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Prediction of vegetation dynamics using NDVI time series data and LSTM

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Abstract

Understanding and analyzing the changes in vegetation cover is very important in several aspects including climatic changes, water budget, ecological balance and specially to undertake necessary conservation measures. The concept of neural network has gained much significance in the analysis of vegetation dynamics using remote sensing satellite data. In the current study an attempt has been made to predict the vegetation dynamics using MODIS NDVI time series data sets and long short term memory network, an advanced technique adapted from the artificial neural network. The dataset of 861 NDVI images from January 2000 to June 2016 is used for making the time series. The data is segregated into three sets which comprises of training set (70%), validation set (20%), and testing set (10%). To check the reliability of the experiment we have finalised two different regions after extensive research for investigation. These include different terrains in the Great Nicobar Islands, one region along the coast where vegetation has severe ecological damage due to 2004 Indian Ocean tsunami and the other, an interior region which remained imperturbable during the tsunami. Long short term memory network, an advanced neural network is trained with these NDVI values for both the regions separately to predict the future vegetation dynamics. To measure the accuracy of the LSTM network, root mean square error is calculated. The resulting plots from both the experiments indicate that the long short-term memory neural network follows the series in addition to coinciding with the required time series. Also, an unanticipated change in the trend of the NDVI series were well adapted by the network and was able to predict the future NDVI values with good accuracy maintaining RMSE less than 0.03 without providing any supplementary data. By adopting the prescribed method in the paper, anticipation of vegetation changes can be done accurately much ahead of time and take proactive measures accordingly to safeguard and improve the vegetation in any area.

Keywords Time series · Normalized Difference Vegetation Index · Long short term memory · Great Nicobar · Neural networks

Introduction

Analysing the vegetation dynamics is important in the context of their sustainability. Vegetation structure changes rapidly due to various reasons influenced by both anthropogenic and natural factors, potentially resulting in the degradation and destruction. Vegetation phenology is impacted by life-cycle patterns, season and climatic conditions resulting in changes of their spectral reflectance patterns (Rußwurm and Korner 2017). Spatio-temporal mapping and monitoring of vegetation helps in assessing the health of vegetation and imply better management practices to safeguard them. The availability of the spatio-temporal satellite data aids in visualizing changing vegetation dynamics in due course of time. Further, development of vegetation indices using remote sensing satellite data provides better insights about the growth patterns, seasonal changes and health conditions of the vegetation (Wang et al. 2016).

Normalised Difference Vegetation Index (NDVI) is one of the most widely acknowledged indices for vegetation related studies (Xue and Su 2017). NDVI is a numerical indicator of the greenness of vegetation derived using the visible and near infrared (NIR) bands (Jeevalakshmi et al. 2016; Eslamian and Eslamian 2017). Typically, the NDVI values are normalized between $+1$ and -1, and a higher NDVI value indicates greener and denser vegetation (Peckham

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and Jordan 2007). The negative NDVI value denotes other non-vegetated classes like water, urban areas, barren lands, snow, etc (Anonymous 2000). The generalized annual NDVI profile for vegetation increases with the plant growth and reaches a peak or plateau (Jose et al. 2002). Later the profile falls off eventually with plant death or leaf senescence. Thus, NDVI series provides a means to describe plant phenology (Viovy et al. 1992; Wang et al. 2016). However, the phenological changes in concurrence with time appear to be very minimal or obscure, as observed in the vegetation of tropical rainforest due to subtle climatic variations (Valtonen et al. 2013).

The analysis of time series is widely used approach in many studies as they work with data of high temporal resolution and low spatial resolution (Petitjean et al. 2014; Khorasani et al. 2016). The availability of time series NDVI data enhances information about the vegetation conditions as well as in assessing and monitoring its changes (Ivits et al 2013). Interim changes are better inferred by time series analyses which cannot be accounted using low temporal satellite data. Time series includes any temporary changes and thus provides better analysis than any other datasets, as the analysis is based on observations of particular time frame. Major seasonal changes and inter-annual patterns can be well defined by analyzing the time series data of vegetation and surface water bodies (Haas et al. 2009; Tulbure and Broich 2013; Cordeiro et al. 2016; Rembold et al. 2015). NDVI time series analysis offers more accurate and efficient results in detecting the change in vegetation cover (Lyu and Mou 2016; Agone and Bhamare 2012), land use and land cover (LULC) classification (Gómez et al. 2016; Anderson 1976), estimation and prediction of vegetation, mapping forest disturbance (Kennedy et al. 2010), etc. Time series analysis also enables to estimate and model biomass (Gómez et al. 2014), analyze forest degradation (Shimabukuro et al. 2014) and assess forest carbon sinks (Gómez et al. 2012).

