A comprehensive study to understand the relationship of urbanization and population density with GRACE ΔTWS for selected study regions in India during 2003-2017

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Abstract:

For the time period of January'2003 to January'2017, this pan-India study investigates the relationship of urbanization and population density with Ground Water Storage (GWS) indicated by Gravity Recovery and Climate Experiment (GRACE) derived terrestrial water storage changes (ΔTWS). Analysis of GRACE ΔTWS across India reveals the evidence of significant declining trend (-0.912 ± 0.455 cm/year) of the same in northern part of India encompassing Ganga-Brahmaputra river basin and North-West India during this time. Interestingly, for the same time period (2002-Quarter1 To 2016-Quarter4), this particular belt with declining ΔTWS, has observed significant positive trend in precipitation (17.89 ± 11.32 mm/year) and no significant trend for temperature. In addition, for the mentioned time period, we've observed higher growth rate in agricultural electricity consumption (80.60% Growth with CAGR of 7.67%) in this region compared to the same for the rest of India (72.30% Growth with CAGR of 7.04%). We believe that the increasing uncertainty in precipitation as indicated by the rising trend of it's temporal variability, could have led to higher dependence on groundwater withdrawal in agricultural sector, measured indirectly using agricultural electricity consumption data. Also, significant negative correlation ($\rho = -0.3128$ & p-Value < 0.05) between changes in ΔTWS and associated changes in population density has been found for this region during the same

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period of 2003-17. These observations strongly suggest that the depletion of TWS in this region could be primarily attributed to anthropogenic activities rather than to changes in meteorological variables. As urbanization drives population density, in order to understand the relationship of the same with ΔTWS, panel data regression analysis has been conducted for 9 selected study sites of 1° spatial resolution across different geographic locations in India during 2003-2017. Population density, precipitation and temperature along with urbanization, have been used as explanatory variables in the panel data regression for understanding the variations in GRACE ΔTWS. Results suggest that precipitation & urbanization exhibit significant positive ($\beta = 14.1535$ & p-Value $= 3.018e^{-06}$) & negative ($\beta = -11.5961$ & p-Value $= 8.394e^{-05}$) slopes respectively with ΔTWS and together they could explain 66.93% of variability of the same. Similarly, it has been observed that interaction effect of urbanization & population density exhibit a significant negative association ($\beta = -0.0053$ & p-Value $= 5.127e^{-07}$) with GRACE ΔTWS and 77.76% of variation in ΔTWS could be explained with the help of the same along with precipitation which demonstrates significant positive slope ($\beta = 14.7984$ & p-Value $= 6.009e^{-08}$) w.r.t ΔTWS. Thus, increase in anthropogenic indicators like urbanization & population density, indicates decrease in GRACE ΔTWS reflecting depletion in GWS.

1 Introduction :

India is one of the largest consumers of groundwater in the world, accounting for more than 25% of global total consumption [1, 2]. Increasing domestic needs coupled with groundwater dependent agricultural practices have resulted in considerable depletion of groundwater in several parts of India [3–5]. Major parts of India have experienced substantial decline of Ground Water Level (GWL) varying from 4 meters to 16 meters during 1980 to 2010 [4]. Around 60.53% of observation wells show a dip in groundwater levels in 2017, when compared to the decadal mean of groundwater levels of the same observation wells during the period of January (2007-2016) [6].

As Ground Water Level (GWL), being the measurement from spatially discrete observation wells for depth to groundwater from ground surface only, can not provide any estimate about the volume of the same. In order to understand availability and associated trends of Ground Water Storage (GWS), Gravity Recovery and Climate Experiment (GRACE) derived variations of Terrestrial Water Storage (ΔTWS) have been widely used in literature [5, 7–11].

In this work we have studied GRACE derived ΔTWS in order to understand changes and associated trends in GWS & GWL across India from January'2003 to January'2017. For studying variations in ΔTWS corresponding to selected regions in India during this period, we have considered anthropogenic indicators (irrigation, urbanization and population density) along with meteorological variables (temperature and precipitation) as explanatory covariates.

Utilization of GRACE data to monitor fluctuations in groundwater storage has been discussed by Rodell et al. [12]. In their research work, Rodell et al. [13] has described the importance of GRACE data for the assessment of groundwater storage in the Mississippi

River basin, USA during January 2002 to July 2005. Changes in GWS in California Central Valley, USA, has been estimated using GRACE data by Scanlon et al. [14] for the time period of April 2006 to September 2009. Analysis by Doell et al. [15] on the global trends for Ground Water Depletion (GWD) and Terrestrial Water Storage (TWS) using GRACE data, has unveiled that highest depletion rate for GWD, which has doubled since the period $1960-2000$, has taken place in United States, Saudi Arabia, Iran, China and India, in the first decade of the 21st century. Using GRACE and Global Land Data Assimilation Systems (GLDAS) data for the state of Tamil Nadu in India during 2002 to 2012, Chinnasamy et al. [16] have studied and analysed the contribution of irrigation on the depleting trend of GWS. Studying GRACE derived variations of Terrestrial Water Storage (ΔTWS), Panda and Wahr [5] have observed that, significant depletion of GWS has taken place in the Punjab state and Ganges Basin in India (depletion rates of 2.1 cm $year^{-1}$ and 1.25 cm $year^{-1}$ respectively) from January 2003 to May 2014. With the help of GRACE derived ΔTWS and Global Land Data Assimilation System (GLDAS), Jiao et al. [10] has observed increase in the Qaidam Basin, North Tibet Plateau during $2003-2012$. Recent study by Rodell et al. has reported a depleting trend in GRACE derived ΔTWS data for around 70% of the regions in the world [17], indicating scarcity of global freshwater in the affected regions.

Although, GRACE derived ΔTWS captures the composite changes in groundwater, soil moisture, snow & ice, it exhibits a strong correlation with groundwater storage & level changes, provided the effects of other components are minimal. Due to this reason, ΔTWS has been preferred and used by researchers for estimating groundwater storage and level variations. For example, Shamsudduha et al. [9] have shown in their research for the Bengal Basin of Bangladesh, that GRACE derived Ground Water Storage changes (ΔGWS) accounts for 44%of the total variation in ΔTWS and there exists a strong correlation

($0.77 \leq |\rho| \leq 0.93$) between ΔGWS and in situ borehole observations. Similarly, in their study for India, Panda et al. [5] has reported the existence of strong correlation between GRACE derived GWS and in situ measurements of GWL from observation wells. Also, using GRACE data Feng et al. [8] has estimated variations in GWL in North China region during 2003 to 2010. Artificial Neural Network (ANN) based Machine Learning (ML) model has been developed by Sun [7] in order to predict changes in GWL for different regions in United States of America using GRACE derived ΔTWS. Mukherjee & Ramachandran [18] has examined the relationship between GWL fluctuations and associated GRACE ΔTWS data for 5 different geographic regions across India and have observed strong significant positive association($0.6040 \leq |\rho| \leq 0.8619$).

Various meteorological and anthropogenic indicators have been studied in order to understand and analyse the trend for GWS & GWL. Among the covariates, temperature and precipitation [5,7,19–29] have been consistently used as explanatory meteorological variables to study and model the variations in groundwater.

Irrigation and population growth are important anthropogenic indicators that influence groundwater [30]. Rodell et al. [3] has suggested that for the time period of August 2002 to October 2008, depletion in GWS in the North-West India has been caused primarily due to unsustainable consumption of groundwater for irrigation and other anthropogenic uses. Further, in the research work [17] on analysis of global trends for freshwater availability during 2002-2016, it has been concluded that primarily or partially human impact has been responsible for depletion of TWS in the northern and eastern region of India. In the recent study [11], it has been identified that for the regions with high level of groundwater stress in North & East India, population stress is also high. Also, urbanization leads to increase in population density which again leads to scarcity of common property natural resources like groundwater [31].

2 Results :

The “Results” section is organised into following 2 sub sections

- Trend Analysis of ΔTWS during 2003-2017 in India with focus on the region of Ganga Brahmaputra river basin & North-West India.

  In this section, we’ve studied changes in ΔTWS across India from January 2003 to January 2017. Particularly for the region of Ganga Brahmaputra river basin and North-West India, where highest level of depletion has been observed during this period, we’ve discussed the trends of various anthropogenic (population density & groundwater irrigation) and meteorological (temperature & precipitation) indicators along with the same for ΔTWS to understand their relationship with ΔTWS and contributions to the depleting trend of ΔTWS in this belt.

- Discussions on the effect of urbanization along with other anthropogenic and meteorological variables for selected study sites in India from 2003 to 2017.

  In order to understand the effect of urbanization along with other anthropogenic and meteorological variables (population density, temperature & precipitation) for the selected study regions during 2003 to 2017, we have discussed the results of panel data regression analysis in this segment.

