COMPUTATIONAL INTELLIGENCE APPROACH FOR REMOTE SENSING APPLICATION: NATURAL RESOURCE MANAGEMENT

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CERTIFICATE

This is to certify that the research work embodied in the thesis **"COMPUTATIONAL INTELLIGENCE APPROACH FOR REMOTE SENSING APPLICATION: NATURAL RESOURCE MANAGEMENT"** is submitted to Jawaharlal Nehru University for the award of the degree of **DOCTOR OF PHILOSOPHY**. The work is original and has not been submitted in part or in full for any other degree or diploma in any other university or institution.

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Introduction

Chapter 1

Introduction

In human terms, a resource is anything we get to satisfy our needs, aspirations and desires. Management of natural resources is of paramount importance in the present context. Zimmerman (1951) defines resources "as means of attaining ends, the ends being the satisfaction of individual wants and attainment of social objectives". Natural resources are properties of the physical environment and are considered wise for satisfying human wants (Johnston et al., 1994).

Natural resources can be classified in various ways; one of the commonest of the classification is based on the availability of resource in time. According to it, natural resource can be classified into Renewable Resources, Potentially Renewable Resources and **N**on-Renewable Resources.

Potential Resources depend upon availability of technology which can help its transformation by value addition. Natural resources are subdivided into non-renewable and renewable. Non- renewable resources have evolved over geological periods of time and cannot be replenished in terms of human life span intervals and thus are referred to as non-renewable. Renewable resources are being replenished at a faster rate either naturally or by humans e.g. animal, plants, soil and wind etc.

Proper management of natural resource is especially important for sustainable development and sustenance of humanity, which by now is the single largest user of natural resources. For sustainable use of the resources it is of foremost importance to know the resource and then apply management practices to plan and manage its use.

Natural Resource Management involves manipulation of resources to preserve or to supply products on a sustained basis (Knight and Bates, 1995). It revolves around but is not limited to the manipulation and analysis of many different types of spatial data. Proper management of the natural resources also brings a balance in resource use as well as minimizing environmental cost of resource exploitation.

The main objective of natural resource management is to create a balance between cost-benefit ratio including environmental and social costs. Such practice will achieve socio-economic development of human society through sustainable use of the resource (Singh, 1999).

In the given circumstances where the greatest dilemma is the population growth and the economic development vis-à-vis protection of our depleting resource base, the developmental planning based on the philosophy of sustainable development can only be a viable option. Such development philosophy meets the needs of the present without compromising the ability of future generation to meet their own needs (UNEP, 1989). It also implies the maintenance, rational use and enhancement of the natural resources base that underpins ecological resilience and economic growth (UNEP, 1989).

1.1. Traditional Approach to Natural Resource Management

Natural resource management involves manipulation of the resource to preserve or supply products on a sustained basis (Knight and Bates, 1995). Traditional or non-spatial approaches rely on data collection from ground based sample surveys. Data is stored in spreadsheets or databases with a Management Information System to create and/or extract information for decision making.

Such approaches have various shortcomings. These include, no-verification of surveyed data, poor visualization, inability to track resources spatially, inability to visualize the scenario in a holistic manner. Therefore, the decision-making process is often time consuming, erroneous with large impact on environment and unsustainable resulting in a constrained decision-making system.

1.2. Geo-Information Sciences and Earth Observation

With the advent of recent advancement in Earth Observation techniques and ever-increasing earth resource observation platform, Remote Sensing and Geographic Information System for Natural Resource Management have become highly pertinent domain of knowledge. Remote Sensing is often defined as “the art and science of extracting information from a target without being in physical contact” (Barret and

Curtis, 1982; Sabins, 1997). Key advantages to use Earth Observation for Natural Resource Management include holistic coverage, temporal repetition, spectral resolution in electromagnetic wavelength bands otherwise invisible to human eyes. Digital Data derived from Earth Observation platform is commonly stored in Raster format and is compatible with computing infrastructure (Drury, 1986; Wirdum, 1993; Sabins, 1997; Mukherjee et al., 2006).

Geo-Information Sciences on the other hand is part of a system comprised of Hardware, Software, Data, Model and Skilled Human Resource. This system provides a way to store, manipulate, analyze, visualize and share data and information. Various analytical tools in GIS are complementary to Remote Sensing System however, they have generally more advance set of decision making tools (Aronoff, 1989; Worral, 1990; Morain, 1999). Thus, GIS enables us to process the data in terms of the people’s need as well as physical realities, hence play very significant role in management of natural resources. GIS is increasingly becoming more and more popular and useful tool in healthcare management and public utilities and services (Pant et al., 2009; Pareta et al., 2009; Dhiman et al., 2011).

1.2.1. Earth Observation Sciences in Natural Resource Management

Various advantages to use Remote Sensing data include synoptic coverage, data collection in inaccessible area, data collection using diverse EM spectrum, 3D data collection directly through LIDAR and indirectly through Stereo-Images all weather coverage using Radar. Although, it is expensive to launch Earth Observation (EO) mission, the cost of data over the period of mission remains economical (Mukherjee, 2004). Data collection through Earth Observation Sensors are primarily digital in nature, hence they utilize the advanced computer technology both in term of hardware and software (Tounshend, et al., 1981).

In the past decade, EO data collection has increased so much that it is no more a limiting factor. The focus is now at improving technology to effectively consume the data meeting its temporal coverage to provide better and timely information for decision makers. When these Remote Sensing data are integrated with other spatial and statistical information the GIS becomes valuable tool in the hand of managers and planners.

From earlier aerial photography based EO to the current state of art LIDAR/RADAR platform (air borne/space borne) provide a limitless opportunity to directly access 3D data for better resource management.

1.2.2. GIS in Natural Resources Management

Geographic Information System is an important tool to manage natural resource. GIS provides data storage, retrieval, manipulation, analysis, visualization and sharing of data and development of Management Plans. GIS also enable Spatial Decision Support System (SDSS) which provide powerful set of tools that help in understanding alternative resource use plans and evaluation of each with respect to their impact on environment and socio-economic condition of the area. GIS also help in understanding underlying patterns, spatial biases (autocorrelation), spatio-temporal trends thereby enabling decision maker to provide optimal solution e.g. spatio-temporal change in climate trend can help decision maker select suitable adaptive and/or mitigation strategies while creating a resource plan.

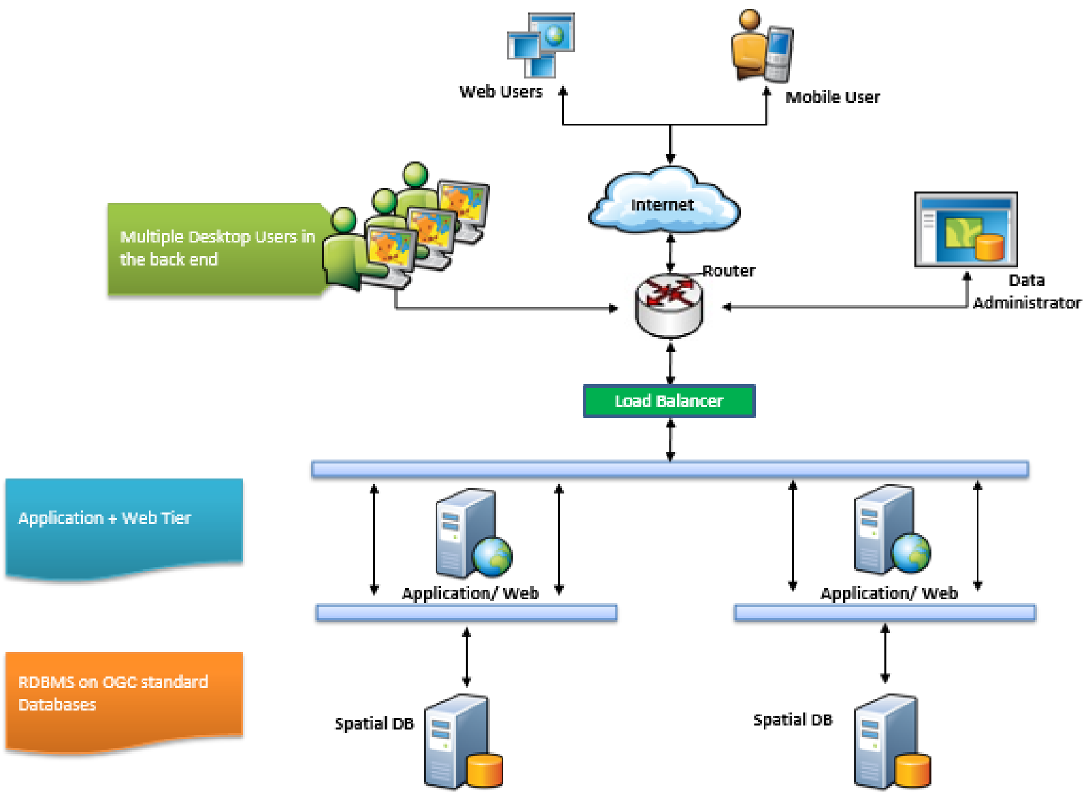

Figure 1.1: An Overview of n-tier Distributed Enterprise GIS Architecture

Another key advantage GIS provide is serving data, processing information, analytics, solution and platform in a distributed environment providing capability to rightful user at right time. Current WebGIS systems (Figure 1.1) are based on Services Oriented Architecture (SOA) using Open Geospatial Consortium Standards (OGC) providing data for viewing (WMS, WMTS), editing (WFS-T), geo-processing (WPS) to a variety of users over different devices thereby effecting the proper use of GIS. For Natural Resource Management, this is a highly valuable property. While manager sits at zonal or regional offices to depend on field teams to collect and update information. The tasks of data collection, monitoring of survey teams, data assimilation to central Geodatabase, analysis, visualization, sharing of reports, maps and applications to the field team can be achieved by a proper implementation of a WebGIS. Further, these solutions are now available as cloud services to the end user. NRSC’s Bhuvan Portal is one such example of a WebGIS implemented with SoA.

Further, all GIS platform rely on Databases as data container for all type of data including spatial (raster/vector/3D), and non-spatial (Tables/flat files). Such a storage help in creating relationship between dataset further enabling the perspective of a decision maker, who can implement various what if, scenarios (Shrivastava, 1992). By using the database integration capabilities of GIS, planners and resource managers gain a better understanding of the complex interrelationship between physical, biological, cultural, economic, and demographic considerations around specific resources. Access to this information and its understanding makes it essential in making sound resource-use decisions. This ensures balanced management and use of the resources.

1.2.3. Integration of Geo-Information and Earth Observation Sciences

There is a significant overlap in functionality between GIS and Remote Sensing. As both systems work on spatial data while remote sensing focuses more on raster based analytics, GIS is equally amenable to both Raster and Vector. Remote Sensing is primarily aligned to provide information extraction from EO images, GIS specializes in consuming such analytical output and adds value by incorporating information and data from other sources.

For a natural resource manager, it is important to understand that data from EO platform will be the primary source of data gathering. Such data shall be pre-processed using Remote Sensing software to extract information. While GIS system will be used to store such data for manipulation, retrieval, reporting, storage, visualization, alignment with other data sources (spatial or non-spatial), collection of data from mobile devices, reporting and sharing information with various stake holders.

This way a combination of Remote Sensing and GIS will provide an effective tool in the hands of a resource manager and planner. Remote sensing data plays a role in primary data collection and analysis, while GIS can combine these outputs with other sources of data including data from other sensor, ground truth data, field collected attribute of environment, real time data feed from environmental sensor etc. The complementing role of these two disciplines has broadened their utility for natural resource management (Meaden and Kapetsky, 1991).

1.2.4. Computational Intelligence Approach

The current generation of earth observation sensors is producing data with great potential for use in scientific and technological investigations in very large and ever-increasing quantities. Whilst such data provide a considerable resource with which to address many fundamental environmental issues, they also present new challenges of the data processing and data interpretation. These challenges must be tackled if the full potential of the data is to be realized. Not only is this necessary for efficient use of the present data, but it also provides an important constraint on the need for, and an influence on the design of, instruments proposed for future sensor platforms.

