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DOI
10.1016/j.geoderma.2023.116699

Publication date
2023

Document Version
Final published version

Published in
Geoderma

Geoderma 440 (2023) 116699

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

SPAMS: A new empirical model for soft soil surface displacement based on meteorological input data

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ARTICLE INFO

Handling Editor: Budiman Minasny

Keywords:
Soil subsidence
Empirical modelling
Holocene
Peatlands

ABSTRACT

We present SPAMS: Simple Parameterization for the Motion of Soils, a model to describe the motion of deformable soils in the Vadose zone, mainly peat and clay, herein called shallow soft soils. The SPAMS model estimates the reversible and irreversible vertical component of surface displacement to within sub-centimetre RMSE, using only four parameters: three scaling factors and an integration time. Requiring only meteorological data as an input, its lightweight nature and simple implementation make it a powerful tool when used as a first approximation in inverse problems like those encountered in remote sensing. It has been validated against in-situ data from five test sites in The Netherlands with different Holocene soil strata.

1. Introduction

While it is clear that shallow soil movements are caused primarily by changes in phreatic groundwater level (Kennedy and Price, 2005; Camporese et al., 2006), modelling the expected motion of soft soils such as peat and clay is an ongoing effort and generally involves accurately parameterizing the material and hydrological properties of every layer within the modelled soil strata. This is of particular importance in The Netherlands, where much of the coastal plain already lies below mean sea level and additional subsidence constitutes a significant threat to the security of the country. Most studies relating soil subsidence to groundwater focus on the effects of extraction from deep confined aquifers, and/or on the effects of settlement in an urban context, for example: (Hsi et al., 1994; Mas-Pla et al., 2013; Peduto et al., 2022). While modelling unconfined (phreatic) subsurface groundwater is an ongoing effort in The Netherlands (van Dam and Feddes, 2000; van der Gaast et al., 2010; De Lange et al., 2014; Erkens, 2021), the relationship between the shallow groundwater system and the corresponding soil displacement is not well understood, as so far the focus has been on studying the effect of phreatic groundwater levels on greenhouse gas emissions, and because in-situ measurements of the phenomenon with adequate temporal sampling were not available until recently (van Asselen et al., 2020). Despite these past efforts, we find there is also a need to be able to describe and predict the motion of these soils simply, with as few model parameters as possible. For example, in inverse problems such as those encountered in remote sensing, one often has only one observable per location and measurement epoch, rendering any highly multivariate model too complex for inversion, as the problems are too unconstrained to be solved without making many assumptions. This motivated us to create a model with the following requirements: (1) the model should depend on as few parameters as possible, (2) all input data should be readily available, (3) the model should be accurate, allowing for minor variations caused by higher-order effects which are not captured, and (4) the model should be validated at all available test locations. This resulted in a Simple Parameterization for the Motion of Soils: SPAMS.

2. Model inputs

To simplify the problem, we consider only the two most dominant drivers of soil movement: precipitation and evapotranspiration (Kennedy and Price, 2005). In previous work (Conroy et al., 2022), we have shown how the direction of ground motion can be reliably predicted using a recurrent neural network for use in SAR Interferometry (InSAR) applications using precipitation, temperature and day of year as model inputs. The use of evapotranspiration is a refinement which captures the effects of temperature and seasonality.

The value for evapotranspiration reported by the Royal Dutch Meteorological Institute (KNMI) is the so-called "De Bruin-Makkink" reference evapotranspiration (de Bruin, 1987; Hiemstra and Sluiter, 2011). This model is applicable to grasslands in The Netherlands, and can be rescaled to model the effects of other vegetation types (Jacobs and de Bruin, 1998). A major advantage to the De Bruin-Makkink model is that only two easily obtainable input values are required: average daily temperature and daily solar radiant exposure. For more information about these quantities, the reader is referred to de Bruin (1987).

