Technical Report

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TR 11-016

A Study of Time Series Noise Reduction Techniques in the Context of Land Cover Change Detection

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August 12, 2011

A STUDY OF TIME SERIES NOISE REDUCTION TECHNIQUES IN THE CONTEXT OF LAND COVER CHANGE DETECTION

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Abstract. Remote sensing data sets frequently suffer from noise due to atmospheric conditions and instrument issues. This noise negatively affects the usability of these data sets and therefore noise reduction techniques are frequently used to reduce the impact of noise. A well-known remote sensing data set, MODIS Enhance Vegetation Index (EVI), measures the amount of vegetation (based on surface reflectance) observed from satellite. This data set has been used for land cover change detection, in both regional-scale and global-scale studies. Many noise reduction techniques have seen proposed in the remote sensing literature but comparative studies to understand relative performance of these techniques are scarce. Furthermore, the existing comparative studies typically evaluate a small number of techniques on a specific geographical region. Therefore, little is known about the global applicability of these techniques. In addition, time series based land cover change detection algorithms are known to be negatively impacted by the presence of noise. This paper investigates the interrelations of regional noise characteristics, change detection algorithms, and noise reduction methods. The methods for noise reduction are applied in three different geographic regions and through comparison we outline the noise characteristics relevant to the performance of land cover change detection.

1. Introduction

Optical remote sensing instruments on satellites are used to collect surface reflectance data that are processed into various data products to be analyzed by earth scientists. One such product that indicates the greenness of the land cover is the Enhanced Vegetation Index (EVI), which is generated from reflectance data collected by the MODIS instrument on NASA's Terra and Aqua satellites. An important use of this data is to monitor changes in land cover like forest fires, deforestation and other natural or human induced changes [14, 6]. A change in the land cover on the ground generally yields a change in the surface reflectance measured, and hence in the vegetation index computed.

Unfortunately, data collected using remote sensors frequently suffers from significant quality issues for a variety of reasons including atmospheric interference (aerosols, clouds, etc.) and instrument issues [10]. The poor quality of observations is an impediment for subsequent data analysis and can dramatically limit the utility of these data sets [5, 16]. For example, a sharp reduction in the EVI value due to cloud cover over forested land might be mistaken for deforestation activity or a fire, resulting in a false alarm by algorithms designed to detect such land cover changes. The accuracy and completeness of land cover change events determines the utility of these methods when used to inform policies of governments and other agencies around the world related to land use and resource management. Therefore, sophisticated, scalable methods for noise reduction are crucial in ensuring the efficacy of these land cover change detection approaches.

MODIS observations are annotated with indicators that describe the quality of the observed data based on atmospheric and sensor conditions at the time of measurement. A naive approach would be to omit low quality observations, using only the high quality observations for subsequent analysis. However, this approach leads to considerable reduction in data coverage. In certain land covers of the world such as tropical rain forests, it leaves only 20-30% of region available for analysis (e.g. see

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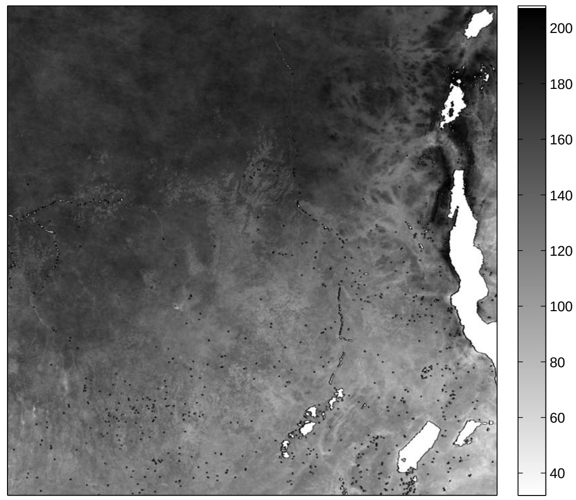


FIGURE 1. A region of the Congo. Darkness indicates number of missing observations for each pixel, if only high quality observations are considered. Data runs from Feb 2000 to Feb 2009 (207 time steps). Data from tropical regions tends to have poorer quality than other regions.

Figure 1). Therefore mechanisms for handling noisy data have to be designed in order to perform global analysis with reasonable data coverage.

The task of time series noise reduction in remote sensing data has been studied for some time and several approaches have been used in the literature for this purpose [8, 4, 13, 9, 22, 15]. These include transformation based methods like Fourier transforms, wavelet transforms, and smoothing techniques that use function fitting like the Savitzky-Golay method. Most of the work in this area has been focused on using existing noise reduction techniques or designing a new technique for a specific region. In most cases, the local noise characteristics are known by domain experts, and an appropriate technique is then designed to work well in the region.

The focus of this paper is to study the effects of noise and noise reduction with particular focus on land cover change detection for remote sensing data sets. In contrast to previous studies, we illustrate the need for special consideration on the influence of noise characteristics on subsequent change detection performance. Second, we present differing noise characteristics by comparative study of change detection algorithm performance in conjunction with noise reduction methods. The evaluation is performed using independently generated validation data for forest fires in Yukon (Canada), California (USA), and deforestation in Pará (Brazil).

In the paper, Section 2 introduces the related work of noise reduction methods and their comparisons. Section 3 describes the remote sensing data set used and study areas. Section 4 provides an overview and basic definition of the reviewed techniques. We present our evaluation methodology in Section 5. The results of the experiments are discussed in Section 6. Finally, we give our concluding remarks in Section 7.