Traditionally, image classification is performed via statistical classifiers. There can be two types of such classification: Supervised and Un-supervised. The former where *a priori* understanding of distribution of spectral data related to an information class is provided through a set of training pixels. The classifier uses the pixels in the training set to estimate the behavior of the pixel population representing the class. To easily model this, distribution of data is assumed to be normal. The whole purpose of the classification is to assign test pixel a class based on its affinity to the training sets. The affinity can be based using Euclidean distances or probabilistic measures. In case of unsupervised classification, no training set is provided. The algorithm randomly seeds pixels to a number of classes (number of classes is an input) and tries to allocate all pixels to these randomly picked seeds. While doing so, it can change the initial seed with an updated one (Abrams et al., 1985; Mukherjee, 2005).

The statistical classifier assumes a data distribution model and uses statistical distance to separate the pixels in the feature space to various classes. This model has several limitations, including non-conformity of the real data with any defined data distribution model. Generally, spectral information must be converted to information class. The spectral data linked to a information class may or may not follow a normal distribution.

To overcome this, an interesting methodology came into existence. Here, impetus is given for automated information extraction from remote sensing data (Abrams et al., 1985; Mukherjee, 2005). The underlying approach is to use the properties of human mind, motivated by the realization that the human brain is very efficient at processing vast quantities of data from a variety of different sources. Neurons in the brain receive inputs from other neurons and produce an output (if the sum of the inputs is above a certain threshold), which is then passed on to other neurons.

For quite some time now, it has been recognized that a mathematical approach based on the actions of biological neurons may be implemented to process and interpret many different types of digital data (Rosenblatt, 1958). While it is not possible or desirable to reproduce the complexity of the human brain on a computer, artificial neural networks that are based on the architecture of simple processing elements like neurons are proving successful for a wide range of application, including processing and interpreting remotely sensed data.

This type of image classifier attempts to replicate the kind of synthesis done by human analyst using the visual interpretation process. Accordingly, they tend to be much more complex and computationally intensive. The process is similar to the way we do visual interpretation of an image, which involves the categorization of image pixels on the basis of their spatial relationship with pixels surrounding them. These classifiers can consider aspects such as image texture, pixel proximity, feature size, shape, directionality, repetition and context.

In this context, neural networks are an artificial intelligence (AI) technique and, therefore are successor to the family of expert systems and knowledge–based classifiers.

1.3. Problem Statement

With advent of Geo-Information sciences, a large number of natural resource management satellite missions are currently operational. Data not being a limiting factor, the challenge is to find improved and efficient methods for information extraction.

Statistical classifiers while using underlying premise of normal distribution of spectral data, were found not effective dealing with information class which falls within multiple spectral classes or where spectral data does not follow normal distribution. This challenge of resolving spectral classes in the feature space with no-prior knowledge of data distribution is handled more efficiently with Artificial Neural Net.

In the rapidly developing urban environment, the growth of impervious land cover surpasses all the other land cover types resulting in degradation of environment and living conditions of the cities. Delhi, the capital city of India, shares a similar fate. With rapid urbanization, it keeps on encroaching the natural land cover types. The impact of these encroachments is most severe at the Yamuna flood plain passing through the North-North East of the city. Various image classification strategies including Statistical, Decision Support System based image segmentation and Artificial Neural Net were applied to understand the extent and rate of encroachment of Yamuna flood plain.

In rural and semi-urban environment where cropland is the major land cover type, plantations are becoming common. Plantations as intensive farming or along with other crops are found to be part and parcel of rural India. These Agroforestry initiatives not only provide additional income but support overall health of the ecosystem. In a case study, we use Computational Intelligence approaches to efficiently map the land cover in training and testing site in Haridwar district of Uttarakhand. Subsequently we check the efficacy of the classification approaches by comparative accuracy assessment. The training neural nets were then used for an additional area to test its generalization capability.

1.4. Scheme for Natural Resource Management

In the present study, Statistical and AI based classification approaches shall be used to address Natural Resource Management Challenges. The results shall be compared to understand efficacy of each method. Flood plains of river provide various environmental services including ground water, surface water, rejuvenation of the basins with fresh sediments and biodiversity augmentation. The rapid encroachment of Yamuna Flood Plain in Delhi shall be modelled using statistical classifier as well as AI. Initially, the study maps the existing various land cover classes over the study area on a decadal temporal dataset. Based on the ground truth data and field data collection accuracy assessment of various approaches and comparisons are also conducted.

A similar approach is used to map land cover in Haridwar district (Uttarakhand, India). The focus is to map plantations as part of Agroforestry. Various parameters considered in the present study for natural resource management include (i) hydrology or water resources, (ii) land use/land cover pattern, (iii) geology and geomorphology, (iv) demography or human resources, (v) bio-resources, (vi) climate, and (vii) topography.

1.5. Research Objectives

- Comparative assessment of Neural Network based classification models (e.g. Multi-layer perceptron, Artificial Immune Networks.) with statistical classification approaches (e.g. Maximum Likelihood Classification).
- Implementation of Neural Net based approach for extraction of natural resource management information in Haridwar district of Uttarakhand.
- Implementation of Neural Net based approach for extraction of impermeable surfaces to detect encroachment in Yamuna River Flood plain in Delhi.
- To develop the trained neural network model and verify the generalization potential of the same by applying it in other areas.

Chapter 2

Review of Literature

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Review of Literature

This chapter presents a succinct review of pertinent literature on the recent advances in Artificial Intelligence (AI) and its various approaches applied in data interpretation for Remote Sensing using Geographical Information System (GIS). According to Luger (2002), AI is defined as “the branch of computer science that is concerned with the automation of intelligent behavior”. This is a popular definition bundled with prejudice of science which will one day take on the humanity. AI implementation can be segmented into three stages based on the its application in information extraction. These are Rule based system, Machine Learning and Contextual Adaptive System. Following section briefly discusses these stages.

Stage-wise Categories of Artificial Intelligence

a) **Rule Based System:** Here domain experts help codify knowledge about their domain of expertise and characterize it into a set of rules which can be processed by computers. The computer can also study the implication of those rules. Decision Support Systems, Knowledge Classifiers belong to this category of systems. These systems enable reasoning to a narrowly defined domain but they lack learning capabilities and poor handling of uncertainty. They are logical but not perceptive. Even with disadvantages, these are relevant systems with simple decision-making.

b) **Machine Learning:** These methods employ probabilistic technique and Statistical learning. For implementing these methods systems are needed to be created which help in providing context in which a computer can learn. This is a time-consuming step and requires a large set of training data. These systems are good in perception of the natural world and are also good at learning, however, they are not so good in logical reasoning. Also, they do not perform well in abstracting information from one domain to another domain. Their strength lies in classifying data and prediction while are weak in understanding context and reasoning.

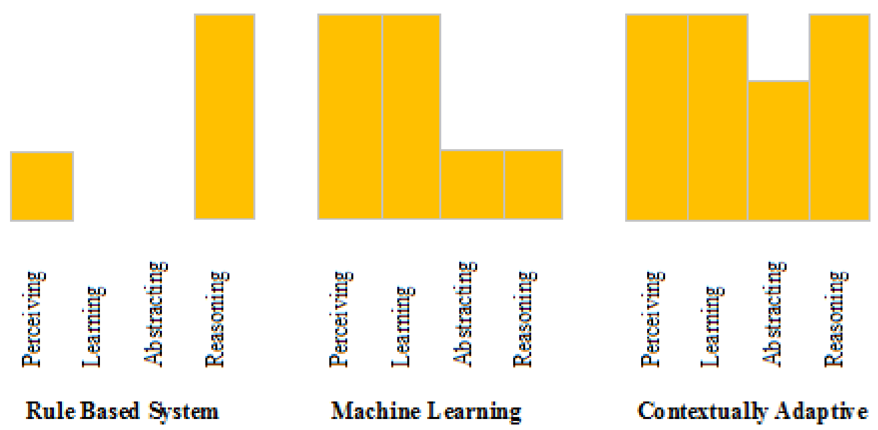
Data in real world situation generally follows a complicated distribution model in contrast with simple assumption of data distribution. Spectral classes linked to information classes can be distributed as manifold or even more complex patterns.

To separate such data into distinguished classes, these algorithms convolute the feature space so as to provide clean separation of individual data manifold.

For instance, Neural nets are layered set of data computation where we start with data in the first layer. In each step, it will conduct random computation of the feature to ensure that by the final step data manifolds are cleanly separated. This process is then looped back linking it to the final separability of classes using training data set. Two defining steps compute outputs from inputs then adjust weights by error propagation. Tuning happens over a period of time resulting in the acceptable separation. There is possible combination of rule based system and machine learning approaches.

Although, it is not a perfect technology yet they are statistically accurate but individually unreliable. They are good in reflecting what they are receiving but are not perceptive. Skewed training data causes mal-adaptation.

c) **Contextual Adaptive System:** These systems have mechanisms to build underlying explanatory models that allow them to characterize real world phenomenon. Because of this property they require a significantly less number of training data as compared to machine learning system. These systems over time has potential to learn about how model should be structured and will be able to perceive the world in terms of that model and use it to reason, decision making and even to abstract the data for further use. Contextual adaptive system in image processing is still in its infancy. However, this is a promising direction toward future information extraction research.



Going through this evolution of computational intelligence systems a revised definition of AI can be:

“AI is the study of the mechanisms underlying intelligent behavior through the construction and evaluation of artifacts designed to enact those mechanisms” (Luger, 2002).

This literature review is in relation with application of Artificial Neural Networking techniques in context of Natural Resource Management. We will analyze the main areas of application and technological insights.

2.1. Machine Learning Approach

Among various computationally intelligent approaches machine learning approaches were applied from very beginning. Most of the approaches include performance validation between Artificial Neural Net (ANN) and statistical classification methods. Most of the ANN models used include feed forward, back propagation and Hopfield network.

Pioneering studies were still challenged by the unavailability of decent computing power as ANN’s algorithms by their design were suitable for parallel computing. The models were composed of many non-linear computational elements operating in parallel and arranged analogous to biological neural model. Lippmann (1987) using new net topologies and algorithms with analog VLSI implementation techniques providing sufficient parallelism was able to review six important neural net models to be used for pattern classification. In their work, a possibility of replicating performance of clustering algorithms using single layer nets was also considered. Bayesian image classification are one of the most reliable statistical classification. Early comparative assessment of these classifier with ANN on multisource remote sensing and geographic data was conducted by Benediktsson and Sveinsson (1997). Both methods were found to have advantages and disadvantages.

Back Propagation Neural Network (BPNN) involves two phases. The first phase involve propagation of the training pattern’s input through the neural network and the second phase involves update of weights. Heermann (1992) estimated the suitability of BPNN for classification of multispectral image data. The performance was benchmarked by comparison with results obtained from statistical contextual algorithm, supervised piecewise linear classifier and an unsupervised multispectral clustering algorithm.

Bischof et al., (1992) conducted similar studies to comparing 3-layer BPNN for classification of Landsat TM data and comparing it with Gaussian Maximum-Likelihood Classification (MLC). BPNN could intake textural information as part of the input data and the result clearly indicate ANN's superiority over MLC.

Urban land use provides a complex environment for any classification algorithm with high probability of false positives. Paola and Schowengerdt (1995a, b) conducted a detailed comparison of the Backpropagation Neural Network and Maximum-Likelihood Classifiers for urban land use classification. Both classification results were found to be similar, however, ANN result were visually more accurate. ANN's were found to be more robust to train site heterogeneity where one land use class is a mixture of multiple land cover classes. A disadvantage of BPNN were their computing performance. They were found to be significantly slower than corresponding MLC.

Sebastiano (1995) in a step-wise approach applied feed-forward network to solve multisensory classification problem. In a subsequent step these networks are training to solve the problem by the error backpropagation algorithm. The resulting equivalent networks may be interpreted as a hierarchical arrangement to accomplish the classification by testing input data for defined conditions.

Paola and Schowengerdt (1995a, b), devised a scheme for selection of competing patterns and found that while searching multiple images normalization method can successfully overcome the image calibration problem. Further, ANN's were found to be agnostic to image compression.

Multilayer perceptron structure with a feed forward neural network model was used by Moody et al., (1996). Training was done using backpropagation algorithm responding to subpixel class composition for real and simulated data.