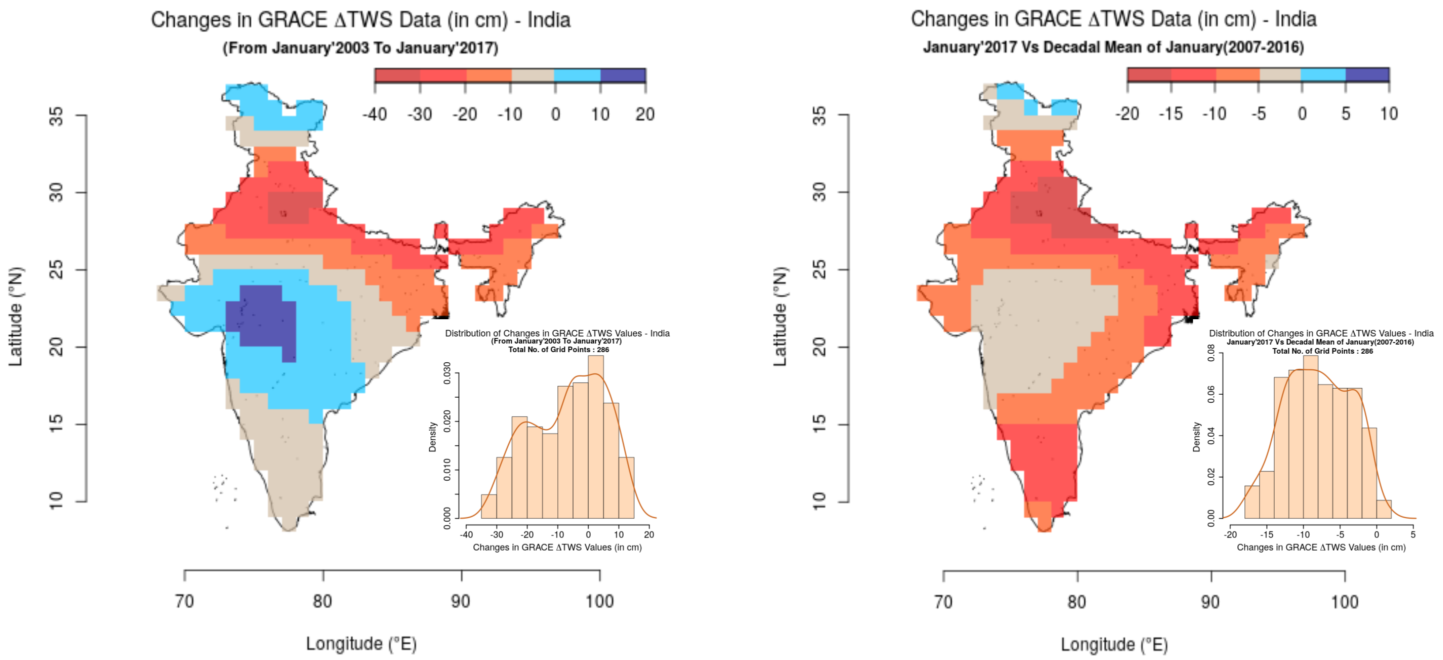
2.1 Trend Analysis of ΔTWS during 2003-2017 : India and Ganga Brahmaputra river basin & North-West India

This work finds evidence of significant decline of ΔTWS levels in certain regions of India, despite receiving higher precipitation over the years 2003-2017.

We have analysed the changes in GRACE derived ΔTWS data for 286 grid points of 1° spatial resolution, representing entire India during the period of January 2003 to January 2017. Among the 286 grids, 186 (65.04%) show a decline in ΔTWS for January 2017, when compared to the same for January 2003 (Figure 1a). Out of these 186, the highest depletion ($\geq$ 20 cm) is observed for 55 grids that include Ganga-Brahmaputra river basin (consists of states namely Uttarakhand, Uttar Pradesh, Jharkhand, Bihar, West Bengal, Arunachal Pradesh, Assam, Meghalaya & Nagaland) and North-West India covering the states of Rajasthan, Punjab & Haryana.

In addition, for the mentioned 286 grid points covering India, we also have compared ΔTWS for January 2017 with decadal mean of ΔTWS for the month of January (2007-2016). Comparison with decadal mean reveals that 98.25% (281/286) of the grids have a negative ΔTWS change (Figure 1b). It can be clearly observed that grids, especially in the Ganga-Brahmaputra river basin and North-West India witness the highest drop in ΔTWS levels ($\leq$ 10cm) in January 2017, compared to the decadal mean for January (2007-2016). Spatial distributions of ΔTWS in Ganga Brahmaputra river basin and North-West India for January 2003 and January 2017 have been shown in Figure 2a & Figure 2b respectively.

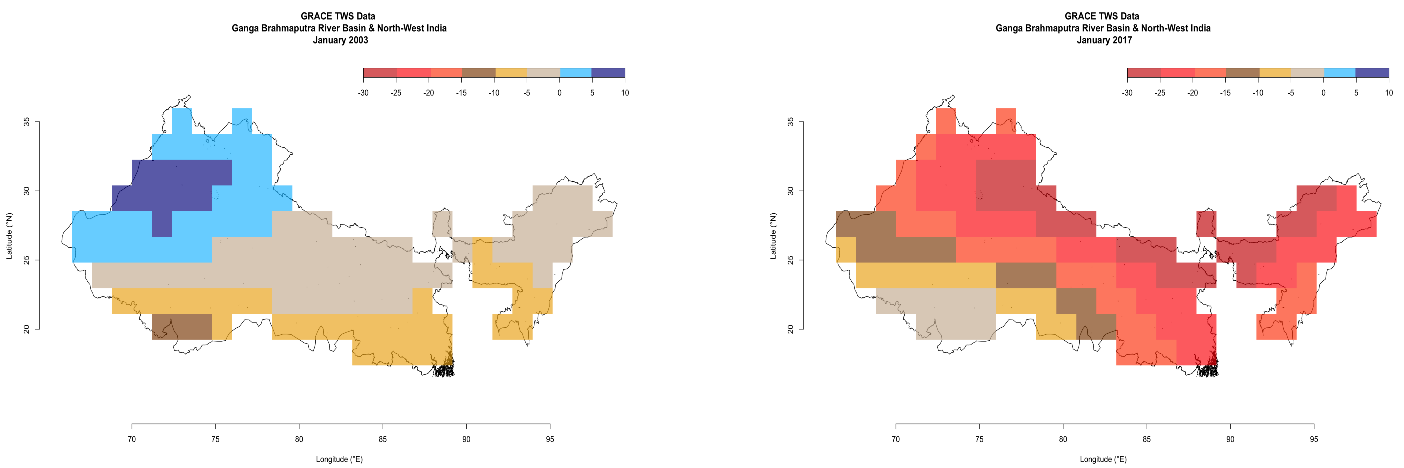
We have also investigated the nature of linear trend for ΔTWS from January 2003 to January 2017 (Figure 3a). Among the 286 grids considered, only 156 points have a significant (p-value < 0.05) linear trend in ΔTWS. Majority of these grid points (140/156) show a negative trend in ΔTWS. Grid points with significant negative linear trend primarily



(a) ΔTWS change
January 2003 To January 2017

(b) ΔTWS change
ΔTWS of January 2017 compared to decadal mean of ΔTWS for January (2007-2016)

Figure 1: GRACE ΔTWS changes for 286 grid points in India



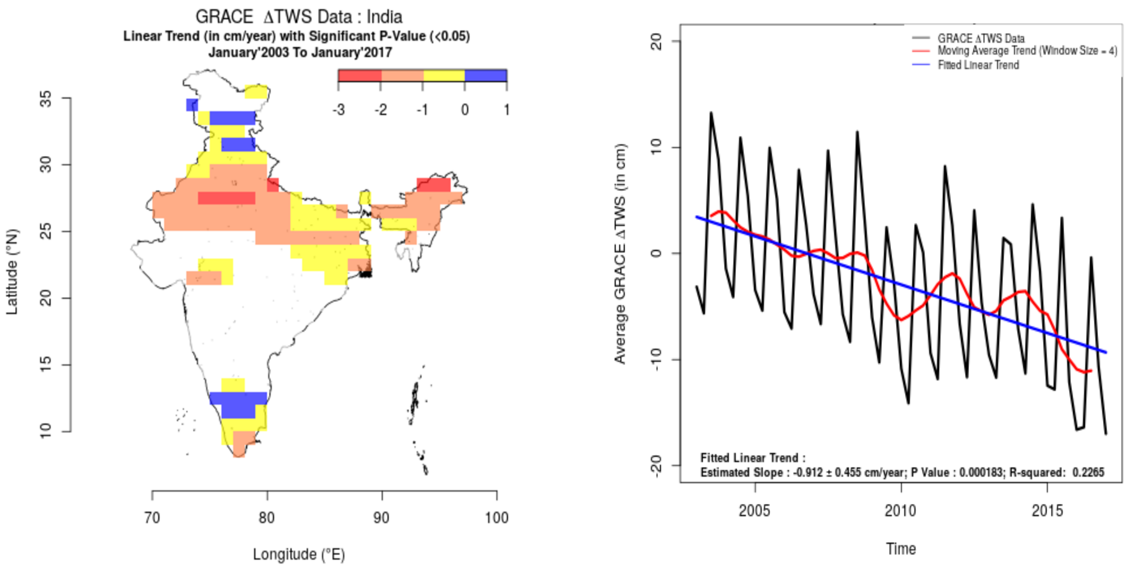
(a) ΔTWS : January 2003

(b) ΔTWS : January 2017

Figure 2: GRACE ΔTWS - January 2003 & January 2017
Ganga Brahmaputra River Basin & North-West India

represent Ganga-Brahmaputra river basin and north western part of India. These regions exhibit a significant declining trend in ΔTWS with estimated slope ranging from −2.20 cm/year to −0.01 cm/year (Figure 3a). Analysing the pattern of quarterly average ΔTWS (Figure 3b), for the same belt during this period (January 2003 - January 2017), we find that there exists a significant negative linear trend (-0.912 ± 0.455 cm/year). These computed quarterly ΔTWS slopes are in conformance with previously reported values [17]. Although, positive changes in ΔTWS (Figure 1a) have been observed in central part of India for January 2017 compared to the same in January 2003, we could not find any significant positive linear trend (Figure 3a) for the same corresponding to this region.

