Dealing with noise in multi-temporal NDVI datasets for the study of vegetation phenology: Is noise reduction always beneficial?

Jennifer N. Hird[1] and Greg McDermid[2]

1 Foothills Facility for Remote Sensing and GIScience, Department of Geography, University of Calgary, jnhird@gmail.com,
2 Foothills Facility for Remote Sensing and GIScience, Department of Geography, University of Calgary, mcdermid@ucalgary.ca

Abstract

The prevalent, limiting effects of noise on the application of remotely-sensed VI time series in the remote sensing of vegetation phenology is well-recognized. A multitude of noise-reduction approaches exist in the literature, but rarely are the benefits of such techniques in the study of vegetation growth and development ever questioned. We present a two-part statistical analysis examining when and where the application of noise-reduction algorithms to a multi-temporal NDVI dataset are beneficial. Both a root mean square error (RMSE) analysis and a phenological metric analysis were conducted, examining noise reduction under a variety of conditions. Results showed that although statistically significant benefit was seen under particular conditions, under many conditions it was not observed. The complex interplay of multiple factors (e.g. level of noise, biogeographical region) on the effects of noise reduction was also clearly demonstrated through statistical interaction effects. Our work raises questions regarding the wide-spread application of noise reduction in the remote sensing of vegetation phenology.

Background and Relevance

Satellite remote sensing has become an important and widely-used tool in the study of vegetation phenology. Application of these datasets typically involves the per-pixel analysis of multi-temporal vegetation indices (VIs), which are frequently subject to high-frequency fluctuations (i.e. noise) caused by changing atmospheric conditions and varying sun-sensor-surface geometries (Duggin, 1985). A broad range of time series noise-reduction strategies are found in the literature, (e.g. Moody & Johnson, 2001; Van Dijk, Callis, Sakamoto, and Decker, 1987; Beck, Atzberger, Hogda, Johansen, & Skidmore, 2007; Sellers et al., 1994). However, rarely are the benefits of applying such techniques to remotely-sensed VI datasets questioned. In light of this, we set out to enhance current understandings of noise reduction in the remote sensing of vegetation phenology, by conducting a rigorous statistical analysis designed to: 1) investigate whether a series of noise-reduction strategies is indeed beneficial to maintaining signal integrity, and to the subsequent extraction of phenological metrics; 2) examine the circumstances under which benefits may or may not be observed; and 3) explore the factors that might influence this benefit (e.g. annual variations, noise-reduction strategy).

Methods and Data

To avoid the large constraints imposed on effective evaluation by the difficulties of acquiring suitable reference data for satellite datasets, we adopted the analytical framework described by Hird and McDermid (2009). Their model environment employs simulated, idealized NDVI time series containing varying levels of introduced noise to test the benefit of noise reduction. The data consisted of a multi-temporal 16-day 250 m NDVI dataset collected by Terra's MODIS sensor, and covering the front ranges of the Rocky Mountains in west-central Alberta, Canada, for 2003 through 2005. Six common noise-reduction techniques were used, on the basis of their successful applications within the literature, and accessibility to researchers. These were: Beck et al.'s (2006) double logistic function-fitting, Jönsson and Eklundh's (2002) asymmetric Gaussian function-fitting, Chen et al.'s (2004) modified Savitzky-Golay filter, Ma and Veroustraete's (2006) MVI filter, Velleman's (1980) 4253H, Twice filter, and Filipova-Racheva and Hall-Beyer's (2000) autoregressive combination ARMD3-ARMA5 filter. Our analysis comprised two components: 1) root mean square error (RMSE) calculations, to provide a measure of mean difference (Willmott, 1982) between noise-reduced and the original, ideal NDVI time series; and 2) phenological metric calculations, to examine the effects of noise reduction on these estimations. We focused on a start of spring growing season metric (SOS) and a maximum NDVI metric (maxNDVI), as these are two of the most widely-used metrics found in the literature (e.g. Pettorelli et al., 2005; Schwartz, Reed, & White, 2002). Statistical analysis of the RMSE and metric results involved a series of two-way repeated measure ANOVAs (analysis of variance), as well as simple effects pair-wise comparisons involving Bonferroni correction – to account for multiple combinations effects. Noise-reduction approach, including the no noise reduction option, provided our within-subject factor, , while between-subject factors included level of noise, biogeographical region, and (for metric results only) year. Significance was observed for the 0.05 level.

Results

Two, two-way repeated measures ANOVAs of RMSE values showed that the selection of a noise-reduction approach was a significant within-subject effect (F = 12.404, p < 0.001; F = 7.471, p < 0.001). Biogeographical region did not have a significant effect on RSME (F = 1.380, p = 0.299), but an interaction effect between biogeographical region and noise-reduction technique was observed (F = 3.611, p < 0.001). The amount of noise (e.g. 10%, 40%, or 70%) did produce a significant effect on RMSE results (F = 7.724, p = 0.005). No interaction effect was observed between level of noise and noise-reduction technique (F = 1.551, p = 0.121). Main effects testing showed that each noise-reduction technique provided a significantly better RSME than applying no noise reduction, indicating that it was indeed beneficial overall.

Three, two-way repeated measures ANOVAs analyzing the effects of noise reduction with biogeographical region, level of noise, and year on each set of metric calculations revealed that noise-reduction showed a significant effect on both SOS values (F = 14.995, p =< 0.001; F = 14.310, p < 0.001 ; F = 13.170, p < 0.001), and maxNDVI (F = 75.567, p < 0.001; F = 84.797, p < 0.001; F = 69.306, p < 0.001). Biogeographical region was a statistically significant factor in SOS estimations ($F = 3.580$, $p = 0.008$), and this effect varied with noise-reduction technique. In addition, the effect of noise-reduction technique varied significantly with biogeographical region and percent noise, as demonstrated by the interaction effects. Closer examination in the form of simple effects pair-wise comparisons showed that significant improvement in SOS estimates by the application of noise reduction was only seen in the Alpine time series, and only at the 70% noise level. Neither level of noise, nor annual variation, was a significant factor on its own.

With regard to maxNDVI. biogeographical region also produced a significant effect, but again, neither level of noise, nor year, had a significant effect on this metric. However, all three of these factors did demonstrate significant interaction effects with noise-reduction approach ($F = 2.343$, $p < 0.001$; $F = 8.004$, $p < 0.001$; $F = 1.842$, $p = 0.041$)). Simple effects testing showed more significant effects from the application of noise reduction on the extraction of maxNDVI than for SOS. However, the data show that these were significant degradations (i.e. lowering) of maxNDVI metric values, rather than improvements. In other words, in the majority of cases, noise reduction produced a less accurate result when compared to a lack of noise reduction.

Conclusions

We found that while NDVI time series noise reduction did offer a statistically significant benefit both in the general removal of spurious, high-frequency fluctuations in the data, and in the subsequent extraction of more accurate phenological metrics, this benefit occurred much less often than might be assumed given the current plethora of noise-reduction strategies. We suggest that noise reduction is not universally beneficial, and can, in fact, be detrimental in some situations. In particular, careful consideration must be taken when the extraction of phenological is the ultimate goal.

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