Artificial Neural Networks were tested to use multi-angle and multi-spectral data from Adanvced solid-state Array Spectroradiometer for land cover mapping by Abuelgasim et al., 1996. A multilayer feed-forward neural network is trained to identify five land cover classes. Key findings include significant impact of directional radiance in land cover discrimination and overall classification accuracy.

Forest age determination from satellite image uses expert knowledge about the species, physiognomy of the species and other ancillary information. Kimes et al., (1996) tested use of ANN to find forest age of young stands using Landsat Thematic Mapper (TM).

Apart from multispectral remote sensing data, hyperspectral data was also used to test the efficacy of ANN algorithms by Gong et al., 1997. Comparison between linear discriminant analysis was compared with ANN algorithm. Overall performance of the ANN was found to be better than the Linear Discriminant Analysis.

Foody and Arora (1997), evaluated the factors influencing the accuracy of the classification. For agricultural land, four factors were selected for sensitivity analyses. The four factors were dimensionality of the remote sensing data, neural network architecture and characteristic of training and testing sets. Dimensionality of the dataset as well as the training and testing set characteristics were found to affect the classification accuracy significantly.

Benediktsson and Sveinsson (1997) evaluated various feature extraction methods including Principal Component Analysis, Discriminant Analysis and decision boundary feature extraction method. The later was found to be the best among the tested classifiers.

Impervious surface quantification based on ANN was conducted by Civco and Hurd (1997) using Landsat TM data. The classification was conducted at sub-pixel level using ANN capable of nonlinear, complex mapping of input patterns into output percentages.

Feed forward back propagation multi-layer perceptron (MLP) is a common ANN algorithm used in remote sensing. Atkinson and Tatnall (1997) provided a detailed understanding of MLP’s structure.

Arora and Foody (1997) evaluated simultaneous impact of several variables using log-linear modeling. The four variables studied include training set size, waveband combination, classification algorithm and testing set size. ANN algorithms are found to be most sensitive to Training set size where larger training sets produce better classification.

Atkinson et al., 1997 evaluated sub-pixel classification accuracies between ANN, mixture modeling, fuzzy and fuzzy c-means classification. ANN outperformed all approaches in accurately classifying data at sub-pixel levels.

Chen et al., (1997) applied fractal dimensions along with multi-spectral intensity to classify image using ANN. The Neural Net was a modified multilayer perceptron trained using a Kalman filter. Advantage of this method was non-back-propagation, fast convergence, build-in optimization function and global scale.

Kanellopoulos (1997) examine best practices while applying ANN for classification. Key directions involve network architecture selection, use of optimization algorithm, scaling of input data, avoidance of chaos effect, use of enhanced feature set and hybrid classification method.

Kaminsky and Wilkinson (1997) studied texture information along with multispectral data was used as input to the ANN. In the second approach, a sliding window filter was used to classify pixel in a small neighborhood to classify the central pixel. The third approach is based on the candidate elimination of the version space resulting in faster computations and less requirement of training datasets.

Feature tracking to map moving feature of interest was implemented using ANN by Cote and Tatnall (1997). Hopfield neural network were used to perform feature tracking and recognition. Advantage of using ANN was better classification, precision, speed, low sensitivity to deformation and capacity to detect rotational motion and to provide cross and along isopycnal components of displacement vectors.

Keiner and Yan (1998) applied ANN in study of coastal water biomass by detecting cholorophyll concentration present along with suspended sediment in the surface waters.

ANN were found to be successful in modelling a geophysical transfer function between chlorophyll and sediment concentration and radiance.

Bruzzone (1999) applied a data fusion approach to the classification of multi-source and multitemporal remote-sensing images. MLP were used for a non-parametric estimation of posterior class probabilities. The results indicated effectiveness of ANN to classify multisource and multi-temporal data.

Gopal et al., (1999), classified Annual NDVI data of global coverage using MLC as well as ANN (ARTMAP). ANN outperformed MLC, however, with significantly higher amount of training. This showed ANN to be better and viable alternative for global landcover classification due to increased accuracy and the ability to provide additional information on uncertainty.

Application of ANN to assess soil physical properties using multi-temporal remotely sensed data and soil moisture map was done by Chang (2000). Two ANN were constructed based on physical linkages among space-time distribution of brightness temperature, soil moisture and soil media properties.

Woodcock et al., (2001) showcased generalization capability of ANN algorithm between temporal dataset of same area of interest. They worked with temporal dataset from Landsat 7 ETM+ and found the approach using ANN to be faster and more accurate.

Han et al., (2002) demonstrated classification of high resolution aerial photographs using four-layer ANN. Adaptive back–propagation algorithm was used which speeded the learning rate and decreased the error. The classification was also found to show large degree of generalization.

Murthy et al., (2003), evaluated statistical and ANN classification strategies to extract wheat crop from multi-temporal data. Sequential MLC, PCA MLC and iterative MLC was used. Backpropagation ANN were also used. Overall accuracy was found to be higher with iterative MLC while ANN was better in extracting wheat class.

Mannan and Ray (2003), evaluated Crisp and fuzzy competitive learning network schemes. For supervised learning, and extension of competitive learning network with a Grossberg layer, sometimes known as a ‘forward only’ Counter-propagation Network (CPN) This model is found to yield much better accuracy than the crisp Kohonen’s network and marginally better accuracy than the Maximum Likelihood Classifier.

Kavzoglu and Mather (2003), studied various factors for optimum design of an ANN. Various strategies for assessing optimum condition for ANN parameter were compared.

Fernandes (2004), evaluated statistical classifier, ANN, a clustering approach, multivariate regression and linear least square inversion for subpixel classification of land cover. “Hard” classification performed poorly in estimating proportions or continuous fields. The neural network, look-up-table and multivariate regression algorithms produced good matches but were found to exhibit bias due to training set data. Linear least square inversion provides most unbiased result with lower precision.

Mertens et al., (2004), proposed method to increase spatial resolution by sub-pixel sharpening by making use of wavelets and ANNs. The method resulted in images with higher spatial resolution showing more details than the original the source imagery. Also, the algorithm was evaluated for its performance both visually and quantitatively using established accuracy indices.

Olthof et al., (2004), evaluated application of ANN, multiple regression, linear discriminant analysis and MLC to assess damage to sugar maple (Acer Saccharum Marsh.) crop due to severe ice-storm using pre-and post-storm image data. ANN performed best to provide object damage maps for natural resource managers.

Shupe and Marsh (2004), evaluated statistical and ANN classifier to map desert vegetation which is difficult to identify given mixed with reflectance of bright desert soil. Multisource dataset increased accuracy while MLC performed better than ANN. The accuracy of ANN increased with change in transfer function from sigmoid to hyperbolic.

Verbeke et al., (2004) focused on methods to overcome disadvantages related with ANN as supervised classifiers. In their study, the proposed method aims at faster processing of network learning, improving classification accuracies and reducing variability by random weight initialization.

Mas and Flores (2007), reviewed the limitations, optimizations, main architecture and learning algorithm of ANN. Finally, they also review implementation of ANN in popular image processing software packages.

Yuan et al., (2009), two ANN models were evaluated including an unsupervised Kohonen’s Self Organizing Mapping (SOM) neural network module, and a supervised Multilayer Perceptron (MLP) neural network module using the Backpropagation (BP) training algorithm. Two training algorithms were provided for the SOM network module: the standard SOM, and a refined SOM learning algorithm which incorporated Simulated Annealing (SA). It is concluded that our automated ANN classification system can be utilized for LU/LC applications and will be particularly useful when traditional statistical classification methods are not suitable due to a statistically abnormal distribution of the input data.

Gong et al., (2010), used algorithm inspired from functioning of immune system to optimize the ANN. This Artificial Immune Network Based classification was named OPTINC. The algorithm preserves the best antibodies (test set) for each land cover class. The algorithm ensures mutation rate is self-adaptive improving model convergence. It also uses both Euclidean distance and Spectral angle mapping distance to measure affinity between two features vectors. While compared to a DSS, Multilayer feed-forward back propagation neural network and aiNet it performed best. It was also found to be less sensitive to training sample size.

Van Coillie et al. (2004), in order to reduce the number of training sets suggested a method to reuse past experience gained in training. The impact of reuse of past training was found to be more effective in certain classes.

Kanellopoulos and Wilkinson (1997), evaluated best practices in using ANN including Network Architecture Selection, use of optimization algorithm, scaling of input data, avoidance of chaos effect and use of enhanced feature sets and hybrid classifier. They asserted the availability of vast amount of accumulated experience which can help ensure reliable use of ANN for routine Remote Sensing Requirements.

Support Vector Machines (SVMs) are another class of computationally intelligent systems providing optimized ways of separating classes in a feature space with adaptive boundaries. Mountrakis et al., (2010), evaluated application of SVM for classification of air photographs.

Kavzoglu and Mather (2003), evaluated various parameter used in ANN to find an optimum network structure. Various optimization strategies were tested while the selected best were independently tested amongst each other.

Kumar et al., (2015), evaluated the performance of ANN with respect to various learning parameters and assessed the optimum level of parameters. The larger value of learning rates resulted in high fluctuations and less accuracy. The results show their bias toward data set used by different sensor.

2.2. Rule Based Classification

Rule based classification are based on expert knowledge of the system and provide sound reasoning behind classification. These knowledge classifiers were used for classification for specific domains.

Penaloza and Welch (1996), applied fuzzy logic based expert system for land cover classification in arctic. In their work, inter-comparison among divergence, histogram analysis, and discriminant analysis approaches is done for their effectiveness in feature selection. They concluded that these methods produced highest classification accuracy and also were computationally no so heavy. Also, reduction in the set of features produced by the divergence method resulted in an overall classification accuracy of over 95%, however this increase in accuracy has an attached cost, that of being computationally heavy.

Friedl and Brodley (1997), compared different type of decision tree classification with MLC. Decision tree classification used include univariate decision tree, multivariate decision tree and a hybrid decision tree. Decision tree classifier consistently outperform MLC and other statistical classification. Decision tree classification provided advantages of being non-parametric, flexible and robust with respect to MLC and other statistical classification schemes.

Matsakis et al., (2000), attempted to develop tools in the field of satellite image classification by on the basis of fuzzy partition evaluation. The advantage of fuzzy partition over traditional crisp partition is that the former represents a large amount of quantitative data while the latter specializes in qualitative information.

Pal and Mather (2003), univariate and multivariate decision tree (DT) classifier were tested on multispectral as well as hyperspectral data. DT are in general computationally faster and like ANN make no prior statistical assumptions. The level of classification accuracy achieved by the DT is comparable to results from back-propagating ANN and the ML classifiers except for high-dimensional data.

Colstoun 2003, applied decision tree classifiers to regional land cover analysis with high accuracy tested post-classification.

Remote sensing images at coarse spatial resolutions are highly contaminated, in recent times, the decision tree classifiers have become increasingly popular and successful for land cover classification from remote sensing data. Many workers have reported its implementation as a per-pixel based classifier to develop hard or crisp classification (Xu et al., 2005). Xu et al., (2005) employed a decision tree regression approach for determining class proportions within a pixel so as to develop soft classification using remote sensing data in their study. This was followed by comparison of the classification accuracy with widely used maximum likelihood classifier, implemented in soft mode and a supervised version of the fuzzy c-means classifier.

Blaschke (2010), reviewed application of Object based image analysis in remote sensing. Object based image analysis depends on segmentation of image which is suitable to high resolution image which provide multiple scale compared to low resolution images.

2.3. Hybrid Machine Learning and Rule Based Classification

Hybrid Machine learning and rule based classification apply logical reasoning of rule based classification and learning by training of ANN. These classifications generally perform better than either of the parent classification strategies.

While neural networks, does not require *a priori* assumption about the data distribution, they remain perceived as ‘black box’ model. Decisions tree classification strategies are also non-parametric however they explicitly provide reasoning behind decisions. Thus, a hybrid approach of ANN and Decision tree classifier result in accurate and generic classification.

Ito and Omatu (1997), applied a new category classification method which was supervised and non-parametric method. It employed both a self–organizing neural network and a k-nearest neighbor method. One of the features of the category is represented by the neuron weights after training the neural network based on a competitive learning role. From experimental results, we can see that the proposed method obtains superior classification results compared to other methods.

