Change in our MIDST: Toward Detection and Analysis of Urban Land Dynamics in North and South America

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***Abstract*— We describe a new approach to monitoring urban land dynamics—the MIDST (Multiple Indicators Detecting Significant Trends) system—that we are in the process of building. One of the main foci of the project are the megacities and major conurbations of both North and South America. Here we look at the result of a simple nonparametric trend analysis applied to a MODIS NBAR NDVI image time series of southeastern interior Brazil.**

II. INTRODUCTION

We are building an innovative system to quantify and localize change, characterize environmental processes, and examine the function of land surface change within the Earth System. We call this system MIDST, short for Multiple Indicators Detecting Significant Trends. Here we introduce the concept and discuss its relevance to exploring patterns and processes in urban and peri-urban land dynamics.

Our broader science question is: Where in the western hemisphere is the vegetated land surface changing significantly during the past 15 years in response to direct human impacts? We are using the Human Influence Index (HII) [1] and Anthromes v2.0 [2][3] to partition the Americas spatially. Both are cross-disciplinary indicators of direct human influence on terrestrial ecosystems. In addition, we will use the complementary spatial partitioning provided by the World Wildlife Fund (WWF) global ecoregions [4].

Our testable hypothesis about changes in the vegetated land surface in and around cities states: Areas of significant negative changes that occur in areas with high human impact appear predominantly associated with the expansion of human settlements, particularly cities.

II. MOTIVATION

We describe the process of change analysis as a sequence of tasks: (1) detection of changes; (2) quantification of changes; (3) assessment of changes; (4) attribution of changes; and (5) projection of the potential consequences of changes.

Change detection is a fundamental remote sensing task, along with geolocation and entity labeling; thus, there are myriad ways to perceive differences and there is a long history of tuning techniques to specific applications. *Change quantification* may not, at first glance, appear to rank as a distinct task, but accurate measurement of the magnitude of perceived differences, especially across sensors lacking onboard calibration, can require its own set of approaches. *Change assessment* asks whether the magnitudes of the differences are statistically significant. This task involves addressing the intertwined issues of data variability, sources of uncertainty, and the duration of the data record relative to the recurrence interval of the phenomena of interest (e.g., phenologies, seasonalities, extreme events).

Change attribution aims to identify or to infer the proximate cause(s) of significant changes. As change agents are rarely identifiable through remote sensing, this task typically requires invoking data, models, and expertise outside of remote sensing science. Change attribution is rarely straightforward. Building a plausible narrative from even multiple lines of evidences is no guarantee of arriving at an accurate mapping from the observed pattern to the underlying processes. However, it may be easier to exclude specific possibilities as likely drivers by linking multiple datastreams through conceptual models of the change dynamics.

Change projection explores the potential consequences of the observed significant changes. This task again falls outside of remote sensing science proper and requires engagement of

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multiple disciplinary perspectives, rich ancillary data, and simulation modeling.

The MIDST system will implement solutions to the first three "detection" tasks and produce georeferenced polygons of significant changes in one or more datastreams. The system will then evaluate plausible links of candidate drivers to identified polygons of significant change.

Here we provide an example of detecting (peri-)urban land dynamics in Brazil outside of the megacities.

III. METHODOLOGY

To detect, quantify, and assess the significance of land surface changes, we are using the nonparametric Seasonal Kendall (SK) trend test corrected for first-order temporal autocorrelation [5-8]. The older, more familiar Mann-Kendall (MK) nonparametric trend test simply sums the number of times a given observation has a higher value than any previous observation. The MK test has been widely used in climatology and hydrology to evaluate trends in annual data. The SK test is built up from the MK by calculating the MK statistic for each compositing period separately and then summing the MK statistics for all composites. Correcting the SK test for first-order autocorrelation is a necessary step that significantly complicates the calculation, but greatly attenuates the risk of committing a Type I error (finding a significant difference where none exists). The SK test statistic has the advantage of being asymptotically normal with a zero mean. Variance of SK test statistic is the sum of variances for each composite plus the sum of the autocorrelation-corrected covariances for every combination of composites.

It may be objected that many land surface changes occur as abrupt step changes rather than as trends. While this is indeed true, it does not invalidate the utility of the trend analysis. Just as a trend can be conceived as a series of non-significant step changes predominantly in one direction, a significant step change can be considered a trend with a particularly steep gradient in time. In either case, the SK trend test is effective in capturing the changes. As the power of the SK test is a function of the duration and density of the time series, we are exploring a windowed version of the SK test to facilitate temporal localization of abrupt step changes.

A recent study demonstrated the advantages and robustness of the MK test within the context of trends analysis of annual vegetation index time series [9]. The SK test offers more power than the MK test while retaining its robustness. An argument has been made lately for the existence of a Modifiable Temporal Unit Problem with simulations illustrating the hazards it can pose for trend analysis [10].

While choices of aggregation intervals that disregard seasonality and phenology can generate artifacts, the MTUP is not a fundamental problem like the Modifiable Area Unit Problem for the simple reason that we know *a priori* the direction of causality in time series. In contrast, questions about who influences whom in spatial and spatio-temporal contexts are open and require the researcher's scientific understanding to sort and order the interactions [11][12].