Various types of remotely sensed imagery and processing methods have been introduced and used to predict NDVI time series. Autoregressive integrated moving average (ARIMA) models are used for forecasting NDVI time series (Stepchenko 2016; Manobavan et al. 2002). These models use the adjoining data to predict the next values in the time series, but as these models are parametric and assumption of the data to be linear and stationary, makes them inappropriate for precise prediction of time series. Markov chain model simply constructs a probability mass function incrementally across the possible next states (Stepchenko and Chizhov 2015a, b). It is memory-less as it considers only the present state of the process to predict future. It is a simple and effective method for prediction, but uses a fixed window (Kriminger and Latchman 2011).

Neural networks have become popular in the analysis of remote sensing data with the increase in availability of satellite data, as they are non-parametric unlike most of the statistical methods (Foody 2006; Mas and Flores 2008). Many studies have shown that neural networks work well as they are non-linear models and perform well with noisy data as well (Atkinson and Tatnall 1997). Some of the applications of neural networks in remote sensing are land cover mapping (Zhou and Yang 2008), forest change detection (Gopal and Woodcock 1996), and predicting vegetation changes (Kang et al. 2016). Different neural networks from the Multiple Layer Perceptron (MLP) (Atkinson and Tatnall 1997), Artificial Neural Network (ANN) (Silva et al. 2014; Miller et al. 1995; Wagh et al. 2016) to advanced neural networks like Back-propagation (BP) neural networks (Zhang and Chang 2015) and Convolution Neural Networks (Maggiori et al. 2016) are used for classification of remote sensing satellite imagery (Atkinson and Tatnall 1997).

ANNs can be used for forecasting NDVI index (Kang et al. 2016; Nay et al. 2016), but as ANNs have no memory to store the information of the past data in the time series, results are less efficient. Recurrent neural network (RNN), which has memory can also be used for predicting the time series (Stepchenko and Chizhov 2015a, b; Stepchenko 2016), by training the RNN with some past NDVI values but vanishing gradient problem of RNNs makes them less suitable (Bengio et al. 1994). Further, they require a substantial amount of preceding values as input to the network for prediction of the succeeding values and thus involve lot of computational overhead compared to Long Short-Term Memory (LSTM) network. The LSTM is a variant of RNN, which has an internal memory to store the information received till time t, for a long time in the model (Skymind 2016; Budama 2015). This property of LSTM makes them very much preferable for predicting the time series. LSTM is a deep learning neural network which is highly preferred in predicting time series due to its long-term memory (Gamboa 2017).

Monitoring vegetation changes is inevitable in the context of current climatic change conditions and rapid human interventions. Vegetation, especially island ecosystems are vulnerable to both human induced disturbances and natural forces like tsunami and volcanic eruptions. Seasonal changes are common in vegetation. However, it is also effected by climate change and may lead to drastic change due to catastrophes (Verbesselt et al. 2010). Change detection methods help in assessing the change in vegetation (de Beurs and Henebry 2005) and the methods available so far are able to identify changes using low temporal resolution or decadal gap remote sensing data (Coppin et al. 2004). They are able to track the extent of areal changes but are incapable of identifying the minor seasonal or any gradual changes.

Alternatively, time series data with higher temporal resolution depict better changes in vegetation (seasonal, gradual or sudden abrupt changes) and is widely adopted

in assessing minor/shorter phenomenal changes (Jana et al. 2016). Further the use of index derived from time series data (such as NDVI) is beneficial in identifying the changes compared to typical satellite data analysis, where only areal extent is calculated and compared. Time series data can be analysed using varied ANN methods and the best one proposed in recent past is the use of LSTM. Though LSTM gained specific significance in different themes (like LULC, soil moisture studies, predictions/forecasting an event), its application in vegetation studies is still in nascent stage. The research of Rußwurm and Korner (2017) can be cited as one example of LSTM study adopted for crop identification using Sentinel data. However, no specific studies have been carried out with reference to use of LSTM in forest vegetation and the current study is first of its kind to be cited as an example of LSTM study in prediction of forest dynamics as well as for the study area selected.

In the view of above context, the main objective of current research is to predict vegetation dynamics using MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI time series data. Time series is a sequence of correlated scalars or vectors which vary with time. In the present study, the sequence consists of the scalar NDVI values. Time series can be predicted, if one knows the past values in the series up to time t, and then estimating the value at time $t + s$, $s = 1$, 2... The study considered $s = 1$. LSTM network is trained to predict the NDVI value at $t + 1$.