2. Related work

Many noise reduction techniques used in remote sensing are extensions of previous statistical and signal processing filters. The different approaches can be broadly categorized under frequency domain approaches and temporal domain approaches. The temporal domain approaches can further be divided into parametric and non-parametric approaches. Some of the techniques based on these approaches are asymmetrical Gaussian function fitting (AG) [11], double logistic function fitting

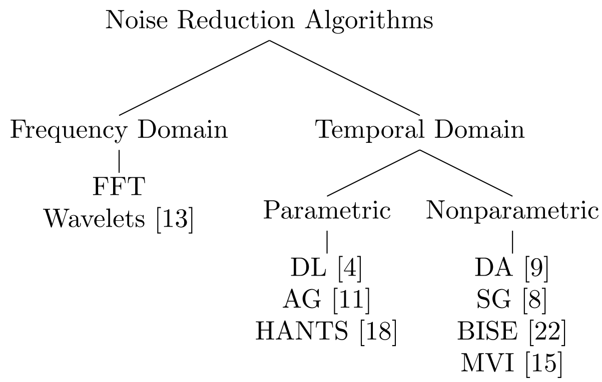


Figure 2. Taxonomy of noise reduction algorithms.

(DL) [4], Savizky-Golay (SG) [8], Fourier-based fitting (HANTS) [18], Best Index Slope Extraction (BISE) [22], mean-value iteration (MVI) [15]. Figure 2 shows a taxonomy of the selected noise reduction techniques in the context of a broader . These studies generally introduce a method and compared it with existing techniques to show that the new technique outperforms the others according to some evaluation criteria such as time series reconstruction error.

Previous studies have performed a comparative analysis across some or all of the above methods. For example, Hird and McDermid [10] compared the performance of six noise reduction methods: AG, DL, SG, 4253H twice, MVI and ARMD3-ARMA5. Chen et al. [8] gave a qualitative evaluation on BISE, HANTS and SG. Beck et al. [4] tested HANTS, DL and AG by calculating the RMSE and residuals. Julien and Sobrino [12] assessed the reconstruction performance of HANTS and DL with iterative interpolation for cloud-free data reconstruction. Arvor et al. [2] compared BISE, MVI, Weighted Least Squares and SG by their performance on classifying crop classes.

However, large scale studies that compare several approaches and evaluate on data sets spanning substantially different geographical regions are scarce. For example, Hird and McDermid [10] compared the results in the area located along the front ranges of the Rocky Mountains in west-central Alberta, Canada. Chen et al. [8] evaluated 438 pixels in different kinds of vegetation type area in China. Beck et al. [4] used 500 one-year time series which were extracted from 100 pixels uniformly distributed over the entire study area located on the borders of Finland, Norway and Sweden from the years 2000 and 2004. Julien and Sobrino [12] selected 17 points randomly within each IGBP land cover class (as there are 17 kinds of land cover types) around the world. And Arvor et al. [2] tested 3 crop classes in Mato Grosso, Brazil.

Finally, to our knowledge, no previous study has examined the performance of noise reduction techniques in the context of improving land cover change detection performance.

3. Data and Study Area

Global remote sensing data sets are available from a variety of instruments at different spatial resolutions as a sequence of global snapshots of measurement values. We use the Enhanced Vegetation Index (EVI), a data product based on measurements taken by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on NASA's Terra satellite and distributed through the Land Processes Distributed Active Archive Center [1]. EVI essentially measures the "greenness" signal (area-averaged canopy photosynthetic capacity) as a proxy for the amount of vegetation at a particular location. MODIS surface reflectance data has been used to generate a continuous record of the EVI index at spatial resolution of 250 meters from February 2000 to the present. This index is generated at a temporal frequency of 16 days. Each observation within the MODIS EVI time series is a composite using the highest quality data from 16 daily raw observations.

We use MODIS EVI data for Yukon, California and Pará. The data for California is at 250 meter spatial resolution (from the MODIS MOD13Q1 data product). The other dataset used is at 1 km spatial resolution for Yukon and Pará (from the MODIS MOD13A2 data product). The California dataset includes the locations bounded by the rectangle with top-left (33.636, -117.977) and bottom-right geocoordinates (34.499, -116.001) with a total of 255,309 points. Similarly, the Pará dataset is bounded by (-3.751, -51.359), (-4.99, -50.1920) for a total of 333,337 points. Finally, the Yukon dataset includes the entire province and includes 551,275 points. These geographic areas are considered as they have very different typical noise characteristics. In our experience, we generally observed outlier values with high EVI in Canada. In Pará, the noise has a seasonal pattern with fluctuating EVI signal due to clouds for several months each year and are regularly annotated as low quality for many consecutive timestamps. California has a wide variety of vegetation types, yielding a variety of noise characteristics. Together, these areas constitute a rich data set to evaluate noise reduction techniques in a global context.

Auxiliary quality data is available with each of the above data products. This information indicates detected atmospheric conditions at the time of observation such as cloud cover, aerosol, snow and ice presence in observed location, and summarized confidence in the observation. These quality indicators are reflected in the figures of this study according to a mapping of quality to data-point colors. The colors, (1) black, (2) red, (3) cyan, (4) green, and (5) magenta correspond to (1) 'Good Data', (2) 'Marginal Data', (3) 'Snow/Ice', (4) 'Cloudy' and (5) 'Fill/No Data' respectively according to the MODIS data product 'pixel reliability' definitions. The figures in this study also generally include blue and pink time series, corresponding to (1) original data and (2) data processed by a noise reduction technique, respectively.

4. Overview of Noise Reduction Techniques

The aim of this section is to provide an overview and basic definition of the reviewed noise reduction techniques. Before proceeding to these methods, we define the following notation:

Definition 1: $X = [x_1, x_2, ..., x_n]$, the observations of the time series, where x_i is the value of the i^{th} timestamp.

Definition 2: $Y = [y_1, y_2, ..., y_n]$, the observations of time series processed by a given noise reduction technique, where y_i is the value of i^{th} timestamp.

