Investigation of Sentinel-1-derived land subsidence using wavelet tools and triple exponential smoothing algorithm in Lagos, Nigeria

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Abstract
Lagos has a history of long-term groundwater abstraction that is often compounded by the rising indiscriminate siting of private borehole and water well. This has resulted in various forms of environmental degradation, including land subsidence. Prediction of the temporal evolution of land subsidence is central to successful land subsidence management. In this study, a triple exponential smoothing algorithm was applied to predict the future trend of land subsidence in Lagos. Land subsidence time series was computed with SBAS-InSAR technique with Sentinel-1 acquisitions from 2015 to 2019. Besides, Matlab wavelet tool was implemented to investigate the periodicity within land displacement signal components and to understand the relationship between the observed land subsidence, and groundwater level change and that of soil moisture. Results show that land subsidence in the LOS direction varied approximately between −94 and 15 mm/year. According to the wavelet-based analysis result, land subsidence in Lagos is partly influenced by both groundwater-level fluctuations and soil moisture variability. Evaluation of the proposed model indicates good accuracy, with the highest residual of approximately 8%. We then used the model to predict land subsidence between the years 2020 and 2023. The result showed that by the end of 2023 the maximum subsidence would reach 958 mm, which is approximately a 23% increase.

Keywords Triple exponential smoothing · Wavelet analysis · Land subsidence · Temporal evolution · Prediction

Introduction
Rapid population expansion combined with rising day-to-day commercial activities often create different forms of interactions between humans and the environment, including the ground surface. These interactions usually impact the natural evolution of the landscape and physical processes. The impacts of such interactions are evident in Lagos metropolis. The long-term excessive groundwater abstraction, compounded by the indiscriminate private borehole and water well proliferation (NERC 2003; Oyeyemi et al. 2015), has resulted in various forms of environmental degradation, including flooding, coastal erosion, and land subsidence. Land subsidence is an irreversible downward displacement of the Earth’s surface that can potentially, and perhaps permanently, deform the affected areas if inadequately monitored (Zeitoun et al. 2013), making it a treat to environmental sustainability. Land subsidence is particularly problematic when the ground under a physical structure is undergoing differential settling. Land subsidence of devastating proportion has been reported in several parts of Lagos metropolis (Cian et al. 2019; Ikuemonisan et al. 2020) with impacts ranging from the collapse of foundation structure to coastal erosion and inland seawater intrusion, among others. All of this translates to major financial losses. Therefore, timely monitoring and prediction of the temporal evolution of land subsidence are important for the attainment of a sustainable environment, because it will help to mitigate and prevent land subsidence and subsidence-induced hazards.

Excessive ground fluid withdrawal has been reported in several kinds of literature as a major triggering factor for land subsidence (Hu et al. 2014; Abidin et al. 2015). In Lagos, almost every household has at least a private borehole and/or a water well for the purposes of domestic consumptions and irrigation. The rising number of manufacturing
industry in and around the metropolis also heavily impacts the groundwater-level fluctuations, manifesting direct consequence in the form of land subsidence (Cian et al. 2019). Furthermore, the increasing rate of reclamation of coastal areas is an equally verified reason for a widespread land subsidence in parts of the Lagos metropolis (Olatinsu et al. 2019). Several attempts made by the regulatory authorities to regulate groundwater abstraction in Lagos were often confronted with stiff resistance by the inhabitants for many reasons, including poor public water supply system (Balogun et al. 2017).

In the past, different monitoring methods have been used by various authors to study land subsidence in Lagos. These include persistent scatterer synthetic aperture radar (PS-InSAR) analysis (Cian et al. 2019), small baseline subset interferometric (SBAS-InSAR) analysis (Ikuemonisan and Ozebo 2020) and geostatistical modelling (Ikuemonisan et al. 2020). Some of the existing studies concentrate only on the contribution and response of groundwater abstraction to land subsidence, while a few others focus on the impacts of land subsidence on Lagos infrastructure and the spatial variability of subsidence rate. In all the existing studies, restricted attention is given to the prediction of future scenarios of land subsidence. Nevertheless, accurate monitoring and prediction of land subsidence are essential for urban planning and risk assessment.

Although several studies demonstrate that InSAR technology has the capability to accurately monitor land displacement over a wide area at high spatial resolution (Hu et al. 2014; Chen et al. 2017), InSAR technology uses historical observations to reveal temporal evolution but is insufficient to predict future scenarios of land deformation. This underscores the need for an integration of InSAR results and time series modelling techniques to predict future scenarios. Against this background, this research is aimed at predicting the temporal evolution of land subsidence in the Lagos metropolis by integrating SBAS-InSAR results and the triple exponential algorithm. In addition, wavelet analysis was performed to establish the physical relationship between land subsidence and groundwater level changes and soil moisture variability. For the first time, this study presents the future trend of land subsidence in Lagos and establishes the correlation between land subsidence and groundwater level changes and soil moisture variability. With the wavelet tools, this study also investigated the periodicity of land subsidence and groundwater level changes. Wavelet is a time series processing tool that can be used to study temporal patterns in non-stationary phenomena (Torrence and Compo 1998). Wavelet is particularly useful for extracting attributes from time series data with a low signal-to-noise ratio and for identifying localized intermittent periodicities that affect land deformation dynamics (Grinsted et al. 2004).