Murai and Omatu (1997), proposed a pattern classification method for remote sensing data using both a neural network and knowledge-based processing. A neural network could recognize complex patterns, and classifies them to one of the classes. A knowledge-based system which uses human geographical knowledge improves the classification results, compared with a conventional statistical method.

Qiu and Jensen (2004) developed a hybrid system which was an improvement over neuro-fuzzy image classification system based on the synergism between neural networks and fuzzy expert system. The algorithm developed here were used to automate the derivation of fuzzy set parameters for the fuzzy ‘if-then’ rules in a fuzzy expert system. This method resulted in an accuracy significantly superior to those of the back-propagation based neural networks and Maximum Likelihood approaches.

Murai (2010) proposed a pattern based classification method for remote sensing data using both neural network and knowledge based processing. The system is divided into two subsystems consisting of recognition and error correction. The method helps in correcting misclassification caused by neural network based approaches.

Im et al., (2011), used the hybrid classification approach using DSS and ANN which resulted in higher accuracy of classification as well as enhanced optimization kept the algorithm more generic. In their study, the hybrid approach was demonstrated for detection of Impervious surfaces.

Chapter 3

Land Cover Assessment of Haridwar District of Uttarakhand: Performance Comparison between ANN and Traditional Maximum Likelihood Classifiers

Chapter 3

Land Cover Assessment of Haridwar District of Uttarakhand: Performance Comparison between ANN and Traditional Maximum Likelihood Classifiers

3.1. Study Area

Uttarakhand formerly called Uttaranchal is the 27^{th} state of North India carved out on 9^{th} November 2000 from Himalayan Region and adjoining North-Western districts of Uttar Pradesh (http://uk.gov.in). The state is bound between 28^{0} 43’ N to 31^{0} 27’ N latitude and 77^{0} 34’ E to 81^{0} 02’ E longitude (Figure 3.1). Often referred to as the land of the gods due to the many holy Hindu shrines, temples, pilgrimage centers and mythological history associated with its ancient past. The state is known for its aesthetic beauty, pristine environment and natural beauty of the Himalayas, the Bhabhar and the Terai (http://utrenvis.nic.in).

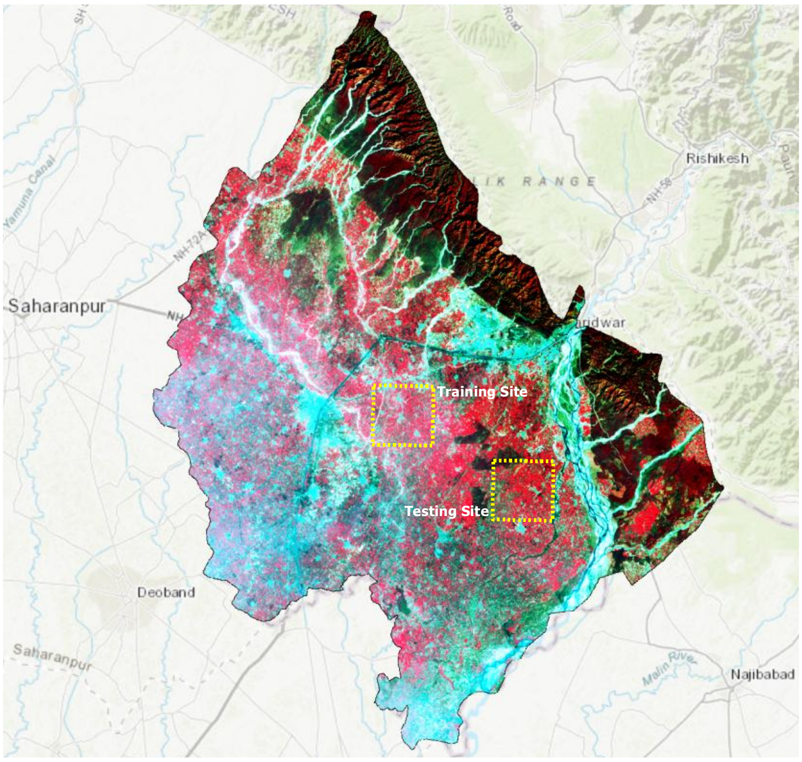


Figure 3.1: Study Area Training and Testing Site in Haridwar District – Uttarakhand

Two of the most important perennial rivers of the Indian subcontinent originate in the regions, namely the Ganga from Gangotri Glacier and the Yamuna from Yamunotri Glacier, these two along with Badrinath and Kedarnath form the "Chota Char Dham", a holy pilgrimage for the Hindus. The state is well forested with a total area under forest 34651 sq.km. which is 64.79% of the total area of the state (53483 sq.km). The selected site in the state of Uttarakhand is a densely populated district of the state with an area of 2360 sq.km., and a population of 18,90,422. The district has the highest male (10 million) and female population (8.8 Lakh) with a sex ratio of 880, and a very high population growth rate. The district has 63.34% rural population and 36.66% urban population (http://utrenvis.nic.in). The selected study area falls in the district of Haridwar from where the Ganges flow and come down to plain areas.

3.1.1. Physiography

The Great Himalayas, though youngest are the most dominating physical feature on the face of earth. The mountain chain extends from the Indus gap at the base of the Nanga Parbat Massif in the North-West to the Brahmaputra gap at the base of Namcha Barwa peak in the East. The Himalayan mountain chain may be divided into the following three distinct regions:

- Western Himalayas: spread in the Indian states of Jammu and Kashmir, Himanchal Pradesh, and Garhwal & Kumaun divisions of Uttarakhand
- Central Himalayas: mainly in Nepal
- Eastern Himalayas: spread in the Indian states of North Bengal, Sikkim, Bhutan and Arunachal Pradesh

Uttarakhand is an interesting physical and physiographic setup. The state extends between Tons-Yamuna river in the West to the Kali River in the East. In the West, it shares boundary with Himanchal Pradesh. In South at Terai, it shares boundary with Uttar Pradesh and in East, the Kali river forms the boundary between Uttarakhand and Nepal. To the North of this region is Tibet. The entire region can be divided into following sub divisions or zones:

- Sub-Montane Zone
- Shiwalik Zone
- Main Himalayan
- Trans Himalayan Zone

Haridwar one of the southernmost district, situated on the foothills contains Sub-Montane (Terai & Bhabar) and Shiwalik zones.

Sub-Montane Zone

This is the Southernmost physical division of Uttarakhand. It lies to the North of the plains of Western Uttar Pradesh and to the South of Shiwalik hills. The general slope of the terrain is towards South. The sub-montane zone is made up of Bhabar and Terai tract which is well developed in the Southern part of Nainital district.

Bhabar

Rivers descending from the Himalayas deposit their load along the foot hills in the form of alluvial fans. These fans, consisting of gravel and unassorted sediments, have merged together to build up the Bhabar, which forms the Northern boundary of the great plain. Here, the seasonal torrents, traversing the Southern scarps of the Shiwalik, generally disappear and the surface remains dry. This belt is comparatively narrow in the East and extensive in the Western and North – Western hilly region. Because of the related differences in site, topography, drainage, soil-depth and fertility, natural vegetation human habitation and occupation, the region exhibits a prominent landmark of the whole Uttarakhand region.

Terai Region

The southern belt of the Bhabar is known as Terai region. With an approximate width of 10-25 km, this zone is running parallel to bhabar soil and is rich in nitrogen and organic matter, but deficient in phosphates. This belt is comparatively levelled and is more fertile. This area is generally covered by tall grasses and forests and is also suitable for several crops, such as, wheat, rice, sugarcane, jute and soybean. Therefore, humid climate, marshy areas and fertile soil are main features of the Terai region.

Shiwalik Zone

This physical division lies to the North of the Terai and Bhabar tract. It is made up of shiwalik hills and duns. The Shiwalik hills extend in a more or less North-West to South-East trend all along Southern Uttarakhand. The West of these hills is in the form of ridge that is well developed between the river Ganga and Yamuna. A number of rivers draining Uttarakhand here cut gorges across Shiwalik hills. They included Ganga, Yamuna and Ramganga.

3.1.2. Hydrology and Drainage

The drainage system of Uttarakhand consists of following river systems:

- The Ganga River System
- The Yamuna River System
- The Ramganga River System
- The Kali River System

The Alaknanda and Bhagirathi, after joining at Devprayag, are exclusively called the Ganga and it finally descends into the plains from Haridwar. This river has cut across the Shiwalik hills of Haridwar to enter the plains of Northern India Region. The Bhagirathi and the Alaknanda originate from the opposite sides of the Chaukhamba peak. After flowing in the opposite directions, they bend toward Devprayag, forming a garlanded shape.

3.1.3. Climate

The climate of this relatively small state varies from sub-tropical to alpine. The wide range of climatic conditions is present mainly due to altitudinal variation but with different aspects (the direction a slope faces), the vegetal cover and presence of water bodies also make substantial impact on rapid and unpredictable change in micro-climate and local weather. The temperature and rainfall, the two most prominent climate factors show large spatial variation over the region as well as from valley bottom to hill top within the same region.

The state has two distinct climatic regions, one the predominant hilly terrain and the other the small plain region.

Summer Season

In Uttarakhand, summer season is locally called Ruri, beginning from May to June ending in monsoons by the end of June. During this season, the valley experiences hot steamy tropical to sub-tropical climate, while the high and lofty mountains covered with snow experience chilly climate.

Monsoon Season

The monsoon or rainy season is locally called Chaumas or Baskal. The monsoon commences in the month of June and ends in the last week of September. Most of the rainfall occurs in the period between July and September. The sky remains generally clear in the middle of September and October. The annual rainfall shows a decreasing trend from East to West.

Winter Season

The winter season in hilly regions is a prolonged one from mid-November to March. The winter season is locally known as Hyund. January is the coldest month. During the winter, cold waves in the wake of western disturbances cause temperature to fall significantly. During the winter months humidity increases toward the afternoon at certain high stations. Frost of radiation type is common, although in valleys such Dehradun and in Bhabar Terai tract, pool frost is more prevalent.

Winter depression cause snowfall for 7 to 8 days in each of the three months from January to March in higher areas.

Humidity

The relative humidity is high during monsoon season, generally exceeding 70% on an average. The driest part of the year is the pre-monsoon period when the humidity may drop to 35% during the afternoon. During the winter months, humidity increases towards the afternoon at certain high-altitude stations.

Rainfall

Most part of Uttarakhand receive very heavy rainfall from early July to the end of September. In general, the rainfall averages between 37-50 cm from July-September in the frontal zone and 20-25 cm in the rear. The rainfall at different places has been varying from about 175-300 cm, of which about 7% occurs during the winter season and 80% during the monsoon period.

The trend of decreasing amount of rainfall from East to West in the Bhabar belt of the region can be well illustrated here. Kalagarh at the extreme South-East corner of the region, receive an annual rainfall of 140 cm, Kotdwara about 83 Km west receives 127 cm, Laldhang another 48 Km in the same direction has 91 cm while Haridwar in the south-western part receives only 76 cm rainfall.

3.1.4. Land Use and Cropping Pattern

In Uttarakhand, about 65% of the main working population is directly engaged in agriculture. The net sown area is 14% of the geographical area of this state.

Land Use Pattern

In a mountainous terrain, land use should be closely associated with landform types. Generally, the low-lying areas in the valleys are dominated by wet rice cultivation and have compact settlements, the mid slope spurs are moderately cultivated for dry rice, Jhangora and Mandua, and the surrounding low hills of the valleys are occupied by reserved forests with scattered settlements.

The Green Revolution of Punjab, Haryana and parts of other states could not effectively spread across Uttarakhand. In the case of Uttarakhand, almost 72% of the land holdings were of the size less than 1 hectare and such holding together account for 27% of the total area. 5% of the cultivated area had large size land holding (10 hectare of more) which formed about 0.2% of the total number of land holdings. Only, around 44% of the total cultivated area in Uttarakhand is irrigated.

Important Crops of the State

Wheat is the main crop of Uttarakhand. It covers 42% of the gross cropped area. It is grown mainly in Dehradun, Uttarkashi, Pithoragarh, Almora, Nainatal and Pauri Garhwal. Kharif crop is mainly rice and other vegetables. It accounts for about 36.9% of the gross cropped area in the state. It is the main crop of Nainital district, Almora, Pithoragarh, Dehradun and Haridwar are the other important districts for rice growing.