4.1. **Savitzky-Golay method.**

The Savitzky-Golay method is a convolution method which processes data based on a polynomial function fitting procedure, with a window centered around an observation [19]. Given the size of the window $2m + 1$ and the degree of the polynomial function d, Savitzky-Golay coefficients $C = [c_1, c_2, ..., c_k]$ are fetched from a pre-computed table. Then, the processed data Y is computed as a weighted moving average with weights given by C. The SG method is given by:

$$y_j = \frac{1}{2m+1} \sum_{i=-m}^{m} c_i x_{i+j} \tag{1}$$

4.2. **Iterated to upper envelope Savitzky-Golay method.**

The Savitzky-Golay Method iterated to upper envelope (SG-Itr) [8] is developed based on Savitzky-Golay. The method was designed for NDVI data and the authors assume clouds and poor atmospheric conditions decrease the value of NDVI and the Savitzky-Golay method can be improved by iterating to the upper envelope of the original data. However, EVI data is often not limited to negatively biased noise characteristics like NDVI, and often has temporal outliers with high EVI values. Therefore, the iteration step is not relevant for MODIS EVI and SG-Itr is omitted from further analysis.

4.3. **Harmonic Analysis of Time Series Method.**

The Harmonic Analysis of Time Series (HANTS) technique [18] was developed to identify and remove cloud-contaminated observations in time series with irregularly spaced observations. Based on the assumption that noise is high frequency signal, it builds the model based on the lowest k frequency components given by:

$$Y = a_0 + a_1 \cos\left(\frac{2\pi}{n}(t-1)\right) + b_1 \sin\left(\frac{2\pi}{n}(t-1)\right) + \ldots + a_n \cos\left(k\frac{2\pi}{n}(t-1)\right) + b_n \sin\left(k\frac{2\pi}{n}(t-1)\right) \tag{2}$$

The parameters are determined by ordinary least square method (OLS). Because OLS is sensitive to noise, this method uses an iterative procedure to remove noise, identified as a large deviation from the fit curve.

4.4. **Double Logistic function fitting method.** The Double Logistic function fitting method (DL) [4] is designed to process NDVI data at high latitudes. In these regions, snow is present throughout winter months and therefore no vegetation cover is observed. So observations in winter can be considered as a small constant value. Because the authors assume noise in the NDVI index is negatively biased, they use an iterated approach to find the upper envelope. As mentioned, the upper envelope is unsuitable for EVI. In this study, we only use a basic model fitting to process EVI data. The DL model is given by:

$$y_i = w + (m - w)\left(\frac{1}{1+\exp(-mS(t_i - s))} + \frac{1}{1+\exp(mA(t_i - A))} - 1\right) \tag{3}$$

where, w is a fixed winter value, m is the maximum value during the growing year, S is the inflection point as the curve rises, A is the inflection point as the curve drops, mS is the rate of increase of the curve at inflection points and mA is the rate of decrease of the curve at inflection points.

4.5. **Data Assimilation method.** The Data Assimilation method [9] aims to reconstruct high-quality NDVI data with the intuition that auxiliary or 'background' data other than the immediate temporal neighborhood of an observation can be used improve the quality of the time series. The DA method introduces a cost function defined as:

$$J(y_i) = \frac{(y_i - b_i)^2}{BEV_i} + \frac{(y_i - x_i)^2}{OEV_i} \tag{4}$$

where, b_i is the background value of the time series. BEV_i and OEV_i are background and observation error variance of the time series.

The processed value y_i is computed by setting the gradient of the cost function to zero. Then, the DA method is defined by:

$$y_i = b_i + w_i * (x_i - b_i) \tag{5}$$

Where,

$$w_i = \frac{BEV_i}{BEV_i + OEV_i} \tag{6}$$

Because it is difficult to directly estimate the error variances, the authors apply the QA flag to determine w_i empirically.

4.6. **Simple Outlier Detection method.** For comparison purposes, we describe a naive outlier identification and imputation scheme (SO) that uses only the EVI observations of the time series to identify outliers instead of relying on the quality annotations as in the DA method. The mean (μ_X) and sigma (σ_X) of the time series are computed. All time steps where $|x_i - \mu_X| \geq \alpha\sigma_X$ are flagged as outliers and imputed as the mean of the EVI values of their first available (unflagged) temporal neighbors. Based on experimental analysis we set $\alpha = 4$.

5. Evaluation Methodology

Our aim is to investigate noise reduction methods for remote sensing time series data with a specific focus on improving the performance of land cover change detection methods. It is therefore important to evaluate the selected noise reduction methods based on the improvement in accuracy for change identification. In this section, we describe the change detection algorithm, and the evaluation method used in this study to understand noise reduction techniques in the context of land cover change detection.

5.1. **Change Detection Algorithm.** We use the Yearly Delta change detection algorithm which was studied in [5]. The intuition behind the Yearly Delta algorithm is that some changes in land cover such as forest fires cause an abrupt decrease in the EVI signal. Thus, for the time step corresponding to the date of fire occurrence, the difference between the annual mean EVI of previous and following year will be high. The Yearly Delta algorithm assigns a change score to each time step as the difference between the mean annual EVI of the previous year and the following year. The yearly delta score (YD) for a pixel is the maximum change score across all time steps and the time step with the maximum score is considered the change point. The pixels are ranked based on their YD score and a certain number of the top ranked pixels are considered as changed. This algorithm assumes that the pixels which have a fire event will receive a higher score than those which do not have a fire event because the undisturbed pixel typically do not have an unusually high EVI decrease in a year. We use this score as our change detection score in this paper. Note that this method assumes that there is a single occurrence of fire in the time series. Since multiple fires rarely occur in the relatively short span of 10 years, this does not significantly impact our evaluation. In addition, land cover changes in Pará are often only for a 6 month period. This is because the leaf cover recovers in less than a year from deforestation. Therefore we use a modified version of the algorithm in Pará that uses mean difference in EVI for a 6 month window instead of entire year. To take seasonality into account, the compared model is constructed from the same 6 month window in the previous year. Furthermore, we define a modification in Yearly Delta algorithm which uses the mean of the Manhattan distance between the consecutive years as the change score. We call this the Manhattan Delta algorithm. While Yearly Delta can only identify changes in annual means, Manhattan Delta can also find phenological changes that may not cause a change in the annual mean.

