Socioeconomic and Biophysical Drivers of Agricultural Intensification in India: A Dynamic Panel Analysis using Remotely-Sensed Data and Administrative Surveys (An Economic Characterization of India's Land Use Change)

Team Members:
Gargi Gupta 2015029
Tushita Rathore 2015108

BTP report submitted in partial fulfillment of the requirements
for the Degree of B.Tech. in Computer Science & Engineering

on April 21, 2019

BTP Track: Research Track

BTP Advisor
Dr. Gaurav Arora
Dr. Saket Anand

Indraprastha Institute of Information Technology
New Delhi

Student's Declaration

We hereby declare that the work presented in the report entitled **An Economic Characterization of India's Land Use Change** submitted by us for the partial fulfillment of the requirements for the degree of *Bachelor of Technology* in *Computer Science & Engineering* at Indraprastha Institute of Information Technology, Delhi, is an authentic record of our work carried out under guidance of **Dr. Gaurav Arora** and **Dr. Saket Anand**. Due acknowledgements have been given in the report to all material used. This work has not been submitted anywhere else for the reward of any other degree.

.... **Place & Date: ....**
Gargi Gupta

.... **Place & Date: ....**
Tushita Rathore

Certificate

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

.... **Place & Date: ....**
Dr. Gaurav Arora

.... **Place & Date: ....**
Dr. Saket Anand

Abstract

Agriculture is not only the primary source of food for the population of ∼1.3 billion people in India but also a source of livelihood, directly or indirectly for more than 50% of its working population a. It is also the major source of raw material for agro-based industries in India. A growing population puts pressure on the agricultural sector and hence drives the need to increase food production which can be met by increasing productivity or extending cropping to non-agricultural land.

We conduct a spatio-temporal analysis of district-wise cropland use dynamics using high-resolution raster data obtained from ISRO's Bhuvan portal from 2005-2014. We have evaluated the land use changes using satellite data combined with coarse administrative surveys. Next, we estimate first-order transition probabilities using Logistic Regression to see the influence of the factors that drive these changes.

Keywords: LULC, Geospatial, Agriculure, Physical Environment, Market Environment, Policy Environment, Spatio-temporal, Logistic Regression, Markov Model

Acknowledgments

We would like to acknowledge the role of Dr. Gaurav Arora for giving his insightful feedbacks and constant guidance.
We would also like to thank and Dr. Saket Anand without whose guidance this project would not have been possible.
We would also like to cite our work which has been submitted in ACM COMPASS 2019:
Gargi Gupta, Tushita Rathore, Saket Anand, Gaurav Arora. "Socioeconomic and Biophysical Drivers of Agricultural Intensification in India: A Dynamic Panel Analysis using Remotely-Sensed Data and Administrative Surveys"

Work Distribution

This semester we focussed on collecting data for the various regression parameters. We also worked on logistic regression model to determine the influence of the various factors on cropping intensity.

Contents

Chapter 1

Introduction

Land use pattern of any region shapes its economy, is correlated with its economic growth and also plays a major role for judicious management of its resources. A growing economy, population, and wages lead to higher food demand and generate pressure on the farming sector.The Indian Census reported nearly 185% population increase (361 million to 1,028 mil- lion) during 1951-2011 [2]. Options for increasing food production include increasing productivity, cropping more frequently on existing lands, or extending cropping to non-agricultural lands, e.g., forests and grasslands. According to a report by the World Bank, the agricultural acreage hasnt increased much since the 1980s (from 58.8% of total area in 1961 to 61% in 1984 and 60% in 2015 [3]) rather there has been large-scale agricultural intensification.

The farmers in India depend extensively upon each year's Monsoon rainfall, which is their major source of irrigation. Besides the natural endowments like rainfall and soil quality, some technological progress has occurred in terms of better seeds, groundwater, and canal irrigation, access to highways, storage facilities, markets, etc. However, the progress is inadequate amidst the pressure to provide for an ever-increasing population coupled with the land availability constraint of India's smallholder farmers.

Land use change detection offers a means to understand land use dynamics, identify the spatio-temporal land use patterns, understand the factors that drive these changes and design interventions where necessary [15]. It is imperative to not only increase agricultural output but also design policies for sustainable growth and development.