Study area

The Nicobar Islands are a group of 28 islands covering an area of 1841 km^2, located between 6°45′–9°15′N latitude and 92°42′–93°56′E and are separated from Andaman group of islands by a ten-degree channel (Prasad et al. 2009). The Great Nicobar Island (GNI), the current area of interest is the southernmost island of the Nicobar Islands with an area of 1045 km^2 (Fig. 1) extended between 6°45′–7°15′N latitude and 93°38′–93°55′E (Sridhar et al. 2006; Mehal et al. 2009). The GNI has two National Parks (Galathea Bay and Campbell Bay) and was declared as a biosphere reserve (85% of island) in 1989 owing its high biological diversity and richness (Mehal et al. 2009; Sridhar et al. 2006). The climate is typically moist and humid with warm temperatures relatively throughout the year having dry season from October to March followed by rainy season from April to September (Mehal et al. 2009). The seasonal changes are observed to be minimal in these islands as they receive rainfall from both southwest and northeast monsoons representing wet and evergreen conditions with few months of dry conditions (Velmurugan et al. 2015). However, observations of Velmurugan et al. (2015) from the climate data of 30 years, reported climate of Nicobar as hot and humid with temperature ranging between 23 and 30.2 °C with an average relative
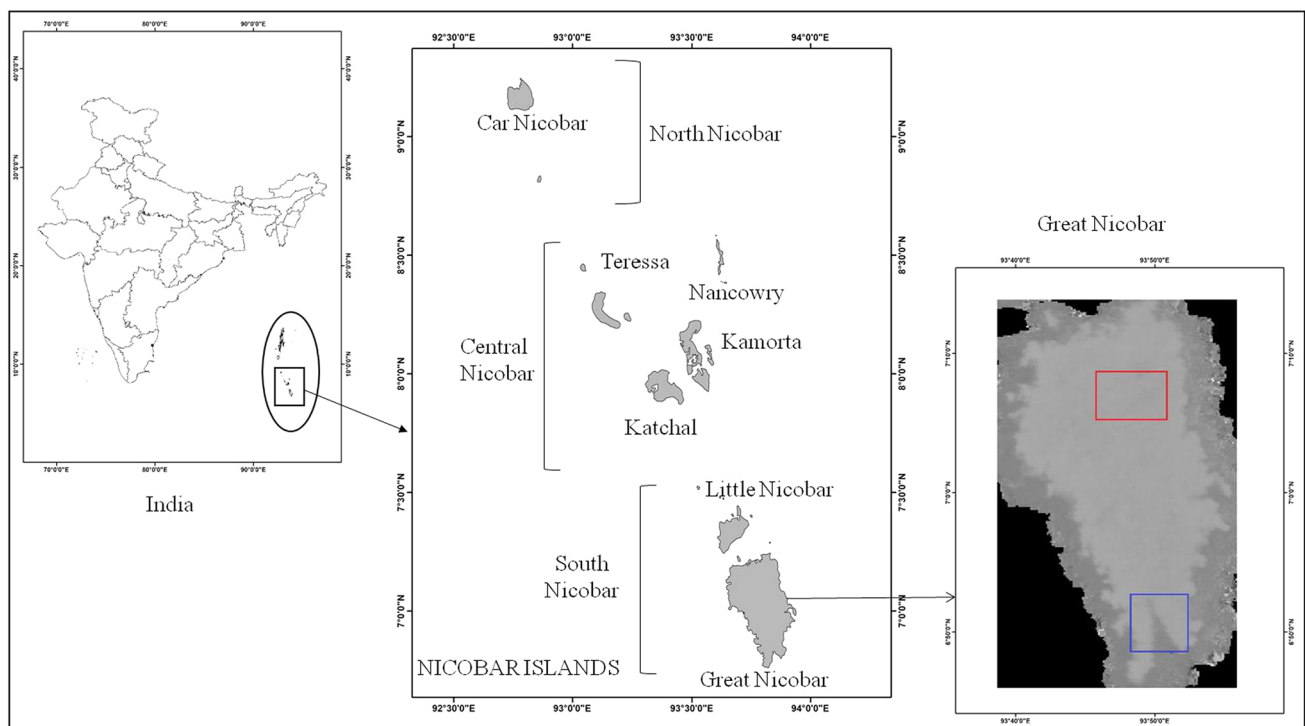

Fig. 1 Location map of Study area showing the Great Nicobar Islands

humidity of 79%, recording maximum rainfall during May to December and dry periods from January to March months. Overall, the climate is unpredictable without clear demarcation of wet and dry seasons affecting the vegetation condition in view of current changing climatic conditions.

The vegetation types of GNI include evergreen, mixed evergreen, moist deciduous, lowland swamp, littoral and mangrove forest (Anonymous 2003). The interior site selected for study shows dominant Andaman evergreen forest, while the coastal site is characterised by lowland swamp forest, *Syzigium* swamp, mixed mangroves in addition to evergreen forest (Porwal et al. 2012), The GNI was severely affected by the tsunami occurred in 2004 in Indian Ocean and the vegetation along the coastline is damaged, especially mangroves (Prasad et al. 2012). The study of Sridhar et al. (2006) observed a loss of 531.70 ha of mangrove vegetation on south-west and south-eastern side of GNI due to tsunami. While Porwal et al. (2012) reported submergence of 34% of mixed evergreen forest located near the coast. Now the vegetation seems to restore gradually under natural conditions (Prabhakaran and Paramasivam 2015). Thus, the selected sites for present experiment found to best suitable areas to trace the variation in the NDVI patterns capturing seasonal changes along with deforested and regenerating vegetation conditions.