There are various types of subsidence modelling methods. These include time series modelling, which has been classified by various authors (Deng et al. 2017; Shrestha et al. 2017; Bagheri et al. 2019). The time series modelling method can be classified into the theory-based model and the data-based model. The data-based model is generally referred to as an empirical model. The theory-based time series model involves the study of the system’s internal dynamics and the various driving mechanisms to provide a mathematical representation of the objective physical phenomenon. Although theoretical models can be used to model and predict the temporal evolution of land subsidence, the possibility to accurately model land subsidence is mostly hindered by inadequate information on the hydrogeological parameters describing the aquifer system of the objective area. Also, regular monitoring of land subsidence on a regional scale is computationally expensive. The inconsistency in the data collected by various satellite missions equally makes the analytical investigation of land subsidence more problematic.

On the other hand, the data-based model uses mathematical formulations derived from the observation data to predict future values. It is useful when the various factors triggering the phenomenon under investigation cannot be easily accounted for (Deng et al. 2017). Ikuemonisan et al. (2020) attributed land subsidence in Lagos to various causes, which include overexploitation of groundwater, oxidation of peatland, and decomposition of organic matter. These factors cannot be easily modelled by physical models, thus making an empirical time series model a conceivable alternative method to accurately model land subsidence in Lagos. The empirical model has been widely used to monitor future scenario of time-varying phenomena. In this study, an empirical model method, known as the triple exponential smoothing, is used to model and predict the temporal evolution of land subsidence in the Lagos metropolis. Triple exponential smoothing algorithm (also known as Holt Winter model) has been successfully used to predict future scenarios of time series variables (Yang et al. 2017). Triple exponential smoothing can manage time series data with trends and seasonal changes, in addition to random fluctuations and error terms.

Geographical and geological setting of the study area

Administratively, the name Lagos is used for both a state and a metropolis. Metropolitan Lagos is an area of land around the Lagos harbour (Longe et al. 1987), and it is our study area in the present study. Metropolitan Lagos is approximately bounded between latitudes (6.4°–6.7°) N and
longitudes (3.1°–3.7°) E. Geologically, it is situated within a zone of coastal creeks and lagoons, largely enclosed by the Lagos lagoon system created by boundary breaches linked to sand deposits (Hill and Webb 1958). The study area is underlain by sedimentary deposits of coastal plain sand, generally known as the Benin Formation. The coastal plain sand consists mainly of sand, silt and clay, with a multi-aquiferous succession featuring alternating sand and clay layers (Ayolabi and Peter 2005).

The coastal plain sand is an outcropping formation overlying the Ilaro and Ewekoro Formations and the Abeokuta Group in the mainland area. Three primary aquifers are identified within the basin and are characterized as follows (Kampsax-Kruger and Sshwed Associates 1977): recent sediments, coastal plain aquifer, and Abeokuta Formation. The recent sediment layer forms the surface aquifer and is dominant within the coastal plain sands, while the most abundant aquifer is found within the Abeokuta Group. The topography of Lagos is generally low-lying, flat in most parts with several points at sea level, thus exposing the area to prevalent seasonal flooding. The map of the study area is shown in Fig. 1.

Detailed descriptions of Lagos surface geology have been reported in the literature (e.g. Olowofela et al. 2012). Metropolitan Lagos occupies an area of about 1171 km², yet it is one of the most populated cities in Africa, with a current population of approximately 25 million inhabitants and 4% annual growth. Due to its proximity to the Atlantic Ocean and the abundance of coastal resources, coupled with its status as the country’s former capital, Lagos has witnessed a dramatic population increase in recent years. To manage this growing population, government and private sectors are embarking on massive infrastructural development such as roads, rain tracks, event centres, shopping malls, schools, residential and industrial estates, all of which underscore the possibility of over-dependence on the available groundwater resource and increasing demand for land reclamation.

Methods and data used in this study

Data source

This section presents an overview of the research method and the datasets. The approach considered in this study was a hybrid technique involving wavelet analysis and triple exponential smoothing algorithm. The data used were obtained from three major sources: Sentinel-1 (land subsidence), gravity recovery and climate experiment (GRACE), for groundwater level changes; and global land data assimilation system (GLDAS) for soil moisture. Groundwater level changes (Landerer and Swenson 2012) and soil moisture datasets (Rodell et al. 2004) corresponding to conceivable triggering factors and the third dataset corresponding to the displacement time series of the InSAR derived land subsidence were used as input variables in the proposed model. The work flow of the methodology used in this study is shown in Fig. 2.