Maize is the third most important cereal crop of Uttarakhand covering 4.8% of the gross agriculture area. It is grown mainly in Dehradun, Pithoragarh, Nainital and Haridwar.

Sugarcane covers 9.85% of the gross cropped area. Nainital and Dehradun are main producing districts. Pulses comprises both Kharif crops (Arhar/Tur, Moong, Urd, Moth etc.) as well as Rabi crops (Gram, Peas, Masur, Urad etc.). It forms an important ingredient of diet in this state, providing protein. About 90% of the area under pulses is rainfed. It covers 4.19% of the gross cropped area. Dehradun, Nainital, Uttarkashi and Tehri Garhwal are the main producing districts.

Oilseeds are mainly produced in Uttarkashi, Tehri Garhwal, Nainital and Chamoli. It covers 3.03% of the gross cropped area. Tea plantations are grown mainly in Nainital, Almora and Dehradun. Pungaras are the agricultural fields locally known as pungara in Garhwal region and Patav in Kumaun region. These are of various sizes and shapes depending mainly on the terrain.

3.1.5. Forests

Uttarakhand has 64.7% of its total geographical area under forest. It ranks 5th among other states of India in terms of forest area. It is just behind Himanchal Pradesh among its neighboring states whereas Jammu and Kashmir and Uttar Pradesh are far behind Uttarakhand.

Recorded Forest Area

According to the state forest report 2013, the recorded forest area of the state is 34,651 Km^2, which constitute 64.79% of its geographical area. Reserved forests constitute 71.11%, Protected Forests 28.52% and Unclassed Forests constitute 0.35% of the total forest area. In terms of forest canopy density classes, the state has 4,785 Km^2 area under very dense forest, 14,111 Km^2 area under moderately dense forest and 5612 Km^2 area under open forest.

Protected Areas

The state has six National Parks, six Wildlife Sanctuaries and two Conservation Reserves covering a cumulative area of 7,376 Km^2 which constitute 3.79% of its geographical area. The famous Corbett Tiger Reserve (Asia's one of the older national park) is in the state covering an area of 0.13 million hectare. Nanda Devi Biosphere Reserve with an area of 0.59 million hectare is also located in the state.

Forest Cover in Different Forest Types

Forest type mapping using satellite data have been undertaken by Forest Survey of India (FSI, Dehradoon) with reference to Champion and Seth classification of 1956. As per this assessment, the state has 34 minor forest types which belong to eight forest type groups viz. Tropical Moist Deciduous, Tropical Dry Deciduous, Sub-Tropical Pine forest, Himalayan Moist Temperate, Himalayan Dry Temperate Forests, Sub-Alpine Forests, Moist Alpine Scrub and Dry Alpine Scrub. Thus, the state is one of the richest in terms of floral diversity.

Natural Resource

Uttarakhand has about 64.79% of the land under forests. Most of it is managed by the forest department. The variation in the landscape has created great diversity of flora and fauna and consequently, resources. The department has added to these resources through plantation activities. The resources pertaining to forest areas are briefly mentioned below:

Timber Resources: The plain area of Terai and Bhabar have plantations raised for commercial use. Important one include Teak, Sal, Eucalyptus and Poplar etc. Poplar is one of the most commonly integrated with Agroforestry landscape. Hills too provide timber from coniferous like Deodar.

Non-Timber Forest Produce: These include resin from Chir Pine, Bamboos, fuel and fodder for use by local people, plywood material from *Eucalyptus* (Safeda), *Populus deltoids* (Poplars). Silk worm industry is blooming in Alaknanda and Dehradoon valley with *Ricinus* and *Terminalia* spp as the major host of Eri and Tasar silkworms. *Jatropha* spp., is also being raised in several areas as a bio-fuel crop.

3.2. Data

In order to assess land cover of Haridwar district of Uttarakhand using traditional and Artificial Neural Network, satellite image Data was carefully selected. Landsat -8 is the latest in the series of Earth Resource Mapping Satellite. The data from OLI/TIRS sensors provide adequate spatial and spectral resolution for regional land cover mapping (Claverie et al., 2015). Other relevant advantage includes good temporal coverage, comprehensive documentation of sensor metadata and use in scientific research (Bischof, 1992). Landsat data of year 2016 was downloaded from http://glovis/usgs.gov. High resolution data from Google Earth was also extracted to be used for visual reference and was helpful in field visit and accuracy assessment. Details of data collected are provided in Table 3.1.

Table 3.1: Data Collected

Date Acquired	Dataset	Sensor	Scene Reference
2016 January 30	Landsat	OLI/TIRS	LC08_L1TP_146039_20160130_20170330_01_T1

3.3. Field Data

Ground truth data was collected in the study area for calibration and validation of the classification models used. Sampling strategies influence the performance of classification hence care should be taken to select one (Jensen, 2005). Common strategies include random sampling, stratified random, systematic and cluster sampling.

The optimization helps in reduction of sample size and keeping the sampling work cost efficient however it is not always possible to have an understanding of population distribution. Hence, this study used random sampling to collect ground truth information to train and test the classification model. The study area was divided into two parts; one to train the ANN and other to test its efficacy. The trained network was implemented at the other part of the study area to test the capability of generalization.

600 random points were located within the training site and 300 in test site. Land cover of these sites was verified by field visit and using high-resolution satellite data from Google Earth (Im et al., 2012). Post ground verification for each of these points were assigned one of six land cover classes including Build up, Agricultural land, Fallow land, Forest, Plantations and Water Bodies (Table 3.2-3.3)

At the training site, three hundred randomly selected samples were used to train the classification model while the remaining samples were used for model validation (Table 3.2).

Table 3.2: Ground Truth Data for Training Site

Build up	Agricultural Land	Fallow Land	Forest	Plantation	Water Bodies
152 (76/76)*	174 (87/87)	136 (68/68)	54 (27/27)	34 (17/17)	50 (25/25)

* training and validation

Table 3.3: Ground Truth Data collected for Testing Site

Build up	Agricultural Land	Fallow Land	Forest	Plantation	Water Bodies
78	85	64	28	15	30

3.4. Work Plan

A layered feed forward Neural Network Classification and Maximum Likelihood Classification was selected. A comparison based on relative classification accuracy was designed to measure classification performance. Ground sample of land cover were collected and photographed. These were used for training the classification and testing the accuracy of the overall classification. Further, trained Neural Networks were implemented at testing site for land cover classification. Accuracy assessment was conducted to understand their generalization potential. Haridwar district presents a homogenous land cover type. Two sites were selected within the district one to train the neural network and the other to test the potential of generalization. The sites were selected carefully to represent similar land cover characteristics. Ground sample were collected for training as well as testing site. While Ground sample for training site were divided into training and testing samples, the ground sample for testing site only consist of samples for testing.

3.5. Methodology

3.5.1. Image Pre-processing

Radiometric correction including conversion of Digital Number (DN) to Radiance to Top of Atmosphere Reflectance was conducted (Raghavswamy, 1982; Ritter, 1988; Mukherjee, 1999, 2006). Reflectance images were further processed for atmospheric error to extract at ground reflectance images. Atmospheric correction was conducted using dark body subtraction being one of the simplest and non-data intensive method (Mukherjee, 1999). Reflectance image were georeferenced and co-registered with other ancillary datasets with an RMSE<0.5 pixel ensuring vertical integration of datasets. Ground truth data using random sampling was located for 600 sites in training site. The data was randomly chosen to prepare training and testing sample data. At testing site 300 randomly selected samples were located. Ground based photograph to record land cover type was captured. Photographs were Geo-tagged and aligned with other spatial data (Raghavswamy, 1982; Ritter, 1988; Mukherjee, 1999).

3.5.2. Classification

Artificial Neural Network

A layered feed-forward neural network classification was employed with backpropagation for supervised learning (Anderson and Rosenfield, 1988; Atkinson et al., 1997, 1995; Beale et al., 1990). Hyperbolic activation functions were used as suggested by other workers (Chandrashekhar and Manikiam, 1992; Bruzzone et al., 1999). Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output (Bishop, 1995; Civco et al., 1997). The error is backpropagated through the network and weight adjustment is made using a recursive method (Bernard et al., 1997; Gong et al., 2011, Im et al., 2012).

Optimized parameter for Training Threshold Contribution, Training Rate, Training Momentum and number of hidden layers were provided**.** There have been extensive studies providing heuristics to deduce these parameter for a given situation (Schaale and Furrer, 1995; Kanellopolous and Wilkinson, 1997; Mukherjee, 1999; Romshoo, 2004). Landsat Image of year 2016 was classified for the training site and the result exported to vector features for further analysis.

Maximum Likelihood Classifier

Ground sample data collected for training was used to train the Supervised MLC classification. The training step provides information about the distribution of pixels constituting an information class in the n-dimension feature space. Each class is then codified based on a distribution with known measure of central tendency and variance. Each pixel with a certain probability belong to a distribution and thereby to an information class. Separation of the pixel based on this probability with an assumption of distribution of pixels in feature space is central to MLC (Paola and Schowengerdt, 1995a, b, c; Schetselaar et al., 2000; Olthof and Fraser, 2007; Pant and Mukherjee, 2017).

Unless a probability threshold is not selected, all pixels get classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than a threshold specified, the pixel remains unclassified.

Training dataset were used to train the MLC algorithm. Classified images were smoothened using nearest neighborhood resampling to reduce salt and pepper texture in the classified image. Final classified image was converted to vector data to be processed further in GIS (Pal and Mather, 2003; Olthof and Fraser, 2007; Okujeni et al., 2015; Pant and Mukherjee, 2017).

3.5.3. Comparative Accuracy Assessment-Training Site

Accuracy assessment is a process to compare an output map of information class with a reference dataset (map, sampling points etc.). A total of 600 randomly distributed ground samples were collected during the field visit at the training site. Out of these roughly 50% were randomly selected as training samples, while remaining 50% were used as testing samples (Paola and Schowengerdt, 1995a, b; Im et al., 2012; Pant and Mukherjee, 2017). User accuracy for each class and kappa statistics for each classification were calculated (Table 3.4).

3.5.4. Generalization Potential Estimation – Test Site

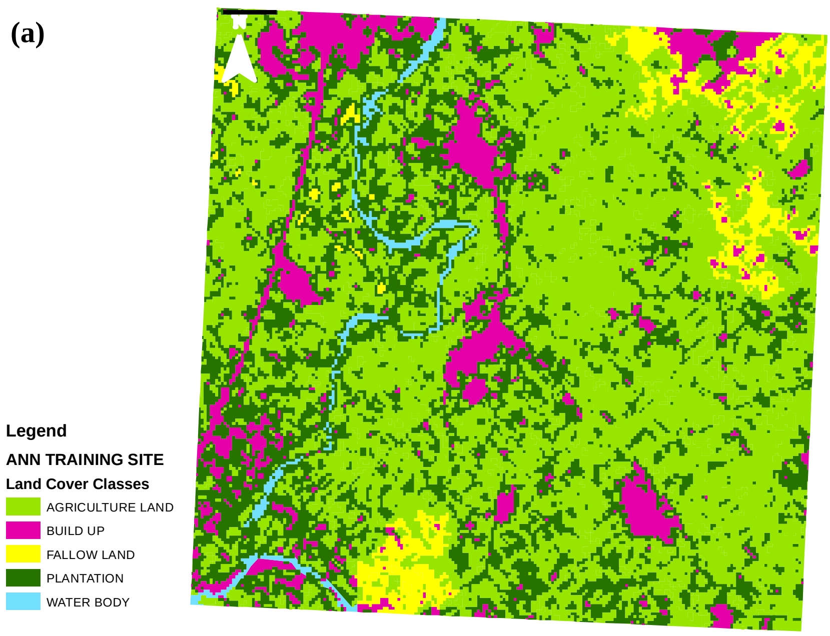
Trained ANN were exported as rule images. These were then used to classify test site. The network was not trained. The classification results were subjected to accuracy assessment using sample test dataset collected. The result of accuracy assessment of classification at test site were compared with the training site (Table 3.5).