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https://doi.org/10.1016/j.geoderma.2023.116699
Received 29 June 2023; Received in revised form 19 October 2023; Accepted 20 October 2023
Available online 3 November 2023

3. Model definition

Our goal is to create an empirical model for observed shallow soil displacement, in first approximation, rather than a complete description of all processes occurring in the shallow subsurface. In SPAMS, the overall relative soil surface height, H, in a given reference system and relative to a start time t_0, is modelled as a combination of reversible (ex. shrinkage and swell) and irreversible processes (ex. oxidation):

$$H\big(x, P(t), E(t)\big) = R\big(x, P(t), E(t)\big) + I\big(x, P(t), E(t)\big), \tag{1}$$

where R is the reversible component and I is the irreversible component. P and E are daily mean precipitation and evapotranspiration in millimetres as reported by KNMI, respectively. x is the set of lithology dependent parameters which will vary with location. We do not consider irreversible subsidence due to compaction or creep, only model the behaviour of unloaded soils with respect to changes in phreatic groundwater level and soil moisture.

The reversible component is obtained by considering the balance between the dominant source and sink of ground water, i.e., precipitation and evapotranspiration, respectively. This balance is sometimes referred to as the rainfall or water surplus and its integral over time as the cumulative rainfall/water surplus (Kennedy and Price, 2005; Yihdego and Webb, 2013). We modify this concept by introducing a scaling factor between the precipitation and evapotranspiration terms in order to model the material and hydrological properties of a given region. Different locations will have different soil stratigraphies, land use, and land parcel geometries, thus resulting in different responses to meteorological conditions. This also rescales the reference evapotranspiration value to one better suited to the vegetation cover of the area. Thus, the reversible component is modelled as the scaled difference between precipitation, $P(t)$, and evapotranspiration, $E(t)$, integrated over a period of time τ:

$$R\big(x, P(t), E(t)\big) = \sum_{\tau} \big[x_P P(t) - x_E E(t)\big], \tag{2}$$

where x_P and x_E are unknown relative scaling factors which will differ per location. These factors reflect the relative effect on soil height each respective process has, i.e., their relative strengths based on seepage and infiltration, as well as the scaling from cumulative groundwater balance to soil surface height. The unknown integration time τ is also different for different soils, as the memory/hysteresis of the system will differ based on material properties and geometry.

The irreversible component of soil subsidence is often modelled and reported as a constant linear rate (Hoogland et al., 2012; Erkens et al., 2016). However, we note that this ignores the effect of water in the system, and the fact that oxidation primarily occurs while there is a net loss of water in the system. We can make a simple improvement to this approximation by taking into account when the soil is wetting or drying. We retain a constant linear rate, but modulate its activity based on the scaled water surplus of Eq. (2). Thus the irreversible component is estimated by

$$I\big(x, P(t), E(t)\big) = \sum_{-\infty}^{t} x_I \cdot f\big(x, P(t), E(t)\big), \tag{3}$$

where x_I is an unknown constant rate of irreversible subsidence, and

$$f\big(x, P(t), E(t)\big) = \begin{cases} 0, & \text{for } R\big(x, P(t), E(t)\big) > 0 \\ 1, & \text{for } R\big(x, P(t), E(t)\big) \leq 0. \end{cases} \tag{4}$$

When $R > 0$ (see Eq. (2)), the precipitation term dominates and the soil is considered to be wetting. When $R \leq 0$, the evapotranspiration term dominates and the soil is considered to be drying, and undergoing oxidation. As-is, the model ignores the effects of compaction below the Vadose zone; that-is, compaction in the saturated zone caused by the mass of the water above. This could be included by setting the zero-term in Eq. (4) to an unknown constant.

There are four unknown parameters to estimate for a given location: the scaling factors x_P, x_E, and x_I, and the integration time τ. While these parameters are clearly linked with the physical makeup of the area of study, at this point we simply use them as empirical factors; additional study is possible to link the parameter values with soil and hydrological properties, as well as other factors such as parcel size and shape, land use, or ground water management factors such as freeboard or ditch water levels.