Theoretical background

The SBAS-InSAR technique is a method for generating surface deformation from InSAR time series using interferometric pairs of small temporal gap baselines. SBAS-InSAR has been successfully used in land subsidence monitoring.
Initializing smoothing parameters where \( N \) is the number of SAR images. Given any two differential interferograms (phase difference between the overview is highlighted in this paper. The principle of SBAS-InSAR analysis has been reported in previous literature (Berardino et al. 2002), for the sake of correctness only SBAS-InSAR analysis has been reported in previous literature (Zhang et al. 2019; Zhou et al. 2018). The method of processing of SBAS-InSAR can be classified into four main steps. These include selection of short spatial–temporal baseline, interference management based on the given baseline subsets, retrieval of unwrap deformation phase, and separation of the error component of the unwrapping phase to generate actual deformation. The atmospheric artefacts are removed by the application of low pass filtering procedure in the 2D spatial domain and then by a temporal high pass filtering. Although a detailed theoretical framework for SBAS-InSAR analysis has been reported in previous literature (Berardino et al. 2002), for the sake of correctness only the overview is highlighted in this paper. The principle of SBAS-InSAR is based on Eq. 1. Given the quantity range of \( M \) differential interferograms (phase difference between co-registered images) generated by \( N + 1 \) SAR images at the same area with ordered time \((t_0, t_1, t_2, \ldots, t_N)\), it can be expressed that:

\[
\frac{N + 1}{2} \leq M \leq N \left( \frac{N + 1}{2} \right),
\]

where \( N \) is the number of SAR images. Given any two differential interference interferograms \((t_0 > t_n)\), the phase difference between two co-registered images can be expressed as:

\[
\phi_{x,i} = \phi_{\text{flat},x,i} + \phi_{\text{displ},x,i} + \phi_{\text{elev},x,i} + \phi_{\text{atm},x,i} + \phi_{\text{noise}},
\]

(2)

\[
\delta \phi = \phi_{x,t(b)} - \phi_{x,t(a)},
\]

(3)

where \( \phi_{x,i} \) is the \( i \) SAR image and the interference phase of the \( x \) pixel. \( \delta \phi \) is the phase difference between two registered SAR images. \( \phi_{x,t(b)} \) and \( \phi_{x,t(a)} \) are the interference phases at two different times. \( \phi_{\text{flat},x,i}, \phi_{\text{displ},x,i}, \phi_{\text{elev},x,i}, \phi_{\text{atm},x,i}, \phi_{\text{noise}} \) are the phase difference for flat phase, ground displacement phase, terrain phase, atmospheric phase, and error phase, respectively. The respective phases can be obtained as follows:

\[
\phi_{\text{flat},x,i} = -\frac{4\pi}{\lambda} \frac{B_z}{\tan \theta},
\]

(4)

\[
\phi_{\text{displ},x,i} = \Delta \phi_x(x,r) = \frac{4\pi}{\lambda} \phi(t_i, x, r) - \phi(t_i, x, r),
\]

(5)

\[
\phi_{\text{elev},x,i} = -\frac{4\pi}{\lambda} \frac{\Delta q}{\sin \theta} \frac{B_z}{R},
\]

(6)

\[
\phi_{\text{atm},x,i} = \phi_{\text{atm}}(t_i, x, r) - \phi_{\text{atm}}(t_i, x, r),
\]

(7)

where \( B_z \) is the vertical baseline, \( \Delta q \) is the digital elevation model difference, \( R \) is the distance along LOS, \( \phi(t_i, x, r) \) is the unknown phase of the image involved in the interferogram generated between the time \( t_0 \) and \( t_n \), \((x, r)\) is the pixel of range and azimuth coordinates, \( \phi(t_i, x, r) \) and \( \phi(t_i, x, r) \) are the radar line-of-sight (LOS) of the cumulative deformation at time \( t_i \) and \( t_n \), respectively. \( \lambda \) is the radar wavelength. The incremental displacement can be expressed as:

\[
\phi_{\text{displ},x,i} = \frac{4\pi}{\lambda} \sum_{i=0}^{t_i} v_i (t_i+1 - t_i),
\]

(8)

where \( v_i (i = 1, \ldots, \ldots, n) \) is the deformation rate in the time interval between two interferograms. Thus, the SBAS-InSAR technique generates displacement multitemporal time series for each pixel.

**Sentinel-1 data processing**

SBAS-InSAR’s ability to accurately monitor land subsidence and generate cumulative ground displacement resulting from various triggering factors has already been verified (Chen et al. 2017; Scifoni et al. 2016). To understand the land subsidence history of our study area, LOS displacement (land subsidence time series) was generated by processing a

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**Fig. 2** Work flow of methodology used in the study

(Zhang et al. 2019; Zhou et al. 2018). The method of processing of SBAS-InSAR can be classified into four main steps. These include selection of short spatial–temporal baseline, interference management based on the given baseline subsets, retrieval of unwrap deformation phase, and separation of the error component of the unwrapping phase to generate actual deformation. The atmospheric artefacts are removed by the application of low pass filtering procedure in the 2D spatial domain and then by a temporal high pass filtering. Although a detailed theoretical framework for SBAS-InSAR analysis has been reported in previous literature (Berardino et al. 2002), for the sake of correctness only the overview is highlighted in this paper. The principle of SBAS-InSAR is based on Eq. 1. Given the quantity range of \( M \) differential interferograms (phase difference between co-registered images) generated by \( N + 1 \) SAR images at the same area with ordered time \((t_0, t_1, t_2, \ldots, t_N)\), it can be expressed that:

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\frac{N + 1}{2} \leq M \leq N \left( \frac{N + 1}{2} \right),
\]

where \( N \) is the number of SAR images. Given any two differential interference interferograms \((t_0 > t_n)\), the phase difference between two co-registered images can be expressed as:

\[
\phi_{x,i} = \phi_{\text{flat},x,i} + \phi_{\text{displ},x,i} + \phi_{\text{elev},x,i} + \phi_{\text{atm},x,i} + \phi_{\text{noise}},
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\]

(6)

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(7)

where \( B_z \) is the vertical baseline, \( \Delta q \) is the digital elevation model difference, \( R \) is the distance along LOS, \( \phi(t_i, x, r) \) is the unknown phase of the image involved in the interferogram generated between the time \( t_0 \) and \( t_n \), \((x, r)\) is the pixel of range and azimuth coordinates, \( \phi(t_i, x, r) \) and \( \phi(t_i, x, r) \) are the radar line-of-sight (LOS) of the cumulative deformation at time \( t_i \) and \( t_n \), respectively. \( \lambda \) is the radar wavelength. The incremental displacement can be expressed as:

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\]

(8)

where \( v_i (i = 1, \ldots, \ldots, n) \) is the deformation rate in the time interval between two interferograms. Thus, the SBAS-InSAR technique generates displacement multitemporal time series for each pixel.
total of 135 archived Sentinel-1 images acquired on ascending orbits (Track 1) from 2015 to 2019. The processing was performed using the SBAS-InSAR service of the Geohazards Exploitation Platform (GEP), which is a web-based platform developed to support the exploitation of satellite Earth Observation (EO) for the purpose of monitoring geohazards. Through the GEP’s SBAS-InSAR service, a multitemporal InSAR analysis via the Parallel SBAS (P-SBAS) algorithm (Berardino et al. 2002; Casu et al. 2014; De Luca et al. 2015) was performed.

Wavelet-based analysis of InSAR, moisture, and groundwater time series

Continuous wavelet transform (CWT) is a useful tool for expanding time series data into two-dimensional time–frequency space and identifying localized regular periodicities within a time series (Grinsted et al. 2004). CWT has been successfully applied to analyse geophysical time series data. To successfully implement CWT, the time series input parameters need to be regularly spaced in time (Tomás et al. 2016). Sentinel-1A satellite has a revisit time of 12 days, which makes CWT a suitable tool to analyse the Sentinel-1 SBAS-InSAR derived vertical deformation time series without further transformation. SBAS-InSAR analysis usually estimates ground displacements as a combination of both linear and non-linear components. While the linear component indicates a continuous period over time in the frequency domain, the non-linear component, on the other hand, may include different periods with higher-frequency patterns at different time intervals, including seasonal variations.

However, to investigate the physical relationship between the two different time series of interest, cross wavelet transform (XWT) and wavelet transform coherence (WTC) tools were used. The XWT analysis provides a two-dimensional representation of the absolute value and the phase of the complex number in the time–frequency space, which can be used to identify similarities in the trend of the two time series data. XWT computes the CWT of the time series and the complex conjugate of the other time series and multiplies the two results, detecting regions characterized by high common power to show the correlation within a local phase. The phase of the XWT shows the presence of time lag between the two time series. For instance, 0° implies that the two time series are in-phase or in temporally coincidence; approximately − / + 180° indicates anti-phase or temporally inverse. In this study, the cross wavelet and wavelet coherence toolbox (Grinsted et al. 2004), a Matlab toolbox, was used to analyse SBAS-InSAR land subsidence time series, and the correlation between the groundwater level changes and soil moisture variability. The wavelet toolbox can be assessed at http://www.glaciology.net/wavelet-coherence. Prior to the wavelet analysis, the groundwater level changes time series and soil moisture time series were interpolated to make them temporally consistent with the dense InSAR time series. The key components of the wavelet tools utilized in this research are presented in Table 1.

### Triple exponential model

Considering that the land subsidence dynamics is a complex response to several triggering factors, time series analysis can provide useful information on the combined impact of various triggering factors. A triple exponential algorithm is a powerful tool for analysing and forecasting land subsidence because it is capable of managing various components of a time series data. The basic idea behind the triple exponential algorithm technique is to decompose a time series into various components: linear trend, seasonal, and random change. Once the trend, incremental, and seasonal changes are computed, a predictive model is defined to extrapolate the predicted value. The principle of triple exponential smoothing is stated below. For the original time series determined by SBAS-InSAR γ(t)n = γ(1), γ(2), γ(3), γ(4), …, γ(n), the exponential triple model can be expressed as:

\[
L_t = \alpha \frac{y_t}{S_{t-1}} (1 - \alpha) (L_{t-1} + T_{t-1}),
\]

\[
T_t = \beta (L_t - L_{t-1}) + (1 - \beta) T_{t-1},
\]

\[
S_t = \gamma \frac{y_t}{L_t} (1 - \gamma) S_{t-1},
\]