5.2. **Validation Data Sets.** Change detection studies are frequently plagued by the lack of good ground truth data [17] which forces the evaluation to be more qualitative in nature. In this study, we have utilized high quality validation data from three different sources, one each for Yukon, Pará and California. The validation data for Yukon consists of fire polygons from the National Fire Database (NFDB) compiled by the Canadian Forest Service, which consists of forest fire data from the 13 provincial fire management agencies. The data collection methods include aerial surveillance, satellite-based mapping and ground surveillance [20]. Brazil's space research agency, the Instituto Nacional de Pesquisas Espaciais (INPE), provides what is regarded as a gold standard in land change detection. Its PRODES product is based on supervised image analysis of 30m Landsat satellite imagery, yielding polygons marking boundaries of land use change in Brazil on an annual basis. This is used for validation in Pará. The state of California maintains historical databases with detailed information of fire incidents that affect an area larger than a certain size. One of the key aspects of the database is that it contains accurate boundaries of the fires. We obtained fire boundaries for California for the years 2000 through 2008 from the Ecosystem Modeling Group at NASA Ames Research Center. The validation data is in the form of polygons which represent the boundaries of forest fires. MODIS EVI data is georeferenced by the latitude and longitude value for the pixel center. Thus, a pixel is considered inside a polygon if the pixel center is inside it, otherwise it is considered outside the polygon.

5.3. **Evaluation Methodology.** *Precision* and *recall* are two well-known metrics used to evaluate the performance of algorithms in information retrieval, machine learning and data mining [21]. Table

		Predicted	
		Fire	No Fire
Validation Data	Fire	*TP*	*FN*
	No Fire	*FP*	*TN*

Table 1. Confusion matrix with respect to fire event validation data.

1 shows a confusion matrix related to evaluation against a fire event validation data set, where TP refers to true positive, FP refers to false positive, FN refers to false negative and TN refers to true positive.

We evaluate performance by examining the *sorted* list of change scores. Specifically, performance is measured in terms of the number of instances correctly identified and the number of instances missed in the top-n ranked instances. We use a precision metric (called p_n) employed in the context of information retrieval [3] and anomaly/outlier detection [7], which is appropriate for the top-n ranked setting, defined as:

$$\text{Precision, } p_n = \frac{TP_n}{TP_n + FP_n}$$

Recall (defined in the information retrieval context as the ratio of the number of relevant instances retrieved to the number of relevant instances that could have been retrieved from the validation data set) is defined as:

$$\text{Recall, } r_n = \frac{TP_n}{M}$$

To compare the relative performance of different techniques, we plot the precision and recall curve for the ranked list of pixels for the values $1 \leq n \leq M$. An ideal change identification algorithm should have a precision of 1 and a steadily rising recall from 0 to 1 as n increases from 1 to M.

6. Relationships Between Noise Reduction and Change Detection Methods

The purpose of this section is to introduce concepts relevant to performance of (i) change detection algorithms within (ii) various regional contexts with differing noise characteristics according to (iii) differing strategies of noise reduction. The relevant interrelations of these three elements are presented, and focused analysis is presented from the perspective of varying (i) and (iii) for a comparative analysis across (ii).

We enumerate three general data characteristics, especially relevant for MODIS EVI data, which a given noise reduction technique may take advantage of:

- **Neighborhood coherence**: Because the vegetation remote sensing signals can be regarded as discrete samples from of an unknown continuous model (the natural vegetation growth at the observed location) responding to physical constraints, any timestamp which does not follow the trend (an outlier with respect to the observation's temporal neighbors) could be viewed as a noisy observation. This is considered the most important data characteristic in DL, AG, HANTS and SG methods.
- **Quality annotation**: This auxiliary data is included in the MODIS products for each observation. According to MODIS, observations labeled as low quality are more likely to be noisy. Therefore, many applications consider only high quality data. Noise reduction methods use this property by associating more trust to higher quality timestamps. The DA method uses this characteristic.

- **Background model**: When there is no significant change in the land cover caused by events like fires and droughts, the vegetation response generally follows approximately the same annual growth cycle. Therefore, building and maintaining a good model based on historical data can be used to remove noise. However, such methods need special consideration in the event of a land cover change. DA is an example of a method primarily utilizing this data characteristic.

For any noise reduction technique we identify the following two questions to be of relevance:

- Which observations in the time series should be imputed?
- How are these observations to be imputed?

Based on the first question, the reviewed methods can then be organized into (1) *selective* and (2) *non-selective* imputation methods for noise reduction.

Selective methods identify some observations that they consider noisy and ought to be imputed. The identification of noisy observations can be based on quality annotation such as in DA where all data annotated as low quality are considered noisy and imputed or based on some statistical likelihood such as in SO where all observations that are incoherent with their temporal neighborhood are imputed. On the other hand, in the non-selective methods every observation is imputed. The smoothing-based methods such as HANTS, DL, AG and SG belong to this category. We consider the selective methods to be more conservative as they modify fewer observations as opposed to the non-selective methods which modify every observation and therefore no processed data value corresponds exactly to the original observation. Intuitively, if an observation is not clearly anomalous and is annotated as a high quality observation, the value reported by the MODIS is as trustworthy as can be ascertained.

Time series smoothing methods should thus be considered the most aggressive because generally every observation of the original time series is modified without identifying trustworthy observations. Note that typically the imputations of selective methods will modify the observation by large magnitude because large outlier values are imputed in this case. The non-selective methods are less conservative and modify each value but the total modification in the value itself is of smaller magnitude for most observations.

Imputation is done primarily based on the three characteristics of neighborhood coherence, quality annotation, and background model. Smoothing-based methods rely on neighborhood coherence and use function fitting on temporal neighbors to eliminate the noise. These methods do not incorporate the quality information or background model in their imputation step. In contrast, DA does not account for the temporal coherence of the values in the EVI time series and uses the background model for the imputation of low quality time steps. While all three properties play an important role when removing noise there is no method that uses them all.