We develop a dynamic panel model for farmers crop intensification (single-to-double crop transition) decisions as a function of rainfall, irrigation acreage, soil quality, infrastructure, and agricultural policy. To estimate this model we combine the spatially delineated remotely-sensed land use data with publicly available district-level administrative surveys. This is carried out to not only quantify the amount of change but to explain the statistical influence of the factors driving these changes.

1.1 Related Work

Remote sensing using GIS data has been used in the past for land use change detection. The studies have mainly focused on classifying the raster data using Maximum Likelihood Classification into various classes and calculating the cover and the changes in cover using geospatial techniques [14, 18, 19].

We used a high-resolution remotely sensed data for analyzing land use change during 2005-2014, made available by NRSC, ISRO's Bhuvan portal which was already classified by them using a hybrid approach (Decision Tree - See5 or Supervised MXL or both) into 18 different categories. Prior work on land use change have primarily focused on district-level or city-level changes. The study area was treated to be isolated from the remaining country, which restricted their scope due to the possibility of local factors dominating the changes in these places [14,18]. In contrast, we study the entire country, incorporate some factors driving these changes on a country-wide level.

Significant research exists on the land use transitions and their drivers for developed countries, but limited work has been done for the developing country setup. Studies on India's land use change have been limited in scope with regards to time, (i.e., focus on two or three time periods), geography, (i.e., focus on a small area), and methodology (i.e., focus only on land use transitions and not on the formal identification of its drivers) [6, 8, 10, 14, 15].

Some of the previous works also used Markov modeling to study land use dynamics and predict future changes [8, 20]. But these approaches considered only a very limited number of years, (usually two or three) for studying the patterns which could lead to erroneous identification of land use trends.

Studies that are stationed in the developed countries have modeled land use transitions using multinomial logistic regression models to estimate the impact of various relevant factors on land use change [7, 9]. The regression coefficients provided the odds of a change in land cover due to changes in the corresponding factors. We extend this literature by providing a national-scale land use change analysis and the role of potential drivers over a period of 10 years. A model of the emerging economy setting encounters the peculiarities of weak institutions, social distrust, and relatively poor infrastructure. So we include variables that would explicitly control for changes in rural cash flows through policy reforms, which is unique to this study, along with the infrastructure network through access to demand terminals and irrigation.

1.2 Econometric Model

The per acre profit earned by a farmer can be expressed as:

$$\pi = p.y - C \tag{1.1}$$

Eq.(1.1)implies that the farmer's objective is to maximize per-acre farm profit (π), which is defined as per-acre revenue market price-per-kilogram (kg), p, times per-acre-output or crop yield, y, minus the per-acre cost, C, i.e., investment incurred by the producer.

Now, adapting this economic principle to our problem of single (S) vs. double (D) cropping the profit maximization problem is: $max(\pi) = \pi^S(l^S) + \pi^D(l^D)$ such that
the total land area between categories remains fixed, i.e., $l^S + l^D = L$

where π^S and π^D are the profits generated from land use A and B respectively, and l_S and l_D represent the land area in acres being used for A and B respectively and L is the total land available which is fixed.
On maximizing the profit function, (1.2) over the given constraint, we obtain the following:

$$\frac{\partial \pi^S}{\partial l_S} = \frac{\partial \pi^D}{\partial l_D} \tag{1.2}$$

This is the optimal condition [16] for land allocation by a rational farmer. The land would be allocated from use A to use B by a rational farmer when the marginal returns per acre from land use A is lower than from land use B. Mathematically,

$$\frac{\partial \pi^S}{\partial l_S} < \frac{\partial \pi^D}{\partial l_D} \tag{1.3}$$

As more and more land is taken out from S to D, $\frac{\partial \pi^S}{\partial l_S}$ decreases and $\frac{\partial \pi^D}{\partial l_D}$ increases at a decreasing rate due to the law of diminishing marginal returns [17]. Thus, after some time, the farmer would return to optimal land allocation, i.e., at (1.2).