Restricting our focus to the region of Ganga-Brahmaputra river basin and North-Western



(a) Grid points with significant linear trend in ΔTWS (2003-2017)

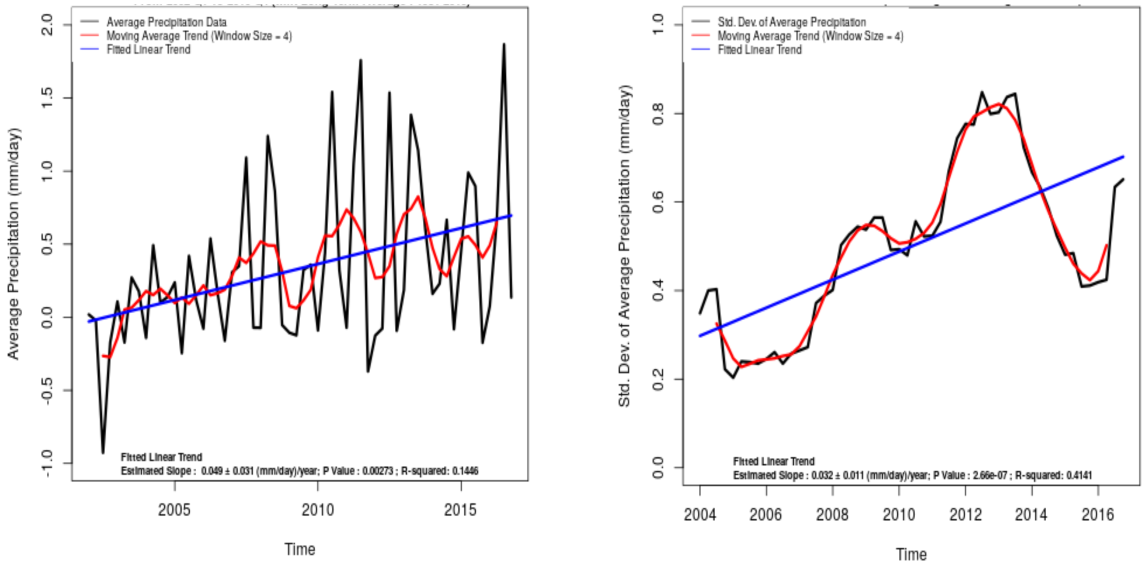
(b) Quarterly average ΔTWS for Ganga-Brahmaputra river basin & North-West India (2003-2017)

Figure 3: Trends in ΔTWS during January 2003 To January 2017 : India and Ganga Brahmaputra river basin & North-West India

part of India, where significant decline of ΔTWS is observed, we have analysed the trends of meteorological variables such as precipitation and temperature for this belt. Consistent with recent studies [17, 32], quarterly average precipitation data (reported with respect to long term mean of 1981-2010) for this region from 1st Quarter of 2002 to 4th Quarter of 2016, reveals a significant positive linear trend with slope of 0.049 ± 0.031 (mm/day)/year or 17.89 ± 11.32 mm annually (Figure 4a). Temporal variability in precipitation (Figure 4b), expressed as standard deviation of quarterly average precipitation with window width of 8, clearly shows increasing uncertainty in precipitation during the time period of 2004-Quarter1 to 2016-Quarter4. Also, we could not observe any evidence of significant linear trend in temperature during the same time period for this region. For the considered time period, in spite of the increasing trend in precipitation, decreasing trend in ΔTWS has been observed in this region of interest. This motivated us further to study the anthropogenic activities that could possibly impact ΔTWS changes in this area.

First, the region including states in Ganga-Brahmaputra river basin along with north-western part of India, experiences dense cultivation as the percentages of cultivable and cultivated land for this region (63.64% & 53.67% respectively) are higher compared to the same for the rest of India (50.58% & 43.54% respectively). Electricity consumption in agricultural sector serves as a natural proxy for measuring the extent of groundwater pumped for irrigation. With respect to year 2006-07, the agricultural electricity consumption in 2015-16 for the entire region of interest has increased from 30898.1 to 55801.20 GWh (Growth : 80.60%; CAGR[1] : 7.67%), but for the rest of India it has increased from 68125.29 to 117384.17 Gwh (Growth : 72.30%; CAGR : 7.04%) during the same time period (Figure 5). This clearly indicates higher growth rate of extraction of groundwater in the Ganga Brahmaputra river basin and North-West India when compared to the rest of India. This could be attributed to the increased uncertainty in precipitation (Figure 4b) in the region over the discussed period of time. The dependence on groundwater is also exacerbated by the nature of

[1] CAGR : Compound Annual Growth Rates



(a) Quarterly average precipitation for Ganga-Brahmaputra river basin & North-Western part of India (2002-Quarter1 To 2016-Quarter4)

(b) Temporal standard deviation (window width = 8) of quarterly average precipitation for Ganga-Brahmaputra river basin & North-Western part of India (2004-Quarter1 To 2016-Quarter4)

Figure 4: Trend and Temporal Variations in Precipitation : Ganga Brahmaputra river basin and North-West India

heavy subsidies provided by these states for pricing agricultural electricity. For the states that belong to the region of Ganga Brahmaputra river basin and North-West India, ratio of electricity charges for agricultural consumption to the same for domestic consumption varies from 0 to 0.6949 with an average of 0.3557.

Second, we've studied the the changes in ΔTWS and associated changes in population density with the help of LandScan dataset [33, 34], for the region of Ganga Brahmaputra river basin and North-West India during 2003-2017. Spatial distributions of population density across grid points corresponding to this region of interest for the years of 2003 and 2017 have been shown in Figure 6a and Figure 6b respectively. The absolute population density and the growth in population density for the mentioned region (307.31 to 382.54

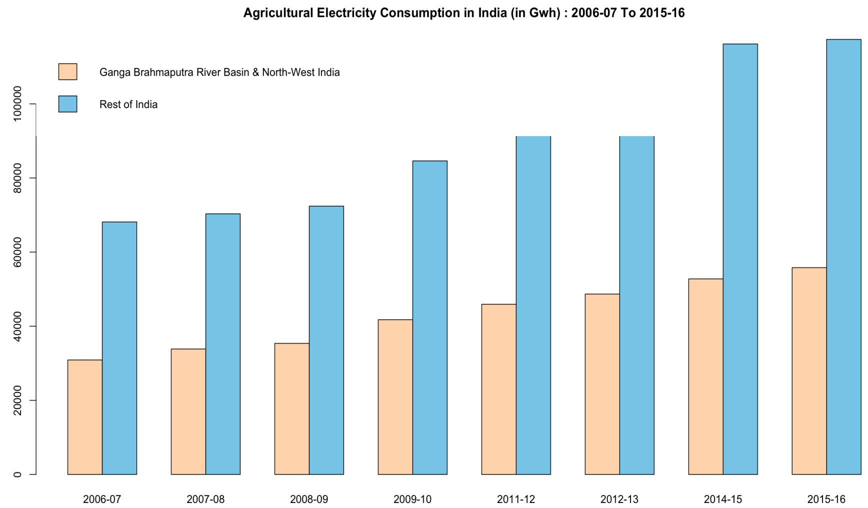


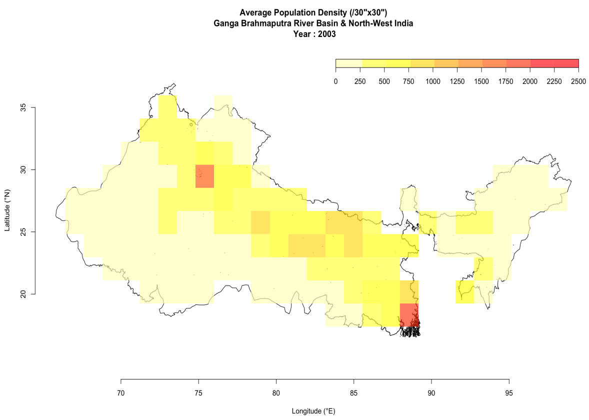
Figure 5: Agricultural Electricity Consumption during 2006 – 07 To 2015 – 16 : India and Ganga Brahmaputra river basin and North-West India

or 24.97% increase) are considerably higher than that of rest of India (207.85 to 248.74 or 19.67% increase).

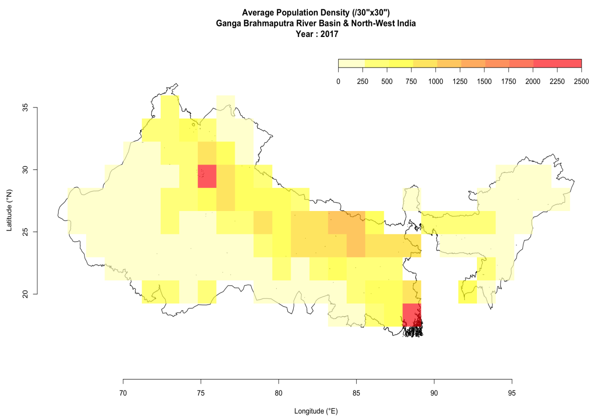
For the region of interest, we have found the population density to have a strong negative correlation ($\rho = -0.3128$, p-value < 0.05) with corresponding ΔTWS changes.

2.2 Relationship of urbanization, population density and meteorological variables with ΔTWS : Selected study sites in India from 2003 to 2017

Presence of significant negative correlation between ΔTWS and population density in the region of Ganga Brahmaputra river basin and North-West India, has influenced us to



(a) Population Density : 2003



(b) Population Density : 2017

Figure 6: Population Density - 2003 & 2017:
Ganga Brahmaputra river basin and North-West India

investigate the relationship between ΔTWS and urbanization which elevates population density.