Material and method

Satellite data and processing

The satellite data required for the study is obtained from the data service platform developed by University of Natural Resources and Life Sciences (BOKU), Vienna. The dataset consists of a total of 861 MODIS NDVI images (Vuolo et al. 2012), extracted from MODIS Terra (MOD13Q1) satellite with a spatial resolution of 250 m from January 2000 to June 2016 at an interval of 7 days. The NDVI time series obtained from the satellite imagery is often contaminated by the clouds, haze and other environmental disturbances and thus leads to noise in the data or loss of some NDVI values in the time series (Chen et al. 2004; Cai and Liu 2015). A smoothing technique or noise reduction filter is required to eliminate perturbations and obtain a smooth and continuous time series data (Geng et al. 2014). Whittaker smoothing technique was used to filter the NDVI images and to fill out any gaps in the data (Eilers 2003). The average of the NDVI values is taken to obtain a time series for further analysis. The obtained NDVI values are normalized between 0 and 1.

Method: LSTM

For predicting the vegetation dynamics using NDVI, LSTM network, an advanced technique adapted from ANN was considered. The concept of ANN is inspired by the functionality of neurons in a human brain (Gershenson 2003; Pratap and Shelja 2013). ANN is made up of neurons and links connecting the nodes. Nodes process the information and output the information received by them to other neurons through the links connecting the nodes. All the links are associated with some weights (Agatonovic-Kustrin and Beresford 2000). ANNs learn all the functional relationships of the data by varying the weights associated with the links. This property of ANNs makes them well suited for situations where a lot of data is available without sufficient knowledge about the data. Also, as they learn the hidden dependencies in the data based on the past values, they are very useful in predicting the time series and work fairly even with the noisy data (Obitko 1999; Gamboa 2017).

LSTM network is a modified structure of RNN. RNN is a feed forward network with a feedback loop and internal memory (Lyu and Mou 2016). They remember the information in a sequential order analogous to human beings. (Lipton et al. 2015; Gamboa 2017) They store this sequence in their internal memory for a long time of span which helps in taking the decision for the next step accurately compared to the traditional feed forward network (Skymind 2016). However, the recurrent structure in LSTM is a gated structure unlike RNN (Ordóñez and Roggen 2016). LSTMs have a long-term memory compared to RNN, making them suitable for time series prediction (Wu et al. 2017). Further, the vanishing gradient descent problem in a standard RNN is resolved in LSTM networks by introducing the concept of the memory cell (Wildml 2015; Colah 2015). Memory cell consists of gates which take care of what information should be stored, read or written to the network. They preserve the error that is back propagated for a long time. They can learn from a large number of time steps, over 1000 and so are very suitable for time series prediction.

A memory cell (Fig. 2) is composed of four main components—forget gate, input gate, output gate and a candidate hidden state (Zhou et al. 2016). These gates are composed of a sigmoid layer. They let the information pass through them if the sigmoid layer's output a non-zero value. If the output is zero, no information is passed through the gate; else if it is one, all the information is passed through the network (Colah 2015).

A standard LSTM network works as follows—The first step is to decide which information is to keep in the network (Xu et al. 2015; Skymind 2016). This is decided by forget gate layer, f_t. It takes into account the previous hidden state and the current input and outputs a value between 0 and 1. If the output is zero, then the information is completely

Fig. 2 The internal gated structure of a memory cell in LSTM
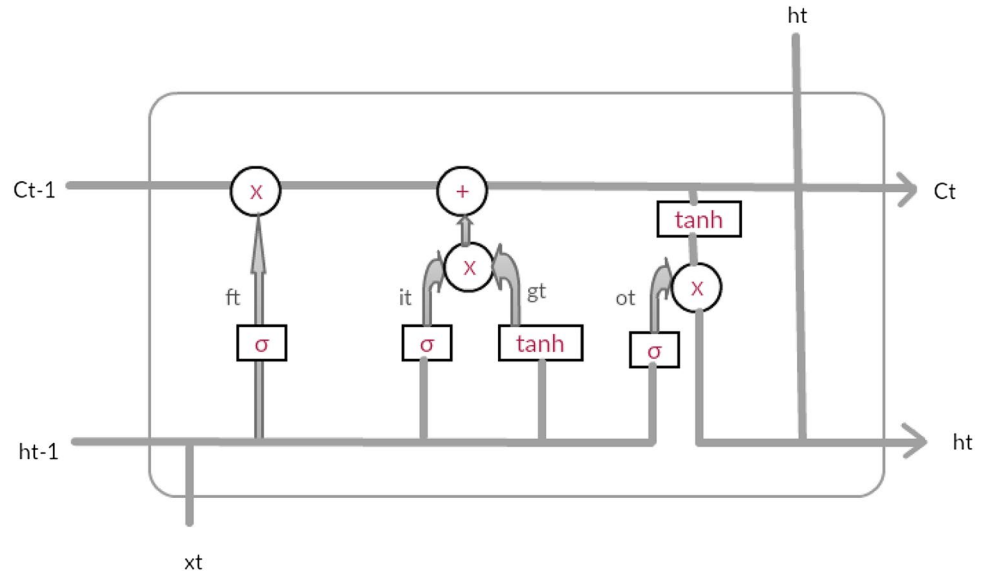
forgotten likewise if it's one, all the information is retained by the network (Jia et al. 2017) (Eqs. 1–7 adopted from Colah 2015; Kang et al. 2016)

$$f_t = \sigma(W_f * h_{t-1} + V_f * x_t + b_f). \tag{1}$$

Then the network needs to decide what new information should be stored in the cell. First the input gate layer, i_t decides which values are to be updated and then the new information g_t is added to the cell state (Xu et al. 2015).