We hypothesize that farmers' decision-making is influenced by three types of variables: market (e.g., crop prices), environmental (e.g., weather) and policy (e.g., fertilizer subsidy). To empirically model the agricultural land use dynamics, we specify a first-order Markov transition probability matrix that characterizes the land use transitions for parcel i at time-period t,

$$P_{it} = \begin{bmatrix} \phi_{it}^{S,S} & \phi_{it}^{D,S} \\ \phi_{it}^{S,D} & \phi_{it}^{D,D} \end{bmatrix} \tag{1.4}$$

where, $\phi_{it}^{S,S}$ is the probability of parcel i being single-cropped in and transitioning to single-cropped in period t. Similarly, $\phi_{it}^{D,S}$ is the probability of parcel i being single-cropped in and shifting to double-cropping in year t, and so on. As the total transition probability from each state in eq. (1.4) should be equal to 1, we have:

$$\phi_{it}^{S,S} + \phi_{it}^{D,S} = 1 \ \ and \ \ \phi_{it}^{S,D} + \phi_{it}^{D,D} = 1 \qquad \forall i, t \tag{1.5}$$

The logistic regression is given by the following equation:

$$y = G(X'\beta) = \frac{e^{X'\beta}}{1 + e^{X'\beta}} \tag{1.6}$$

where G is the logistic distribution, X is the vector of explanatory variables and β is the coefficient vector of each variable. The regression of the form given by eq. (1.5) can be written as:

$$\begin{aligned} y_{i,t} = \beta_0 \, + \, \beta_1 Rain_{i,t} \, + \, \beta_2 Rain^2_{i,t} \, + \, \beta_3 Irrig_{i,t} \, + \, \beta_4 Elv_i + \\ \beta_5 NDef_i \, + \beta_6 Road_i \, + \, \beta_7 Y_{W_{i,t}} \, + \, \beta_8 Y_{R_{i,t}} \, + \, \beta_9 Tr_t \, + \, \beta_{10}(Tr_i Irrig_{i,t}) + \\ \beta_{11}(Tr_t Elv_i) \, + \, \beta_{12}(Tr_t NDef_i) \, + \, \beta_{13}(Tr_t Road_i) \, + \, \beta_{14}(Tr_t D_1 0) \, + \, \varepsilon_{i,t} \end{aligned} \tag{1.7}$$

The dependent variable $y_{i,t}$ which denotes the change from one land use category to another can be written as:

$$y_{i,t} = \begin{cases} (D_t - S_{t-1})/S_{t-1}, & \text{if } (D_t|S_{t-1}) \\ (D_t - D_{t-1})/D_{t-1}, & \text{if}(D_t|D_{t-1}) \end{cases}$$

where 'S' denotes Single crop and 'D' denotes Double/Triple Crop. It represents the ratio of pixels that have transitioned to double/triple cropping and the total agricultural pixels at time t-1.

We calculate the transition probabilities for first order Markov chain model and also the Marginal effects.

The Marginal effect is a measure of the effect that a change in an explanatory variable has on the predicted probability, when the other variables are kept fixed.

It can be calculated and written as given by the equation below:

$$\frac{\partial y}{\partial x_i} = \frac{\beta_i e^{X'\beta}}{(1 + e^{X'\beta})^2} = \beta_i \frac{dG(X'\beta)}{dX'\beta} \tag{1.8}$$

Chapter 2

Data

2.1 LULC Raster Data

Our land cover data constituted of raster data of whole of India from the year 2005-2014, provided by National Remote Sensing Centre, ISRO's Bhuvan Portal [1]. The resolution of the dataset is 56m x 56m viz., each pixel constituted information for a single dominant land use type in the area of $3136m^2$ (56m x 56m). A minimum of 20 sample points was considered for each class to estimate the accuracy of the classified dataset.

The classified raster data consisted of the following categories: built-up, agriculture(single, double/triple, current fallow), forests, water bodies, others (snow cover, swamps, grasslands etc). For our study, we have focused only on single and double/triple agricultural lands and category changes occurring within them. We again categorized the data according to our requirements using ERDAS Imagine. We then calculated the area of each category using Histogram function on ERDAS and then used this data to calculate percent changes in each category over the decade.

Using the raster data obtained, we calculated the areas of agricultural land use categories in India.

