Noise Reduction of MODIS 8- day composite EVI Time-series data: Comparative study of various filtering algorithms

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ABSTRACT

Time Series analysis of remote sensed data has gained special attention supported by availability of wide-coverage and high temporal satellite data; to estimate vegetation phenological parameters, or to monitor temporal changes in Land Use Land Cover and environment. However these Remote sensing data sets frequently suffer from noise due to instrumental errors, atmospheric scatter and cloud effects. This noise must be reduced before time-series data sets are used for further investigation. Several filtering techniques have been developed in the past for de-noising time series vegetation index data from various satellite sensors, however very few studies have compared these filtering algorithms systematically and broadly. This research investigated six techniques: Asymmetric Gaussian (AG), Double Logistic (DL), Savitzky Golay (SG), Stationary Wavelet Transform (SWT), Whittaker Smoother (WS) technique and new Compound smoothing technique (CS) for smoothing multi-temporal Satellite sensor EVI observations with ultimate purpose of determining the best filtering technique. The research used Moderate Resolution Imaging Spectroradiometer (MODIS, spatial resolution: 500 meter) terrestrial Enhanced Vegetation Index (EVI) data composited at 8 day interval over the period 2001 to 2014 covering the Uttarakhand region in India. The de-noising techniques were evaluated using root mean square error (RMSE), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The techniques were also evaluated using phenological parameters Start of Season (SOS) and End of Season (EOS) calculated for various vegetation species. The results indicate that Compound Smoothing, Whittaker smoother and Stationary wavelet transform techniques performed better than other techniques. The noise filtering technique varies with the different vegetation cover and EVI values. The appraisal results are consistent in respect of four evaluation indexes. The study will be helpful in choosing the best filtering techniques for time series vegetation index data for detecting trend and seasonality of various vegetation cover.

1. Introduction

The changes in the phenological regimes across different ecosystems are being increasingly considered as indicators for the climatic variability (IPCC AR5 2014). These changes are captured through different approaches like ground based permanent observatories as well as continuous studies using long term ecological research station (Hubbard Brook publication). One of the most effective is a space based earth observation platform which provides high temporal data of various bio-physical parameters like vegetation reflectance, etc. These datasets have been extensively used for understanding the impacts of climate change (Sakamoto et al., 2005; Beck et al., 2006; Zhou et al., 2003; Seneviratne et al., 2012; Sellers et al., 1997; Solomon et al., 2007; Tucker, Townshend, & Goff, 1985). Time series Vegetation index (VI) datasets such as Normalized Difference vegetation index (NDVI) data, Enhanced Vegetation Index (EVI) data provide information on vegetation characteristics.

However, these time series VI datasets have inherent noise due to cloud cover varying atmospheric conditions, and other sensor and viewing geometry effects. (Holben, 1986; Josef, 1996; Li & Strahler, 1992; Tucker et al. 1985; Cihlar et al.1994; Kobayashi, H., Dye, D.G., 2005; Hird, J.N., McDermid, G.J. 2009). Even though maximum value composite (MVC) approach is used to generate the time series VI datasets, still significant residual noise remains in the datasets which affects the accuracy of the information extracted and significantly reduces the significance of the interpretation. To obtain meaningful information these datasets, need to be filtered and smoothened for further analysis and interpretation.

Phenology is extensively dependent on the vegetation type and the community formations. In case of gregarious formations in which a single species constitute more than 60% of the population, the phenology is more or less definite and can be picked up by satellite sensors. But in case of mixed formations the phonological stages are not sharp i.e. leaf flush and the leaf fall are not synchronous. Due to this detecting the sharp boundary of the leaf fall and flush in temporal data is difficult as process may be staggered. Hence identification of appropriate noise reduction techniques is important for extracting meaningful information from temporal data stacks.

Noise reduction in remote sensing data are the extensions of image and signal processing filters and are broadly classified into two domains: spectral and temporal. Since we will be concentrating on the time series data smoothing will not take up the spectral domain. The temporal domain is further classified into parametric and non-parametric approach. The non–parametric approaches are normally thresholding techniques like Data Assimilation (DA) (Gu J. 2009), Whittaker smoother (WS) (Eilers, 2003) technique, Best Index Slope Extraction (BISE) (Viovy et al., 1992), moving window based: Savitzky-Golay (SG) (Chen et al., 2004), Mean Value Iteration filter (MVI) (Ma and Veroustraete, 2006), and ARMD3-ARMA5 filter technique (Filipova-Racheva, D. 2000). Parametric or function fitting methods such are Double Logistic (DL) (Beck et al., 2006), Asymmetric Gaussian (AG) (Jönsson and Eklundh, 2002), and Harmonic Analysis of time series (HANTS) (Menenti et al., 1993; Roerink et al., 2000; Verhoef et al., 1996) Non-Parametric: threshold method choosing the appropriate technique among the various filtering techniques is the research challenge.

