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Urbanization and agricultural land loss in India: Comparing satellite estimates with census data

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ABSTRACT

We examine the impacts of urbanization on agricultural land loss in India from 2001 to 2010. We combined a hierarchical classification approach with econometric time series analysis to reconstruct land-cover change histories using time series MODIS 250 m VI images composited at 16-day intervals and night time lights (NTL) data. We compared estimates of agricultural land loss using satellite data with agricultural census data. Our analysis highlights six key results. First, agricultural land loss is occurring around smaller cities more than around bigger cities. Second, from 2001 to 2010, each state lost less than 1% of its total geographical area due to agriculture to urban expansion. Third, the northeastern states experienced the least amount of agricultural land loss. Fourth, agricultural land loss is largely in states and districts which have a larger number of operational or approved SEZs. Fifth, urban conversion of agricultural land is concentrated in a few districts and states with high rates of economic growth. Sixth, agricultural land loss is predominantly in states with higher agricultural land suitability compared to other states. Although the total area of agricultural land lost to urban expansion has been relatively low, our results show that since 2006, the amount of agricultural land converted has been increasing steadily. Given that the preponderance of India's urban population growth has yet to occur, the results suggest an increase in the conversion of agricultural land going into the future.

1. Introduction

Although India's urban population has increased significantly over the past two decades, from 217 million in 1991 to 377 million in 2011 (Census of India, 2011), most of the country's urban transition has yet to occur. According to the United Nations, India's urban population will increase by nearly 500 million between 2010 and 2050 (United Nations, 2012). In many countries, urban land expansion resulting from urban population growth has put pressures on the country's agricultural resources. For example, in China, urbanization has increased agricultural land-use intensity (Jiang et al., 2013) and resulted in the direct loss of agricultural land (Jiang et al., 2012; Seto et al., 2000). In India, the land required for urban growth has similarly resulted in the conversion of agricultural lands (Chadchan and Shankar, 2012; Fazal, 2001). In addition to conversion to urban uses (Fazal, 2001; Rahman et al., 2011), agricultural land is facing pressures such as intensification (Mishra, 2002), abandonment (Reddy and Reddy, 2007), and the widespread degradation (Varughese et al., 2009). Varughese et al. (2009) reported that roughly 50% of India's land resources are degraded. Aside from pressures on agricultural land, population increase and decreases in food grain production have contributed to a decline in the per capita availability of food grains such as pulses and cereals, other than rice and wheat (NRAA, 2011; Veni and Alivelu, 2005). Some have argued that in order to increase per capita food grains availability in India, food grain production will need to be increased. Mishra (2002) analyzed the impacts of population growth on agricultural intensification in India during 1951–1991 and concluded that population growth resulted in increased agricultural intensification, including an increase in cropping frequency, chemical fertilizer use, and irrigation infrastructure, supporting Boserup's hypothesis of land intensification (Boserup, 1965). Nevertheless, it remains unclear how the anticipated urban population growth and increased land pressures will affect food production.

Over a fifty-year period, the area of land under non-agricultural uses has more than doubled, from 9.36 million hectares in 1951 to 22.97 million hectares in 2001 (Chadchan and Shankar, 2012). India continues to lose its agricultural land to: a) urban conversion (Fazal, 2001; Wakode et al., 2013), b) reduction in suitability for cultivation

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(Lal, 2000; Prokop and Poreba, 2012; Xiao and Ximing, 2011), and c) agricultural land abandonment (Dhanmanjiri, 2011). The country currently faces the dilemma of needing to increase agricultural productivity while highly productive agricultural lands are being converted to urban uses (Brahmanand et al., 2013; Chadchan and Shankar, 2012; Fazal, 2001; Kalamkar, 2009). The sustainable management of agricultural lands is a prime concern amongst the science and policy communities (Dhanmanjiri, 2011; Fazal, 2001), and a first step towards finding a solution is to develop a scientific understanding of agricultural land loss due to urban expansion.

Two common approaches to examine the area of agricultural land lost to urban growth are to use data from national yearbooks and estimates from remote sensing (Kaufmann and Seto, 2001; Seto et al., 2000). Data from yearbooks lack detailed spatially explicit information and often remote sensing estimates lack detailed temporal information (Boucher and Seto, 2009; Kaufmann and Seto, 2001). Studies have utilized multi-temporal remote sensing images to investigate urban growth and have reported significant loss of agricultural lands in different Indian cities including Vadodara (Sandhya Kiran and Joshi, 2013), Saharanpur (Fazal, 2001), Hyderabad (Rahman et al., 2011; Wakode et al., 2013), and Aligarh (Farooq and Ahmad, 2008). Most studies using multi-temporal remote sensing images analyze land-use change over a defined period of five years (Farooq and Ahmad, 2008; Wakode et al., 2013), ten years (Fazal, 2001; Wakode et al., 2013), or other time periods, depending upon the availability of images. Due to a lack of temporal detail, such studies are limited in identifying exactly *when* land-use change occurred and thus commonly report land-use changes over an entire period. In this context, coarse resolution high frequency data from sensors such as the Moderate Resolution Image Spectroradiometer (MODIS), Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS), and SPOT Vegetation (SPOT-VGT) are valuable for determining when land-use changes occur. Knowing *when* agricultural land conversion took place is important to examine the effectiveness of policies and their implementation (Boucher and Seto, 2009; Kaufmann and Seto, 2001).