Table 2.1: **Land Cover Area (in '000 km^2)**

Year	Single	Double/triple	Others
2005-06	844.12	453.03	1,873.26
2006-07	818.97	490.63	1,871.91
2007-08	744.55	554.29	1,881.19
2008-09	773.75	582.10	1,859.59
2009-10	691.11	630.37	1,861.34
2010-11	740.41	633.44	1,818.19
2011-12	735.42	641.09	1,814.05
2012-13	738.81	624.00	1,831.20
2013-14	720.75	693.56	1,807.81
2014-15	758.60	681.67	1,791.28
Areal Change	-85.52	228.65	-81.98
Percent Change	-10.13	50.47	-30.8

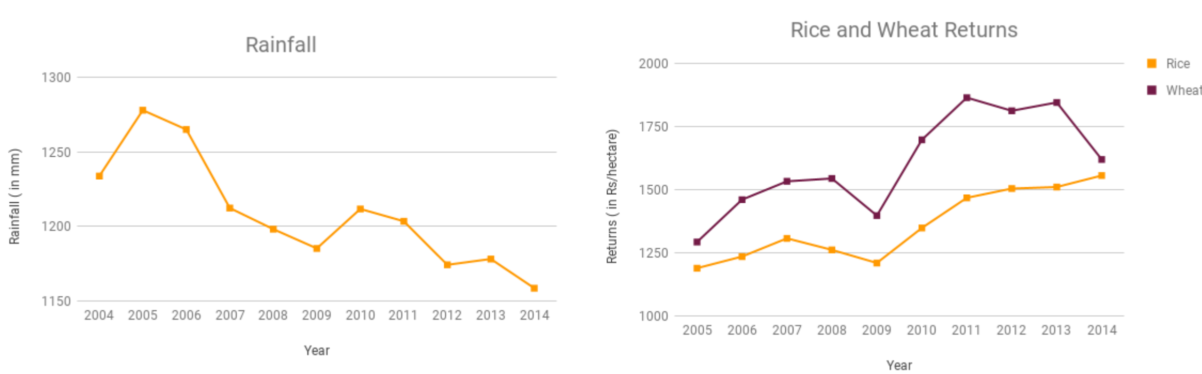
2.2 Administrative Survey Data

The independent variables in the binomial logistic regression are constructed using administrative surveys of Central and State governments during 2005-'14 and across 660 districts. Even though the data is publicly available, there is no consolidated annual database. Hence, we had to collect this data from different sources, which made the process tedious. Nevertheless, this was crucial for our study as a standalone spatio-temporal analysis of the LULC data would only reveal the areal changes and would not capture the influence of any potential driving factors.
These variables include district-level rainfall, gross irrigated area, wheat and rice yield, road density, soil nutrient deficiency, and slope (see Table 2.2).
From figure 1, we can see that there has been low variability in rainfall which is a positive sign for farmers. It provides them an incentive to grow crops in more than one season at minimal costs.

Table 2.2: **Explanatory variables and their description**

Variable	Notation	Description(data source)
Rainfall	*Rain*	District-wise annual rainfall in mm (IMD [5])
Irrigated Area	*Irrig*	District-wise gross Irrigated area in hectares (Ministry of Agriculture and Farmers' Welfare (MOAFW) [4])
Elevation	*Elv*	Elv=1 if a district is hilly or 0 otherwise (State government websites)
Soil Nutrient deficiency	*NDef*	District-wise percentage of Nitrogen and Organic Carbon deficiency. Though these data are available for 2016-17, we assume soil quality is either time invariant or changes proportional across districts. (MOAFW [4])
Road Density	*Road*	Total road length incl. urban roads and highways (km) divided by the district area (km) [1].
Wheat Yield	Y_W	District-wise yield in kg per hectare. (MOAFW [4])
Rice Yield	Y_R	District-wise yields in kg per hectare. (MOAFW [4])
Trend	*Tr*	Tr = 1 in 2005-06, = 2 in 2006-07, ... , = 10 in 2014-15.
Dummy	D_{10}	D_{10} = 1 if Tr ¿ 5, i.e., post-2010 policy reforms including large loan waivers, an employment guarantee scheme and increase in minimum support price (safety net against price volatility) for crops circa 2009.

We have graphs for the mean data of variables for each year which we can use to estimate trends in the factors used for the analysis.



(a) Rainfall

(b) Returns/hectare of Rice and Wheat

Figure 2.1: Trend graphs for Rainfall and Crop Yields

From these graphs we can observe that:

1. There has been low variability in rainfall apart from 2009 (sharp decline) which is a positive sign for farmers.
2. Returns per hectare of the major crops have been continuously increasing apart from 2009 where there was a sharp decline. We have been able to confirm from various online news sources that 2009 was a drought year.