Studies by Hird and McDermid 2009 has highlighted that each technique has its own advantage and limitation. Different algorithms have been used to extract various vegetation parameters like land use/ land cover, seasonality parameters etc. BISE algorithm (Xiao et al.2002), Fourier based fitting (Moody and Johnson, 2001; Andres, 1994), Asymmetric Gaussian function fitting (Jonsson and Eklundh, 2002), Double Logistic function fitting (Beck et al.2006), HANTS (Menenti et al., 1993; Roerink et al., 2000), Savitzky-Golay (Chen et al., 2004), wavelet (Lu et al, 2007; Sakamoto et al., 2005) and Whittaker smoother (Eilers, 2003). All these reconstruction techniques suffer from some limitations and they require fine tuning of parameters such as setting threshold value, size of the moving/sliding window or temporal neighborhood and number of harmonics (Atkinson et al, 2009 & 2012). Each reconstruction technique has some advantages and limitations over another technique. Jönsson and Eklundh 2002 showed that AG is superior to BISE and the Fourier-based technique. Chen et al. 2004 highlighted that SG, BISE, and the Fourier-based transformation (FT) are effective techniques for reconstructing NDVI time-series data sets However, Jönsson and Eklundh 2004 showed that the AG technique was better than SG filter and harmonic analysis. Ma and Veroustraete 2006 highlighted MVI (Mean value Iteration) performed better than the M-BISE and Fourier transform. Beck et al. 2006 showed that the new Logistic function fitting technique of DL is better because it can handle outliers effectively. Hird and McDermid 2009 demonstrated the superiority of the DL and AG function-fitting techniques. Julien and Sobrino 2010 showed IDR (iterative Interpolation for Data Reconstruction) technique performed better than HANTS and DL. Moreover Geng et al. 2014 compared various denoising techniques and highlighted that optimal VI reconstruction techniques changes with vegetation and data source. Therefore, developing compound smoothing technique that effectively uses the strength of individual technique will be highly significant. Various studies have been done on developing compound technique and results indicate that the compound techniques performed better than the individual techniques (Hermance et al.; 2007; Z. Li, 2011).

Very few studies comparing the performance of Stationary wavelet transform (SWT) with other filtering techniques are reported. Secondly these comparisons have been done on pixels and regional scale, only few studies have considered the land cover type or vegetation types/species, for evaluation of time series. The present research aimed to compare five noise reduction techniques: Asymmetric Gaussian (AG), Double Logistic (DL) function fitting technique, Savitzky-Golay (SG), Stationary Wavelet Transform (SWT) and Whittaker smoother (WS), for smoothing EVI time series datasets of Terra MODIS satellite sensor and to develop a compound smoothing method to effectively reconstruct EVI time series using the five denoising techniques. The research also aimed to compare the performance of the compound smoothing technique with other individual techniques for determining the appropriate filtering technique to study phenology for different vegetation type varying at different altitudes.

2. Study Area and Datasets

2.1 Study Area

Uttarakhand is a state located in the northern region of India with total geographical area of 51,125 km² of which 92.57% is covered by Hill and 7.43% is the Plain Area. 63% of Uttarakhand is covered by the Forest. The state is situated between **Longitude** 77° 34' 27" East to 81° 02' 22" E and **Latitude** 28° 53' 24" North to 31° 27' 50" N. It borders Tibet in the north and Nepal to the east, while its neighbor Indian states are Himachal Pradesh to the North West, Haryana to the west and Uttar Pradesh in the south. Physiographically, the state can be divided into three zones namely, the Himalaya (elevation from 10,000 to 25,000 feet), the Shiwalik (elevation 6,500 to 10,000 feet) and the Tarai Region with the elevation from 1,000 to 10,000 feet. The state is situated on the southern slope of the mighty Himalayas. The climate and vegetation of different cities of the state vary with the altitude and location. The state has a temperate climate, marked by seasonal variations in temperature but also affected by tropical monsoons. The vegetation varies greatly with elevation, from glaciers at the highest elevations to tropical forests at the lower elevations. The type of natural vegetation cover include Deodar forest, Pine forest, Oak Forest, Sal and Sal mixed moist deciduous forest, Himalayan moist temperate and temperate coniferous forest, Subalpine and Moist alpine pastures and grasslands(ISRO-Geosphere Biosphere group).

2.2 Satellite Data

Temporal (8-day) composites of MODIS (Moderate-resolution Imaging Spectro-radiometer) data (MOD09A1 product) for the period 2001 to 2014 were downloaded for entire Uttarakhand state from the Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (https://lpdaac.usgs.gov/get_data) with the help of United States Geological Survey (USGS) Earth Explorer (EE) tool (http://earthexplorer.usgs.gov/). The MOD09A1 product contains 1-7 bands of 500-meter spatial resolution in an 8-day gridded level-3 product. Each of its pixels contains L2G observations during an 8-day period particularly by high-observation coverage, low-view angle, the absence of clouds or cloud shadow and aerosol loading.

