	4.21E+00	1.28E+00	30
(f)	450	1.04E-03	6.28E-04	60	1.22E-03	1.22E-04	10	9.81E+00	2.21E+00	23	4.26E+00	1.00E-01	2
	475	2.34E-04	1.21E-04	52	1.82E-03	2.52E-05	1	9.87E+00	1.38E+00	14	4.67E+00	1.21E+00	26
	500	2.34E-04	6.28E-05	27	1.66E-03	2.12E-04	13	1.00E+01	1.37E+00	14	4.68E+00	1.21E+00	26
	525	9.93E-04	6.28E-04	63	1.93E-03	2.18E-04	11	8.82E+00	1.32E+00	15	4.77E+00	1.10E+00	23
(g)	550	9.96E-04	6.28E-04	63	1.76E-03	2.18E-04	12	8.82E+00	1.81E+00	21	4.77E+00	7.90E-01	17

Table 4: Log-normally distributed result uncertainty of settlement prediction using the Monte Carlo approach.

Sub area	location	6-year settlement prediction			10-year settlement prediction			20-year settlement prediction		
		mean	standard deviation	COV	mean	standard deviation	COV	mean	standard deviation	COV
	[-]	[m]	[m]	[%]	[m]	[m]	[%]	[m]	[m]	[%]
(a)	0	6.05E-02	1.31E-02	22	7.78E-02	1.70E-02	22	1.01E-01	2.19E-02	22
	25	5.74E-02	9.51E-03	17	7.38E-02	1.23E-02	17	9.61E-02	1.59E-02	17
	50	5.74E-02	1.47E-02	26	7.38E-02	1.89E-02	26	9.61E-02	2.47E-02	26
	75	5.73E-02	1.34E-02	23	7.38E-02	1.72E-02	23	9.60E-02	2.25E-02	23
(b)	100	4.50E-02	7.67E-03	17	5.77E-02	9.89E-03	17	7.51E-02	1.29E-02	17
	125	4.28E-02	7.45E-03	17	5.51E-02	9.60E-03	17	7.15E-02	1.24E-02	17
	150	4.28E-02	7.76E-03	18	5.50E-02	9.98E-03	18	7.17E-02	1.30E-02	18
	175	4.53E-02	7.74E-03	17	5.81E-02	9.96E-03	17	7.57E-02	1.29E-02	17
(c)	200	5.02E-02	9.09E-03	18	6.45E-02	1.16E-02	18	8.39E-02	1.51E-02	18
	225	4.87E-02	1.05E-02	22	6.27E-02	1.35E-02	22	8.15E-02	1.76E-02	22
	250	5.02E-02	8.08E-03	16	6.45E-02	1.04E-02	16	8.39E-02	1.35E-02	16
	275	5.02E-02	1.41E-02	28	6.45E-02	1.81E-02	28	8.38E-02	2.37E-02	28
(d)	300	4.99E-02	8.10E-03	16	6.41E-02	1.04E-02	16	8.34E-02	1.35E-02	16
	325	4.99E-02	1.40E-02	28	6.41E-02	1.80E-02	28	8.34E-02	2.33E-02	28
	350	5.22E-02	1.29E-02	25	6.70E-02	1.65E-02	25	8.73E-02	2.14E-02	25
	375	4.38E-02	9.02E-03	21	5.62E-02	1.16E-02	21	7.32E-02	1.51E-02	21
(e)	400	4.74E-02	9.40E-03	20	6.08E-02	1.21E-02	20	7.93E-02	1.57E-02	20
	425	4.28E-02	1.10E-02	26	5.51E-02	1.42E-02	26	7.15E-02	1.84E-02	26
	450	4.29E-02	1.10E-02	26	5.50E-02	1.41E-02	26	7.16E-02	1.84E-02	26
	475	4.25E-02	1.09E-02	26	5.46E-02	1.41E-02	26	7.10E-02	1.83E-02	26
(f)	500	4.19E-02	1.09E-02	26	5.38E-02	1.40E-02	26	7.00E-02	1.82E-02	26
	525	4.40E-02	1.17E-02	27	5.65E-02	1.51E-02	27	7.35E-02	1.97E-02	27
(g)	550	4.40E-02	1.29E-02	29	5.65E-02	1.66E-02	29	7.34E-02	2.14E-02	29

Fig. 1. Flowchart of the DInSAR data assimilation for settlement prediction.