2.3 LULC Change Detection Matrix

From the area under each category, we can see that land cover has not remained static over the years. It has undergone continuous changes. To understand category transitions, we calculate an overall change matrix from 2005-2014. From the table, we can see that 286.54 thousand km2 of single crop area was converted to double/triple crop area which is a large number when we compare it to the area of double/triple crop that has remained in the original category itself. This huge transition from single to double/triple is an important reason that determining the factors and their effect on land cover changes is an important socio-economic problem.

Table 2.3: **Change Matrix (in '000 km^2) from 2005-06 to 2014-15**

Category	Single	Double/triple	Others
Single	433.40	286.54	74.64
Double/triple	122.84	293.09	23.93
Others	215.10	50.93	1,665.56

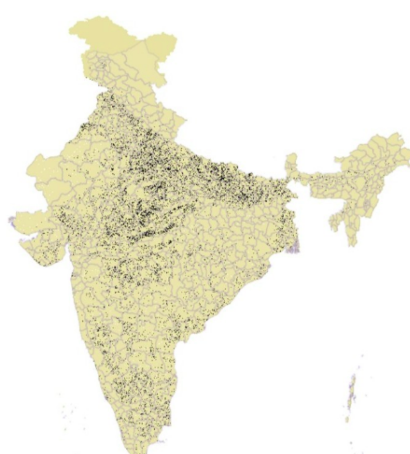


Figure 2.2: Visual representation of crop intensification between 2005-06 to 2014-15 (The black dotted regions show the transition from single crop to double/triple crop)

Chapter 3

Results

Table 3.1 provides the marginal effects of each potential land use driver on single to multi-season crop transitions. The marginal effects give the instantaneous change in the dependent variable as a function of a change in a specified independent variable keeping all the other variables constant.

We included annual rainfall and rainfall-squared to explain land use transitions across the country. Since Indian agriculture is highly dependent on seasonal rains, also known as the Monsoon rain, it is likely that single-to-double cropping switch occurred during the years of relatively high rainfall and/or districts that on-average receive higher precipitation. In models 1 and 2 in table 4, we find that higher rainfall leads to agricultural intensification and the effect is statistically significant. Specifically, an increase of 1 mm rainfall in a year causes the 9.2% increase in shift from single to double cropping. However, the coefficient on rainfall-squared is negative but statistically insignificant, which signals that too much rainfall across space (e.g., a district receiving abnormally high rainfall) and time (e.g., a flood year) can inhibit crop intensification.

Table 3.1: **Estimated marginal effects from the dynamic model for annual share of single to double/triple crop transitions**

Variable	**Model 1**	**Model 2**
Rain	0.095***	0.095***
	(0.021)	(0.021)
$Rain^2$	-0.038*	-0.039*
	(0.021)	(0.021)
Irrig	-0.037	-0.037
	(0.028)	(0.028)
Elv	-0.036	-0.034
	(0.036)	(0.031)
NDef	-0.099***	-0.036
	(0.030)	(0.036)
Road	0.093***	0.099***
	(0.031)	(0.030)
Y_W	-0.036***	0.106***
	(0.014)	(0.041)
${Y_W}^2$		-0.051***
		(0.041)
Y_R	-0.035**	-0.035
	(0.014)	(0.293)
${Y_R}^2$		0.092
		(0.293)
Tr	-0.035	-0.036
	(0.048)	(0.048)
$Tr \times Irrig$	0.096***	0.096***
	(0.030)	(0.030)
$Tr \times Elv$	-0.044*	-0.044
	(0.037)	(0.037)
$Tr \times NDef$	-0.040	-0.039*
	(0.044)	(0.044)
$Tr \times Road$	-0.034	-0.035
	(0.037)	(0.037)
$Tr \times D_{10}$	0.102***	0.102***
	(0.035)	(0.035)
RMSE	0.31	0.34

*Standard error in parenthesis. *** means significant at 99% CI, ** 95% CI, and * 90% CI.*

Chapter 4

Discussion

From the results of the various regression, we can draw some inferences regarding the effects of these variables on our response variable. We find access to irrigation by an additional acreage, as captured by *Irrig* has not played a mjor role in cropland intensification. But over years, it has become of more importance in agriculture as farmers cannot only depend on rainfall. This is well reflected by the interaction variable *Trend x Irrig*, which suggests that the importance of irrigation in cropland intensification has *weakly* increased over time. This could be explained by movement from Kharif into Kharif & Rabi seasons (where Rabi is the dry season that generates demand for irrigation).