Ancillary data used for the LULC classes is Land Use Land Cover (LULC) map for different types of vegetation in Uttarakhand region generated as a part of National assessment program on Biodversity characterization at Landscape level in India conducted by ISRO-Geosphere Biosphere group with a spatial resolution of 24 meter is shown in Figure1. Vegetation fractional cover is generated for a grid size of 500 meter to match the resolution of MODIS data: Grids containing vegetation fraction>80% was considered for further analysis.

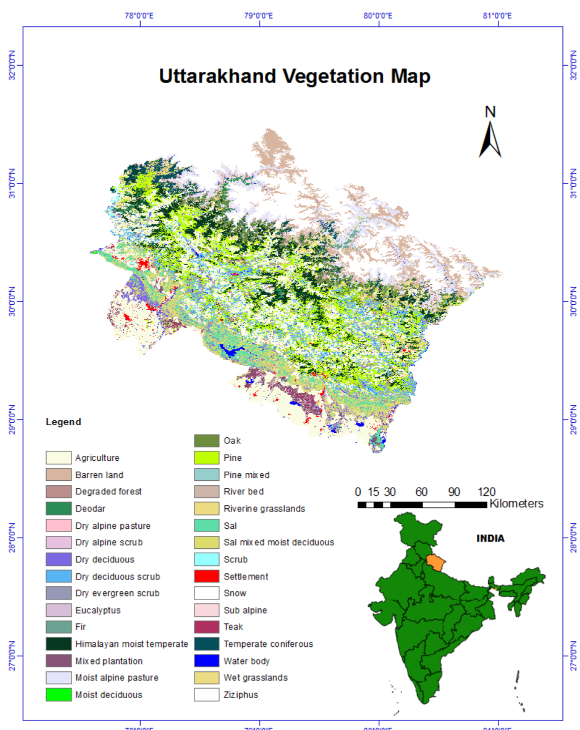


Figure 1 Land Use Land cover map of Uttarakhand vegetation (Source: ISRO-Geosphere Biosphere group).

3. Methodology

Any filtering/reconstructing algorithm applied on time series satellite data works in two steps; identify missing or anomalous values and correct it with the neighboring values within a temporal trajectory and then apply smoothing function by persevering the phenological (seasonal) characteristics. A number of satellite time series filtering methods has been developed and tested. This research aim to develop the compound smoothing method by making use of predefined noise reduction techniques and to compare the performance of proposed compound smoothing method with the other five smoothing algorithms to test their effectiveness in preserving the phenological characteristics of different vegetation species present in the Himalayan region viz; Deodar, Dry deciduous scrub, Fir, Chir-Pine, Oak, Pine, Sal, Sal mixed moist deciduous, Sub-alpine scrub, Temperate coniferous. The five time series data smoothing techniques selected for this research are: Asymmetric Gaussian (AG) (Jönsson and Eklundh, 2002), Double Logistic (DL) (Beck et al., 2006) function fitting, Savitzky-Golay (SG) (Press et al., 1994, Chen et al., 2004), Stationary Wavelet transform (SWT) (Pesquet et al., 2003)and Whittaker Smoother (WS) (Eilers,2003; Atzberger & Eiler, 2011). The first three techniques i.e. AG, DL and SG were executed in TIMESAT (Jonsson, P.; Eklundh, L.2004) where as for SWT and WS code has been written in MATLAB using SWT de-noising functions and function file provided by (Eilers 2003) respectively.

To test these algorithms pure pixels are considered. To locate a pure pixel on MODIS 500m data the vegetation fraction map at 500 m was first generated using a high resolution LULC map. Then pixels with >80% fraction corresponding to each class are extracted for generating the temporal VI profile. The EVI profile for each class was preprocessed to remove the affect cloud/missing values etc. using least square interpolation technique, which considers a temporal neighborhood of available data on both sides of a dropout values. Also sudden spikes and outliers are removed using temporal median filtering. Preprocessed time series datasets are then subjected to five filtering techniques and results evaluated using performance measuring criterion.

The varying parameters used in all the techniques greatly affect the performance of filtering and reconstruction results. The smoothing parameters are tuned until satisfactory result is obtained. For SG the half width of smoothing window is taken as 4 and degree of polynomial was set to 6. For SWT, Daubechies3 (db3) is used as the mother wavelet and signal is decomposed up to level 3, threshold values are set to 0.2 but when the outliers are more threshold value is set to 0.4. For WS, λ was taken as 15 because the entire study area contains vegetation types of single season (as explained by Atkinson et al.2012). AG and DL are executed in TIMESAT so the only need is to set the median filter parameter, which was taken as 2 to remove spikes and noise.