For the purpose of reaching a generalized conclusion by avoiding any region specific bias, 9 study areas of 1° spatial resolution have been considered across different geographic regions in India (Figure 7) to study the relationship between urbanization and ΔTWS. Each study region is a grid of 1° Latitude$\times 1^\circ$ Longitude with covering area of approximately 12100 sq.km. We have labelled the study sites according to the largest urban settlements encompassed by the grid. Details about the study sites with location, total population and population density estimates from LandScan dataset [33, 34] have been mentioned in Table 1. To understand the impact of urbanization on groundwater, panel data regression analysis has been conducted for studying variations in GRACE ΔTWS corresponding to these selected study sites with the help of population density, urbanization (percentages of urban settlements) along with meteorological covariates (temperature and precipitation) for the time period of 2003 to 2017. It could be noted here that we have avoided coastal

Table 1:
Selected Regions to study the relationship between Urbanization & ΔTWS

Study Site	Location		Population Density ($/30'' \times 30'' \approx 1km^2$)		Population (in Lakhs)	
	Latitude (°N)	Longitude (°E)	2003	2017	2003	2017
Delhi	28.0-29.0	77.0-78.0	1656.73	2210.48	238.57	318.31
Kanpur & Lucknow	26.0-27.0	80.0-81.0	834.33	967.91	120.14	139.38
Ahmedabad	23.0-24.0	72.0-73.0	544.51	677.23	78.41	97.52
Vadodara	22.0-23.0	73.0-74.0	425.38	499.08	61.26	71.87
Indore	22.0-23.0	75.0-76.0	314.01	404.00	45.22	58.18
Aurangadabad	19.0-20.0	75.0-76.0	285.81	343.09	41.16	49.40
Hyderabad	17.0-18.0	78.0-79.0	550.47	755.07	79.27	108.73
Bangalore I	12.0-13.0	77.0-78.0	602.81	797.62	86.81	114.86
Bangalore II	13.0-14.0	77.0-78.0	383.47	468.52	55.22	67.47

areas as other meteorological factors like tide level could affect groundwater [28] in coastal regions. Selection of mentioned (Table 1) study sites are primarily based on 2 criteria, namely (i) observation of significant growth in urbanization and (ii) availability of good quality cloud-free Landsat7 satellite imagery that have been used to compute percentages of urban settlements within the study region for the entire time period of 2003-2017. Details of methodologies for computation of urban sprwal (in terms of percentages of "built-up" pixels) and other explanatory variables have been discussed in "Methods" section. Data points of all considered variables and final classified "built-up" pixels from Landsat7 satellite imagery for selected study regions during 2003 - 2017 have been included in Section I & II respectively of "Appendix : Supplementary Results & Images" section that has been provided separately. In order to circumvent monthly and seasonal variations, GRACE ΔTWS for the month of January of selected years (2003, 2007, 2012 & 2017) have been considered in the cross-sectional time series regression model.

Results of panel data regression analysis have been summarised in Table 2. As discussed in "Methods" section, in order to decide whether fixed or random effect model needs to be applied, "Hausman Test" [35, 36] has been conducted. If the associated p-Value

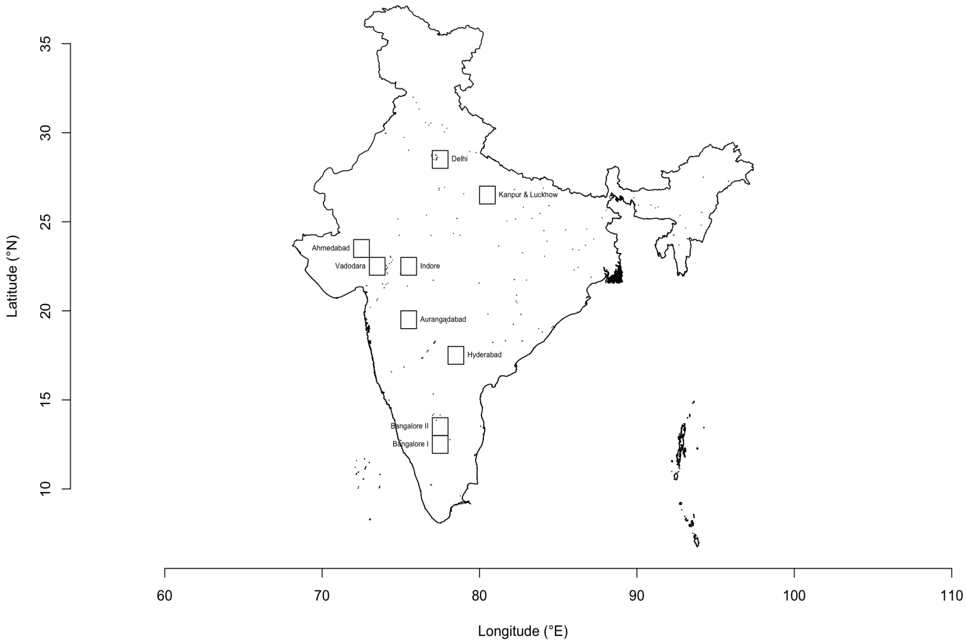


Figure 7: Study Area - Selected study sites in India.
Each study site corresponds to an area of 1° Latitude×1° Longitude ≈ 12100 sq.km

Table 2:
Panel Data Regression Analysis for understanding variations in GRACE ΔTWS
Selected Study Sites : 2003 To 2017

Explanatory Variables	p-Value of Hausman Test	Panel Data Regression Results		
		Coefficient β	p-Value	R^2 Value
% of Urbanization	0.0374	-9.4194	0.0183	0.1959
Population Density	0.0756	-0.0046	0.0737	0.0860
Avg. Max. Temp.	0.7462	0.9563	0.7355	0.0033
Avg. Min. Temp.	0.8777	7.1511	0.0605	0.0939
Avg. Prcpt.	0.8607	12.7975	$2.733e^{-06}$	0.3928
I(% of Urbanization & Population Density)	0.0113	-0.0042	0.0051	0.2648
Avg. Prcpt. (a) & % of Urbanization (b)	0.0001	14.1535 (β_a) -11.5961(β_b)	$3.018e^{-06}(p_a)$ $8.394e^{-05}(p_b)$	0.6693
Avg. Prcpt. (a) & I(% of Urbanization & Population Density) (c)	$7.3e^{-09}$	14.7984 (β_a) -0.0053(β_c)	$6.009e^{-08}(p_a)$ $5.127e^{-07}(p_c)$	0.7776

"I" in the above Table denotes Interaction Effect between the variables mentioned within parentheses.

for Hausman test is significant (i.e. p-Value $\leq$ 0.05), fixed effect model has been used, otherwise random effect model has been considered.

Initially, for the dependent variable GRACE ΔTWS, we've developed panel data regression models with the help of each explanatory variable separately. It can be clearly observed from Table 2 that while applying each explanatory variables separately to build the panel data regression model, only "% of Urbanization" and "Avg. Prcpt." (Average Precipitation) have been significant (p-Value corresponding to panel data regression model is less than 0.05) to account for the variability of dependent variable GRACE ΔTWS. Also, by studying R^2 values associated to the panel data regression models in Table 2, we could observe that "% of Urbanization" and "Avg. Prcpt." could individually explain 19.59% & 39.28% of variability in ΔTWS respectively. Negative value of coefficient β for "% of Urbanization" indicates that decrement in GRACE ΔTWS is associated with increment in "% of Urbanization" and vice versa. Similarly, positive sign of β for "Avg. Prcpt." clearly suggests that the movements of the variables ΔTWS and "Avg. Prcpt." are in the same direction.

Also, interaction effect of "% of Urbanization" & "Population Density" has been considered separately as an explanatory variable for GRACE ΔTWS. Panel data regression results (Table 2) suggest that it has a significant negative slope associated with ΔTWS and accounts for 26.48% of variations in the same.

While applying "Avg.Prcpt." and "% of Urbanization" together as independent variables in the panel data regression model, we could observe that both variables are significant (p_a & p_b in Table 2 are less than 0.05) and jointly they could explain 66.93% of variability in GRACE ΔTWS. Positive and negative values of β for "Avg.Prcpt." and "% of Urbanization" imply that the movement of mentioned variables with respect to ΔTWS are in same and opposite direction respectively.

In addition, interaction effect of "% of Urbanization" & "Population Density" along with "Avg. Prcpt." have been used as predictor covariates in the panel data regression and it has been observed that together they could account for 77.76% of variations in ΔTWS. As shown in Table 2, both "Avg. Prcpt." and interaction effect of "% of Urbanization" & "Population Density" are significant (p_a, $p_c < 0.05$) to model GRACE ΔTWS and exhibit positive and negative slopes respectively w.r.t the same.

Thus, it could be summarized from panel data regression results that both "Avg.Prcpt." and "% of Urbanization" are significant variables for GRACE ΔTWS. Positive values of β for 'Avg.Prcpt." imply the increment of ΔTWS is associated with increment of 'Avg.Prcpt." and vice versa. Similarly, movement of variables ΔTWS and "% of Urbanization" in opposite directions is indicated with the help of negative values of β for "% of Urbanization". Also, we could observe that though "Population Density" on it's own is not significant for ΔTWS, interaction effect of the same with "% of Urbanization" is significant in explaining variability of ΔTWS and could account for higher percentages of variations in ΔTWS compared to the same explained by "% of Urbanization" alone. Similar to the variable "% of Urbanization", interaction effect of "Population Density" and "% of Urbanization" exhibits significant negative slope with ΔTWS, demonstrating existence of inverse relationship between them.