Fig. 1

160x102mm (300 x 300 DPI)

Fig. 2. a) Cumulative thickness of soft soils in The Netherlands (courtesy of Deltares); b) cumulative thickness of organic material in Netherlands Delta area (GeoTOP Data). The red dotted line and rectangle indicate the area of the Hoekse Line.

Fig. 2

231x103mm (96 x 96 DPI)

Fig. 3. a) Longitudinal section of the most likely soil types under the Hookse line from GeoTOP: 0: manmade; 1: peat; 2: clay; 3: clay sand and sandy clay; 4: fine sand; 5: medium sand; 6: coarse sand; 7: gravel; 8: shells. Probability of occurrence of clay (b) and peat (c) at different depths along the Hookse line (source GeoTOP). Elevation values refers to Normaal Amsterdams Peil (NAP).

Fig. 3
250x283mm (96 x 96 DPI)

Fig. 4. Comparison of soil stratigraphy along the west-eastward direction derived from GeoTOP and empirical CPT correlations for the investigated area highlighted in Fig. 5 and shown in Fig. 6. Elevation values refers to Normaal Amsterdams Peil (NAP). In the legend, 0: anthropogenic; 1: peat; 2: clay; 3: clay sand and sandy clay; 4: fine sand; 5: medium sand; 6: coarse sand; 7: gravel; 8: shells.

Fig. 4

70x48mm (600 x 600 DPI)

Fig. 5. a) PS distribution and average velocity and b) DInSAR-derived cumulative settlements along the railway embankment with indication of the portion analyzed using DInSAR data assimilation for settlement prediction.

Fig. 5
245x341mm (96 x 96 DPI)

Fig. 6. a) Domains used for DInSAR and CPT geostatistical analysis with indication of the homogeneous sub-areas identified; b) settlement time series of PS falling within the red labelled domain.

Fig. 6

250x270mm (96 x 96 DPI)

Fig. 7. DInSAR-derived displacement rates and related uncertainty along the analyzed railway track.

Fig. 7

161x105mm (150 x 150 DPI)

Fig. 8. Mean and standard deviation of cumulative thickness of peaty (a), clayey (b) and sandy layers (c) along the railway track.

Fig. 8
152x227mm (150 x 150 DPI)

Fig. 9. Sample (one out of seven) cross-section of the equivalent subsoil used for settlement modelling via D-Settlement software.

Fig. 9
160x73mm (150 x 150 DPI)

Fig. 10. Results of deterministic analysis of creep for each one of seven homogeneous sub-areas.

Fig. 10

160x82mm (150 x 150 DPI)

Fig. 11. Prediction of creep settlements via deterministic approach.

Fig. 11

161x88mm (150 x 150 DPI)

Fig. 12. Mean values (a) and standard deviations (b) of the cumulative thickness of peat before and after variational data assimilation analysis.

Fig. 12

246x182mm (96 x 96 DPI)

Fig. 13. Mean value (a) and standard deviation (b) of the cumulative thickness of clay before and after variational data analysis.

Fig. 13
243x177mm (96 x 96 DPI)

Fig. 14. Secondary compression index C_{α} of peat (a) and clay (b) after fitting using variational data assimilation.

Fig. 14
243x184mm (96 x 96 DPI)

Fig. 15. Predicted settlements after fitting: a) mean value and b) standard deviation.
Fig. 15
241x211mm (96 x 96 DPI)

Fig. 16. Comparison between 6-year predicted settlement and the cumulative thickness of soft soils.

Fig. 16

160x93mm (150 x 150 DPI)

Fig. 17. Comparison between the results of the deterministic (dotted lines) and the stochastic approach (solid lines).

Fig. 17

160x77mm (150 x 150 DPI)