The proposed new compound smoothing technique is based on two concepts 1) the filtering techniques should not only remove noise but also retain as much as high quality data as possible and 2) that most of the denoising techniques can effectively reduce the noise in the data. The compound smoothing technique is estimated in the following steps:
Step 1) Calculate the modification rate (ΔEVI^i) between the filtered EVI (EVI^i) and original EVI (EVI^O) for all five techniques using formula: $\boldsymbol{\Delta EVI^i = \text{Absolute} (EVI^O - EVI^i)/ EVI^O}$ (1)
Step 2) Count the number (N) of ΔEVI^i values that are greater than 0.05. Here, 0.05 is a threshold for determining the noise in the data for each of the five techniques.
Step 3) If count $N \geq 3$ then EVI^O values was replaced by median value of the five denoised EVI datasets i.e. $mEVI^i = median(EVI^1, EVI^2,..,EVI^5)$ to replace the noisy data, otherwise if $N < 3$ then EVI^O is considered as high quality value and was not amended. Finally new EVI time-series data was obtained.

3.2 Evaluation Techniques

To measure the performance of each filtering two approaches are used, first the results were validated using three statistical indicators: Root Mean Square Error (RMSE); Akaike Information Criterion (AIC); and Bayesian Information Criterion (BIC). Secondly by comparison of seasonality parameters start of season (SOS) and end of season (EOS) estimated for each vegetation species using the noise free smoothened time series.

RMSE is a most widely used quantitative error indicator for determining the quality of fit among various models. The RMSE indicates the square root of the difference between the mean EVI time series obtained from the five filtering techniques (smoothened EVI data) and the corresponding observed time series which is needed to be filtered (noisy EVI data). It is calculated using Equation 2.

$$\sqrt{N^{-1}\sum_{t=1}^{N}\left(EVI^*(t)-EVI(t)\right)^2} \qquad (2)$$

RMSE was calculated for each pixel between the original MODIS EVI data and the smoothened EVI data and also for the selected homogenous pixels for the major vegetation species in the study area. Akaike Information criterion (AIC) (Akaike, 1973) is a goodness of fit indicator among several parameterized techniques by penalizing the large number of free parameters. It seeks a filtering technique that has a good fit to the truth but few parameters. AIC is calculated using Equation 3.

$$AIC = 2k + n[\ln(RSS/n)] \qquad (3)$$

Bayesian Information Criterion (BIC) (Schwarz, 1978) is another model selector similar to AIC for estimating the best filtering technique. It is calculated using Equation 4.

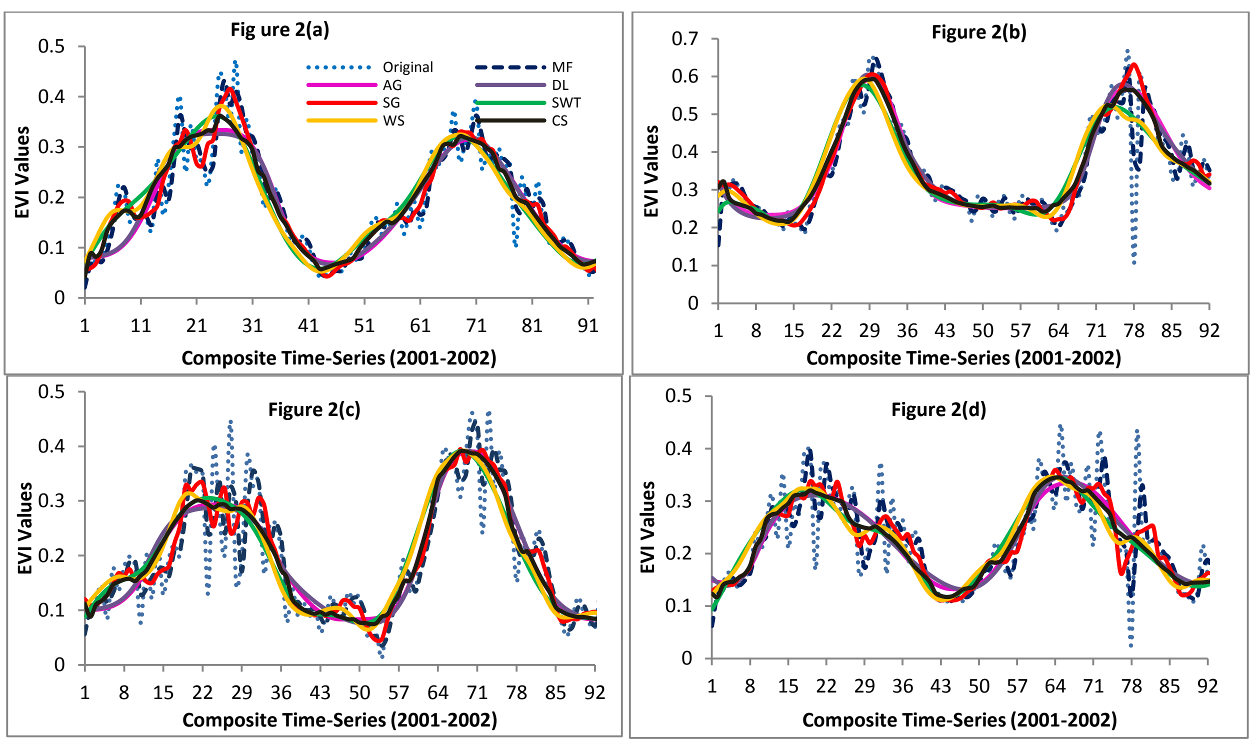
$$BIC = k\ln(n) + n[\ln(RSS/n)] \qquad (4)$$

