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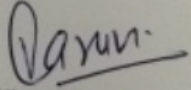

Varun Narayan Mishra

TABLE OF CONTENTS

CERTIFICATE	i
DECLARATION BY THE CANDIDATE	ii
COPYRIGHT TRANSFER CERTIFICATE	iii
ACKNOWLEDGEMENT	iv
TABLE OF CONTENTS	vii
LIST OF FIGURES	xiii
LIST OF TABLES	xvii
LIST OF ABBREVIATIONS	xx
PREFACE	xxii
CHAPTER 1: INTRODUCTION	1-52
1.1 CONCEPT OF REMOTE SENSING	1
1.2 BRIEF HISTORY OF REMOTE SENSING	2
1.3 TYPES OF REMOTE SENSING	4
1.3.1 Passive remote sensing	4
1.3.2 Active remote sensing	4
1.4 EMR IN REMOTE SENSING	5
1.5 INTERACTION OF EMR WITH ATMOSPHERE	6
1.5.1 Scattering	7
1.5.2 Absorption	7
1.6 INTERACTION OF EMR WITH THE EARTH'S SURFACE	8
1.6.1 Spectral reflectance curves	9
1.7 CHARACTERISTICS OF REMOTE SENSING IMAGE	10
1.7.1 Spatial resolution	11
1.7.2 Spectral resolution	11
1.7.3 Radiometric resolution	11
1.7.4 Temporal resolution	12
1.8 IMAGE RESTORATION	12
1.8.1 Geometric distortions and its correction	12
1.8.2 Radiometric distortions and its correction	14
1.8.2.1 Atmospheric correction	15

1.9 REMOTE SENSING APPLICATIONS	16
1.10 WHAT ARE LAND USE, LAND COVER, AND LAND CHANGE?	16
1.11 NEED OF LULC INFORMATION AND LAND CHANGE ANALYSIS	17
1.12 NEED OF LAND CHANGE MODELING	19
1.13 POTENTIAL OF REMOTE SENSING IN LULC AND LAND CHANGE STUDIES	20
1.14 RESEARCH QUESTIONS	21
1.15 RESEARCH OBJECTIVES	22
1.16 STUDY AREA	23
1.17 DATA USED	25
1.17.1 Collection of ground truth data	26
1.17.2 Collection of remote sensing data	26
1.17.3 Auxiliary Data	27
1.18 METHODOLOGY	29
1.18.1 Preprocessing of remote sensing images	30
1.18.2 Texture analysis	30
1.18.3 LULC classification scheme and accuracy assessment	32
1.18.4 Land change analysis, modeling and prediction	34
1.19 MOTIVATION OF STUDY	35
1.20 REVIEW OF LITERATURE	38
1.21 ORGANIZATION OF THESIS	49
CHAPTER 2: TEXTURE ANALYSIS OF DUAL POLARIMETRIC C-BAND SAR DATA FOR LAND USE AND LAND COVER CLASSIFICATION	53-80
2.1 INTRODUCTION	53
2.2 STUDY AREA	55
2.3 MATERIALS AND METHODOLOGY	56
2.3.1 Field data collection and identification of LULC classes	56
2.3.2 SAR data collection and preprocessing	57
2.3.3 Regions of interest (ROIs) and signature analyses of backscatter data of LULC classes	59