3.6. Results and Discussion

3.6.1. Classification Performance

Landsat image of the study area of year 2016 were classified into land cover classes using ANN, and MLC classification algorithm (Figure 3.2). Visual assessment of the classification result showed ANN classification to produce result with better handling of spectral variance within an information class (Pant and Mukherjee, 2017). MLC classification result was filtered with a low pas filter to reduce noise.

(a)



(b)

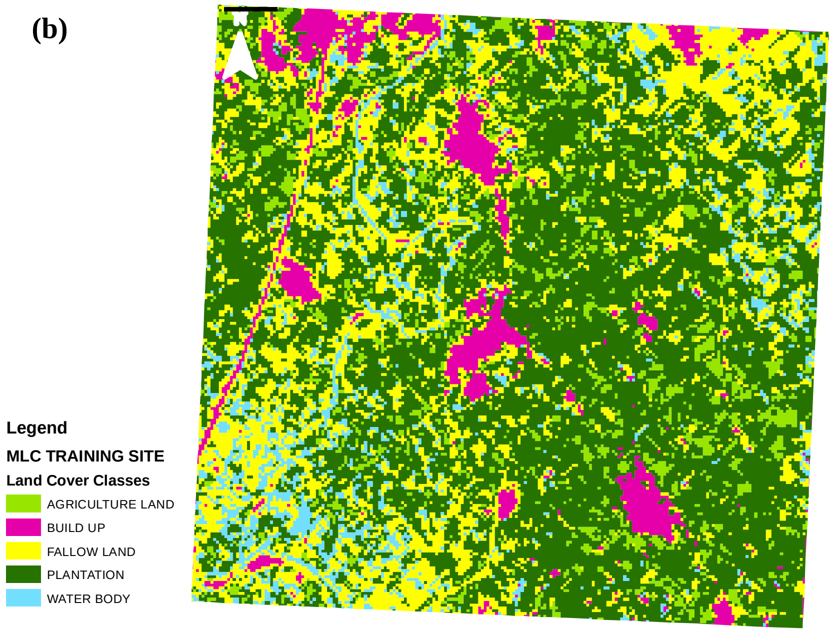


Figure 3.2: Classification Result at Training Site a) ANN, b) MLC

Table 3.4: Accuracy Assessment for ANN & MLC Algorithms – Training Site

Classification Method	Land Cover Classes	Validation	
		User Accuracy	**Kappa (*K*)**
ANN			
	Build up	89%	
	Agricultural Land	85%	
	Fallow Land	87%	0.87
	Plantation	85%	
	Water Bodies	90%	
MLC			
	Build up	80%	
	Agricultural Land	78%	
	Fallow Land	83%	0.79
	Plantation	78%	
	Water Bodies	78%	

Accuracy assessment indicated ANN to be more accurate classification method. They scored best for user accuracy as well as kappa statistic 0.87 compared to MLC (*K = 0.79*).

The performance of ANN can be attributed to them being non-parametric. As they do not assume *a priori* distribution, they are flexible to extract information class from spectral manifold within n-dimensional feature space based on the training from sample of land cover types (Pao, 1989; Qiu and Jensen, 2004).

MLC are simple and robust classification algorithm. Simple assumption of a distribution within feature space allows them to be repeatable. Because they constrict themselves to the distribution, they are not able to resolve information classes which are represented by pixels loosely distributed within the n-dimensional feature space (Van Coillie et al., 2004).

Table 3.5: Accuracy Assessment for ANN Algorithm – Test Site

Classification Method	**Land Cover Classes**	**Validation**	
		User Accuracy	**Kappa (*K*)**
ANN			
	Build up	78%	
	Agricultural Land	80%	
	Fallow Land	70%	0.80
	Plantation	79%	
	Water Bodies	95%	

3.6.2. ANN Generalization Potential

In order to test the generalization potential classification was conducted at the test site using the previously training ANN algorithm (Figure 3.3). Accuracy assessment of classification showed that for some classes like water body and urban area the ANN could perform equally good, it however failed to reach the level of accuracy as compared to results at training site. Fallow land class was overclassified while plantation was under classified. Water body class was correctly identified however, this can also be attributed to only confined presence of the class in the study area. Overall accuracy of classification was reduced at the test site ($K = 0.80$) compared to training site ($K = 0.87$) (Table 3.4, 3.5).

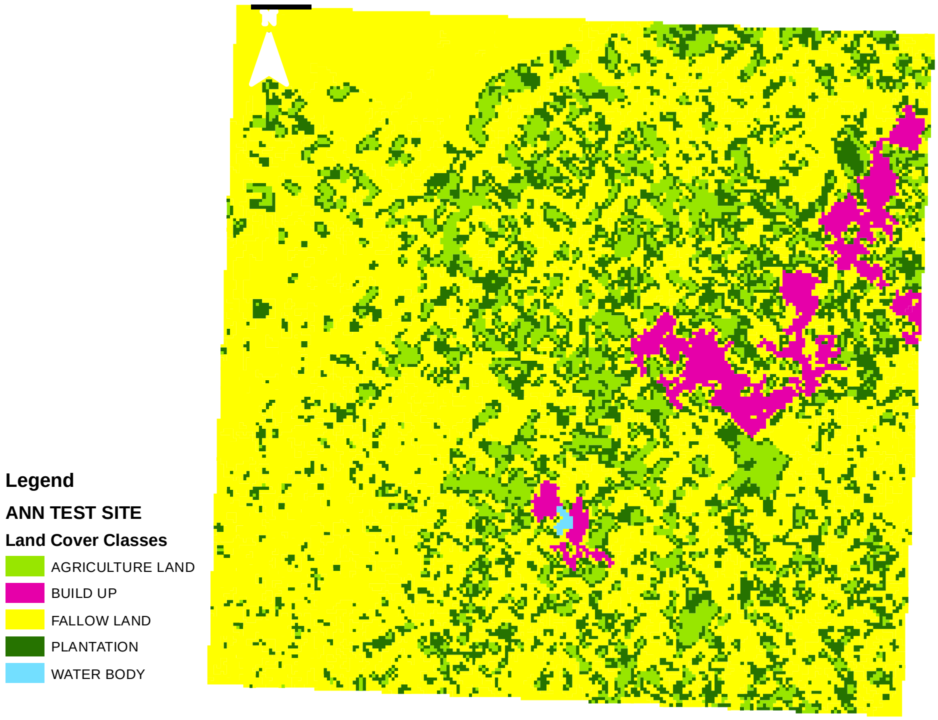


Figure 3.3: Classification Result at Test Site - ANN

Chapter 4

Impervious Surface Quantification using Artificial Intelligence, Object Based Image Analysis and Statistical Classification from Multi-Sensor Data

Chapter 4

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4.1. Study Area

The region of Delhi is located in northern India between the latitudes of 28°-24'-17" and 28°-53'-00" North and longitudes of 76°-50'-24" and 77°-20'-37" East. Delhi shares borders with the States of Uttar Pradesh and Haryana. Delhi has an area of 1,483 sq. km. Its maximum length is 51.90 km and greatest width is 48.48 km (Figure 4.1).

Delhi being a city of historical importance and capital of Pre- and post-independent India since Mughal Empire was established along the banks of river Yamuna for the obvious reasons of a perennial source of water. The banks of river Yamuna are studded with archeological sites which depicts its importance for sustenance of a city. In modern times, the river has important role in providing water, supporting local biodiversity especially avian fauna, maintaining livelihood and socio-economic condition of local fisherfolk, various ecosystem services as well as drainage services to carry city's waste. Within the city limits, the river is barraged twice to collect water for three of its water treatment plants to supply potable water to Delhi and neighboring areas (National Capital Region, NCR). It also sustains fragile but important ecosystems of Delhi (Mukherjee, 1998, 2004, 2007, 2008). However, in past decades rapid urbanization coupled with un-regulated growth and increased demand to supply ratio has led to encroachment of the river's flood plain. This situation is alarming as on one hand it can lead to increased vulnerability to flooding and decreased climate resilience of the city, it also impacts heavily on the declining state of the ecosystem supported by the river (Mukherjee and Sarin, 1990; Mukherjee, 2005).

4.1.1. Physiography

Delhi at a macroscopic level falls in Gangetic Plains adjacent to western Himalayas and Indus Plain. It is characterized by the Indo-Gangetic alluvial plains in the North and East, Aravalli hill ranges in South and Thar desert from the west. The overall terrain is flat except for a low NNE-SSW ridge which is part of the Aravalli hills of Rajasthan. The ridge enters Delhi from South-West and extends to Okhla in South while disappears under Yamuna alluvium in the NE.

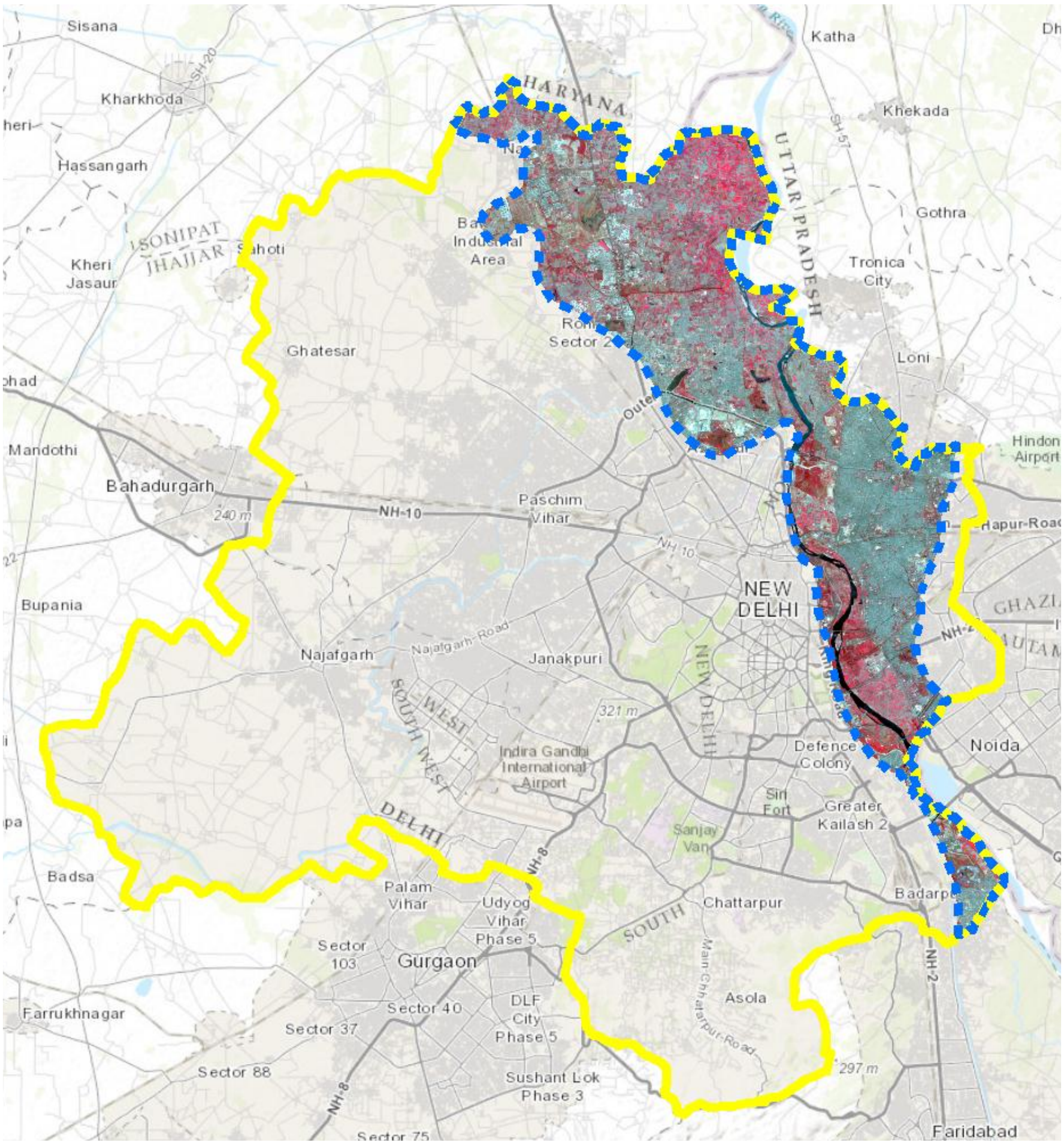


Figure 4.1: Study Area - River Yamuna Flood Plain

The important physiographic features of Delhi are associated with River Yamuna, Aravalli ranges and the flood plain formed in-between (Mukherjee, 2001). The Delhi Ridge just barely meets with the river in the north and the east while remaining confined to the right bank. The Ridge acts as a barrier between the Thar desert and the plains slowing down the movement of dust and wind from the West. It also bears most of the natural forest of the city having a moderating influence on the local climate as well as sustaining Delhi's floral and faunal biodiversity.