During the past few years we have been working with a fast implementation of the SK trend test specifically for image time series. The custom code generates two output layers from a single input series: a map of the magnitudes and polarities of SK test statistics and a map of the corresponding significance levels. Using these two layers together we classify areas in terms of positive or negative trends at exact significance levels and generate specific significance classes, e.g., $p>0.05$ or *not significant*, $p\leq0.05$ or *significant*, $p\leq0.01$ or *highly significant*. The change polygons then have the following attributes: type of variable or index, polarity of trend, significance of trend, geolocation, areal extent, and temporal location.

IV. DATASET

From the MODIS Nadir BRDF Adjusted Reflectance (NBAR) Collection 5 data, we calculated the Normalized Difference Vegetation Index (NDVI) at 500 m resolution for 46 8-day composites from 2001-2012.

V. RESULTS & DISCUSSION

Figure 1 shows significant changes in northern São Paulo and western Minas Gerais states in Brazil from 2001-2012. Significance classes were overlaid on the average NDVI. Bright green indicates significant positive trends at $p<0.01$. Bright orange indicates significant negative trends at $p<0.01$. The application of a 3x3 median filter highlights the larger hotspots of significant change. Tan areas have been screened for low NDVI and low seasonality. They correspond to cities, towns, and settlements.

The largest tan patch in the lower middle part of Figure 1 is the city and municipality of Ribeirão Preto, located in the northeastern part of the state of São Paulo, and 300 km north-northwest of the megacity of São Paulo. In 2010 Ribeirão Preto was the eighth largest municipality in São Paulo state. Estimated population in 2014 is greater 650,000 and over 99% of the population lives within the city limits. The population grew 20% between 2000 and 2010.

The gray tones in Figure 1 represent average NDVI over the 12 years. Lighter (darker) tones in more (less) vegetated areas. While the tan overlay captures the urbanized areas exhibiting very low and unvarying NDVI, around the periphery of the city there are bright orange patches evident. These patches indicate a statistically significant reduction in NDVI from 2001-2012. Note the prevalence of orange from Riberão Preto to São José do Rio Preto to the west and São Carlos to the south. Some of these areas of reduced NDVI are close to the cities and settlements in tan, while others occur in highly vegetated areas and indicate loss of forest cover. In contrast the far more prevalent bright green patches indicate significantly increased NDVI from 2001-2012, associated with increasing agricultural activity in the region. The NDVI time series represents but a single indicator. We will use others, too, such as the MODIS 4 μm band [13].

This SK trend analysis does not provide an estimate of the rate of change. Rather, this detection of significant change is only retrospective; *it is silent on the prospect of future dynamics mimicking past dynamics*. Moreover, this implementation of the trend analysis does not determine when the changes may have occurred. Temporal specificity may be possible using a windowed version of the SK test to maintain constant power across the time series, but there are lower limits determined by the length of the entire series. We are working on an appropriate protocol for the windowed SK trend test.

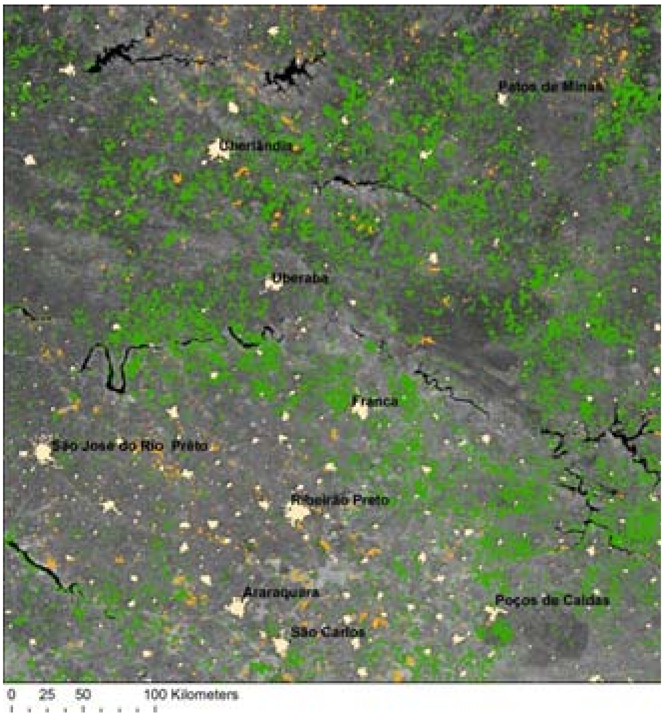

Fig. 1. Significant changes in northeastern São Paulo and southwestern Minas Gerais states in Brazil from 2001-2012 as revealed by 46 MODIS NBAR NDVI 8-day composites at 500m. Bright green indicates significant positive trends at $p<0.01$. Bright orange indicates significant negative trends at $p<0.01$.

VI. CONCLUSION

Understanding urban land dynamics requires a broader remote sensing perspective than that afforded by very high spatial resolution inventories within city limits. Changes in nearby lands also influence urban dynamics. We have briefly described a novel system—MIDST—to detect significant changes in urbanized areas. We expect the trends detection subsystem of the MIDST system to be operational by the fourth quarter of 2015. Change polygons will be made available in kml/kmz format for easy viewing in Google Earth.

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