2.3.4	Extraction of texture features and selection of appropriate textural images	61
2.3.5	LULC classification using MLC based on different scenarios	63
2.3.6	Comparison of LULC classification results using different classifiers	64
2.3.6.1	MLC based classification	64
2.3.6.2	ANN based classification	65
2.3.6.3	RF based classification	65
2.3.6.4	SVM based classification	66
2.3.7	Assessment of classification accuracy	67
2.4	RESULTS AND DISCUSSION	68
2.4.1	Identification of suitable polarization and textural images	68
2.4.2	Comparison of LULC classification results among scenarios	70
2.4.3	Comparison of LULC classification results using different algorithms	75
2.5	CONCLUSION	78
CHAPTER 3: THE ROLES OF TEXTURAL FEATURES IN IMPROVING LAND USE AND LAND COVER CLASSIFICATION ACCURACY		81-104
3.1	INTRODUCTION	81
3.2	STUDY AREA	84
3.3	METHODOLOGY	85
3.3.1	Remote sensing data collection and preprocessing	85
3.3.2	Field data collection and map legend definition	86
3.3.3	Extraction of textural features	87
3.3.4	Selection of suitable textural features	88
3.3.5	SVM based LULC classification	88
3.3.6	Evaluation of LULC classification results	91
3.4	RESULTS AND DISCUSSION	92
3.4.1	Analysis of the best combination of textural features	92
3.4.2	Analysis of overall LULC classification results using textural features	97
3.4.3	Comparative analysis of overall LULC classification performance among multi-sensor and multi-resolution data	102

3.5 CONCLUSION	104
CHAPTER 4: DUAL POLARIMETRIC SAR DATA AT C-BAND FOR RICE CROP MAPPING USING DECISION TREE METHOD	105-130
4.1 INTRODUCTION	105
4.2 STUDY AREA	109
4.3 MATERIALS AND METHODOLOGY	110
4.3.1 Collection of satellite images and ground truth information	110
4.3.2 Preprocessing of satellite images	110
4.3.2.1 RISAT-1 image	110
4.3.2.1.1 Regions of interest for training and validation of classification algorithm	111
4.3.2.1.2 Backscattering response analyses of rice crop and other land cover features	112
4.3.2.2 Landsat 8-OLI image	114
4.3.3 QUEST DT algorithm for rice crop mapping	116
4.3.3.1. Variable selection	117
4.3.3.2. Split point selection	117
4.3.4 Assessment of classification accuracy	119
4.4 RESULTS AND DISCUSSION	121
4.4.1 Rice crop maps using RISAT-1 and Landsat 8-OLI images	126
4.4.2 Validation of rice crop maps using ROC curves	127
4.5 CONCLUSION	128
CHAPTER 5: GEOGRAPHICALLY WEIGHTED METHOD FOR ANALYSIS OF SPATIAL VARIATION IN CLASSIFICATION ACCURACY	131-148
5.1 INTRODUCTION	131
5.2 STUDY SITE AND MATERIALS	133
5.3 METHODOLOGY	134
5.3.1 OLSR	135
5.3.2 GWR	136
5.3.3 GWLR	138

5.3.4 Comparison of OLSR and GWLR	139
5.4 RESULTS	140
5.5 DISCUSSION	147
5.6 CONCLUSION	148
CHAPTER 6: LAND USE AND LAND COVER CHANGE	149-178
INVESTIGATION OVER A DECADE (2000-2014)	
USING EARTH OBSERVATION DATASETS	
6.1 INTRODUCTION	149
6.2 STUDY AREA	152
6.3 MATERIALS AND METHODOLOGY	152
6.3.1 Image preprocessing and data preparation	153
6.3.2 Spectral separability analysis	154
6.3.3 LULC classification procedure	156
6.3.4 Assessment of LULC classification accuracy	157
6.3.5 LULCC detection and analysis	158
6.3.6 Analyses for statistical significance of LULCC	158
6.4 RESULTS AND DISCUSSION	159
6.4.1 LULC classification results using multi-temporal images	159
6.4.2 Accuracy assessment of LULC classification results	163
6.4.3 LULC distribution	166
6.4.4 Assessment of LULCC	169
6.5 CONCLUSION	176
CHAPTER 7: MODELING AND PREDICTION OF SPATIO-TEMPORAL	179-210
LAND USE AND LAND COVER DYNAMICS USING	
GEOSPATIAL TECHNIQUE	
7.1 INTRODUCTION	179
7.2 STUDY AREA	181
7.3 MATERIALS AND METHODOLOGY	182
7.3.1 Pre-processing of remote sensing images	182
7.3.2 LULC classification and accuracy assessment	183
7.3.3 Analysis of LULCC	183