Crop intensification seems to have reduced in the hilly areas over the years. Movement of double cropping to the plains makes sense economically because cropping is quite costly on the hills due to the nutrient runoff on steep slopes. On the other hand, nutrient deficient soils are supporting higher crop intensification even though it would be a costly venture. A plausible explanation would be that given the total land area is fixed crop intensification ha now starting to move on worse soils. Cropping on subprime soils would raise serious concerns with regards to climate and market sensitivity of the agricultural production systems and their viability in sustainably generating higher incomes for farmers. Road density, which is a measure of the access to demand terminals, supports higher crop intensification in a statistically significant manner.

To control for agricultural productivity, which then drives crop returns, we include wheat and rice yields in model 1 and add their squared variants in model 2. Wheat is primarily a dry-season (Rabi) crop, rice or paddy is a wet-season (Kharif) crop. The combined results from models 1 and 2 suggest that while higher wheat yields may be critical to support cropland intensification only very high values of wheat yields support such a shift. This suggests that farmers would double their efforts or cost of farming if the corresponding returns are high enough (e.g., higher by a threshold that covers for costs incurred).

Last but not least, the impact of agricultural policy on cropland intensification is captured by the dummy variable, D_{10}. This variable controls for three major policy interventions circa 2009.

First, a national rural employment guarantee scheme, MGNREGA[1] was rolled out; second, mass loan waiver was provisioned for small farmers; and third, the Minimum Support Prices increased significantly providing a better safety net to farmers from price fluctuations. Overall, the three policies would result in higher cash flow in rural areas. We find that whenever the value of D_{10} switches to 1, i.e., post-2010 the farmers' propensity to transition into a double or triple cropping system increases statistically significantly by 10.1%. This variable reveals the importance of policy in agricultural land use transitions.

4.1 Robustness of Model

We tried removed outliers based on the change that occurred in a particular district. We removed samples where the dependent variable was less than 0.10 i.e. the percentage change was less than 10%. This step improved the value of the RMSE to 0.27 from 0.29. This is not a very significant change and hence, the results can be considered to be quite robust.

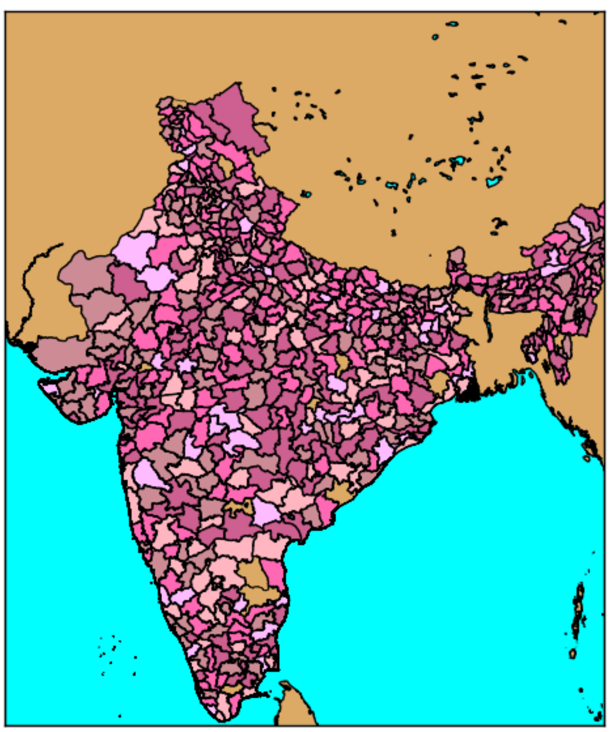


Figure 4.1: Percentage Change from Single to Double Crop w.r.t. Single Crop

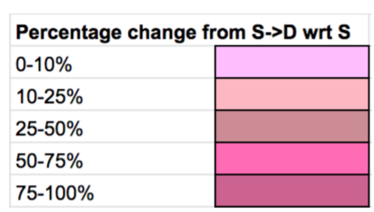


Figure 4.2: Legend

Apart from removal of districts with very less transitions, we also performed the regression analysis by adding and removing variables to see what effect that plays on the other set of variables. We did this with Wheat yields, Rice yields and the dummy variable D_{10}, to see most

[1] MGNREGA - Mahatma Gandhi National Rural Employment Guarantee Act aimed to provide at least 100 days of work in rural areas for unskilled manual labour.

of the variables had a similar effect on the crop intensification. We have included these set of Results in the Appendix.