3 Summary & Conclusions :

In this work, we've studied changes in GRACE derived ΔTWS for entire India during 2003-2017. As ΔTWS serves as a strong indicator for GWS and GWL, the observed declining trend of the same in Ganga Brahmaputra river basin and North-West India imply significant depletion of groundwater in this belt from January 2003 to January 2017. Interestingly, during the same time period (2002-Quarter1 to 2016-Quarter4), not only no significant trend for temperature has been noticed but also significant positive trend for precipitation has been detected for this area of interest. Also, higher annual growth rate (in terms of CAGR) of agricultural electricity consumption has been noted for the region which consists of states corresponding to Ganga Brahmaputra river basin and North-West India compared to the same for rest of India, suggesting excessive groundwater irrigation in this area. In addition, for this zone, the growth in population density is considerably higher than that of rest of India and changes in the population density exhibits significant negative correlation with changes in corresponding GRACE ΔTWS. Therefore, it could be concluded that anthropogenic impacts are primarily responsible for impoverishment of groundwater in this fertile belt of Ganga Brahmaputra river basin & North-West India.

Further in this study, with the help of panel data regression analysis, we have investigated the relationship of urbanization along with population density, temperature and precipitation with GRACE ΔTWS for 9 selected study sites of 1° spatial resolution during 2003-2017. Panel data regression results indicate existence of significant positive relationship ($\beta > 0$ & p-Value < 0.05) of precipitation with ΔTWS. Also, existence of significant negative slopes ($\beta < 0$ & p-Value < 0.05) w.r.t. GRACE ΔTWS have been observed for both urbanization and interaction effect of urbanization & population density, indicating decrease in groundwater with increase in urbanization and population density.

Finally, to conclude, this research work establishes existence of significant negative relationship of groundwater reflected by GRACE ΔTWS, with anthropogenic indicators like irrigation, urbanization & population density and thus calls for re-examination of India's current water management policies in order to ensure sustainability of groundwater storage for the concerned water stressed regions.

4 Methods :

Variations of Earth's gravitational field are primarily caused by changes in TWS [13, 14, 37] and thus deviations in TWS are derived from the changes in Earth's gravitational field, measured with the help of inter-satellite distance between twin satellites of GRACE mission which is a joint programme by NASA (National Aeronautics and Space Administration) and DLR (German Aerospace Centre : Deutsches Zentrum für Luft- und Raumfahrt). As GRACE derived changes in TWS are estimated and reported as measurements w.r.t 2004-2009 time-mean baseline, in this entire article we have denoted the same by ΔTWS instead of TWS. It is to be noted that GRACE derived ΔTWS is not an exact measurement for Ground Water Storage and needs to be adjusted for other components and involves errors due to statistical downscaling methodology [12]. Although, ΔTWS captures the composite changes in groundwater, soil moisture, snow & ice, it exhibits a strong correlation with changes in GWL and GWS, provided the effects of other components are minimal [3, 7, 18]. Due to this, as discussed in the "Introduction" section, in this research, we have studied GRACE derived ΔTWS which serves the purpose of proxy measurement for indicating groundwater condition in terms of GWL & GWS.

Level3 Release05 (L3 RL05) monthly GRACE ΔTWS estimates[2] have been used in this study. ΔTWS data points which are available at 1° spatial resolution grid, have been collected for required grid points covering entire India from January 2003 to January 2017.

In order to understand the changes in ΔTWS across India during January 2003 to January 2017, monthly ΔTWS data for each of the 286 grid points (1° Latitude×1° Longitude) covering entire India has been considered. Deviation of ΔTWS in January 2017 for each

[2] https://podaac-tools.jpl.nasa.gov/drive/files/allData/tellus/retired/L3/grace/land_mass/RL05/netcdf; accessed 19-July-2019

grid points with respect to ΔTWS in January 2003 and w.r.t the decadal mean of ΔTWS for the month of January (January2007 - January2016) have been computed and associated distributions have been analysed. In order to report the significance and magnitude of the linear trends of ΔTWS for mentioned 1° grid points across India during 2003-2017, slopes and associated p-values of the fitted linear trends for each grid points are computed for the time period of January 2003 to January 2017.

As mentioned in the "Results" section, we have observed that during considered time period, the highest amount of significant depletion of ΔTWS has taken place in Ganga Brahmaputra river basin and North-West India. Therefore, we have focused our analysis for this region and have studied meteorological (temperature & precipitation) and anthropogenic (population density and groundwater irrigation) indicators in this region to understand the impact of the same on ΔTWS.

For precipitation and temperature data, Climate Prediction Center (CPC) Global Unified Precipitation and Global Temperature data products, provided by National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Division (PSD)[3] have been used in this study for the same time period of January 2003 - January 2017. These datasets are available daily at 0.5° spatial resolution. Daily long term means of 1981-2010, have been deducted from daily precipitation and temperature data points in order to make the observations relative to the long term means. These long term mean adjusted data points have been averaged out for corresponding 1° grids of GRACE ΔTWS data in order to achieve same spatial resolution.

Quarterly average values have been calculated from daily precipitation and temperature data for each quarter from 2002-Quarter1 to 2016-Quarter4 for all grids corresponding to the region of Ganga-Brahmaputra river basin and North-West India. Mean values of the

[3] https://www.esrl.noaa.gov/psd/, accessed 19-July-2019

quarterly averaged precipitation and temperature data for all grid points corresponding to the mentioned region, have been computed and associated p-values along with slopes of fitted linear trends for the same have been calculated. As we have observed significant positive linear trend only for precipitation, we have further studied temporal variations in precipitation for this region of interest. For calculation of slope and p-value for linear trend of temporal variations in quarterly averaged precipitation data for the concerned region during 2004-2016, window size of 8 has been used, i.e. the data point for 2004-Quarter1 represents standard deviation of precipitation values from 2002-Quarter1 to 2003-Quarter4. Global LandScan population datasets [33, 34, 38, 39], available at high spatial resolution of $30''$, have been used for population estimates for the years of 2003, 2007, 2012 and 2017. Similar to precipitation and temperature data, population data also has been averaged out for 1° grids corresponding to ΔTWS for obtaining population density which is measured in persons per $30'' \times 30''$ spatial resolution. Average population density for the entire region of interest has been obtained by averaging associated values for all grids corresponding to the area.

Percentages of growth have been computed to measure growth in population density for the mentioned region and rest of India. In order to understand relationship between changes in GRACE ΔTWS and corresponding changes in population density from 2003 to 2017 for Ganga-Brahmaputra river basin and North-West India, correlation coefficient (ρ) along with associated p-value (for $\mathrm{H}_0 : \rho = 0$) between the variables have been reported. To elaborate, we have calculated the correlation coefficient between ($\Delta\mathrm{TWS}_{January2017} - \Delta\mathrm{TWS}_{January2003}$) and ($\mathrm{Population\ Density}_{2017} - \mathrm{Population\ Density}_{2003}$) considering all grid points corresponding to the region.

As electricity consumption in agricultural sector serves as a natural proxy for measuring the extent of pumped groundwater for irrigation, it has been used in this study as the indicator for groundwater irrigation. State-wise electricity consumption data for agricultural purpose is provided by Ministry of Agriculture and Farmers Welfare, Government of India and is available in the "Statistical Year Book India 2018"[4], published by Ministry of Statistics and Programme Implementation. Also, state-wise electricity charges for agriculture are sourced from Central Electricity Authority, Ministry of Power, Government of India.

For all states which belong to Ganga-Brahmaputra river basin and North-West India (Punjab, Haryana, Rajasthan, Uttarakhand, Uttar Pradesh, Jharkhand, Bihar, West Bengal, Arunachal Pradesh, Assam, Meghalaya & Nagaland) and for the states that are affiliated to the rest of India, total agricultural electricity consumption have been computed for the time period of 2006-07 to 2015-16 according to the availability of the data provided by Ministry of Statistics and Programme Implementation, Government of India. Growth rates of electricity consumption in agriculture sector during 2006-07 − 2015-16 have been calculated and reported in terms of CAGRs for both regions (Ganga-Brahmaputra river basin & North-West India and rest of India).

Landsat7 ETM+ (Enhanced Thematic Mapper Plus) satellite imagery, provided by USGS[5], have been used in this study to classify built-up pixels for the selected regions (Table 1) and compute percentages of urban settlements accordingly. Google Earth Engine[6] has been used for implementation of classification algorithm for extraction of built-up pixels and associated Landsat7 data has been sourced from Earth Engine repository[7]. Used surface reflectance Landsat7 data is orthorectified, georeferenced and atmospherically corrected. It has spatial resolution of 30m and is available for the entire period of study from January 2003 to January 2017.

Powered B1 Built Up Index (PB1BI) [40] based methodology has been applied to classify

[4] http://mospi.nic.in/statistical-year-book-india/2018/185; accessed 15-July-2020
[5] U.S. Geological Survey : https://www.usgs.gov/land-resources/nli/landsat; accessed 19-July-2019
[6] GEE : https://earthengine.google.com; accessed 19-July-2019
[7] https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LE07_C01_T1_SR; accessed 15-July-2020

built-up pixels from Landsat7 satellite imagery and to compute percentages of urban settlements for selected study regions accordingly. In this index based algorithm, PB1BI (PB1BI $=\text{BLUE}^{\alpha}\times\text{RED}^{-\beta}\times\text{NIR}^{-\gamma}$; $\alpha = 10.5, \beta = 5.0$ & $\gamma = 3.5$. BLUE, RED and NIR are surface reflectance values for respective bands in Landsat7 satellite imagery) has been computed for each pixels of Landsat7 satellite images (1° Latitude×1° Longitude) corresponding to the study regions and built-up pixels have been extracted by applying appropriate upper & lower bootstrap thresholds that have been estimated with the help of training built-up pixels. To elaborate, a pixel (i) would be classified as built-up if $L_{PB1BI} \leq PB1BI(i) \leq U_{PB1BI}$ where L_{PB1BI} & U_{PB1BI} are lower and upper bootstrap thresholds for built-up pixels and PB1BI(i) is the value of index PB1BI for pixel i. Also, for the purpose of reducing misclassification between river sand and built-up [41–46], additional filter using Built-Up & River Sand Separation Index (BRSSI) [40] has been applied. Similar to PB1BI, a pixel (i) would be separated from sedimentation as built-up if $L_{BRSSI} \leq BRSSI(i) \leq U_{BRSSI}$ where L_{BRSSI} & U_{BRSSI} are lower and upper bootstrap thresholds for built-up pixels and BRSSI(i) is the value of index BRSSI for pixel i. Combining these two index based methodologies, a pixel would be labelled as built-up if it satisfies both conditions ($L_{PB1BI} \leq PB1BI(i) \leq U_{PB1BI}$ and $L_{BRSSI} \leq BRSSI(i) \leq U_{BRSSI}$). We have used mentioned index based classification methods as these methods (PB1BI & BRSSI) are not only computationally inexpensive and fast but also matches accuracy performances of machine learning classifiers like Support Vector Machines (SVM) & Artificial Neural Networks (ANN) [40].