7.3.4 Prediction of future LULC scenarios	184
7.3.4.1 ST-MC model	184
7.3.4.2 CA-MC model	186
7.3.4.2.1 Generation of suitability maps for LULC classes	188
7.3.4.3 MLP-MC model	189
7.3.4.3.1 Selection of transitions and variables for model development	190
7.3.4.3.2 Transition potential modeling	193
7.3.5 Validation of predicted results	193
7.4 RESULTS AND DISCUSSION	194
7.4.1 LULC maps and accuracy assessment	194
7.4.2 Analysis of LULCC	196
7.4.3 Spatial trend of change analysis	201
7.4.4 ST-MC model based prediction	202
7.4.5 CA-MC model based prediction	202
7.4.6 MLP-MC model based prediction	203
7.4.7 Validation and selection of model	205
7.4.8 Prediction and analysis of future LULC scenarios for 2030 and 2050 using MLP-MC model	206
7.5 CONCLUSION	208
CHAPTER 8: CONCLUSIONS AND FUTURE RESEARCH	211-214
8.1 CONCLUSIONS	211
8.2 FUTURE RESEARCH	213
REFERENCES	215-240
LIST OF PUBLICATIONS	241-242

LIST OF FIGURES

Figure No.	Description	Page No.
1.1	Remote sensing process	2
1.2	Remote sensing processes (a) passive; (b) active	5
1.3	Electromagnetic spectrum	6
1.4	Electromagnetic spectrum useful for remote sensing	8
1.5	Spectral reflectance curves for soil, vegetation and water	10
1.6	Geographical location of the study area as viewed on Landsat 8-OLI image in FCC	25
2.1	Location map of the study area as viewed on RISAT-1 hybrid FCC image (<i>Red-HV, Green-HH, Blue-HH+HV</i>)	56
2.2	Overview of the methodology adopted for this study	58
2.3	Scatter plot for HH polarization	60
2.4	Scatter plot for HV polarization	60
2.5	Comparison between statistical values of different LULC classes using HH and HV polarizations	61
2.6	Classified LULC maps based on (a) MLC, (b) ANN, (c) RF, and (d) SVM algorithms	76
3.1	Location map of the study area as viewed on LISS-IV FCC image	84
3.2	Overview of the methodology adopted for this study	91
3.3	Comparison of (a) LISS-IV B3 (Red), (b) LISS-IV band 4 (NIR), (c) textural image obtained using the measure 'entropy' on B3 (Red) and a window size of 13×13 pixels and (c) textural image obtained using 'mean' on B4 (NIR) and window size of 13×13 pixels	94
3.4	Comparison of (a) LISS-III B4 (NIR), (b) LISS-III B5 (SWIR), (c) textural image obtained using the measure 'mean' on B4 (NIR) and a window size of 9×9 pixels, and (c) textural image obtained using 'dissimilarity' on B5 (SWIR) and window size of 9×9 pixels	95