Below we present two noise characteristics present in varying degrees in each study region. The effectiveness of noise reduction for change detection methods is closely related to the susceptibility of these methods to these characteristics. First, *unbiased noise* of relatively small amplitude exists as a component of each observation due to variations in atmospheric conditions or instrument imprecision. This noise causes neighboring observations to be arbitrarily different from each other due to phenomena other than vegetation growth, where no land cover change has occurred. Second, the presence of relatively large, positively or negatively *biased noise* produces anomalous observations which do not follow the phenological trend of the time series. These observations tend to occur during periods of persistent cloud cover. Often these observations are annotated with a low quality flag but sometimes may not be recorded accurately in the QA annotation.

Changed Detection methods are impacted by both biased and unbiased noise in the data. A naive algorithm using observation-wise comparisons between the same months in two years will get severely impacted by biased noise and raise many false alarms. Therefore, most algorithms, including those used in this study, consider a more robust statistic like the average over an entire year for change detection. The Manhattan Delta and Yearly Delta algorithms are impacted by biased noise as it can increase the distance considerably and give a false appearance of change in EVI. The Yearly Delta algorithm is robust to unbiased noise in the data as averaging tends to eliminate the effects of white noise. However, the Manhattan Delta algorithm is additively impacted by the unbiased noise per timestamp.

In the following we show that selective imputation methods tend to be more suitable for biased noise, and non-selective imputation for unbiased noise.

6.1. **Unbiased Noise.** The effectiveness of noise reduction in the context of land cover change detection is closely related to the susceptibility of these methods to certain noise characteristics, such as instrument imprecision or aerosol contamination yielding noise of relatively small amplitude due to these variations across the 16 day observation window.

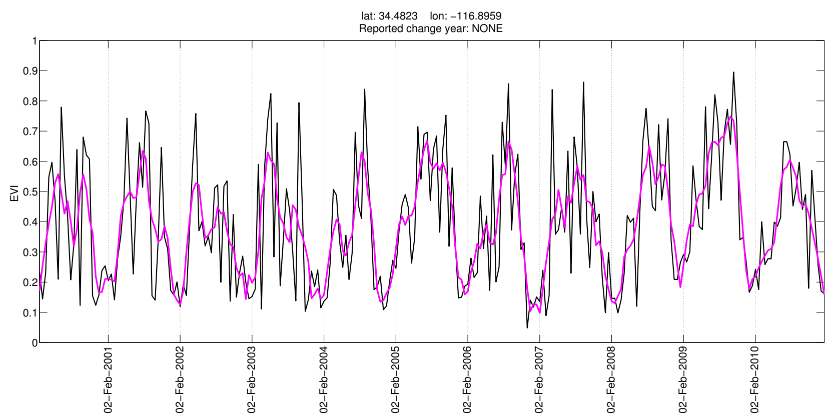
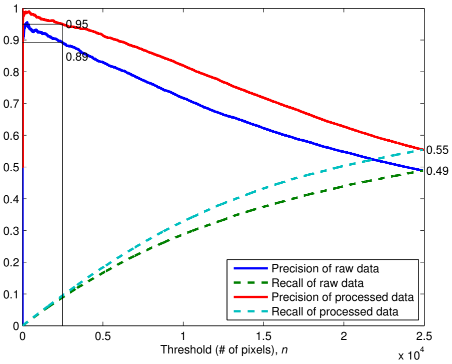


FIGURE 3. This time series in California exhibiting unbiased noise is a false positive before smoothing and true negative after smoothing. The Manhattan-delta yields large distance across each yearly segment, giving a large distance and change score.

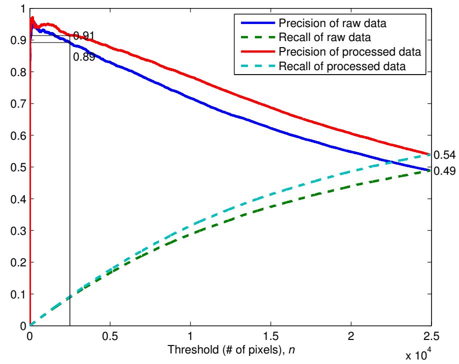
Change detection methods such as the Recursive Merging algorithm [6] utilize an observation-wise distance measure in the temporal domain. Manhattan distance is one of the standard observation-wise distance measurements. The Manhattan Delta algorithm is chosen in our investigation to illustrate the influence of smoothing filters on observation-wise distance measures. Figure 3 shows a time series located in California which is reported changed by Manhattan Delta algorithm. In this figure, the black curve shows the observed values of this time series. Noise introduces high variability and causes a higher change score than actual. Since the noise could be regarded as unbiased, non-selective imputation methods such as SG (shown as pink curve), DL and HANTS can be used to reduce this unbiased noise and reduce the effects of noise in the Manhattan Delta performance (see: Figure 4).

The Yearly Delta algorithm is designed to find a specific change (i.e. a 'sudden drop' event) by using annual mean aggregation. Figure 5 shows the Yearly Delta algorithm is robust to unbiased noise and thus its performance is not significantly influenced by non-selective imputation methods.In fact, the performance is slightly worse after smoothing. However, because only mean value is considered, it has limitation to detect phenological change where the annual mean observation is not significantly affected. Because the Yearly Delta algorithm is better designed to find land cover changes specific to fires, and our evaluation data is related to forest fires, Yearly Delta tends to have better performance than Manhattan Delta in the results of this section.