The BIC generally penalizes free parameters more strongly than AIC, though it depends on the size of n and relative magnitude of n and k. Here k is the number of free parameters in the filtering techniques, n is the number of input data points and RSS is residual sum of squares between the mean EVI data and the filtering techniques. The lower values of RMSE, AIC and BIC indicates the superiority of filtering technique. AIC and BIC are calculated for the homogeneous pixels of vegetation species using the free parameter values as seven for AG, six for DL, two for SG, four for SWT and two for CS as per the parameters defined by the filtering techniques where as for WS the free parameter is 9.37 when λ is 15 as explained by Atkinson et al. 2012.

To further analyze the effectiveness of six filtering techniques two phenological metrics; start of the season (SOS) and end of the season (EOS) for each vegetation species were also estimated The phenological metric start of season is detected using definition: Time for which the left edge has increased to 20% of the seasonal amplitude measured from the left minimum level and end of season is detected using: Time for which the right edge has decreased to 10% of the seasonal amplitude measured from the right minimum level.

4. Results

The 8 day composited MODIS EVI data was analyzed for various curves fitting algorithm for noise reduction. The functions tested were Asymmetric Gaussian function (AG), Double Logistic function (DL), Savitzky-Golay fitting (SG), Stationery Wavelet Transform (SWT), Whitaker Smoother (WS) filters and Compound Smoothing (CS) proposed technique. All these noise reduction algorithms were tested for 10 natural land cover types in Uttarakhand state of India situated in Western Himalaya. The 10 natural land cover types cover almost all the major vegetation types in the region. The noise reduction technique was tested on different vegetation types to capture all the phonological aspects of the vegetation cover in this region.