3.5	Comparison of (a) Landsat 8-OLI B5 (NIR), (b) textural image obtained using the measure 'mean' on B5 (NIR) and a window size of 9×9 pixels, and (c) textural image obtained using 'dissimilarity' on B5 (NIR) and window size of 9×9 pixels	96
3.6	Comparison between RISAT-1 C-band HH and HV images and corresponding textural images; (a), (b), and (c) are HH image and HH-derived MEA7 and CON3 textural images; (d), (e), and (f) are HV image and HV-derived MEA7 and CON3 textural images	96
3.7	Comparison between Sentinel-1A C-band VV and VH images and corresponding textural images; (a), (b), and (c) are VV image and VV-derived VAR11 and CON3 textural images; (d), (e), and (f) are VH image and VH-derived VAR11 and CON3 textural images	97
3.8	Classified LULC maps based on SVM algorithm (a) LISS-IV, (b) LISS-III, (c) Landsat 8-OLI, (d) RISAT-1, and (e) Sentinel-1A	102
4.1	Location map of the study area as viewed on RISAT-1 Hybrid FCC image (<i>Red</i> -HH, <i>Green</i> -HV, <i>Blue</i> -HH-HV)	109
4.2	The ROIs used for training	112
4.3	Comparison between statistical values of different land cover features using HH, HV, ratio, and difference images	113
4.4	The working flow chart for rice crop mapping	119
4.5	Comparison between histograms of different land cover features in four images: (a) HH polarization, (b) HV polarization, (c) ratio image, and (d) difference image	124
4.6	Separability index for class pair separation by various features (HH, HV, ratio, and difference) using RISAT-1 image	125
4.7	Separability index for class pair separation by various features (LSWI, NDVI, and $(NDVI + EVI)/2 - LSWI$) using Landsat 8-OLI image	125
4.8	DT algorithm based classified maps of (a) RISAT-1, and (b) Landsat 8-OLI images	126

4.9	The ROC curves for the rice crop area mapping using (a) RISAT-1, and (b) Landsat 8-OLI images	128
5.1	Location of the study site with the validation points (●) as viewed on FCC of LISS-IV sensor image	134
5.2	GWLR based maps of spatial variation in UA of landscape categories	143
5.3	GWLR based maps of spatial variation in PA of landscape categories	144
5.4	GWLR based maps of spatial variation in OA of landscape categories	144
6.1	The structure of a three-layer ANN	157
6.2	MLC based LULC classification for years (a) 2000, (b) 2005, (c) 2009, and (d) 2014	160
6.3	ANN based LULC classification for years (a) 2000, (b) 2005, (c) 2009, and (d) 2014	161
6.4	SVM based LULC classification for years (a) 2000, (b) 2005, (c) 2009, and (d) 2014	162
6.5	The distribution of LULC classes in different years	167
6.6	The distribution of built up class in different years	167
6.7	Diagrammatic illustration of LULCC (in km ²) during the period 1, period 2, period 3, and period 4	173
6.8	The change values for LULC classes (in %) estimated through SVM during the period 1, period 2, period 3, and period 4	173
6.9	(a) The areas that converted from one LULC class into other, (b) only the areas that changed from agricultural land into built up during the period 2000-2014	174
7.1	Markovian conditional probability images	186
7.2	Suitability images of each LULC class	189
7.3	Explanatory variables (a) DEM, (b) slope, (c) aspect, (d) distance from built up, (e) distance from major roads,	192

	(f) distance from rail network, and (g) Empirical likelihood image	
7.4	Constraints used (a) major roads, (b) rail network	192
7.5	Classified LULC maps of years (a) 1988, (b) 2001, and (c) 2015	196
7.6	Gains and losses of LULC classes (in % change) during period 1, period 2, and period 3	199
7.7	Contributions to net change in (a) built up and (b) agricultural land (in % change)	200
7.8	spatial trends of change in built up and agricultural land during (a) period 1, (b) period 2, and (c) period 3	201
7.9	Predicted LULC maps of years (a) 2030, and (b) 2050	207