Table 1 Overview of wavelet tools components (Tomás et al. 2016)

| S/N | Tool | No. of required time series | Magnitude connotation | Phase interpretation | Resolution type |
|-----|------|-----------------------------|-----------------------|---------------------|----------------|
| 1   | CWT  | 1                           | Time patterns resent  | –                   | Original       |
| 2   | XWT  | 2                           | Time patterns with large power in both time series | Presence of time lag between both series | Original |
| 3   | WTC  | 2                           | Similar time patterns in both time series | Presence of time lag between both series | Degraded |
where \( y_t \) is the observed vertical displacement (subsidence or uplift), \( L_t \) is the level (average value), \( T_t \) is the trend, \( S_t \) is the seasonality, \( \alpha, \beta \) and \( \gamma \) are smoothing coefficients for level, trend, and seasonality, respectively. Accordingly, the prediction is obtained as follows:

\[
P_{t+k} = (L_t + kT_t)S_{t-1+k},
\]

(12)

where \( k \) is the length of the seasonal cycle, known as the time intervals from the moment to the predicted time.

Results and discussion

Sentinel-1-derived surface displacement

To investigate the spatiotemporal evolution of land subsidence in Lagos, for the period of 2015–2019, SBAS-InSAR technique was employed to detect surface deformation. The time series for Sentinel-1 retrievals based on the method described in “Theoretical background” and “Sentinel-1 data processing” was generated. Interferograms of the Sentinel-1 SAR stack provided good coverage for the entire study area, excluding the vegetative, watershed, and water areas. A total of 187,115 deformation data points were revealed by the SBAS-InSAR analysis. The SBAS-InSAR results revealed that the average subsidence rates in the LOS direction ranged between −94 and 15 mm/year for the period of 2015–2019.

Figure 3 shows the histogram of the subsidence rates in the study area. As can be seen in Fig. 3, the histogram is strongly negatively skewed, indicating that some parts of the study area exhibit high subsidence rates reaching about −94 mm/year at the end of 2019. The average subsidence rate for the entire study area is approximately −8.7 mm/year. Figure 4 is a map describing the mean LOS velocity of the study area. In the figure, negative and positive values, respectively, represent subsidence and uplift rates. Accordingly, based on the equation of transformation scenario (vertical displacement = \( \frac{\text{LOS displacement}}{\cos \theta} \)), the vertical displacement for the same period ranged from −115 to 18 mm/year. Kriging
interpolation was adopted to predict deformation values for the locations not determined by the SBAS-InSAR analysis. The result of the interpolation is shown in Fig. 5. The kriging result indicates that the maximum subsidence is dominant in the coastal zones, watershed, and plain areas. Areas where heavy structures are built on unconsolidated sediments are also found to exhibit a considerably high subsidence rate, as corroborated by site inspection.

The time series of vertical displacement typically showed a steady evolutional trend for all subsiding areas but at different rates, as shown in Fig. 6. Most of the subsidence observed in Lagos indicated a slight oscillatory trend, which may be an indication of progressive groundwater abstraction combined with seasonal factors (such as rainfall) in most parts of the study area. Figure 6 shows the vertical displacement time series for points where maximum subsidence rates were observed. The coordinates of the points of maximum land subsidence rates are shown in Fig. 6b. As can be seen in Fig. 6b, the locations of the 36 time series are generally found around/along the coastal lines, which are classified as alluvial deposits (Ikuemonisan et al. 2021). Thus, the observed high subsidence rate in these areas is attributable to rapid compaction of unconsolidated sediments and/or poroelastic response of the aquifer systems to groundwater redistribution. Figure 7 shows the cumulative subsidence map for the study area. From the figure, it is shown that spatial distribution of land subsidence in most parts of Lagos is generally uneven. This suggests that the distribution of and evolution of land subsidence in Lagos are driven by its subsurface geology structures and land use characteristics, including high rate of groundwater exploitation and land reclamation. The areas of high subsidence rates include Ikoyi, Eti-Osa, Surulere, Kosofe, Oshodi, Ajeromi Ifelodun, and Mushin. Parts of Ikorodu and parts of Isheri Olofin also show significantly high subsidence rates. On the other hand, most parts of Ikeja and Alimosho are relatively stable, with uplift of approximately 15 mm/year observed in parts like Ikeja and Alimosho.

Continuous wavelet-based analysis of LOS displacement

The CWT describes the distribution of a frequency component of a signal in relation to time (Tomás et al. 2016). The land subsidence time series and groundwater level changes time series were subjected to continuous wavelet transform analysis to reveal the pattern of periodicity in each time series. Three subsidence sites were selected, all of which corresponded to varying land subsidence rates (high, moderate, and low). The acronyms HLS1, MLS, and LLS denote the sites of the highest land subsidence (HLS1), medium land subsidence (MLS), and lowest land subsidence (LLS), respectively. Furthermore, the terms HLS2, HLS3, and HLS4 are used to denote three other sites next to the highest subsidence rates, respectively. The CWT of land subsidence, along the LOS for the selected sites, is shown in Fig. 8. At HLS, the land subsidence time series generally indicates low power within the 5% significance level and moderate power outside the 5% significance level, suggesting that no periodic signal presents high power above the 5% significance level and low magnitudes.
of vertical ground motion oscillations (Fig. 8a). The CWT power of the subsidence time series from MLS and LLS is shown in Figs. 8b, c, and has an 8–48 month band in the period from 2016 to 2018. However, for the MLS site, the power is quite low, and thus there is low power above the 5% significance level for the entire study period. In general, for HLS and MLS sites, the powers are relatively low, and thus there is no high power above the 5% significance level for the entire study period. Figure 9 shows the CWT of groundwater level change time series. As can be seen in the figure, all sites have commonly high positive values of the wavelet power spectrums at the 12–24 month band and 32–48 month band in the period from mid-2015 to mid-2016 and late 2015 to early 2016, respectively. This finding suggests that groundwater seasonality is periodically affected by groundwater abstraction and/or precipitation. Groundwater level changes time series scalograms show significant periodicities with power between 8 and 16 during the period of mid-2015 and mid-2016, which suggests seasonal groundwater level changes at the study sites. In general, the scalograms for the three sites appear similar. A possible explanation for this result can be attributed to the fact that the GRACE measures groundwater on a regional scale.