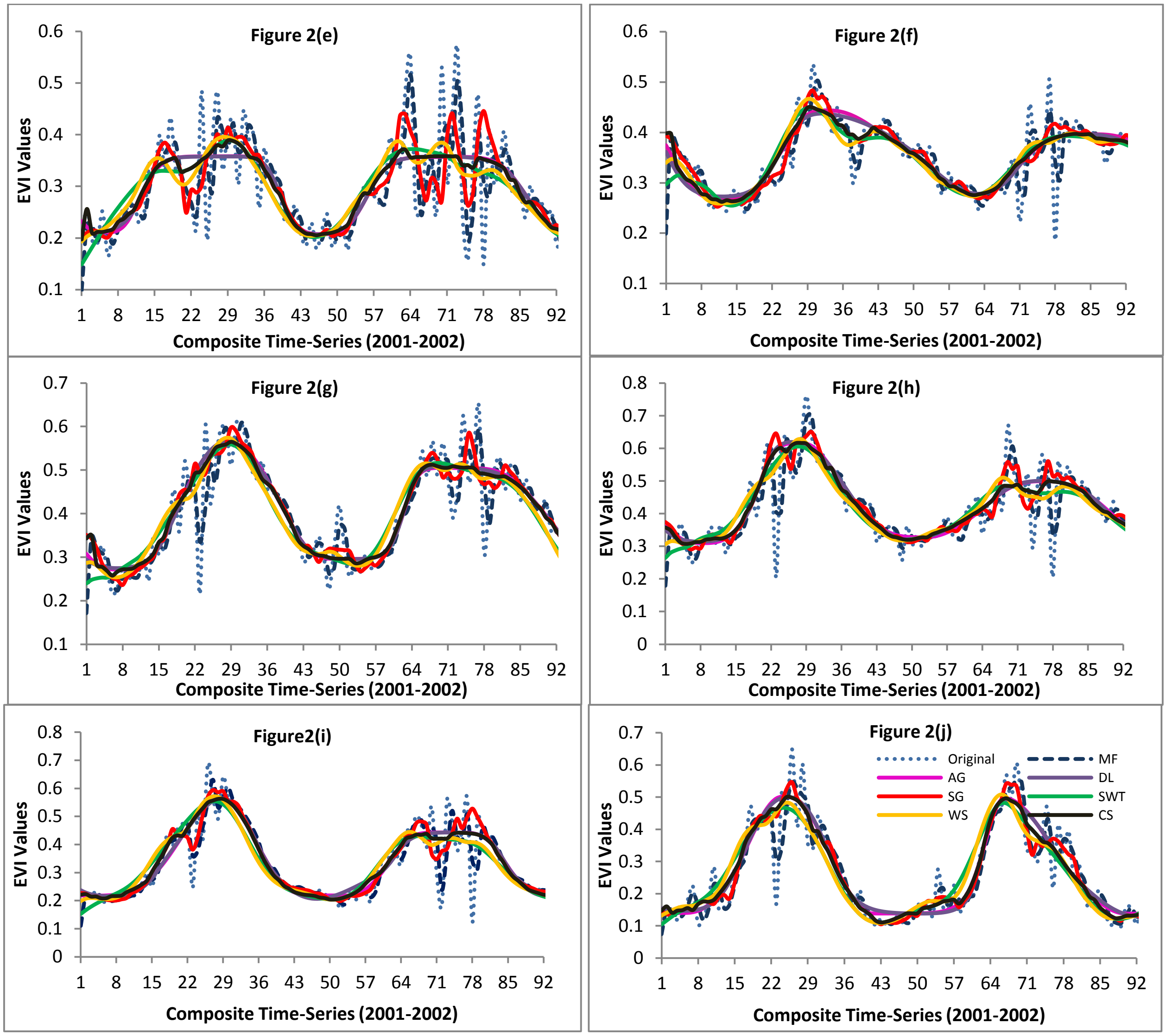
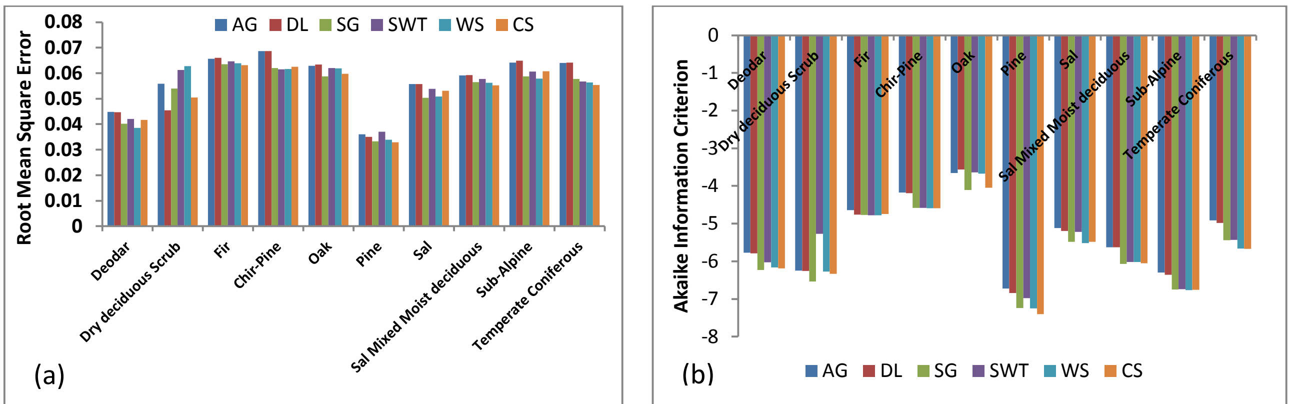


Figure 2 Present the six filtering techniques Savitzky- Golay (SG); Stationary Wavelet Transform (SWT) ; Whittaker Smoother (WS); Asymmetric Gaussian (AG); Double Logistic (DL); Compound Smoothened (CS) fitted to MODIS EVI time-series data (original) and Median filtered (MF) EVI acquired for homogeneous pixels of vegetation types (a) Deodar; (b) Dry deciduous scrub; (c)Fir; (d) Chir-Pine; (e) Oak; (f) Pine; (g) Sal; (h) Sal mixed moist deciduous; (i) Sub-alpine scrub; (j) Temperate coniferous.

Figure 2 (a-j) shows the plot of EVI wore 2001-2002 duration (20 months) and the six different noise reduction function fitting to get a meaningful observation or trend. In all the datasets there were considerable noise. Although in some of the land cover types, mostly the gregarious vegetation types (eg. Sal, Oak, pine etc.) Which has considerable contiguous forest cover; the noise is more random compared to mixed formations. On applying the median filter, out of the 10 land cover classes, the Sal dry deciduous scrub, Pine and Temperate coniferous showed relatively less noise compared to other gregarious classes. In most of the land cover classes, the higher noise coincided with patch contiguity and gregarious forest types.