LIST OF TABLES

Table No.	Description	Page No.
1.1	Major characteristics of multi-source remote sensing data	28
1.2	Multi-temporal remote sensing data	29
1.3	Texture measures used in the study	31
2.1	Preparation of different scenarios for LULC classification using RISAT-1 data at C-band	64
2.2	Number of pixels in each class type used for training and testing of MLC, ANN, RF, and SVM algorithms	68
2.3	Identification of textural images used for LULC classification	70
2.4	MLC based comparison of LULC classification results among the individual band, textural images, and the combination of individual band and related textural images for HH polarization image	72
2.5	MLC based comparison of LULC classification results among the individual band, textural images, and the combination of individual band and related textural images for HV polarization image	72
2.6	MLC based comparison of LULC classification results among the Individual band, textural images, and the combination of individual band and related textural images for NB polarization image	73
2.7	MLC based comparison of LULC classification results based on different combinations of HH and HV, or HH, HV, and NB and their combinations with corresponding textural images	74
2.8	Comparison of LULC classification results obtained from different classification algorithms based on the combinations of HH, HV, and corresponding textural images	77
3.1	Number of training and testing pixels for the SVM algorithm	87
3.2	Selected best combination of textural features for LULC classification	93

3.3	Comparison of accuracy assessment results using LISS-IV image	99
3.4	Comparison of accuracy assessment results using LISS-III image	100
3.5	Comparison of accuracy assessment results using Landsat 8-OLI image	100
3.6	Comparison of accuracy assessment results using RISAT-1 image	101
3.7	Comparison of accuracy assessment results using Sentinel-1A image	101
3.8	Summary of overall classification accuracies for multi-sensor data	103
4.1	A confusion matrix showing the proportion (or number) of pixels in observed map versus predicted map. here 'a' represents true positives; d represents true negatives; b represents false positives; and c represents false negatives	121
4.2	Mean and SD for raw and filtered images of HH polarization	122
4.3	Mean and SD for raw and filtered images of HV polarization	123
4.4	The classification accuracies of Landsat 8-OLI and RISAT-1 images	127
4.5	Area statistics comparison of land cover features	127
5.1	Confusion matrix comparing reference and classified landscape categories, showing 87.48% overall agreement	141
5.2	Summary of the variation in GWLR representing UA, PA and OA for various landscape categories. IQR indicates the variability in probability among pixels. 1 st and 3 rd quartiles represent the 25 th and 75 th percentile probabilities	141
5.3	Comparison of GWLR and OLSR techniques for estimating spatial variation in overall accuracies of various landscape categories	146
6.1	Spectral separability analysis between LULC classes using J-M distance method	155
6.2	Accuracy assessment of LULC classification results using MLC	164
6.3	Accuracy assessment of LULC classification results using ANN	164
6.4	Accuracy assessment of LULC classification results using SVM	165
6.5	LULC distribution for years 2000, 2005, 2006, and 2014 using MLC, ANN, and SVM algorithms (*Percentage area is given in brackets)	168

6.6	Amount of LULCC during period 1 (2000-2005)	169
6.7	Amount of LULCC during period 2 (2005-2009)	169
6.8	Amount of LULCC during period 3 (2009-2014)	170
6.9	Amount of LULCC during period 4 (2000-2014)	170
6.10	Statistics of paired samples	175
6.11	Correlation between paired samples	175
6.12	Paired samples t-test	176
7.1	Markov transition probabilities of change among LULC (1988-2001) for 2015	185
7.2	Transition area matrix (1988-2001)	185
7.3	Area distribution of LULC of years 1988, 2001 and 2015	195
7.4	Accuracy assessments of classified LULC maps of years 1988, 2001 and 2015	195
7.5	Amount of changes in LULC during period 1, period 2, and period 3	198
7.6	Annual rate of change during period 1, period 2, and period 3	200
7.7	Transition probabilities of changes among LULC for Markov chain (1988-2001) for year 2015 in MLP modeling	204
7.8	Transition probabilities of changes among LULC for Markov chain (2001-2015) for year 2030 in MLP modeling	204
7.9	Transition probabilities of changes among LULC for Markov chain (2001-2015) for year 2050 in MLP modeling	205
7.10	Kappa index statistics for ST-MC, CA-MC, and MLP-MC based prediction results	206
7.11	Area distribution of LULC of predicted years 2030 and 2050	206