In order to investigate the impact of urbanization on groundwater for selected study sites (Table 1 & Figure 7), we have considered percentage of urbanization along with population density, temperature and precipitation as explanatory variables for ΔTWS and panel data (cross-sectional time series) regression [36, 47] analysis has been performed to understand the effect of mentioned explanatory covariates on ΔTWS for the years of 2003, 2007, 2012 and 2017. It could be noted here that for a particular study site, due to the consistence of presence across the considered years, the effect of misclassification that could not be eliminated by applying PB1BI & BRSSI, is negligible in the panel data regression analysis. Fixed Effect (FE) panel data regression model explore the relationship between covariates and dependent variable within an entity whose own individual characteristics may or may not influence the outcome. FE panel data regression model assumes (i) existence of correlation between entity's error term and predictor variables and (ii) error and constant terms corresponding to an entity are not correlated with the same for other entities. Equation for fixed effect model could be expressed as $Y_{it} = \beta X_{it} + \alpha_i + u_{it}$ where Y_{it} & X_{it} are dependent and independent variables respectively for ith entity and time t, β is the associated coefficient for X_{it}, α_i is the intercept corresponding to entity i and u_{it} is the error term.

On the other hand, Random Effect (RE) panel data regression model assumes that variations across entities are random and entity's error term is not correlated with the independent covariates. Thus, the equation for RE model becomes $Y_{it} = \beta X_{it} + \alpha_i + u_{it} + \epsilon_{it}$ where u_{it} & ϵ_{it} are between-entity and within-entity errors respectively.

In order to decide whether to consider fixed or random effect model for panel data regression, Hausman test [35, 36] with null hypothesis (H_0) of preferred model as random effect, has been performed. If the associated p-Value for Hausman test is significant (i.e. p-Value ≤ 0.05), fixed effect model has been used, otherwise random effect model has been considered.

ΔTWS corresponding to the month of January for selected years have been considered in the panel data regression model because ΔTWS has monthly and seasonal variations and thus differences between ΔTWS values corresponding to the same month of different years need to be considered in order to reflect changes in ΔTWS.

Percentages of built-up pixels to the total number of pixels in the entire image has been reported as percentage of urbanization for panel data regression. It could be noted here that while quantifying urbanization in terms of percentages of built-up pixels for a particular year and study site, in order to avoid dependencies on the acquisition time of the Landsat7 images, to obtain an averaged value for percentages of built-up estimates and to rectify for errors due to Scan Line Corrector (SLC) failure[8], we have considered median values of each pixels of the study sites for all available Landsat7 images from previous year to next year. For example, while computing percentages of built-up pixel for a particular study site for year 2007 with the help of index based methodologies described earlier, Landsat7 images corresponding to the region of interest from 01-January-2006 to 31-December-2008 have been considered.

For a particular study area and year, values of temperature and precipitation that have been used in the panel data regression models, are average values of the respective variables from previous year considered to the current year. To explain, for a particular study region, the temperature and precipitation values that have been used for 2007 are average values of respective variables from 01-January-2003 to 31-January-2007 as the previous year used in the cross-sectional time series data is 2003. As ΔTWS for the month of January is considered in the panel data, temperature and precipitation data for the month of January for both years have been included.

As discussed, population density estimates provided by global LandScan population datasets, corresponding to study sites for the respective years have been used in the analysis.

[8] https://www.usgs.gov/land-resources/nli/landsat/landsat-7, accessed 19-July-2020

All statistical analysis in this study has been performed with the help of R[9] statistical software packages. Also, R library plm[10] has been utilized for panel data regression analysis.

[9] https://www.r-project.org, accessed 19-July-2020
[10] https://cran.r-project.org/web/packages/plm/plm.pdf, accessed 19-July-2020

References

[1] Pahuja S, Tovey C, Foster S, Garduno H, et al. Report, World Bank. 2010;.

[2] Garduño H, Romani S, Sengupta B, Tuinhof A, Davis R. India groundwater governance case study. Water Papers, World Bank. 2011;.

[3] Rodell M, Velicogna I, Famiglietti JS. Satellite-based estimates of groundwater depletion in India. Nature. 2009;460(7258):999–1002.

[4] Sekhri S, et al. Sustaining groundwater: role of policy reforms in promoting conservation in India. India Policy Forum. 2013;149:149–187.

[5] Panda DK, Wahr J. Spatiotemporal evolution of water storage changes in India from the updated GRACE-derived gravity records. Water Resources Research. 2016;52(1):135–149.

[6] Report, Central Ground Water Board, Government of India. 2017;.

[7] Sun AY. Predicting groundwater level changes using GRACE data. Water Resources Research. 2013;49(9):5900–5912.

[8] Feng W, Zhong M, Lemoine JM, Biancale R, Hsu HT, Xia J. Water Resources Research. 2013;49(4):2110–2118.

[9] Shamsudduha M, Taylor RG, Longuevergne L. Monitoring groundwater storage changes in the highly seasonal humid tropics: Validation of GRACE measurements in the Bengal Basin. Water Resources Research. 2012;48(2).

[10] Jiao JJ, Zhang X, Liu Y, Kuang X. Increased water storage in the Qaidam Basin, the North Tibet Plateau from GRACE gravity data. PLoS One. 2015;10(10):e0141442.

[11] Huggins X, Gleeson T, Kummu M, Zipper SC, Troy T, Wada Y, et al. The social-ecological dimensions of changing global freshwater availability. 2020;.

[12] Rodell M, Famiglietti J. The potential for satellite-based monitoring of groundwater storage changes using GRACE: the High Plains aquifer, Central US. Journal of Hydrology. 2002;263(1):245–256.

[13] Rodell M, Chen J, Kato H, Famiglietti JS, Nigro J, Wilson CR. Estimating groundwater storage changes in the Mississippi River basin (USA) using GRACE. Hydrogeology Journal. 2007;15(1):159–166.

[14] Scanlon BR, Longuevergne L, Long D. Ground referencing GRACE satellite estimates of groundwater storage changes in the California Central Valley, USA. Water Resources Research. 2012;48(4).

[15] Döll P, Mueller Schmied H, Schuh C, Portmann FT, Eicker A. Global-scale assessment of groundwater depletion and related groundwater abstractions: Combining hydrological modeling with information from well observations and GRACE satellites. Water Resources Research. 2014;50(7):5698–5720.

[16] Chinnasamy P, Agoramoorthy G. Groundwater storage and depletion trends in Tamil Nadu State, India. Water Resources Management. 2015;29(7):2139–2152.

[17] Rodell M, Famiglietti J, Wiese D, Reager J, Beaudoing H, Landerer FW, et al. Nature. 2018;557(7707):651.

[18] Mukherjee A, Ramachandran P. Journal of hydrology. 2018;558:647–658.

[19] Adamowski J, Fung Chan H, Prasher SO, Ozga-Zielinski B, Sliusarieva A. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average,

artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. Water Resources Research. 2012;48(1).

[20] Tiwari MK, Adamowski J. Urban water demand forecasting and uncertainty assessment using ensemble wavelet-bootstrap-neural network models. Water Resources Research. 2013;49(10):6486–6507.

[21] Azadeh A, Neshat N, Hamidipour H. Hybrid fuzzy regression–artificial neural network for improvement of short-term water consumption estimation and forecasting in uncertain and complex environments: Case of a large metropolitan city. Journal of Water Resources Planning and Management. 2011;138(1):71–75.

[22] Al-Zahrani MA, Abo-Monasar A. Urban residential water demand prediction based on artificial neural networks and time series models. Water Resources Management. 2015;29(10):3651–3662.

[23] Shirmohammadi B, Vafakhah M, Moosavi V, Moghaddamnia A. Application of several data-driven techniques for predicting groundwater level. Water Resources Management. 2013;27(2):419–432.

[24] Haque MM, Rahman A, Hagare D, Kibria G. Probabilistic water demand forecasting using projected climatic data for Blue Mountains water supply system in Australia. Water resources management. 2014;28(7):1959–1971.

[25] Dos Santos CC, Pereira Filho AJ. Water Demand Forecasting Model for the Metropolitan Area of São Paulo, Brazil. Water Resources Management. 2014;28(13):4401–4414.

[26] Moosavi V, Vafakhah M, Shirmohammadi B, Behnia N. A wavelet-ANFIS hybrid model for groundwater level forecasting for different prediction periods. Water resources management. 2013;27(5):1301–1321.

[27] Karthikeyan L, Kumar DN, Graillot D, Gaur S. Prediction of ground water levels in the uplands of a tropical coastal riparian wetland using artificial neural networks. Water resources management. 2013;27(3):871–883.

[28] Yoon H, Jun SC, Hyun Y, Bae GO, Lee KK. A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. Journal of Hydrology. 2011;396(1):128–138.