It was also observed that CS technique outperformed with the individual techniques by not only removing noise but also retaining the valid EVI values and brings out the phonological characteristics of the vegetation type. AG or DL functions were successful in removing noise but showed larger deviation from original EVI for various vegetation species (eg. oak, pine, Sal). The curve fitting function like SG, SWT or WS actually tried to accommodate the spikes and the troughs introduced in the data due to noise. It is also observed that the statistic evaluation of the function fitting models on the different land cover types showed that compound smoothed EVI for land cover classes like Oak, Pine, Fir and temperate coniferous forests showed lower root mean squared error (RMSE) than Sal, Chir -Pine or Deodar. We can also observe that for the land cover classes with low RMSE, the variation among the different noise reduction is significant. In these cases the curve fitting functions displayed RMSE higher than the smoothing filters. Moreover, CS, WS, and SG outperformed from the other techniques if RMSE, AIC and BIC were chosen as the deciding criterion.

The performance of different noise reduction techniques were also analyzed to test their effectiveness in estimating the phonological variability. The mean day of the year (DOY) in Julian date and standard deviation (shift in the number of days from mean) of phenological metrics SOS and EOS were estimated using TIMESAT for 14 years from 2001-2014 for various vegetation cover types from the data smoothed by the six noise reduction algorithms (Table1). The technique showing smallest discrepancy is considered as best for estimating phenological parameters. The standard deviation of SOS ranges from 8 days to 27 days whereas STD of EOS ranges from 6 days to 51 days. The higher discrepancy up to 51 days was observed in EOS estimation using SG where for SOS it was 27 days using DL and WS. The results indicate



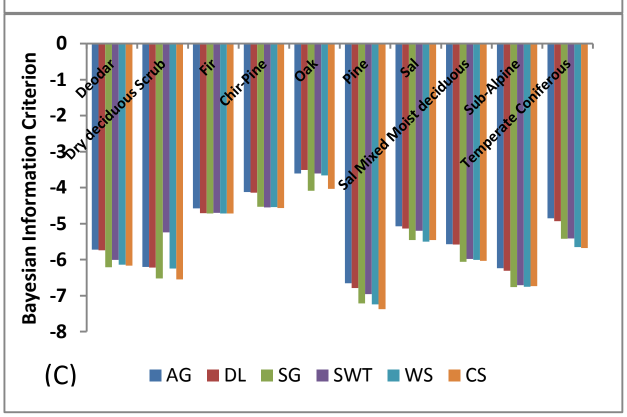


Figure 3 Presents (a) Root mean square error (RMSE), (b) Akaike Information Criterion (AIC) and (c) Bayesian Information Criterion (BIC) based performance measurement for five filtering techniques Asymmetric Gaussian (AG), Double Logistic (DL), Savitzky- Golay (SG), Stationary Wavelet Transform (SWT), and Whittaker Smoother (WS) at sample pixels of different vegetation types.

Table 1 Mean day of year (DOY) in Julian dates and standard deviation (STD) of phenological metrics SOS and EOS detected from EVIs for 2001–2014 for different vegetation species.

Vegetation species		AG		DL		SG		SWT		WS		CS	
		Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Deodar	SOS	64	10	61	13	39	10	36	10	31	10	**44**	**9**
	EOS	**323**	**6**	**323**	**7**	333	14	318	8	324	13	**325**	**8**
Chir-Pine	SOS	54	10	55	14	38	19	49	11	45	14	**41**	**11**
	EOS	291	40	298	41	308	51	332	15	328	22	**317**	**20**
Fir	SOS	96	14	95	18	74	22	80	24	82	22	**78**	**22**
	EOS	311	12	314	20	323	10	**326**	**8**	325	11	315	9
Oak	SOS	73	12	69	13	68	15	64	12	**68**	**13**	63	15
	EOS	328	40	353	15	340	45	**356**	**9**	355	16	345	13
Pine	SOS	179	14	**180**	**11**	177	12	**180**	**11**	183	12	176	13
	EOS	453	17	475	18	**486**	**24**	481	16	**487**	**21**	470	19
Sal	SOS	133	17	132	18	125	20	122	17	**125**	**14**	124	19
	EOS	372	16	378	21	397	28	**392**	**17**	395	21	382	19
Sal mixed	SOS	**148**	**24**	146	27	**148**	**25**	135	34	145	27	141	27
	EOS	376	12	379	14	395	22	392	17	**395**	**18**	381	14
Coniferous	SOS	95	9	99	13	92	19	79	14	**82**	**22**	**82**	**22**
	EOS	310	14	315	16	318	11	324	8	322	5	**312**	**8**

that the phenological metrics for some land cover types like pine, oak, sal and sal dominated moist deciduous forest show similar values using all the six filtering techniques. But for other land cover types like deodar, chir pine, fir and temperate coniferous forests, there are significant variations in the SOS using the noise reduced time series products. The results also shows that compound smoothing EVI can better estimate phenological parameters with overall low standard deviation for different vegetation species. However AS, WS and SWT can also predicted phenological parameters correctly.