LIST OF ABBREVIATIONS

Syntax	Description
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AWiFS	Advanced Wide Field Sensor
CA-MC	Cellular Automata-Markov chain
CSI	Classification Success Index
DT	Decision Tree
EMR	Electromagnetic Radiation
ETM+	Enhanced Thematic Mapper plus
EVI	Enhanced Vegetation Index
FCC	False Colour Composite
GIS	Geographic Information System
GLCM	Gray Level Co-occurrence Matrix
GPS	Global Positioning System
GWLR	Geographically Weighted Logistic Regression
GWR	Geographically Weighted Regression
ICSI	Individual Classification Success Index
IQR	Inter-Quartile Range
IR	Infrared
LISS	Linear Imaging Self-Scanner
LSWI	Land Surface Water Index
LULC	Land use and land cover
LULCC	Land use and land cover changes
MAH	Hellden's Mean Accuracy
MAS	Short's Mapping Accuracy

MC
MLC
MLP-MC
NDVI
OA
OLI
OLSR
PA
QUAC
QUEST
RADAR
RF
RISAT-1
ROC
ROI
RS
RSS
SAR
SSI
ST-MC
SVM
TD
TIR
TM
UA
UTM
WGS-84

Markov Chain
Maximum Likelihood Classifier
Multi-Layer Perceptron-Markov chain
Normalized Difference Vegetation Index
Overall Accuracy
Operational Land Imager
Ordinary Least Square Regression
Producer's Accuracy
Quick Atmospheric Correction
Quick, Unbiased, Efficient, Statistical Tree
Range Detection and Ranging
Random Forest
Radar Imaging Satellite-1
Receiver Operating Characteristic
Region of Interest
Remote Sensing
Residual Sum of Squares
Synthetic Aperture Radar
Speckle Suppression Index
Stochastic-Markov chain
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World Geodetic System-1984

PREFACE

Land use and land cover (LULC) are assumed to be a fundamental constituent of the terrestrial ecosystem. It is an outcome of various natural processes and anthropogenic activities. Accurate and up-to-date LULC information is vital to scientists, planners, and decision-makers in forming strategies regarding economic, demographic and environmental issues from regional to global level. This information also assists to understand the impacts of natural phenomena better and convene the increasing demands for necessary human requirements and welfare. The changes in LULC termed as the alteration of Earth's terrestrial ecosystem by various human or natural activities. These changes are the comparatively new addition to the core concerns of global environmental changes research including climate change, biodiversity loss, global warming and the pollution of water, soils, and air. Remote sensing technologies, especially space-borne sensors offer a tremendous wellspring of information for concentrate understanding of earth's surface and its dynamics. It has been emerged as a powerful tool in deriving LULC information and its spatio-temporal distribution. However, LULC classification and information extraction from remote sensing images still remains a challenging task because of frequent cloud cover, heterogeneity of landscapes and varied climatic zone in countries like India. In the last few decades, the remote sensing technologies have evolved dramatically to include a series of sensors operating at a wide range of imaging scales with potential attention and significance to researchers. The aim of thesis presented here are: (1) to establish a robust classification process in improving LULC mapping accuracy by using multi-source remote sensing data (i.e. optical data, SAR backscatter) combined with textural information, (2) to investigate the

feasibility of dual-polarimetric SAR data at C-band for rice crop mapping, (3) to estimate the spatial variation in accuracy measures of remote sensing image classification, (4) to assess the changes in LULC using multi-temporal remote sensing images, and (5) to model, simulate and predict the changes in LULC over a period by applying an integrated approach of remote sensing, geographic information system and land change modeling tools.