We then performed the Jarque-Bera test to test the goodness-of-fit and see if the given sample follows a normal distribution. The p-value for all the variables(mentioned in Table 2.2) came out to be zero. This means we fail to reject the hypothesis and our data variables all have a normal distribution.

Chapter 5

Conclusion

We investigated the quantitative effects of biophysical and socioeconomic factors on agricultural land use in India during 2005-06 to 2014-15. We modeled the transition from single to double cropping by employing first-order (one-year memory) Markov transition probability model, which was then estimated using logistic regression. This exercise aimed to determine the direction, magnitude, and statistical significance of each potential driver of cropland intensification. We find that that rainfall, irrigation, road density, and agricultural policy influence agricultural land use change in a significant manner, positively from single cropping systems to double or triple cropping systems. Interestingly, cropland intensification has moved into areas having poorer soils raising concerns over their sustainability in the long-run and ability to produce higher profits in the short-run.

We expect that a comprehensive analysis of the land use transitions in India is a significant contribution to the current dearth of formal land use analyses for developing countries. To the best of our knowledge, this study serves as the first formal identification of land use drivers at the national-scale for India.

5.1 Limitations and Future Work

After critical analysis of various driving factors, we tried to understand the impact they have on the changing agricultural land use in India. From the above results, we were able to draw considerable inferences that align with the expected patterns as well as are reflected through the policies implemented.

Finishing this, we moved on to the predictive modelling part. We started by including the regularization terms (L1 and L2 norm) in the Logistic model along with a 5-fold cross validation approach. We trained and tested our data to analyze the marginal effects and their directions with each fold and in the overall average result. Inclusion of a penalty term increased the number of statistically significant coefficients for the various combinations of independent variables we tested on. Along with this, we created scatter plots for the true y values and the predicted y values through which we saw that our predictive model was not giving a plot that would majorly

align on the ytrue = ypredicted line.
This result shows that are predictive model, though with an RMSE close to 0.3 is not predicting very accurately. Following this, we have tried changing small parts in our approach to identify the problem. We started by linearly scaling all the continuous variables in between 0 and 1. We then proceeded to try a Probit model, where the only difference from the Logit model is the way the distribution function is defined. So, shifting to this model did not result in any significant change in the prediction and scatter plots.
On removing the outliers w.r.t. percentage change from single to double cropping, RMSE decreased. It means that working and enhancing our approach in this direction might help us reach a good predictive model which we can further use for performing prediction of land changes after n years in the future.
We have included few of the more results obtained by running the above methods in the appendix.

Bibliography

[1] Bhuvan, Indian Geo-Platform of ISRO-Thematic Services National Remote Sensing Centre, Indian Space Research Organisation. Last accessed on January 30, 2019. Available at: https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php

[2] Office of the Registrar General & Census Commissioner, Ministry of Home Affairs, Government of India. Last accessed on March 10, 2019. Available at: http://censusindia.gov.in/

[3] World Bank. Last accessed on March 10, 2019. Available at: https://data.worldbank.org/indicator/AG.LND.AGRI.ZS

[4] Ministry of Agriculture and Farmers Welfare. Last accessed on March 10, 2019. Available at: https://aps.dac.gov.in/APY/Index.htm and https://www.prsindia.org/policy/discussion-papers/state-agriculture-india

[5] India Meteorological Department(IMD). Last accessed in October, 2018. Available at: http://imd.gov.in/section/nhac/wxfaq.pdf

[6] S. Muthusamy, X. Rosario Arunkumar, T. Naveen Raj, C. Lakshumanan, and M. Jayaprakash. 2010. Land Use and Land Cover Changes Detection Using Multitemporal Satellite Data, Cuddalore Coastal Zone, Se-Coast of India. In *International Journal Of Geomatics And Geosciences, Vol.1, No.3.*

[7] N. P. Hendricks, S. Sinnathamby, K. Douglas-Mankin, A. Smith, D. A. Sumner, and D. H. Earnhart. 2014. The Environmental Effects of Crop Price Increases: Nitrogen Losses in the U.S. Corn Belt. In *Journal of Environment Economics and Management, 63(3), pp. 507526.*

[8] S. Kumar, N. Radhakrishnan, and S. Mathew. 2014. Land use change modelling using a Markov model and remote sensing. In *Geomatics, Natural Hazards and Risk, Vol. 5, Issue 2, pp. 145-156* .