$$i_t = \sigma (W_i * h_{t-1} + V_i * x_t + b_i) \tag{2}$$

$$g_t = tanh(W_g * h_{t-1} + V_g * x_g + b_g), \tag{3}$$

where f_t = forget gate state; i_t = hidden state at time t; σ = sigmoid function, W_f = weight matrix for previous hidden to current hidden states, W_i = weight matrix for previous hidden to current hidden states h_{t-1} = hidden state at time t-1, V_f = weight matrix for input to hidden state links, V_i = weight matrix for input to hidden state links, V_g = weight matrix for input to hidden state links, x_t = input at time t, b_f = bias of the forget gate layer. b_i = bias of the input gate layer, b_g = bias of the input gate layer, g_t = new candidate value.

$$C_t = f_t * C_{t-1} + i_t * g_t \tag{4}$$

Then finally, it decides what the network should output. This is done in two steps. First, the output gate layer, o_t decides what values to output by the network and then the updated cell state in the previous steps is passed through tanh layer to normalize the output to be between − 1 and 1. This is how the cell states are updated in LSTM.

$$o_t = \sigma (W_o * h_{t-1} + V_o * x_t + b_o), \tag{5}$$

where o_t = output gate output at time t, σ = sigmoid function, W_o = weight matrix for previous hidden to current hidden

states, h_{t-1} = hidden state at time t-1, V_o = weight matrix for input to hidden state links, x_t = input at time t, b_o = bias of the input gate layer.

$$h_t = o_t * tanh (C_t). \tag{6}$$

Experimental procedure

The focus of this study is to predict the future NDVI value of the time series (i.e. next 7th day), using the past NDVI values taking into consideration the seasonal changes and any abrupt changes in the NDVI series. Also, the research emphasizes the accuracy, adaptability and efficiency of LSTM networks in predicting the time series by reinforcing the internal dependencies and variances in the data.

The dataset under consideration is categorized into training, validation, and testing datasets. The training set is used to make the network learn the data by propagating the error back to the network and updating the weights. The validation set is used to verify the model if the error of the network is below a threshold then training can be terminated. Testing set helps in analysing the performance of the neural network on new data. Studies have shown that dividing the data in 7:2:1 ratio gives a better assessment of the network (Stepchenko 2016). The dataset of 861 images is divided into 601 training set images, 172 images for validation and 86 for testing.

The two experiments have been formulated to test two different regions in the GNI (Fig. 1) In the first case the average NDVI of an interior part of GNI is taken into account which is not affected by the tsunami and in the second only a specific portion of the island along the southern coast is considered which is affected widely by the 2004 Indian Ocean tsunami (Prasad et al. 2012). The first experiment is done to check if the network is able to learn the seasonal changes

Table 1 RMSE error for different number of epochs for experiment 1

No. of epochs	Training error	Validation error	Testing error
330	0.0080	0.1218	0.0358
350	0.0071	0.1181	0.0255
400	0.0033	0.1229	0.0110
420	0.0052	0.1249	0.0261

in vegetation and the latter to verify if it is able to learn the abrupt changes in the vegetation along with the seasonal changes. The input to the network is the current NDVI value and the output is the next NDVI value, which is the NDVI of the next 7th day. Unlike in RNN, here one need not give many past values as input to the network since the LSTM stores all the information received till the previous moment in its internal memory. All the NDVI values are normalized between 0 and 1 and given as input to the network. The network is stopped when it starts to over-fit the data.

Over-fitting can be understood when the validation error rises continuously for some epochs in a row.

To measure the accuracy of the prediction by the LSTM network, RMSE is used. By changing the number of epochs to train the network, the RMSE in predicting the next NDVI value in the training, testing and validation phases are calculated using the Eq. (7).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{i=n} \left(y'(i) - y(i)\right)^2}{n}}, \tag{7}$$

where n = number of values, y = actual values, y' = predicted values.