The LULC classification using remote sensing data has drawn a lot of attention with the launch of Landsat series satellites in the 1970s. Several classification algorithms have been developed and utilized for LULC classification using multi-source remote sensing data. The selection of a classification algorithm is always vital for successful and accurate mapping of land surface features. In spite of many studies in the field of remote sensing image classification, another current research interest is the reasonable selection of suitable input variables, which may have the same importance as the selection of classifier. Textural features as supplementary information can be incorporated into image bands in improving LULC classification accuracy. The quality of thematic maps derived from remotely sensed data also needs to be studied and requires enhanced methods or tools for estimating and describing the spatial distribution of errors in complex landscape mapping. The timely, accurate, and reliable LULC information provided by remote sensing technologies can be applied efficiently to monitor and analyze the past and current trends as well as to predict future LULC scenario. The multi-source remote sensing images namely the Linear Imaging Self-Scanner-IV (LISS-IV), Linear Imaging Self-Scanner-III (LISS-III), Landsat 8-OLI (Operational Land Imager), Advanced Wide Field Sensor (AWiFS), Radar Imaging Satellite (RISAT-1) and Sentinel-1A SAR data were acquired covering Varanasi district of Uttar Pradesh, India. Also, multi-temporal remote sensing images of Landsat 5-Thematic Mapper

(TM), Landsat 7-Enhanced Thematic Mapper Plus, and Landsat 8-OLI (Operational Land Imager) were acquired over a period of 1988-2015 to study LULC changes. The thesis begins with a brief introduction and state of the art explaining current trends on classification and mapping of LULC using multi-source remote sensing images and approach.

In the first phase, the research work focusing on the incorporation of textural features into spectral/radiometric images for LULC classification is presented subsequently, followed by the comparison of different classification algorithms. The research work provides explicitly a comprehensive evaluation of textural features extracted from the multi-source remote sensing data to examine how the varying spatial resolutions of different sensor image affect the selection of the textural component. The results show the efficacy of incorporating textural features into spectral or radiometric images in improving the LULC classification accuracy than individual datasets. The ability of textural features in reducing speckles and inherent heterogeneity within the same LULC type makes it significant for improved LULC information extraction, especially in case of the SAR and high spatial resolution multispectral LISS IV data. The Support Vector Machine (SVM) was found to provide more reliable and realistic results in comparison to the Artificial Neural Network (ANN), Random Forest (RF), and Maximum Likelihood Classifier (MLC) algorithms for LULC classification of remote sensing images. However, the performances of ANN, RF, and MLC were also found useful. A study was also conducted to explore the feasibility of RISAT-1 SAR data at C-band in delineating rice crop fields from other land cover features using Decision Tree (DT) classifier. The performance of DT classifier was found reasonably good for mapping spatial distribution of rice crop area accurately. The results were further compared with

Landsat 8-OLI optical sensor-derived rice crop map and found very good spatial agreement between both the outputs.

In the second phase, a geographically weighted method was used in combination with logistic regression for producing and visualizing the spatial variation of remote sensing image classification accuracy. This work showed how the logistic regression can be applied to create the probabilities of User's Accuracy (UA), Producer's Accuracy (PA), and Overall Accuracy (OA). The geographically weighted extension to logistic regression generates spatial distributions describing the variation of these probabilities. The results demonstrated that the geographically weighted method could offer additional and valuable insights for examining the spatial variation in the measures of classification accuracies varied across geographical space.

In the third phase, an integrated approach of remote sensing images, geospatial analysis, and modeling, along with the assortment of socio-economic factors and environmental variables was employed to study the changes in LULC and predict the future scenario in Varanasi district of Uttar Pradesh, India. In the first part of this research work, the post-classification method was employed to assess the changes in LULC occurred between 2000 and 2014. A paired samples t-test was also performed to test whether the changes are statistically significant or not between study periods. In the second part, three Markov chain-based hybrid models namely Stochastic-Markov chain (ST-MC), Cellular automata-Markov chain (CA-MC) and Multi-layer perceptron-Markov chain (MLP-MC) were evaluated and compared to model the spatio-temporal changes in LULC between 1988 and 2015 and predict the future scenarios for 2030 and 2050. The t-test only states that the changes do not correspond to a significant quantity statistically, even though LULC changes occurred in

study periods. The outcomes of this research exhibited the overall constant increase of built up area and a considerable reduction in agricultural land. The results also show the potentiality of an integrated MLP-MC model for better understanding of spatio-temporal dynamics and predicting future scenario in Varanasi district of Uttar Pradesh, India. Therefore, the findings of this study might support the planners and decision-makers for sustainable management and development of this area.