The parameters are estimated by minimizing the mean squared error between the model output and a set of training data. In-situ extensometer measurements from five locations in the Netherlands are used as the source of the training and testing datasets, available: (NOBV Consortium, 2023). The extensometers are based in the Pleistocene layer, and consist of several measurement anchors at different vertical levels in the above Holocene. Thus they provide continuous measurements of the movement of the Holocene layer. We use the topmost anchor located at 5 cm depth, which is the shallowest depth at which an anchor can be reliably fixed. A full description of the system is provided in van Asselen et al. (2020). The first part of the measurement time series spanning dates from June 2020–October 2022 is used as the training set which is used to fit the model parameters. The final year of the measurement time series, from October 2022–October 2023 is used as a testing set in order to assess the performance of the model. In a remote sensing context, the training data may be a sparsely distributed set of radar observables. The development of such a methodology is elaborated by Conroy et al. (2023), which shows how the model may be applied to regions where there are no in-situ data available.

4. Results and discussion

A map of the five test locations is shown in Fig. 1 along with corresponding publicly available borehole log data from the immediate vicinity (DINOloket, 2023). The test locations are distributed across various different parts of the Dutch coastal plain and have different combinations of clay, peat and sand in the Holocene sequence, thus providing a representative set of conditions for the region. All locations are managed grasslands used for agriculture.

The SPAMS model is validated by comparing the output to in-situ measurement data, i.e., testing data, taken by extensometer readings from the five test locations, shown in Fig. 1 and Table 1. This demonstrates that our model is able to reliably approximate the relative soil displacement at every test location, each with different Holocene soil stratigraphies and depths. Obviously, potential anthropogenic interventions in the water management would not be covered. While it is clear that the model is too simple to perfectly capture all the high-frequency components of the surface motion, the mean seasonal and sub-seasonal effects are accurately modelled at every location, which is sufficient for our objectives. The best performance is found at sites (b) and (d), which display the lowest overall root mean squared error (RMSE), and the lowest RMSE normalized to the standard deviation of the in-situ data (RMSE/σ) respectively. These sites also have the shortest distance to their corresponding weather station, so it is likely that they have the most accurate input data. The worst performance is encountered at site (a), which exhibits the most complex displacement history, with very large differences between subsequent years. Nevertheless, the model is still able to capture the large variations between seasons.

A major benefit to parameterizing the irreversible component separately from the overall surface displacement is that it allows for an estimation of when the most significant soil volume loss occurs. For example, the irreversible component was significantly greater at sites (a), (b) and (d) in the hot and dry summer of 2022 compared to the previous wetter and cooler summer of 2021. Thus we can compare the irreversible rates between years to gain understanding of how climate stresses on the soil and water system can affect subsidence.

Table 1
Estimated model parameters and performance.

Location Designation	Aldeboarn (a)	Assendelft (b)	Rouveen (c)	Vlist (d)	Zegveld (e)
Distance site-meteo station [km]	17.4	9.8	34.8	7.2	19.4
x_P [m/mm]	$1.7 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$6.3 \cdot 10^{-5}$	$8.0 \cdot 10^{-5}$	$9.7 \cdot 10^{-5}$
x_E [m/mm]	$1.3 \cdot 10^{-4}$	$9.2 \cdot 10^{-5}$	$8.2 \cdot 10^{-5}$	$6.4 \cdot 10^{-5}$	$2.7 \cdot 10^{-4}$
x_I [m/d]	$-1.0 \cdot 10^{-4}$	$-1.4 \cdot 10^{-4}$	$-2.9 \cdot 10^{-5}$	$-2.0 \cdot 10^{-5}$	$-2.3 \cdot 10^{-5}$
τ [d]	80	80	54	86	69
Training RMSE [mm]	10.6	8.39	4.18	4.80	6.64
Testing RMSE [mm]	12.2	6.38	6.03	4.51	10.4
Training RMSE/σ [mm/mm]	0.72	0.43	0.40	0.49	0.27
Testing RMSE/σ [mm/mm]	0.83	0.33	0.58	0.46	0.42
Overall R^2 [ ]	0.43	0.84	0.80	0.77	0.90