Results and observations

The current research is an experimental study to monitor the vegetation dynamics of GNI, typically dominated by evergreen forest in the interior of island and littoral and
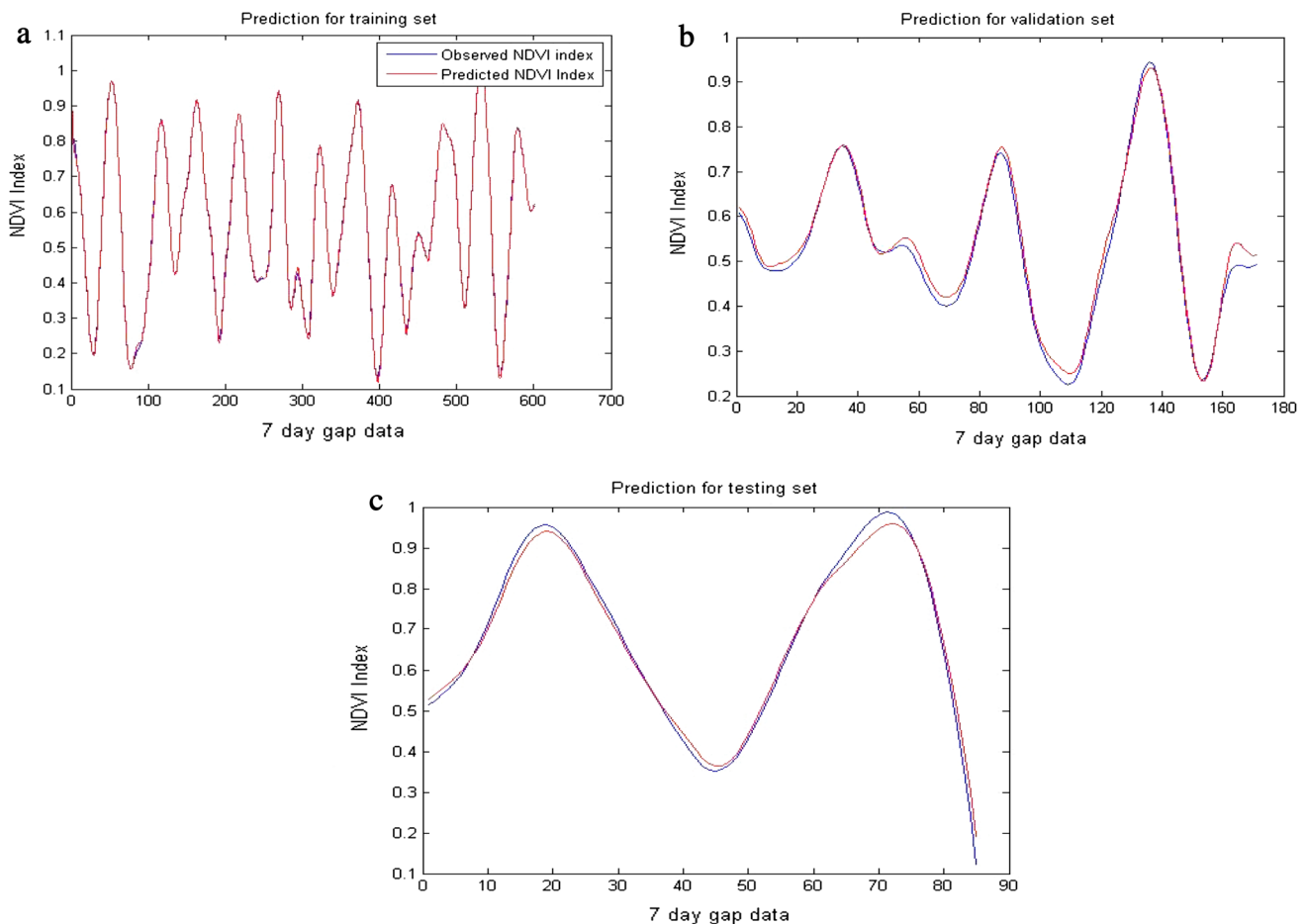

Fig. 3 Figures showing prediction vs. actual NDVI time series for different datasets for an interior region of the Great Nicobar Island which is not affected by tsunami. **a** Results plotted for training dataset. **b** Results plotted for validation dataset. **c** Results plotted for testing dataset

mangrove towards the coast. The interior forest is subjected to human interactions, while the coastal forest is impacted by natural calamities (Prasad et al. 2012). However, the area along the coast selected for experiment is severely eroded by tsunami of 2004 and proves to be better site for representing abrupt changes in the vegetation. Two experiments are done in two different terrains of GNI. The first experiment shows that the LSTM network has self-trained the seasonal changes well and the second experiment shows that the network along with seasonal changes is also able to learn any sudden changes in the NDVI values (here, due to the tsunami) well and predicted the time series well with an acceptable accuracy.

Experiment 1: seasonal changes

After experimenting with a different number of hidden nodes, the optimal number of hidden nodes is found to be 10. The RMSE for training, validation, and testing for a different number of epochs is shown in Table 1. Based on the RMSE (Table 1), 300 is decided to be the optimal number of epochs for testing. The obtained RMSE shows that the LSTM network is good at predicting the NDVI time series by learning the seasonal changes. The training, validation and testing time series seem to follow the same trend as the actual time series and as the predicted time series seems to be below the actual time series, this concludes that there is no over fitting of the data from the network. Original NDVI

time series (blue) versus predicted time series in the training phase, validation phase and testing phase of the LSTM network for 300 epochs are shown in Fig. 3.