4.1.2. Hydrology and Drainage

The Yamuna River originates from Yamunotri glacier in the lower Himalayas at an elevation of about 6387m above mean sea level. Before entering the city, the river is barraged at Tajewala in Haryana. The river enters Delhi near Dahesra border following the Delhi-Uttar Pradesh border and exits into Uttar Pradesh at Madanpur Khadar. Flood plain of Yamuna in Delhi is bound by Aravali ridge from the right bank while it extends into Uttar Pradesh from the left bank (Mukherjee, 2006, 2007). The flood plain consists of dykes on the left bank as the right bank gets natural flood protection from the elevated ridge.

4.1.3. Climate

Delhi has a sub-tropical to temperate climate with distinct summer, winter, monsoon, autumn and spring. The average annual rainfall in Delhi is 714 mm. Most of the rainfall is confined in the monsoon season between July and September. Occasional heavy rainfall in the upstream catchment of Yamuna brings floods to the city. The temperature can rise up to 40-45 degree Celsius in summer and 4-5 degree Celsius in winters. Summer months are between April and June while winter months include December and January.

4.1.4. Land Use

The state of Delhi is partly rural with 144 villages covering an area of 541.5sq.km. According to 1901 Census, more than 48 percent of Delhi's population lived in rural areas. This figure has since then declined with an increase in urbanization due to population growth (Mukherjee, 2007).

4.2. Data

In order to assess encroachment of the Yamuna flood plain, between 1980 to 2015, satellite image Data was carefully selected. Landsat series of Earth Resource Mapping Satellite was primarily selected for their long temporal coverage, comparable data between sensors and a comprehensive documentation of sensor metadata useful for image calibration (Bischof et al., 1992). Landsat data was downloaded from http://glovis/usgs.gov. Data from IRS–LISS-III was also collected for year 2005. Details of data collected is provided in Table 4.1.

Delhi is a rapidly urbanizing city. To understand the temporal change vector of land cover change, a temporal resolution of 5 year was selected. High resolution dataset (1 m) of latest vintage from Quickbird was also acquired. This data was used as reference dataset. Aster GDEM data for elevation was also procured to elevation reference (NASA EOSDIS Land Processes Distributed Active Archive Center-LP DAAC). To support classification, additional datasets including Survey of India Toposheet and Atlas from National Atlas & Thematic Mapping Organization were acquired.

Table 4.1: Data collected

Date Acquired	Dataset	Sensor	Scene Reference
1980-March-01	Landsat	MSS	LM31570401980061AAA03
1986-January-11	Landsat	MSS	LM51460401986011FFF03
1991-March-14	Landsat	TM	LT51460401991073ISP00
1995-March-09	Landsat	TM	LT51460401995068ISP00
2000-December-27	Landsat	ETM+	LE71460402000362SGS00
2005-December-27	IRS	LISS-III	IRS_L3_361
2010-October-12	Landsat	LT	LT51460402010285KHC01
2015-December-13	Landsat	OLI/TIRS	LC81460402015347LGN00

4.3. Field Data

Ground truth data was collected in the study area for calibration and validation of the classification models used. Sampling strategies influence the performance of classification hence care should be taken to select one (Jensen, 2005). Common strategies include random sampling, stratified random, systematic and cluster sampling.

Various methods of sampling have their pros and cons. Further, various sampling strategy optimization methods have been suggested by including use of semi-variogram to understand underlying distribution of variance in the population (Wang et. al., 2005). Any optimization to a sampling strategy requires an *a priori* understanding of the population distribution.

The optimization helps in reduction of sample size and keeping the sampling work cost efficient however it is not always possible to understand population distribution. Hence, this study used random sampling to collect ground truth information to train and test the classification model. A total of 600 random points located within the study area were generated. Land cover of these sites was verified by field visit and using high-resolution satellite data from Quickbird image. Post ground verification each of these points were assigned one of five land cover classes including Build up, Open Land, Vegetation Dense, Vegetation Sparse and Water body (Table 4.2).

Three hundred randomly selected samples were used to train the classification model while the remaining samples were used for model validation.

Table 4.2: Ground Truth Data Collect during Field Visit

Build up	**Open Land**	**Water Body**	**Vegetation Dense**	**Vegetation Sparse**
183 (91/92) *	193 (93/100)	33 (17/16)	101 (51/50)	90 (48/42)

* training and validation

4.4. Work Plan

To understand the impact of these anthropogenic activities it is important to conduct a detailed estimate of land cover change. A multi-decadal study using temporal datasets from Landsat, IRS supported by high resolution Quickbird images and ground truthing were conducted to detect change specially in the built classes. A temporal coverage of the city between 1980 till 2015 with a focus to map the process of urbanization in the Yamuna River Flood Plain was conducted.

Images were radiometrically calibrated to provide reflectance, to ensure a credible change detection using multiple sensors.

4.5. Methodology

4.5.1. Image Pre-processing

To prepare multi-date imageries for comparative assessment, it is required to perform radiometric correction including conversion of Digital Number (DN) to reflectance values. The conversion steps include conversion of DN to Radiance and Radiance to Reflectance. Top of the Atmosphere reflectance value thus generated were converted into at ground reflectance using dark body subtraction atmospheric correction method.

All the reflectance images were transformed into same Coordinate Reference System and were co-registered to each other with an RMSE<0.5 pixel. Geo-rectification provides a way to vertically integrate the dataset to facilitate comparative assessment.

Yamuna river flood plain was delineated using ancillary data as well as high resolution satellite image from Quickbird. The flood plain boundary identified was also verified with past studies including data from NATMO. The area of interest layer was used to subset the image data to extract final extent of image data.

Ground truth data using random sampling method was collected for 600 sites. The data was randomly chosen to prepare training and testing sample data. Ground based photograph collecting land cover type was captured. Photographs were Geo-tagged and aligned with other spatial data.

4.5.2. Classification

Artificial Neural Network

A layered feed-forward neural network classification was employed with backpropagation for supervised learning (Beale, 1990; Atkinson, 1997). both logistics and hyperbolic activation functions were used. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output (Civco and Hurd, 1997). The error is backpropagated through the network and weight adjustment is made using a recursive method (Gong et al., 2011; Im et al., 2012).

ANN applied were provided with optimal parameter Optimal parameter for the following:

Training Threshold Contribution determines the extent of influence of internal weight with respect to the activation level of the node. It helps in adjusting the changes to a a node’s internal weight. A value of 0 will ensure no adjustment of the weights. Adjustment of weights allows for a better classification however, over adjustment leads to poor generalization capabilities (Atkinson et al., 1997; Kanellopoulos and Wilkinson, 1997).

Training Rate defines the magnitude of the adjustment of the weights. This can be used to increase training speed but can potentially lead to oscillations or non-convergence of the training results. Training rate of 0.3 was selected for the analysis (Foody and Arora, 1997).

Training Momentum impedes the oscillation or tendency to non-converge. A higher momentum value can train the network in large steps in proposed direction. A training momentum of 0.4 was provided (Heermann and Khazenie, 1992).

Number of Hidden Layer help in network to learn more complex classification problems increasing the training time and also leads to decreased generalization (Foody 1995b). For nonlinear classification number of hidden layer should 1 or greater. The network was provided with 1 hidden layer (Kanellopoulos and Wilkinson, 1997).

Image of the latest vintage was classified and the result was exported to vector features for further analysis.

Object Based Image Analysis

Object based image classification was used to classify the images (Figure 4.2). Object bases classification are done in two steps, Segmentation and Classification. Segmentation is a process of dividing image into segments based on homogeneity and scale (Blaschke, 2010). While homogeneity is a property of the image and its constituted objects, the scale depends on the choice of the user. This factor is used to control the size of the segment given understanding of the kind of object required to be extracted from the image (Xu et al., 2005). Homogeneity can be based on the spectral/spatial characteristics (Blaschke, 2010).

Images were segmented using multi-resolution segmentation algorithm. Appropriate scale and compactness factors were selected to extract object of similar scale between images.

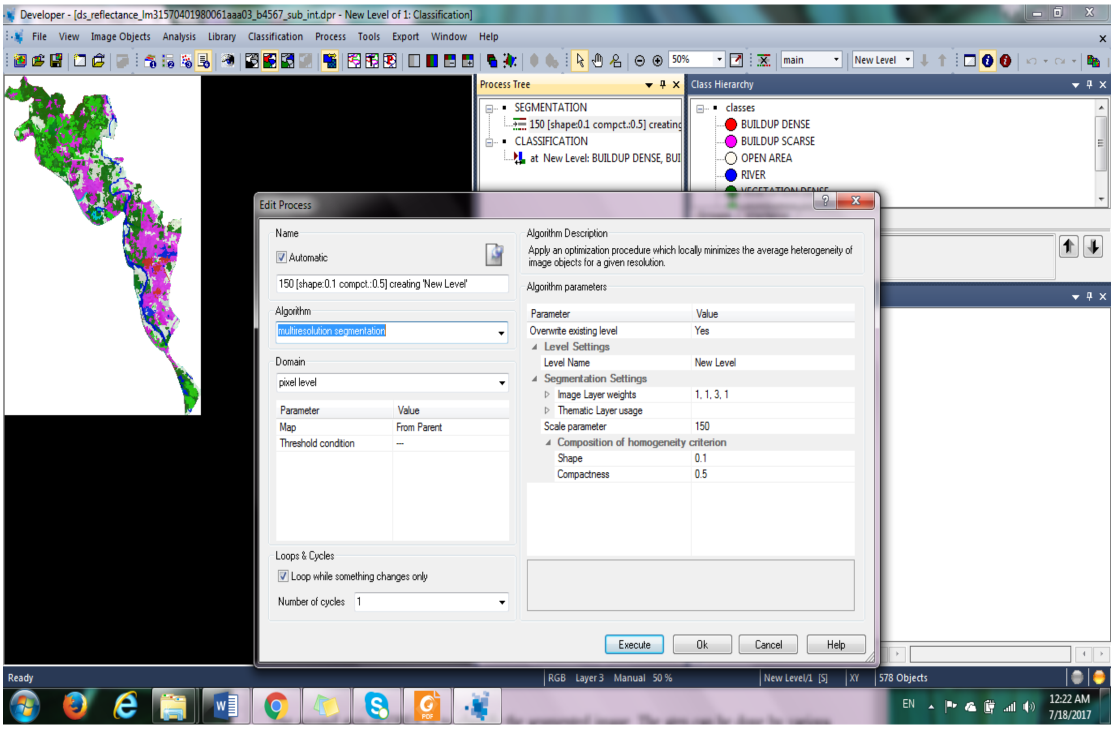


Figure 4.2: Object Based Image Analysis

In a subsequent step the segmented images were classified using decision rulesets. For the classification levels rules based on spectral difference including NDVI and NDBI were used. Classified segmented images was export to GIS for further assessment of classification accuracy.

Maximum Likelihood Classified

Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class (Paola and Schowengerdt, 1995a, b). Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than a threshold you specify, the pixel remains unclassified.

Training dataset were used to train the MLC algorithm. Classified images smoothened using nearest neighborhood resampling to reduce salt and pepper texture in the image. Final classified image was converted to vector data to be processed further in GIS.

4.5.3. Comparative Accuracy Assessment

Accuracy assessment is a process to compare an output map of information class with a reference dataset (map, sampling points etc.). A total of 600 randomly distributed ground samples were collected during the field visit. Out of these roughly 50% were randomly selected as training samples, while remaining 50% were used as testing samples (Paola and Schowengerdt, 1995a, b; Im, 2012).

Test sample was used to analyze accuracy of ANN, OBIA and MLC classification. Overall accuracy for each land cover class and kappa statistics for each classification strategy was calculated (Table 4.3).