[29] Tiwari MK, Adamowski JF. Medium-term urban water demand forecasting with limited data using an ensemble wavelet–bootstrap machine-learning approach. Journal of Water Resources Planning and Management. 2014;141(2):04014053.

[30] Mekonnen MM, Hoekstra AY. Science advances. 2016;2(2):e1500323.

[31] Phansalkar S, Kher V, et al. A decade of Maharashtra groundwater legislation: analysis of implementation process in Vidarbha. Issues in Water Use in Agriculture in Vidarbha Amol Management Consultants, Nagpur, India. 2003;.

[32] Ghosh S, Vittal H, Sharma T, Karmakar S, Kasiviswanathan K, Dhanesh Y, et al. PloS one. 2016;11(7):e0158670.

[33] Bright EA, Coleman PR, King AL. LandScan 2003. LandScan. Oak Ridge, TN: Oak Ridge National Laboratory; 2004. Available from: https://landscan.ornl.gov/.

[34] Rose AN, McKee JJ, Urban ML, Bright EA. LandScan 2017. LandScan. Oak Ridge, TN: Oak Ridge National Laboratory; 2018. Available from: https://landscan.ornl.gov/.

[35] Hausman JA. Specification tests in econometrics. Econometrica: Journal of the econometric society. 1978;p. 1251–1271.

[36] Greene WH. Econometric analysis. Pearson Education India; 2003.

[37] Syed TH, Famiglietti JS, Rodell M, Chen J, Wilson CR. Analysis of terrestrial water storage changes from GRACE and GLDAS. Water Resources Research. 2008;44(2).

[38] Bright EA, Coleman PR, King AL, Rose AN. LandScan 2007. Oak Ridge, TN: Oak Ridge National Laboratory; 2008. CY 2007. Available from: https://landscan.ornl.gov/.

[39] Bright EA, Rose AN, Urban ML. LandScan 2012. Oak Ridge, TN: Oak Ridge National Laboratory; 2013. CY 2012. Available from: https://landscan.ornl.gov/.

[40] Mukherjee A, Kumar AA, Ramachandran P. Development of New Index-Based Methodology for Extraction of Built-Up Area From Landsat7 Imagery: Comparison of Performance With SVM, ANN, and Existing Indices. IEEE Transactions on Geoscience and Remote Sensing. 2020;.

[41] Xu H. Extraction of urban built-up land features from Landsat imagery using a thematicoriented index combination technique. Photogrammetric Engineering & Remote Sensing. 2007;73(12):1381–1391.

[42] Thakkar AK, Desai VR, Patel A, Potdar MB. Post-classification corrections in improving the classification of Land Use/Land Cover of arid region using RS and

GIS: The case of Arjuni watershed, Gujarat, India. The Egyptian Journal of Remote Sensing and Space Science. 2017;20(1):79–89.

[43] Thakkar A, Desai V, Patel A, Potdar M. Land use/land cover classification using remote sensing data and derived indices in a heterogeneous landscape of a khan-kali watershed, Gujarat. Asian Journal of Geoinformatics. 2015;14(4).

[44] Avelar S, Tokarczyk P. Analysis of land use and land cover change in a coastal area of Rio de Janeiro using high-resolution remotely sensed data. Journal of Applied Remote Sensing. 2014;8(1):083631.

[45] Zha Y, Gao J, Ni S. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing. 2003;24(3):583–594.

[46] Pesaresi M, Corbane C, Julea A, Florczyk AJ, Syrris V, Soille P. Assessment of the added-value of sentinel-2 for detecting built-up areas. Remote Sensing. 2016;8(4):299.

[47] Baltagi B. Econometric analysis of panel data. John Wiley & Sons; 2008.

Appendix : Supplementary Results & Images

November 2, 2020

I Table I : Panel Data for Regression Analysis

Table 1:

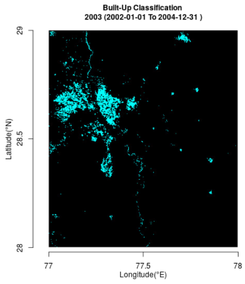
GRACE ΔTWS and Explanatory Variables for selected Study Sites : 2003 To 2017

Study Site	Year	Explanatory Variables					GRACE ΔTWS
		% of Urbanization	Population Density	Avg. Max. Temp.	Avg. Min. Temp.	Avg. Prcpt.	
Delhi	2003	3.7016	1656.73	0.2471	0.1618	-0.5292	4.8880
	2007	4.4273	1804.96	0.3028	0.0489	0.0653	-2.9768
	2012	4.9636	2081.47	0.3436	0.3456	0.2988	-3.6021
	2017	5.8645	2210.48	0.2460	0.0695	0.0613	-26.0051
Kanpur & Lucknow	2003	1.3489	834.33	0.0859	0.2157	-0.2277	-1.3824
	2007	1.5362	864.90	0.4939	0.3636	-0.0698	-4.3659
	2012	1.9733	912.40	-0.0767	0.0427	0.2565	-2.1125
	2017	2.1754	967.91	-0.4955	-0.7403	-0.4853	-19.7740
Ahmedabad	2003	0.3542	544.51	0.4867	-0.2469	-0.5678	-10.2378
	2007	0.3762	587.94	-0.0011	0.1046	0.5313	5.1281
	2012	0.4334	635.53	0.3041	0.6200	0.2410	5.5114
	2017	0.5765	677.23	0.0143	0.2429	-0.0343	-3.0004
Vadodara	2003	0.3535	425.38	0.2230	-0.2871	-0.7384	-12.7506
	2007	0.4329	437.20	0.0224	-0.1801	0.9496	4.6362
	2012	0.533	468.41	0.2231	0.3692	0.5054	5.3569
	2017	0.8158	499.08	0.1416	0.3701	0.1036	-0.8882
Indore	2003	0.3428	314.01	0.0520	0.1675	-0.4807	-12.7615
	2007	0.3803	314.26	0.2820	-0.0095	0.3891	3.5146
	2012	0.4357	379.89	0.0561	0.2519	0.0647	4.9266
	2017	0.7169	404.00	-1.4601	-0.0113	0.6166	0.5854
Aurangadabad	2003	0.1986	285.81	0.1087	-0.1374	-0.2320	-9.6729
	2007	0.2289	289.39	0.2873	0.1067	0.3678	2.6436
	2012	0.2976	323.50	0.3790	0.9823	0.0991	1.5079
	2017	0.3014	343.09	0.0514	0.9397	-0.0263	-0.8276
Hyderabad	2003	0.8167	550.47	0.1655	-0.2696	-0.3197	-11.4511
	2007	1.1747	630.64	0.1712	-0.2413	0.0851	2.4237
	2012	1.6625	705.83	0.3156	-0.0535	0.0303	-1.4400
	2017	1.943	755.07	-0.5238	0.2493	-0.3737	-5.4079
Bangalore I	2003	0.5092	602.81	0.2420	0.0453	0.0323	-5.8530
	2007	0.5453	637.28	0.4385	0.0720	0.1736	1.8212
	2012	0.7437	748.19	-1.1491	0.0594	0.2112	4.3612
	2017	0.9789	797.62	-1.1445	0.3963	-0.5563	-12.5013
Bangalore II	2003	0.4102	383.47	0.1463	0.0448	-0.0247	-6.4785
	2007	0.4594	406.02	0.4174	-0.0397	0.0855	1.3236
	2012	0.5787	443.28	-0.5091	-0.2344	0.3272	3.3807
	2017	0.699	468.52	-0.1735	0.2378	-0.3316	-12.4399

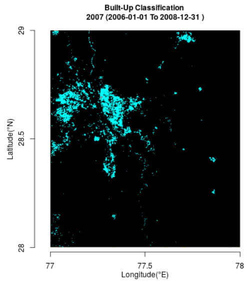
Note : % of Urbanization is reported as the percentages of built-up pixels in the Landsat7 satellite images corresponding to the study sites. **Population Density** has been computed as **Population/30" × 30" spatial resolution**. Average Maximum & Minimum Temperatures (**Avg. Max. Temp. & Avg. Min. Temp.**) and Average Precipitation (**Avg. Prcpt.**) are reported in **°C** and **mm** respectively w.r.t long term means of 1981-2010. **GRACE ΔTWS** is expressed in terms of equivalent liquid water thickness (in **cm**) and is reported as anomalies w.r.t 2004-2009 time-mean baseline.