**XWT and WTC result**

The plot of the CWT modulus of a signal as a function of time and frequency is known as a scalogram. Generally, in scalograms, a thick contour and a thinner black line represent the 5% significance level against the red noise and the cone of influence (COI), respectively. The areas outside the COI are depicted with lighter shadows and can be inaccurate for signal analysis due to the edge effect. Wavelet power spectrum (WPS) is the energy distribution of the time series for an objective wavelet scale and time domain.
colours indicate high power, while low power is indicated by cold colours. The direction of the arrows shows the relative relationship between the two time series. The right-pointing arrow indicates in-phase (or a positive correlation), and the left-pointing arrow implies anti-phase (or a negative correlation). While a direct descending arrow signifies that land subsidence leads soil moisture/groundwater level changes by 90°, the upright arrow signifies that soil moisture/groundwater level changes lags behind land subsidence by 90°.

**XWT and WTC analyses of land subsidence and groundwater level changes**

In this section, the relationship between land subsidence and groundwater level changes is investigated through XWT and WTC analyses. Both XWT and WTC analyses are useful tools for checking the proposed relations between two time series. While the XWT tool allows the identification of common power, WTC tools allows the identification of relative phase in time–frequency space. The GRACE-derived groundwater data between 2015 and mid-2017, and Sentinel-1-derived land subsidence from 2015 to 2019 were analysed. It is important to note that XWT and WTC analyses for subsidence data and groundwater data only cover from 2015 to 2017 because that was the period subsidence time series and groundwater time series temporally overlap for our study area. Before performing the wavelet analysis, linear interpolation was performed on the groundwater time series. As GRACE/GLDAS-derived groundwater data are averaged monthly (30 days temporal gap) and Sentinel-1 data have 12 days temporal gap, the groundwater time series data have to be interpolated to reduce the temporal gap to 12 days and make the two time series data have equal temporal gap.

Figures 10 and 11 depict the WTC and XWT for the Sentinel-1-derived land subsidence and groundwater level time series at the three selected sites, respectively. The statistical significance level of the WTC was computed based on the Monte Carlo technique. WPS describes the spread of a frequency component as a time function which is used to identify the significant coherence between land subsidence time series and groundwater level changes time series. The arrows indicate the relative phase relationship vector, with in-phase pointing towards the right and anti-phase pointing towards the left. The land subsidence leads groundwater by 90° pointing straight down, indicating the phase difference between the land subsidence and groundwater level changes. Inspection of the WTC scale grams (Fig. 10) indicates that there were more areas with higher power above the 5% significance level. Additionally, there was a significant
variation in the phase relationship between land subsidence and groundwater level changes in different periods. In Fig. 10, a significant high power was observed for a period ranging between 2 and 4 months. For all the three sites, the link between both variables appears to be close to anti-phase. As can be seen in Fig. 10a, land subsidence and groundwater level changes were in-phase with substantial common power in the 2 month band in early 2017, but were anti-phase between June 2010 and November 2010. In Fig. 10b, a significant common power was observed up to 5 months between mid-2015 and mid-2017. However, there was significantly low power observed around mid-2016. At the LLS site, several areas revealed significant coherence between land subsidence and groundwater level changes time series up to the 10-month band in several periods, all above the 5% confidence level. Generally, the results showed insignificant
common powers in the three study sites. In Fig. 11, a relatively low common power in the 6- to 12-month band from late 2015 to early 2016 is found above the 5% significance level, as shown in Fig. 11b, c, suggesting the possibility of other triggers of land subsidence besides groundwater level variation. However, Fig. 11a, shows that the observed low power is outside the 5% confidence interval.

**XWT and WTC analyses of land subsidence and soil moisture**

This section presents the relationship between land subsidence and soil moisture as analysed through XWT and WTC.

Monthly averaged soil moisture data were obtained from GLDAS and interpolated to have a uniform temporal gap with the Sentinel-1-derived land subsidence. Figures 12 and 13 show the result of WTC and XWT analysis between land subsidence time series and soil moisture time series for the selected sites, respectively. At HLS (Fig. 13a), XWT reveals a region within the 95% confidence level, yet with low power, between 2016 and mid-2018, where the phase arrows indicate a shift between land subsidence and soil moisture. However, WTC (Fig. 12a) shows regions with significant coherence within the 5% confidence interval between land subsidence and soil moisture, but with common low power.