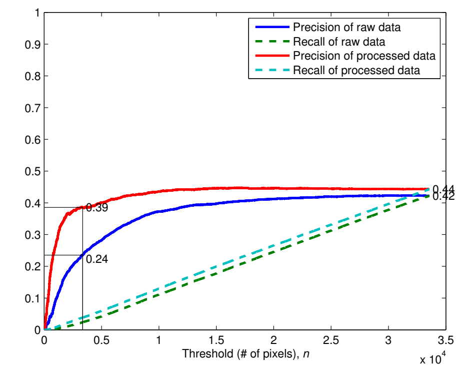
6.2. **Biased Noise.** As introduced above, the presence of *biased* noise impacts the performance of both the Yearly Delta and Manhattan Delta algorithms. We hypothesize from our experience with the MODIS data that the change detection performance in Yukon is primarily degraded by outlier



(a) SG in Yukon



(b) HANTS in Yukon

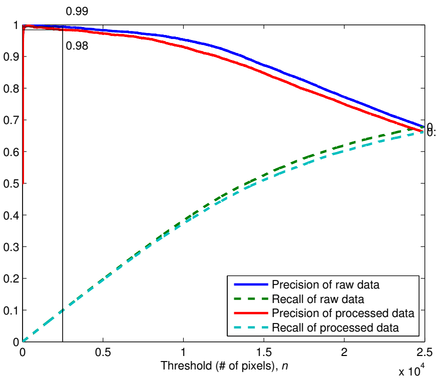


(c) DL in California

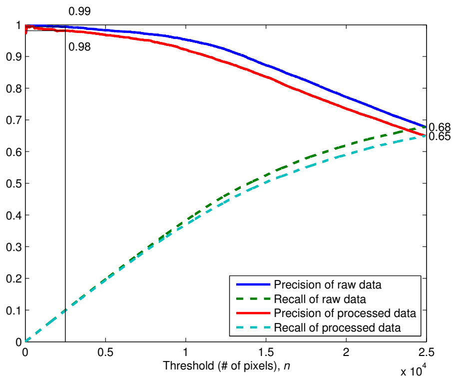
FIGURE 4. The performance of non-selective noise reduction methods with the Manhattan Delta algorithm.

observations with unusually higher EVI values. Figure 6 shows an EVI time series located in Yukon with positive and negative outliers. These noisy observations will significantly affect the distance computation between successive years used for change score computation and therefore lead to a false change at these locations. The performance of the two algorithms can be improved by using an outlier identification and imputation method. We use SO on this data to identify and impute the outliers. The performance on the processed data can be seen in Figure 7 for Manhattan Delta and Yearly Delta respectively. We see that the performance improves only slightly for both algorithms.

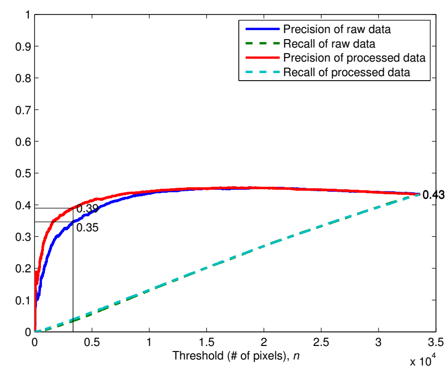
The DA method uses quality to impute the observations performs significantly better on the data (as shown in Figure 8(b)). This is because in Yukon the biased noise is often correctly annotated as low quality and is imputed by DA using the background model built using high quality observations. The SO method alone is not suitable for removing the negative biased noise because these values are not sufficiently far from the mean due to skew of the winter months observations. Figure 11 shows these observations appropriately imputed by DA. Data processing using DA is therefore able to handle instances of positively and negatively biased noise to a significant extend and yields the superior performance in Yukon. A processing step that first applies SO and then DA performs the better than DA alone (as shown in Figure 8(c)). This is primarily due to occasional presence of biased noise with a high quality annotation that is not imputed by DA, but is identified and imputed by SO. Figure 9 shows an EVI time series with an outlier annotated as high quality by MODIS. Conversely, Figure 10 shows a time series in California with a sharp drop in the year 2003 followed



(a) SG in Yukon



(b) HANTS in Yukon



(c) DL in California

Figure 5. The performance of non-selective noise reduction methods with the Yearly Delta algorithm.

by slow regrowth. Most of the timestamps following the change are annotated with low quality, so they are imputed with the background model, thereby obliterating the change event. Because land cover change events such as fires also have associated atmospheric conditions such as smoke, observations immediately following these events may often be annotated as low quality. These cases account for degraded performance of DA in California. In Pará, we observe that the average quality annotation is significantly lower than regions such as California and is regular and seasonal. These characteristics can be observed in the change detection performance, see Figure 8(a).

Non-selective noise reduction methods such as AG, SG, DL and HANTS are generally not suitable in presence of outliers. These methods use parametric or non-parametric function fitting over a temporal window. The outliers in this window are imputed to become more temporally coherent with the neighbors. But the outlier observation also influences the neighborhood imputation and therefore these methods distribute the anomalous observation to the temporal neighborhood. As a result, the mean annual EVI is often unchanged after imputation and the non-selective noise reduction methods shows less influence on the performance of the Yearly Delta algorithm as shown in Figure 12(b). However, the Manhattan Delta method is more affected by this smoothing as shown in Figure 12(a). In regions where the biased noise is not dominant such as in California, the use of SO has no significant improvement in change detection. Figure 13 shows that the processed data has similar performance to the raw data in California using the Yearly Delta algorithm.