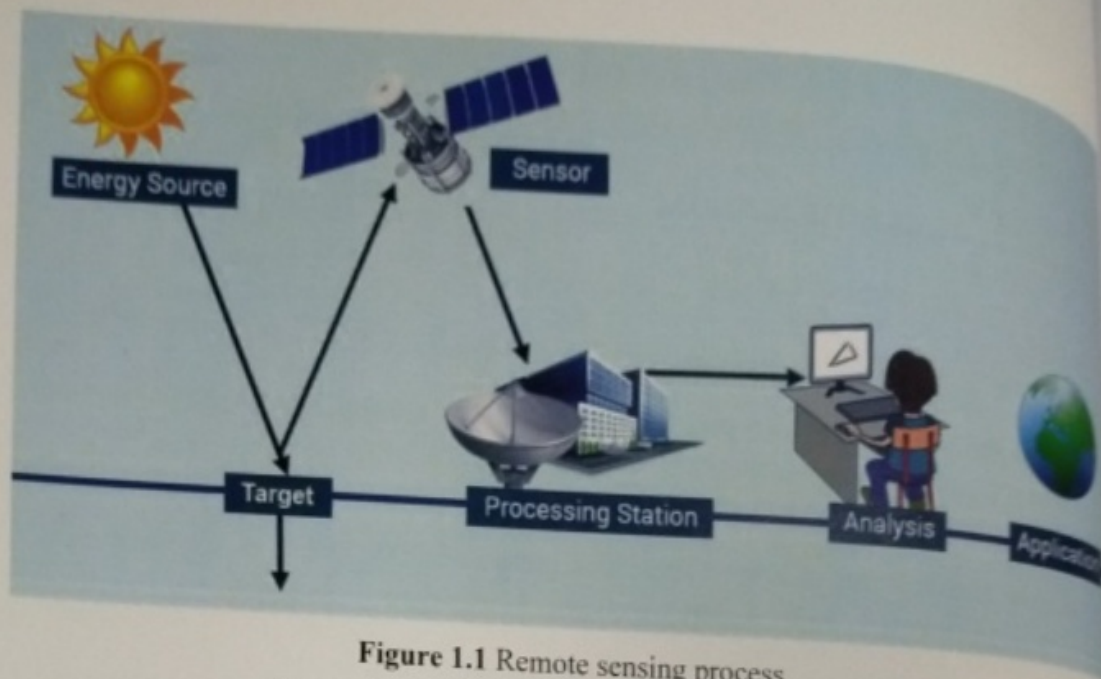


Figure 1.1 Remote sensing process
 (Source: <http://byjus.com/physics/remote-sensing>)

1.2 BRIEF HISTORY OF REMOTE SENSING

Remote sensing has been with us for the longer time. In the 1600s, Galileo used optical enhancements to survey celestial bodies. In 1858, Parisian photographer Gaspard Felix Tournachon used his balloon to made photographs over Bievre, France. In later years, kites, messenger pigeons, rockets and unmanned balloons were also used for the acquisition of images. The modern regime of remote sensing arose with the development of aircraft and satellites. The field of remote sensing has experienced some major changes during the period from 1960-2010.

The word remote sensing was first introduced in 1960s and before that, it was generally termed as aerial photography. During 1960s to 1970s, the airborne platforms carrying remote sensing devices were moved to the spaceborne platforms or satellites. It facilitates observations across larger extents of Earth's surface than is possible by traditional ground-based observations at regular interval. During the 1960s, National Aeronautics and Space