[9] C. Hyandye, C.G. Mandara, and J.Safari. 2015. GIS and Logit Regression Model Applications in Land Use/Land Cover Change and Distribution in Usangu Catchment. In *American Journal of Remote Sensing, 3(1), pp. 616.*

[10] M. W. A. Halmy, P. E. Gessler, J. A. Hicke, and B. B. Salem. 2015. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. 2015. In *Applied Geography, 63, pp. 101112.*

[11] A. Carpentier and E. Letort. 2014. Multicrop Production Models with Multinomial Logit Acreage Shares. In *Environmental and Resource Economics, Vol.59, Issue 4, pp. 537-559.*

[12] R. Marcos-Martinez, B. A. Bryan, J. D. Connor and D. King. 2017. Agricultural land-use dynamics: Assessing the relative importance of socioeconomic and biophysical drivers for more targeted policy. In *Land Use Policy, 63, pp. 53-66.*

[13] D. Kusz, S. Gedek, M. Ruda and S. Zajac. 2014. Endogenous Determinants Of Investments In Farms Of Selected Countries Of Central And Eastern Europe. In *Scientific Papers Series Management, Vol.14, Issue 3.*

[14] S. Reis. 2008. Analyzing Land Use/Land Cover Changes Using Remote Sensing and GIS in Rize, North-East Turkey. In *Sensors, Vol.8, Issue 10, pp. 6188-6202.*

[15] J. S. Rawat, V. Biswas, and M. Kumar. 2013. Changes in land use/cover using geospatial techniques: A case study of Ramnagar town area, district Nainital, Uttarakhand, India. In *The Egyptian Journal of Remote Sensing and Space Science, Vol.16, Issue 1, pp. 111-117.*

[16] D. P. Bertsekas. 1982. Constrained Optimization and Lagrange Multiplier Methods. Academic Press Inc., Massachusetts: United States of America

[17] H. Varian. 1987. Intermediate Microeconomics: A Modern Approach. W. W. Norton & Company, New York: United States of America

[18] M.I. Haque and R. Basak. Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. In *The Egyptian Journal of Remote Sensing and Space Science, 20 (2017), pp. 251-263.*

[19] J. S. Rawat and M. Kumar.Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. In *The Egyptian Journal of Remote Sensing and Space Science, 18(1), 2015, pp. 77-84.*

[20] M. W. A. Halmy, P. E. Gessler, J. A. Hicke, and B. B. Salem. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. In *Applied Geography, 63 (2015), pp. 101-112.*

Appendices

Table 1: **Estimated marginal effects for other variable combinations:Robustness check**

Variable	Model 1	Model 2	Model 3
$Rain$	-0.046** (0.022)	-0.046** (0.022)	0.092*** (0.024)
$Rain^2$	0.116*** (0.023)	0.115*** (0.023)	0.042** (0.019)
$Irrig$	0.115*** (0.028)	0.117*** (0.028)	0.095*** (0.032)
Elv	-0.084** (0.037)	-0.084** (0.037)	-0.037 (0.034)
$NDef$	-0.066** (0.030)	-0.070** (0.030)	-0.035** (0.034)
$Road$	0.093*** (0.031)	0.094*** (0.031)	0.120*** (0.041)
Y_W	-0.051 (0.041)		-0.057 (0.046)
${Y_W}^2$	-0.039 (0.041)		0.105* (0.045)
Y_R		0.109 (0.294)	-0.034 (0.328)
${Y_R}^2$		-0.042 (0.294)	0.092 (0.328)
D_{10}			0.104* (0.058)
Tr	0.102** (0.048)	0.104** (0.048)	-0.056 (0.57)
$Tr \times Irrig$	0.101*** (0.030)	0.100*** (0.030)	0.040 (0.033)
$Tr \times Elv$	-0.051 (0.035)	-0.052 (0.035)	-0.035 (0.041)
$Tr \times NDef$	0.126*** (0.044)	0.125*** (0.044)	0.098*** (0.049)
$Tr \times Road$	0.151*** (0.037)	0.152*** (0.037)	-0.060 (0.041)
$Tr \times D_{10}$	0.103*** (0.037)	0.100*** (0.037)	-0.038 (0.080)