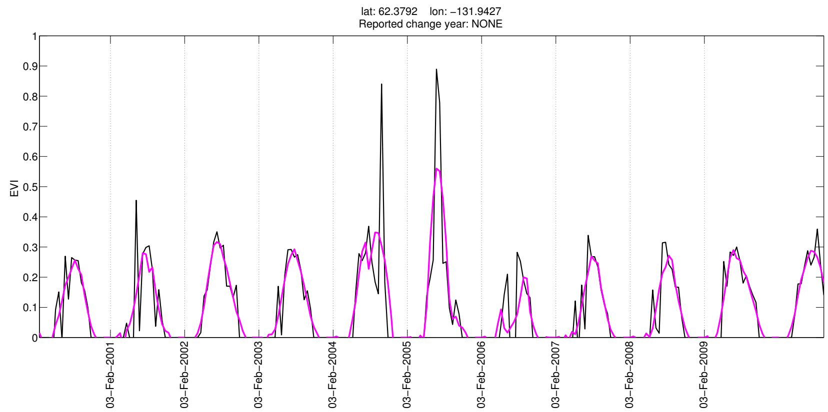
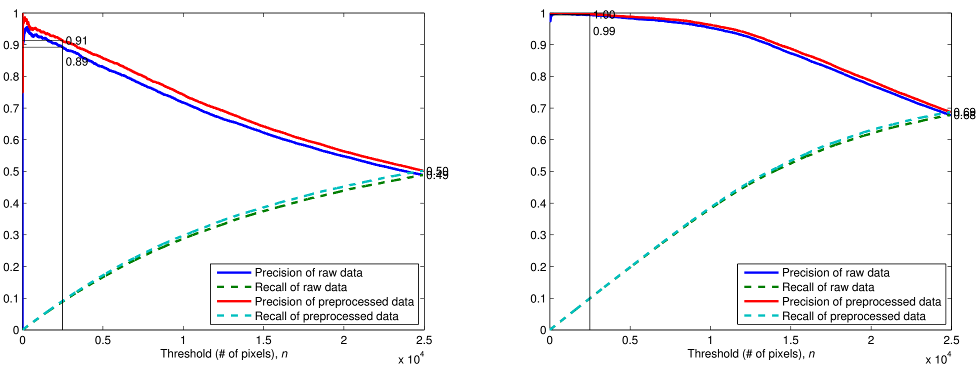


Figure 6. An EVI time series located in Yukon with positive (see 2004 and 2005) and negative (see 2006) outliers.

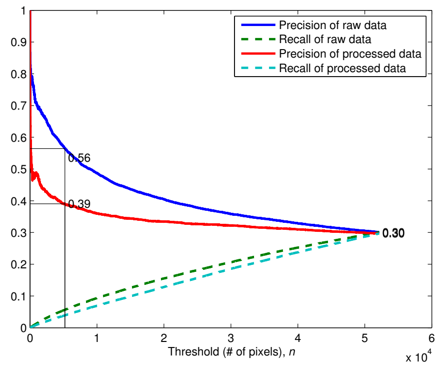


(a) (b)

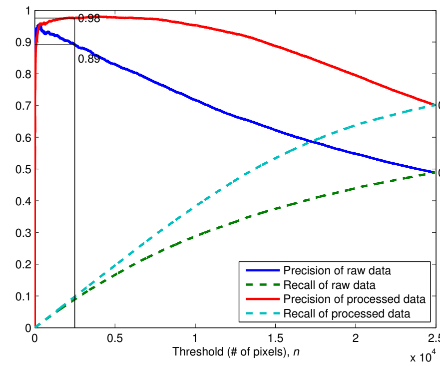
Figure 7. (a) Precision and recall curve of original data and data preprocessed by SO using the Manhattan Delta algorithm; (b) Precision and recall curve of original data and data preprocessed by SO using the Yearly Delta algorithm.

7. Concluding Remarks

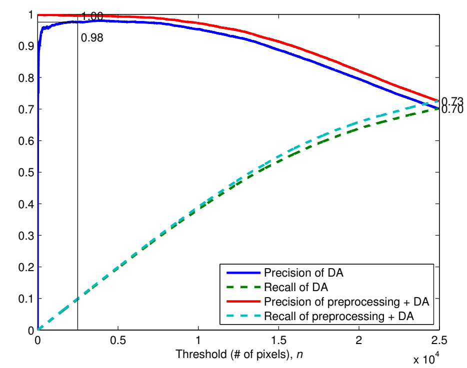
In this paper we have studied the effects of noise and noise reduction with particular focus on the land cover change detection problem. Specifically, our focus is on improving the quality of input data to change detection algorithms. We have shown interrelations between noise characteristics endemic to differing regions, change detection methods, and noise reduction methods. We have provided contrasts between selective and non-selective imputation methods and their effects on biased and unbiased noise characteristics. We conclude that less conservative, non-selective noise reduction methods should generally follow more conservative, selective methods to improve results. Conversely, we conclude that non-selective methods tend to perform poorly in the presence of positively or negatively biased noise. Depending on the susceptibility of the change detection method to each of these noise characteristics, either smoothing or outlier detection may not be necessary. We see in California, for example, utilizing noise-reduction methods for either or both of these noise characteristics yields insignificant improvement in change detection performance.



(a)



(b)



(c)

FIGURE 8. (a) Precision and recall curves of original data and data processed by DA using Yearly Delta in California; (b) Precision and recall curves of original data and data processed by DA using Manhattan Delta in Yukon; (c) Precision and recall curves of data processed by DA with and without SO using Manhattan Delta in Yukon. Note that performance is improved with SO. The difference is attributed to outlier observations of high quality imputed by SO but not DA.

We show that noise reduction methods tend to utilize information from neighborhood coherence, quality annotation, or background models to impute noisy observations in a time series. To our knowledge, no method synthesizes all of this information to perform well in the presence of varying noise characteristics (i.e. on a global scale). Second, no method exists to model the prevalence of noise characteristics in a particular region. Each of these represent directions for future work for developing a sophisticated global framework for reducing the effect of noise in the land cover change detection problem.

8. Acknowledgements

The research described here is supported by the Planetary Skin Institute, NSF Grant IIS-0713227, NSF Grant IIS-0905581, NASA grant NNX09AL60G and the University of Minnesota MN Futures Program. Access to computing facilities was provided by the University of Minnesota Supercomputing Institute.

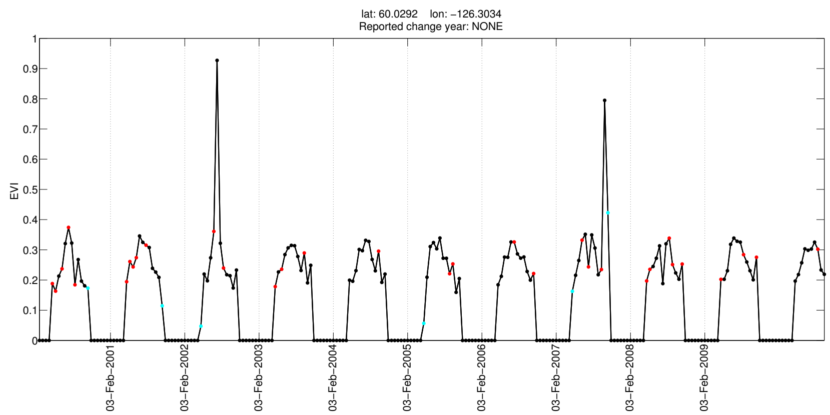


FIGURE 9. An EVI time series with outliers annotated as high quality.