The purpose of this research is to examine the urban conversion of agricultural lands in India, including where and when the land conversions occurred. Our primary objectives are to analyze agricultural land loss throughout the country and to explore the degree and consistency of agreement between estimates from agricultural census and satellite data. This study analyzes agricultural land loss in India between 2001 and 2010 using remote sensing data from multiple sensors. The study also highlights the advantages and limitations of using remote sensing versus census-derived estimates to assess agricultural land loss in India.

2. Material and methods

2.1. Data description

2.1.1. Satellite data

We used the MODIS MOD13Q1 time series dataset (10 tiles each containing 253 time series images) for the period June, 2000 to May, 2011. We preprocessed the data on a tile-by-tile basis with the TIMESAT program (Jönsson and Eklundh, 2004) and applied adaptive Savitzky-Golay filter to minimize negatively biased noise commonly encountered in the NDVI datasets due to cloud and haze cover. In addition, we used the pixel reliability parameter included in the MOD13Q1 dataset to assign higher weights (1) to good quality data points and lower weights (0.25) to marginal quality data points in the time series during preprocessing. Even though preprocessing with the adaptive Savitzky-Golay filter minimized the residual noise, anomalous spikes in the NDVI time series remained for some pixels. Hence we applied principal component based projective filtering (Small, 2012) on the NDVI time-series (Fig. 1).

In addition to the NDVI dataset, we also used nighttime lights (NTL) data—collected by the DMSP/OLS—to characterize urban conversion of agricultural lands (http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html). NTL data measure lights on Earth's surface, including street lights, and has been shown to be correlated with urban economic activity (Chen and Nordhaus, 2011; Henderson et al., 2012; Sutton, 2007), population (Sutton et al., 2001; Sutton, 2003; Zhuo et al., 2009) and the built environment (Elvidge et al., 2001, 2007; Lu et al., 2008; Ma et al., 2012). A recent study shows that NTL data has mixed accuracy in identifying urbanization. In general, it does well identifying urbanization in developed countries but not as well in developing countries (Zhang and Seto, 2013). The lower accuracy in developing countries is likely due to a lack of infrastructure, especially in the outdoor street lighting, as well as limited access to or availability of electricity (Zhang and Seto, 2013). We used a second-order polynomial regression to inter-calibrate the time series NTL (Elvidge et al., 2009), and then calculated the median NTL for a given year by including images for ± 1 year. The rationale for this is to accommodate for any inconsistencies that remain even after inter-calibration and to accurately detect change pixels. We computed the median NTL for 2000 and 2010. To compute median NTL for the year 2000, we used inter-calibrated images of year 1999, 2000, and 2001. The NTL image for 2011 had significant overglow issues even after calibration. Therefore, we computed the median NTL for the year 2010 using calibrated images for 2008, 2009, and 2010. Using visual examination, we observed that the median NTL images were able to capture urban expansion for our study period. It is important to note here that the processed NTL data (median images) used were for the years 2000 and 2010, whereas the MODIS NDVI data were from 2000 to 2011. MODIS NDVI time-series was used until 2011 to accommodate the temporal signature of the crops that were sown in the winter season of 2010 and harvested in spring season of 2011. We resampled the median NTL to 250 m to match the spatial resolution of the NDVI data.

2.1.2. Agricultural census data

We acquired state-wise agricultural land use statistics compiled by the Directorate of Economics and Statistics, Ministry of Agriculture, Govt. of India (http://lus.dacnet.nic.in). The statistics include nine land-use categories: 1) forests, 2) area under non-agricultural uses, 3) barren and un-culturable land, 4) permanent pastures and other grazing lands, 5) land under miscellaneous tree, crops, etc., 6) fallow lands other than current fallows, 7) current fallows, 8) culturable waste land (such as fallow or covered with shrubs, but not put to use during the last five years), and 9) net area sown. Of the nine categories, the conversion of agricultural lands for non-agricultural purposes is captured in the category "area under non-agricultural uses". However, this category also includes land under water such as rivers and canals. The agricultural census does not explicitly label agricultural lands that are irreversibly lost to urban development. Analysis of the agricultural census data shows inconsistencies in the time-series estimates of area under non-agricultural uses. For example, for some states, the total area in "non-agricultural uses" was less than the preceding year, suggesting that the total land occupied by buildings and roads were less than the change in land area under water, which is unlikely and suggests errors in the data. To correct for these inconsistencies in the area estimates over time, we normalized the area under non-agricultural uses with the reporting area and used time series differencing to obtain a normalized estimate of change in area under non-agricultural uses. Although we removed all the values for