II Built-Up Classification : 2003 To 2017

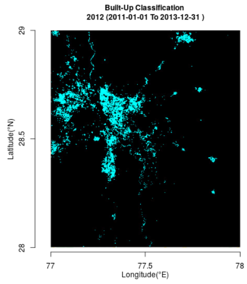
Classified Built-Up pixels from Landsat7 Satellite Images using PB1BI & BSSI for selected Study Sites



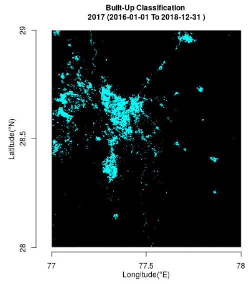
(a) 2003



(b) 2007

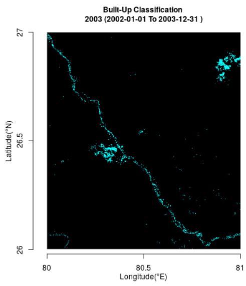


(c) 2012

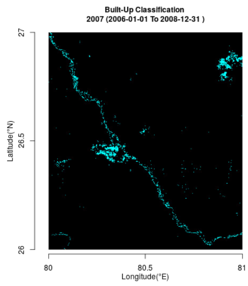


(d) 2017

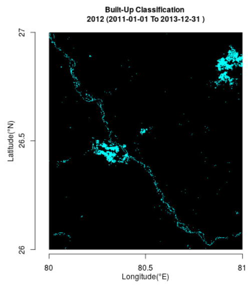
Figure 1: Classified Built-up for Study Site - Delhi : 2003 To 2017



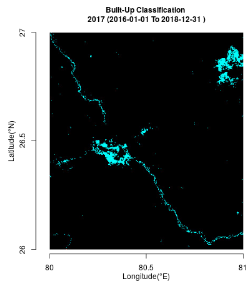
(a) 2003



(b) 2007

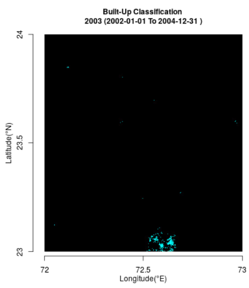


(c) 2012

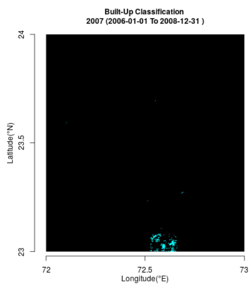


(d) 2017

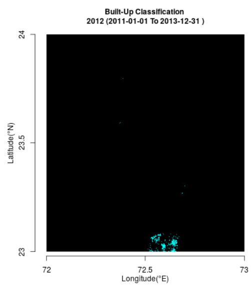
Figure 2: Classified Built-up for Study Site - Kanpur & Lucknow : 2003 To 2017



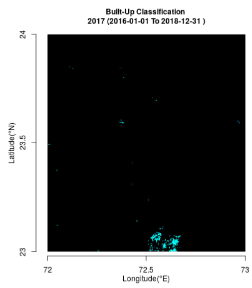
(a) 2003



(b) 2007

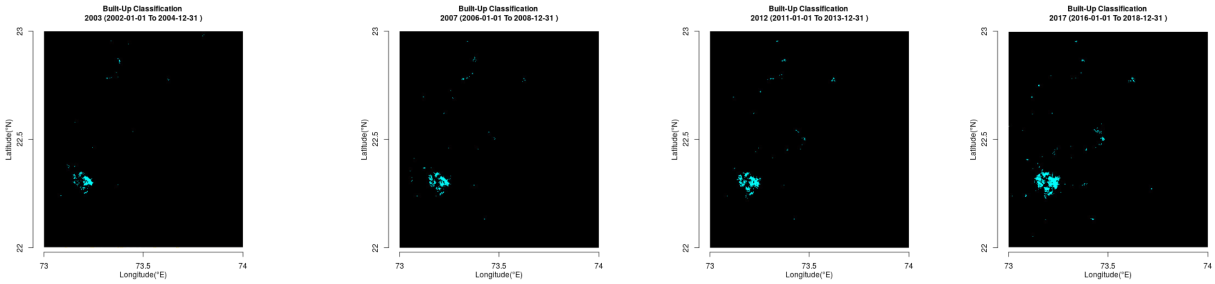


(c) 2012



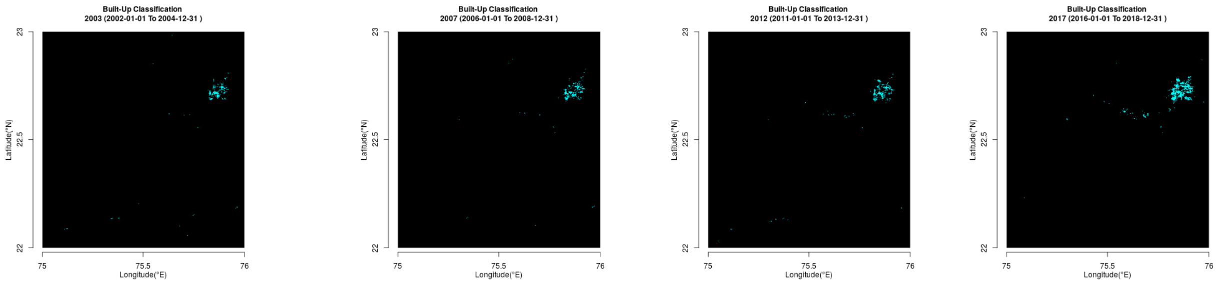
(d) 2017

Figure 3: Classified Built-up for Study Site - Ahmedabad : 2003 To 2017



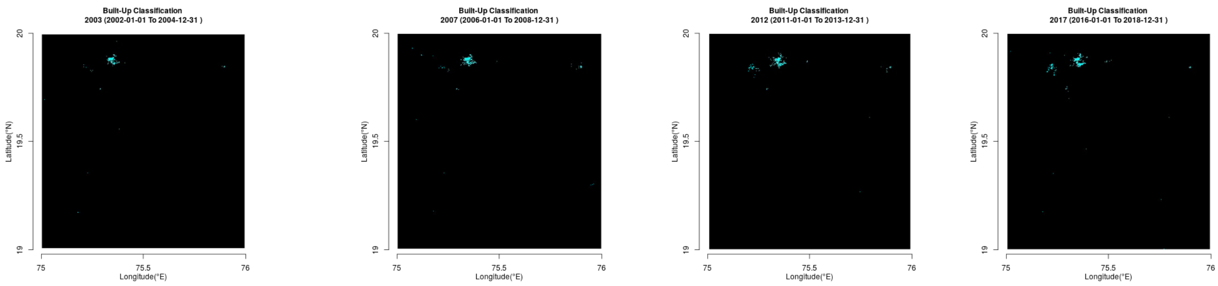
(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 4: Classified Built-up for Study Site - Vadodara : 2003 To 2017



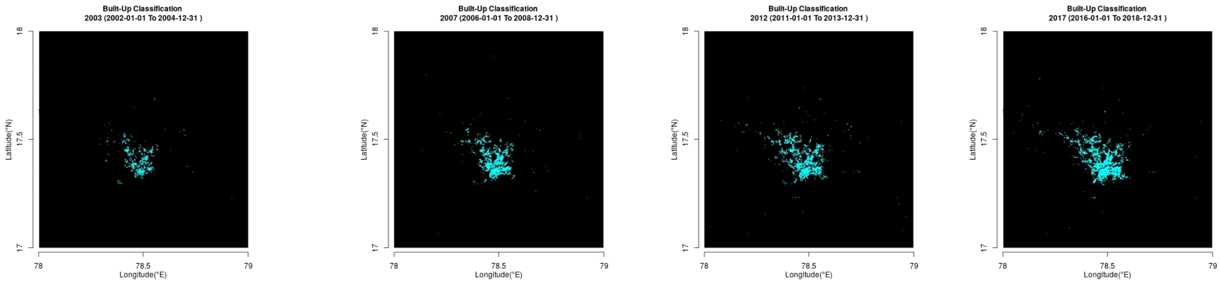
(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 5: Classified Built-up for Study Site - Indore : 2003 To 2017



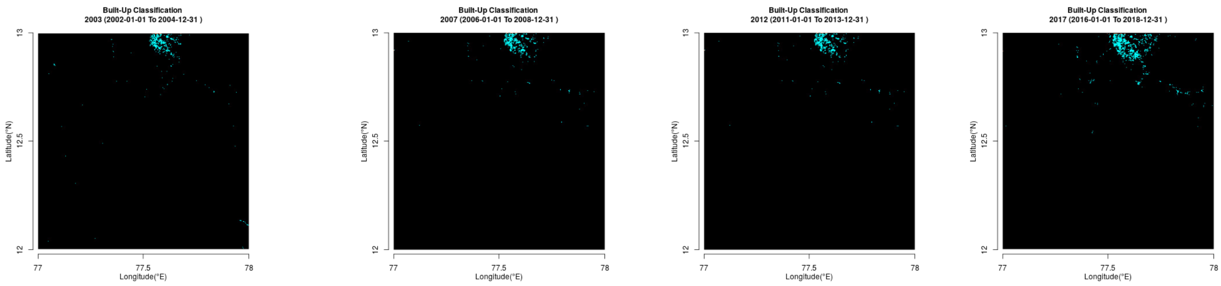
(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 6: Classified Built-up for Study Site - Aurangadabad : 2003 To 2017



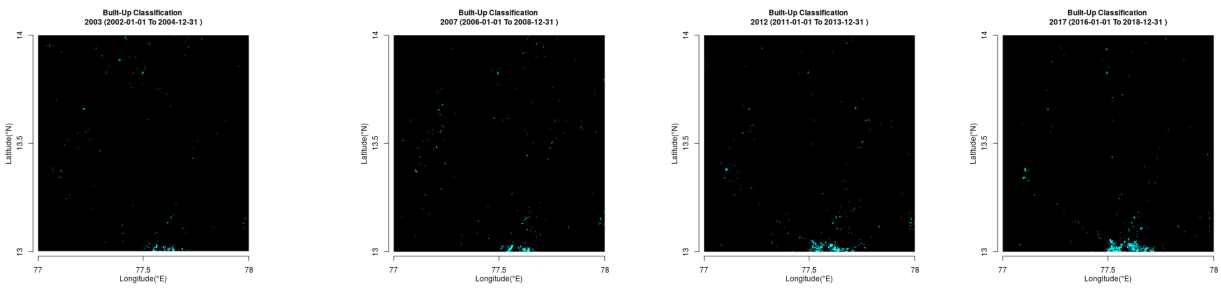
(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 7: Classified Built-up for Study Site - Hyderabad : 2003 To 2017



(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 8: Classified Built-up for Study Site - Bangalore I : 2003 To 2017



(a) 2003 (b) 2007 (c) 2012 (d) 2017

Figure 9: Classified Built-up for Study Site - Bangalore II : 2003 To 2017