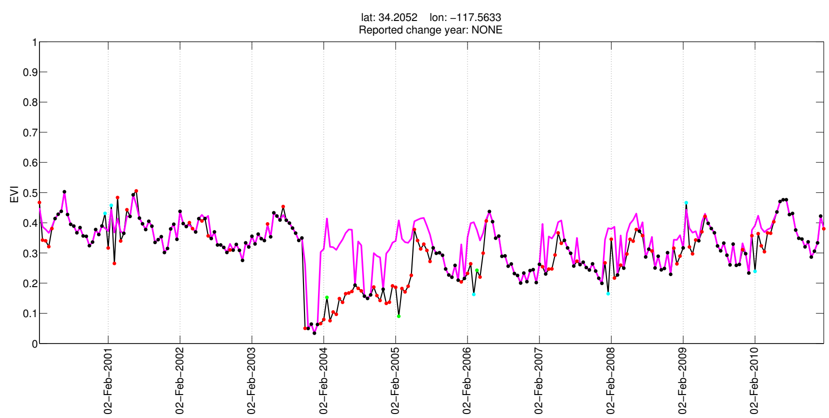


FIGURE 10. A time series with a fire event in 2003 and a regrowth segment comprised of many low quality points. The DA method replaces all these points with the background, resulting in artificial peaks.

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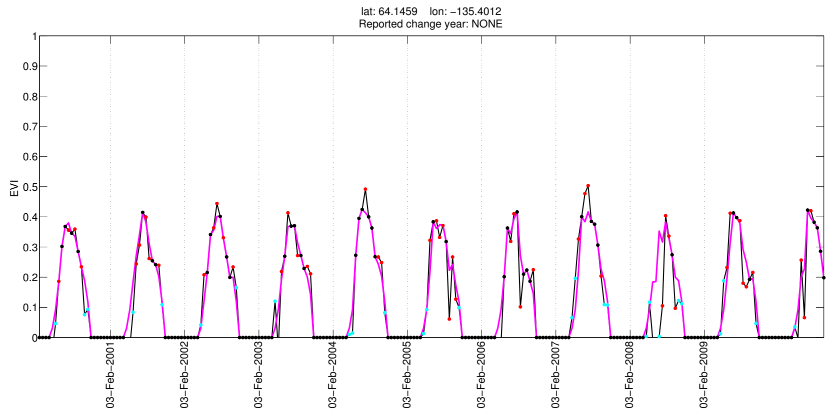
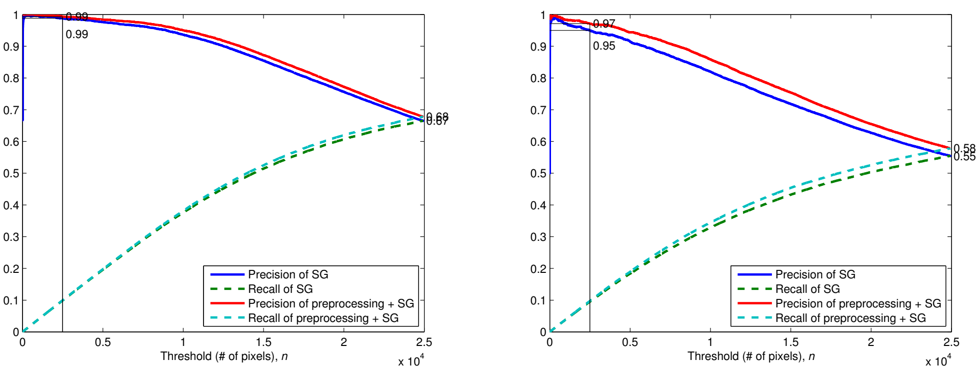


FIGURE 11. A time series from Yukon with negatively biased observations in 2008 causing a spurious change. DA uses the background values to impute these values appropriately.



(a) (b)

FIGURE 12. (a) Outliers imputation does not affect much on the performance of SG in Yukon using the Yearly Delta algorithm; (b) Outliers imputation improves performance of SG in Yukon using the Manhattan Delta algorithm.

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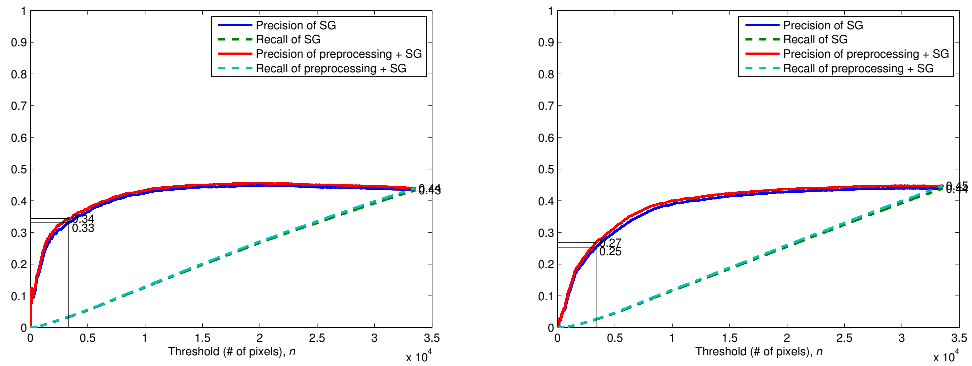

(a) (b)

FIGURE 13. (a) Outliers imputation does not affect the performance of SG in California using the Yearly Delta algorithm (b) Outliers imputation does not affect the performance of SG in California using the Manhattan Delta algorithm.

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