Experiment 2: both seasonal and sudden changes

Similar to the previous experiment by varying the number of hidden nodes and epochs, the optimal values are found to be 10 and 400 respectively. Figure 4 shows how the vegetation is affected by the tsunami in December 2004 and also how it is recovering after the disaster. The RMSE for training, validation, and testing for a different number of epochs is shown in Table 2. Based on the RMSE shown in Table 2, 400 is decided to be the optimal number of epochs.

The obtained RMSE show that the LSTM network is satisfying at predicting the NDVI time series by learning both the seasonal changes and any abrupt changes in the NDVI that may be caused by any natural calamity or deforestation by itself without any additional information fed to the network. Clearly there is no over fitting of the data from the network in this experiment too. Original NDVI time series (blue) versus predicted time series in the training phase, validating phase and testing phase of the LSTM network for 400 epochs are shown in Fig. 5.

All the plots in all the three phases of both the experiments show that the LSTM neural network is able to follow the series well and almost coinciding with the required time series. All the unforeseen changes in the trend of the NDVI
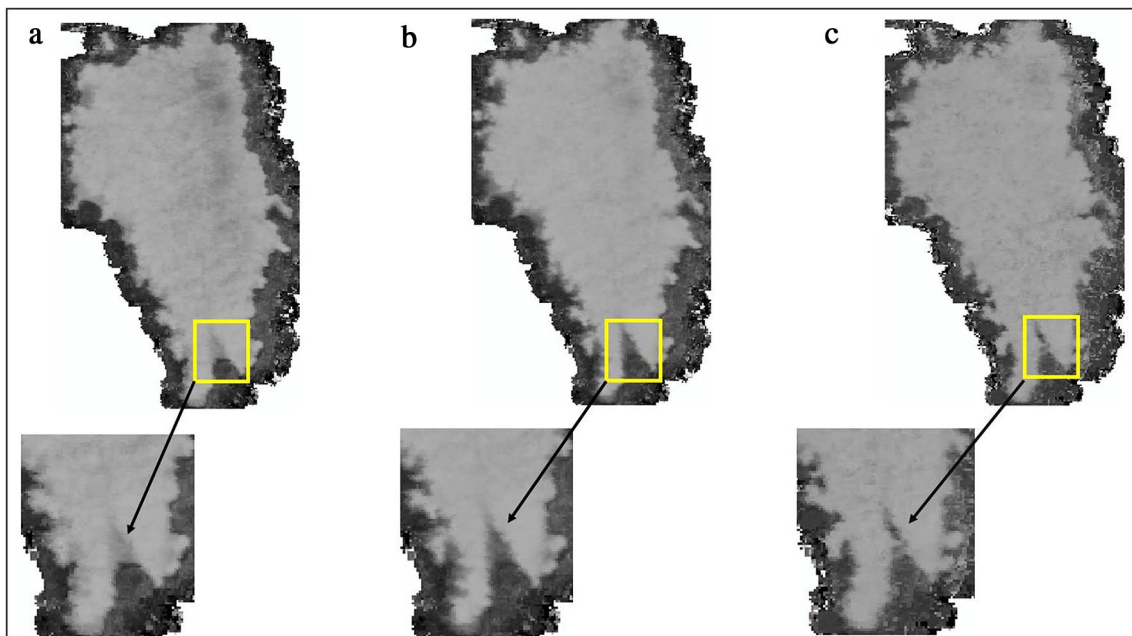

Fig. 4 NDVI images highlighting a region along the coast line of the Great Nicobar island affected by tsunami in 2004. **a** NDVI image of Great Nicobar before tsunami (December 2004). **b** NDVI image of Great Nicobar just after tsunami (January 2005). **c** NDVI image showing vegetation recovery in Great Nicobar vegetation (June 2016)

Table 2 RMSE error for different number of epochs for experiment 2

No. of epochs	Training error	Validation error	Testing error
280	0.0071	0.1901	0.0302
290	0.0064	0.1825	0.0266
300	0.0060	0.1822	0.0201
310	0.0068	0.1860	0.0271

series are well learned by the network without requirement of any additional information. By implementing the proposed method to predict vegetation dynamics using NDVI time series, there is a way to forecast the vegetation in the unfolding years and take necessary measures accordingly to protect and improve the vegetation in any area. Results evidently show that the network is effective in predicting the future NDVI values by learning all the seasonal and annual changes in vegetation, changes due to deforestation or natural calamities, etc. with an appreciable accuracy. Thus, it is recommended to use LSTM network for reliable

and accurate prediction of vegetation dynamics. When the LSTM network is trained with large data, the accuracy is much higher. This makes LSTM very unique and efficient method to use it for prediction of NDVI dynamics than other methods.