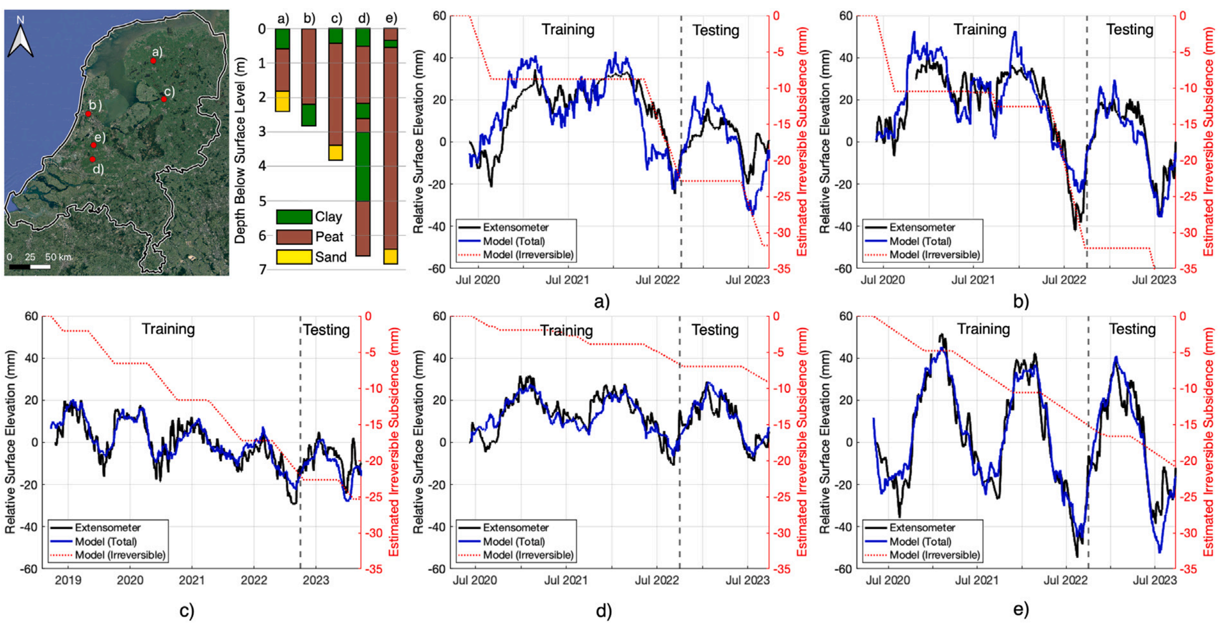

Fig. 1. Model output (blue: total displacement, red: irreversible component) and in-situ measurements (black) for sites (a) Aldeboarn, (b) Assendelft, (c) Rouveen, (d) Vlist, (e) Zegveld. Top left: map of The Netherlands annotated with extensometer locations in red, along with corresponding simplified Holocene borehole lithographies.

5. Conclusion

SPAMS is an empirical soil model which makes accurate predictions in the seasonal and sub-seasonal temporal scale to predict shallow soil surface movement for various soft soils in The Netherlands. The model is very simple and is fully described by only four parameters, and requires only rainfall and evapotranspiration data as inputs. This makes it well-suited for use as a first approximation in inversion problems such as studying subsidence based on remote sensing data.

In a parallel publication, we outline how the model may be applied to other regions where no in-situ data has been collected by means of radar interferometry techniques (Conroy et al., 2023). In the future, this model can also be further developed by considering an additional compaction term which acts on the saturated soils below the Vadose zone. We plan to develop the long-term applicability of the model by integrating historical shallow soil displacement observations spanning decades into a unified wide-area geodetic processing framework.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgements

We would like to thank S. van Asselen, Deltares Institute, for providing us with the extensometer data used in this work. This research is part of the Living on Soft Soils (LOSS): Subsidence and Society project, and is supported by the Dutch Research Council (NWO-NWA-ORC), grant no.: NWA.1160.18.259, URL: nwa-loss.nl.

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