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**Fig. 10** Wavelet coherence of Sentinel-1-derived land subsidence along LOS and GRACE-derived groundwater level changes for the three selected sites. The relative phase relationship is indicated by arrows. a–c Corresponds to sites HLS1, MLS, and LLS, respectively

**Fig. 11** Cross wavelet transform of Sentinel-1-derived land subsidence along LOS and groundwater level changes for the three selected sites. The relative phase relationship is shown as arrows. (a–c) Corresponds to sites HLS1, MLS, and LLS, respectively
(approximately 0.6–1.0) in several periods and phase arrows pointing in varying directions. This is suggestive of the presence of both local correlation and anti-correlation.

Between 2016 and 2017, the phase arrows point rightward, indicating a correlation between the two time series; and between 2017 and mid-2018, the phase arrows point upward, reflecting the presence of time lag between the two time series. Figure 12b and Fig. 13b show the XWT and WTC of land subsidence and soil moisture, respectively, at the MLS site. Figure 12b reveals high common power between land subsidence and soil moisture, approximately in the 12-month period, for the entire study period. WTC also indicates that land subsidence and soil moisture are out-phase (phase shift ~ 180°) in all regions with significant common power. However, in XWT, there is little or no periodic signal illustrating high power above the 5% significance level (Fig. 13b). Within the 95% confidence interval, a significant coherence value is observed for the entire study period, with most phase arrows pointing rightward.
According to the wavelet analysis results of the LLS site, different regions with high power are demonstrated in WTC (Fig. 12c) at bands 0.5–1. Similar to what is observed in the HLS site, the phase arrows point in different directions, which indicates that land subsidence and soil moisture are in-phase between mid-2016 and mid-2018 at the period of 4–7 months and 30–32 months, respectively. The out-of-phase occurred between 2016 and 2017 at periods 3–6. In general, comparing all subplots in Figs. 12 and 13, WTC reveals more regions with common high power than XWT. The reason why WTC can reveal regions characterized by significant coherence is because XWT requires fewer values of individual CWTs to compute high coherence, but signal periodicities in WTC rely only on the time–frequency patterns against the power of components in the CWT. The observed negative correlation in both figures suggests the presence of other triggering factors of land subsidence during the period of study. Another possible reason for the negative correlation may be due to the inability of GRACE satellite to provide accurate data for small basin groundwater monitoring.

**Possible triggering factors of land subsidence in Lagos**

As stated in “Geographical and geological setting of the study area” and in the introduction of this paper, the Lagos aquifer is predominantly coastal alluvial, surrounded by massive water body. Land subsidence in metropolitan Lagos is significantly on the increase as a result of the nature of its geological formation and the rising anthropogenic contributions. As Lagos’ population expands drastically, there is a growing need to withdraw more groundwater for domestic, industrial, and municipal purposes, which will cause groundwater levels to drop considerably. The results of wavelet analysis suggested that groundwater abstraction and soil moisture are triggering factors of land subsidence in Lagos. Nevertheless, the study has identified that there are other triggering factors of land subsidence in our study area besides groundwater abstraction and soil moisture variability. As reported in other literature, other factors that can trigger land subsidence in coastal cities like Lagos may include hydrostatic load, hydrocompaction, and natural compaction of unconsolidated sediments (Abidin 2015). However, further study needs to be conducted to ascertain the other causes of land subsidence in Lagos metropolis.

**Modelling results**

The result of wavelet analysis and reports from existing studies (Ikuemonisan et al. 2020) indicate that the magnitude and spatial distribution of land subsidence in metropolitan Lagos are controlled by a range of factors. These factors encompass groundwater abstraction, soil moisture content, compaction of unconsolidated sediments, and land use characteristics such as land reclamation. Consequently, this paper speculates that the empirical modelling approach would be suitable in this case to model and predict the future scenario of land subsidence in Lagos, Nigeria. Based on this speculation, the triple exponential smoothing algorithm was applied to the time series data of the land subsidence and the prediction models were defined. The three key steps involved in the model implementation are parameters initialization, optimization, and model building. Smoothing parameters $\alpha$, $\beta$, and $\gamma$ were optimized using Excel solver, with minimum RMSE set as the condition for an optimal model.

The triple exponential model predicts subsidence data based on the historical trend in Sentinel-1-derived land subsidence. However, before the modelling, the stationarity of the input time series parameters was tested using descriptive statistics, including the meaning, variance, and autocorrelation. The result of the descriptive statistical analysis indicated the presence of varied mean, variance, and autocorrelation over time, confirming the state of non-stationarity of the subsidence time series. Figure 14 shows the plot of the displacement–time series. For want of space, the yearly displacement–time series was presented for only two selected sites (HLS1 and HLS2). As seen in Fig. 14, there are variations in the annual mean LOS velocity, which confirms non-stationarity presence. The presence of non-stationarity suggests that there is a variation in the driving mechanisms of land subsidence in the area covered in the study. Consequently, before proceeding into the modelling scenario differencing technique was implemented to make the subsidence time series stationary. Four selected sites corresponding to points of highest subsidence rate were considered for the modelling.