5. Discussion

The current research carried with Terra MODIS EVI time Series data from 2001 to 2014 showed that CS denoising technique performed better than the individual techniques. The study also highlighted that WS, SWT and SG can be considered as individual best filtering techniques for estimating phenological parameters on the basis of performance measurement using RMSE, AIC and BIC. The four techniques showed consistently best result as compared to DL and AG. On the basis of four evaluation criterion the denoising techniques can be arranged in order of their performance as: CS, WS, SG, SWT, DL and AG (from higher to lower). The findings are supported by Zhu et al (2012); Jiang et al (2012); both the studies indicate that SG is better than AG and DL techniques in terms of RMSE. However all these studies used simple distance measure to find accuracy, which may not be accurate as it does not consider the number of model parameters. However the recent study done by Peter M. Atkinson (2012) also used AIC and BIC as the performance measuring techniques along with RMSE , the study showed WS is better than AG and DL function fitting. Another comparison done by Liying G (2014) highlights that SG is better than WS; however the comparison is not done for dense vegetation types and forests. Also recent study done by Geng et al., 2016 showed that CS is better than eight other individual techniques used in their study; however CS is estimated using different denoising techniques.

The SWT has not been evaluated in past in specific relation to extraction of phonological parameters, and in current study it performed well in terms of three evaluation indexes RMSE, AIC and BIC and gave better results for some of the vegetation types in terms of RMSE. The main issue with SWT is to choose the optimal model parameters to avoid over fitting and small fluctuations. The threshold value with 0.4 performed well in terms of RMSE and AIC. Based on RMSE, AIC and BIC derived for various vegetation types (Figure 3), SWT is a preferable technique over DL and AG function fitting. When noise distribution is Gaussian than DL and AG performs well in terms of AIC and BIC. This implies that DL and AG are less affected by Gaussian noise for the vegetation species such dry deciduous.

It was observed that vegetation species location and altitude and variability within the vegetation type had an effect on the performance of filtering techniques. At higher altitudes greater than 10000ft CS, WS and SG performed well but depended on the vegetation species, their location and level of noise. SWT smoothed the study area at higher altitude with glaciers more severely than WS and SG, thus can be said that SWT performed well when the level of noise is greater, but at lower altitude (<10000ft) vegetation types with reduced noise WS and SG outperformed SWT. However the performance of each technique is unstable with vegetation species.

The research done by Atkinson et al. 2012 also showed the similar result by comparing the performances of AG, DL, FT, and WS for four vegetation types using Terrestrial Chlorophyll Index (MTCI), the RMSE results indicated that the best technique changed with different vegetation types. Hird and McDermid 2009 also showed that six techniques perform differently for six different vegetation regions. Recently Liying G. 2014 also showed the similar result by comparing the eight reconstruction techniques for five different vegetation types. Since with different vegetation types, the characteristic of noise varied which impacted the performance of each technique, hence one should consider the noise character and the vegetation species type (mixed/pure) for selection of noise reduction algorithm.

6. Conclusion

The current research focused on assessing the reliability and accuracy of five filtering techniques and to develop a new compound smoothing technique for de-noising the time-series EVI time- series data for different vegetation species over the southern slope of Himalayas. By comparing the performance of CS EVI time-series with five individual techniques, we found that new technique can effectively reduce noise while preserving the original data and overcoming the drawback of individual techniques. The new CS technique can better estimate phenological parameters showing lower discrepancy in season dates and STD. The statistical evaluation also showed that compound smoothing and Whittaker smoother are best of all other techniques in terms of RMSE, AIC and BIC but underperforms for some vegetation where significant noise is present. Savitzky-Golay comes out to be the next best technique and performs well where WS and CS fail.

However when considering seasonality parameters as the evaluation method CS comes out to the best with lower discrepancy in dates as compared to Whittaker smoother and SG, however the difference is negligible. The three techniques showed consistently best results for most of the vegetation types. Stationary Wavelet transform is the new technique in terms of smoothing vegetation datasets. SWT emerged as another best smoothing technique and showed improved performance over Asymmetric Gaussian and Double Logistic function fitting. Also for various vegetation species SWT outperformed than SG in predicting seasonality dates. Asymmetric Gaussian performed better than Double Logistics; however both of them performed well when noise pattern is Gaussian in nature. The assessment results are consistent among the four performance measures RMSE, AIC, BIC and phenological metrics for most of the vegetation types.

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