Conclusion

The predicted time series shows that LSTM has far better performance than many other traditional neural networks. The long-term internal memory benefits the network in training well for the given data. The gated memory cell structure is a great advantage for LSTM in predicting the time series. Unlike other neural networks, a large number of past values need not be fed to the network as LSTM can store all the information about the previous values in its internal memory. LSTM has varied applications in the areas like water quality assessment, land use and land cover change detection, monitoring land surface
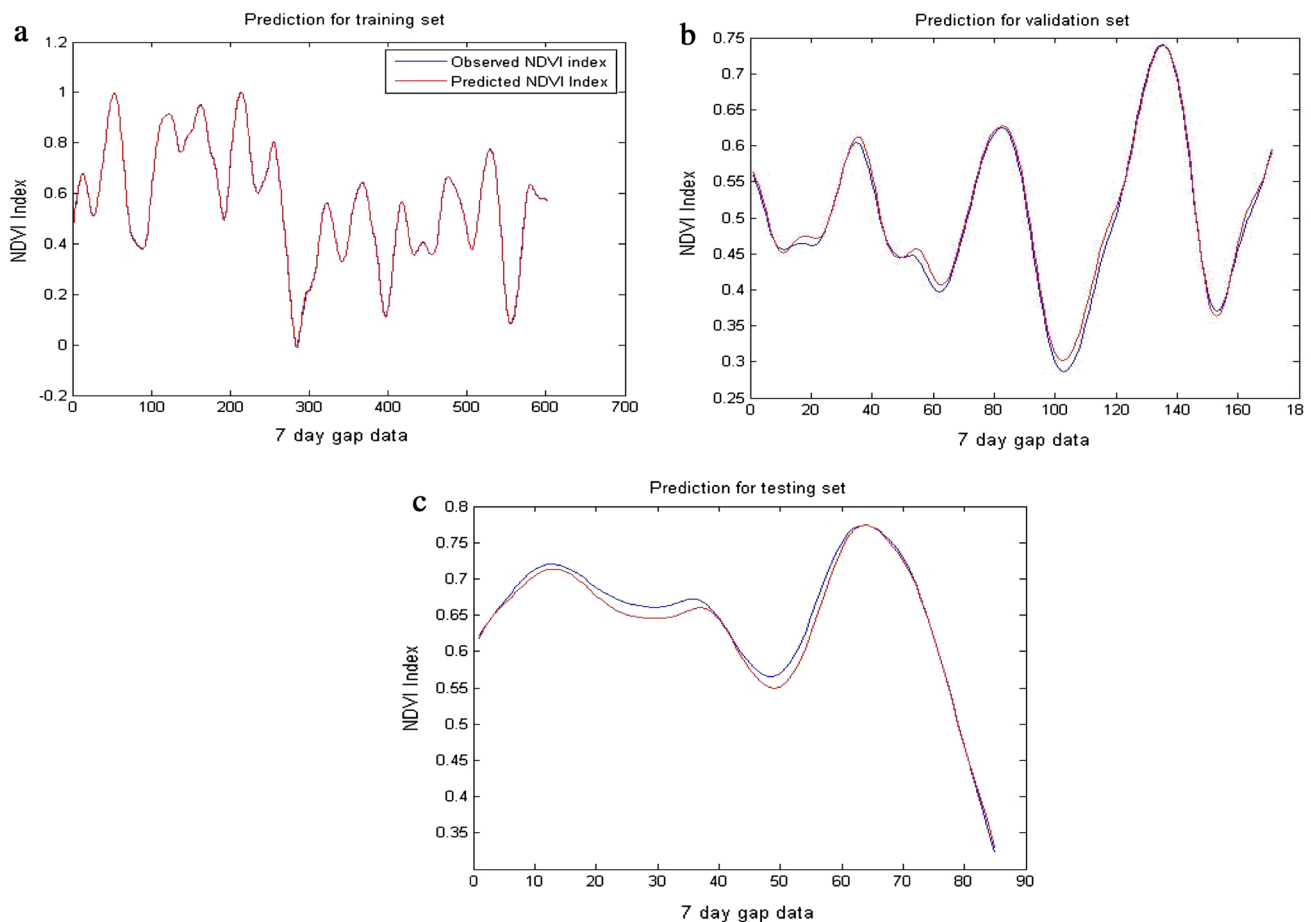

Fig. 5 Figures showing prediction vs. actual NDVI time series for different dataset for a region along the coast affected by tsunami. **a** Results plotted for training dataset. **b** Results plotted for validation dataset. **c** Results plotted for testing dataset

temperature, etc. LSTM model can efficiently predict the time series not just for the next time interval, but up to next 50 intervals which will aid the efforts to take care of vegetation well in advance to avoid any disturbance leading to loss of vegetation. The study is an experiment to analyse the use of LSTM for vegetation dynamics prediction. Since the current study typically shows evergreen nature as well as influenced by both the southwest and northeast monsoons, the phenological or seasonal changes are minimum. Further better interpretation can be made by experimenting LSTM in an area predominated by dry deciduous forest as a future investigation. Additionally, integrating climatic factors may yield a high reliable prediction of vegetation dynamics.

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