Figure 15 and Table 2 present the findings of the modelling scenario. There are two established methods of triple exponential smoothing. These are additive method and multiplicative method. In this study, in comparison to the additive method, the multiplicative technique was found to present minimal error and was used to predict future scenarios. The computed smoothing parameters range between 0.10 and 0.41 for $\alpha$, $\beta$ values range between 0.01 and 0.30, while the values of $\gamma$ lie between 0.20 and 0.30. The selected combinations of smoothing parameters present minimal error and are considered as the best prediction model for the study area. Findings show that the lower the smoothing parameters, the smoother is the line. In Fig. 15, results indicate that land subsidence in parts of Lagos metropolis will increase significantly. At HLS3, subsidence will reach 812 mm by the end of 2023, and the worst-case scenario (predicted lower bound) may be up to 958 mm and 945 mm by the end of 2023 at HLS3 and HLS4, respectively.
Model validation

Model validation is an important part of model formulation as it helps to understand the goodness of fit/accuracy. To quantitatively evaluate the goodness of fit of the proposed model and assess its performance, different accuracy indicators were used, which include mean absolute percentage error (MAPE), mean absolute deviation error (MAD), root mean square error (RMSE), and mean square error (MSE). Model validation was performed by comparing the subsid- ence obtained from the SBAS-InSAR analysis (observed subsidence) with the subsidence that was predicted by the triple exponential algorithm (predicted subsidence). The residuals indicating the model error were computed by subtracting the predicted from the observed subsidence. In the time series model validation, if the residuals were found to be normally distributed, it can be speculated that the quality of the model is sufficient to manage the three components of subsidence time series (cyclic, seasonality, and trend). The result of the accuracy indicator is presented in Table 3.

The normal probability plot of the residuals is shown in Fig. 16. As seen in all the subplots, the residuals are concentrated around the normal line, indicating normal distribution and implying a good fit. Further findings revealed that the residual between the actual and forecasted land subsidence varied between 4 and 8%. The histograms of the model residual show normal distribution function, with error concentrating around zero. The scatter plot of the observed land subsidence versus predicted land subsidence indicates good accuracy, with R-squared value ranging between 0.994 and 0.996, as shown in Table 3. The estimated RMSE ranged between 7.920 and 9.720, which further confirm the accuracy of the proposed model. The triple exponential algorithm captures seasonality, trend, and level in a time series data.

Conclusions

In this study, land subsidence that occurred between 2015 and 2019 due to various activities in metropolitan Lagos was investigated by analysis of 135 Sentinel-1 data
using the SBAS-InSAR technique, wavelet tools, and a triple exponential smoothing algorithm. Wavelet tools were used to investigate the physical correlation between land subsidence and groundwater level changes and soil moisture variability. Findings revealed that the ground surface in the Lagos plain area has been under intense subsidence with a cumulative vertical displacement of approximately 425 mm between 2015 and 2019. Findings

![Fig. 15 Observed land subsidence and predicted land subsidence.](image)

| Table 2 | Summary of model result |
|---------|-------------------------|
| Site    | HLS1 | HLS2 | HLS3 | HLS4 |
| Alpha (α) | 0.10 | 0.15 | 0.25 | 0.41 |
| Beta (β) | 0.01 | 0.21 | 0.15 | 0.30 |
| Gamma (γ) | 0.20 | 0.30 | 0.30 | 0.21 |
| Predicted upper bound by the end of 2023 (mm) | 582.00 | 586.00 | 648.00 | 446.00 |
| Predicted subsidence by the end of 2023 (mm) | 685.00 | 695.00 | 812.00 | 682.00 |
| Predicted lower bound by the end of 2023 (mm) | 776.00 | 884.00 | 958.00 | 945.00 |

| Table 3 | Result of accuracy indicators |
|---------|-------------------------------|
| Site    | HLS1 | HLS2 | HLS3 | HLS4 |
| MAPE (%) | 0.010 | 6.430 | 19.610 | 16.050 |
| MAD (mm) | 3.910 | 7.320 | 6.960 | 7.690 |
| MSD (mm) | 42.650 | 91.780 | 75.940 | 92.380 |
| RMSE (mm) | 7.920 | 9.720 | 8.770 | 9.520 |
| R-squared | 0.996 | 0.994 | 0.995 | 0.994 |
revealed a slight seasonal variation in the land subsidence time series, but a significant variation in groundwater level changes and soil moisture at the monitoring sites. Findings further show that land subsidence in Lagos is partly controlled by groundwater level changes and soil moisture variation. This result suggests the possibility of other triggering factors of land subsidence apart from groundwater level fluctuations. Our proposed model indicates that maximum vertical cumulative land subsidence in parts of Lagos metropolis will reach 849 mm by the end of 2023. Evaluation of the proposed model indicates good accuracy. The highest residual is 8%. The results of this study demonstrated that the SBAS-InSAR technique combined with wavelet transform and a triple exponential smoothing algorithm could be successfully used to analyse and model land subsidence.

**Fig. 16** Normal probability plot of residuals. a HLS1, b HLS2, c HLS3, and d HLS4

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