4.5.4. Spatio-Temporal Change Detection of Impervious Area

ANN classification was implemented to the temporal image dataset of the study area to generate land cover classification for year 1980, 1986, 1990, 1995, 2000, 2005, 2010 and 2015. The classification results were further generalized into pervious and impervious (Weng, 2012). Post classification change detection method was used to detect change in land cover.

Change detection was performed at individual time-steps as well as overall duration. Conversion matrix of land cover change were generated to depict overall change in impervious surface (Table 4.4).

4.6. Results and Discussion

4.6.1. Classification Performance

Landsat image of the study area of year 2015 was classified into following classes using ANN, OBIA and MLC classification algorithm (Figure 4.3). Visually classification results were best of ANN and OBIA. MLC result misclassified build up with water body. OBIA classification were very effective in managing variance within classes. OBIA segment the image based on scale and multi-resolution segmentation. ANN classification result was filtered with a low pass filter to reduce the salt and pepper effect.

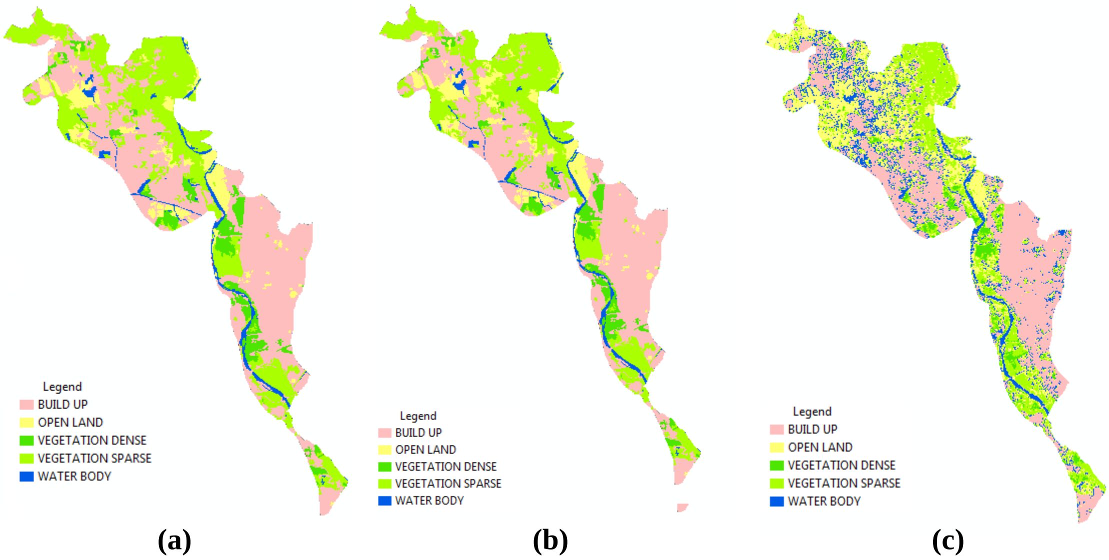


Figure 4.3: a) Classification – ANN, b) Classification – OBIA, c) Classification MLC

Accuracy assessment indicated ANN to be most accurate classification method. They scored best for user accuracy as well as kappa statistic 0.85 compared to OBIA (*K = 0.81*) and MLC (*K = 0.79*). OBIA classification was not effective to classify Sparse vegetation confusing it with Buildup and Open Land classes.

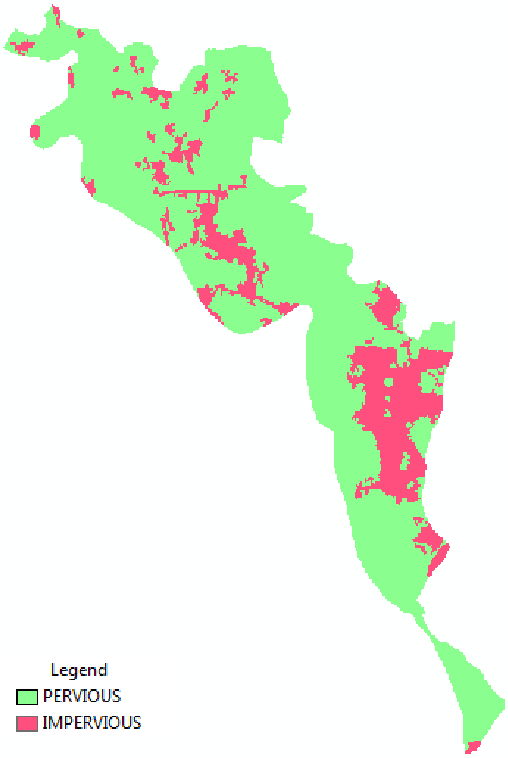
Table 4.3: Accuracy Assessment for all Three Classification Algorithms ANN, OBIA & MLC

Classification Method	Land Cover Classes	Validation	
		User Accuracy	Kappa (*K*)
ANN			
	Build up	89%	
	Open Land	85%	
	Vegetation Dense	87%	0.85
	Vegetation Sparse	85%	
	Waterbody	90%	
OBIA			
	Build up	85%	
	Open Land	80%	
	Vegetation Dense	82%	0.81
	Vegetation Sparse	78%	
	Waterbody	87%	
MLC			
	Build up	80%	
	Open Land	78%	
	Vegetation Dense	83%	0.79
	Vegetation Sparse	84%	
	Waterbody	78%	

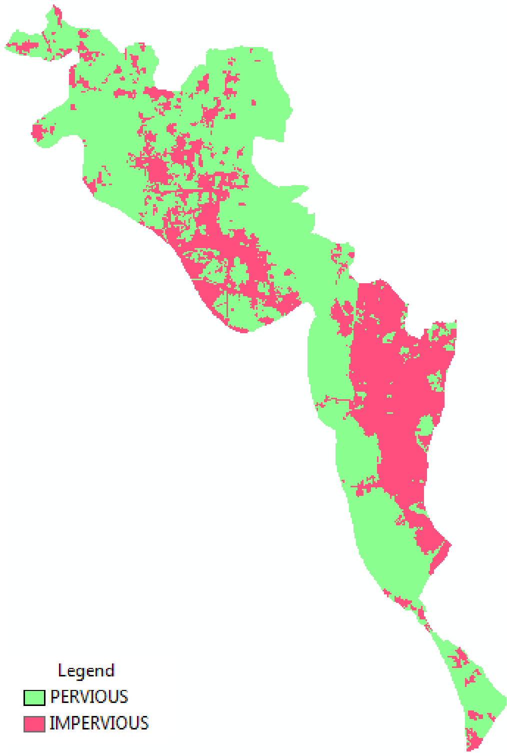
While the Object Based Image Analysis was also found to be very potent classification. it has marginally lower accuracies. These can be attributed to the scaling factor. Scale factor is dependent on user's choice based on understanding of object of interest dimensions. Chosen low will result in smaller segments causing a slow classification step. If chosen high, image segment will take more variance and resulting in a more generic classification.

MLC is one of the best statistical classifier and performed expectedly, however given the variability in feature space there were inaccuracies in classification output. This is normal given that one information class can traverse multiple locations in features space and a linear separation is generally not possible.

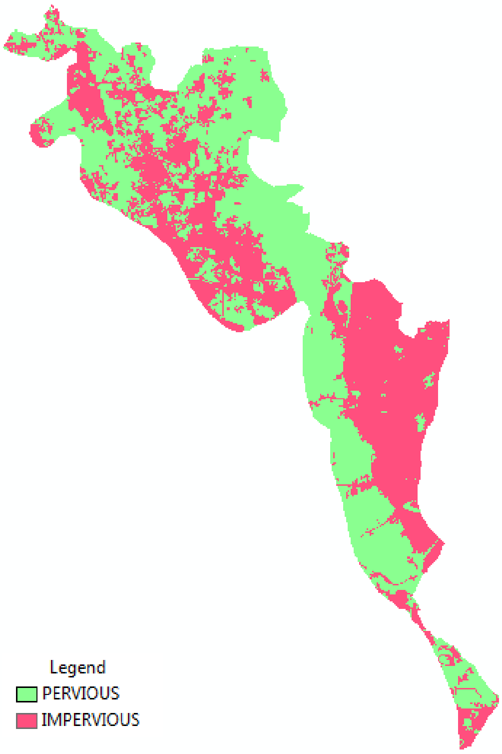
4.6.2. Land Cover Change in Yamuna Flood Plain



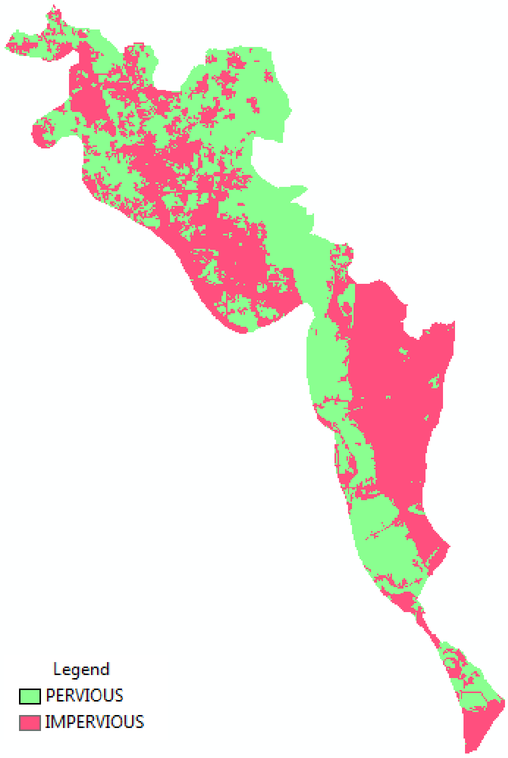
(a)



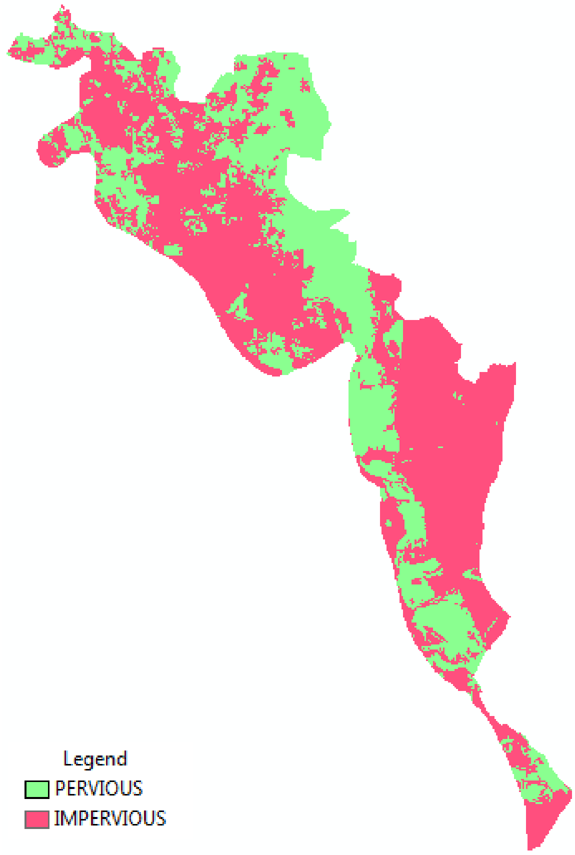
(b)



(c)



(d)



(e)

Figure 4.4: Distribution of Impervious and Pervious Surfaces a) Year 1980, b) Year 1991, c) Year 2000, d) Year 2010, e) Year 2015

To map the change in impervious land cover for the temporal duration between 1980-2015, five time-steps were selected representing a land cover change duration of 10 years. These include 1980, 1991, 2000, 2010 and 2015 (Figure 4.4). The decadal land cover was extracted from the Landsat images using ANN classification. The land cover was further classified into impervious and pervious surfaces. Impervious surface grew by more than 200% between 1980 to 2015.

Table 4.4: Change in Impervious Surface in Yamuna Flood Plain in Delhi between 1980-2015

Land Cover Class	1980	1991	2000	2010	2015
Pervious	23,145	18,673	15,197	13,658	10,806
Impervious	5,753	10,224	13,701	15,240	18,092

Rapid growth is witnessed in the North-East and East District of Delhi on the left bank of River Yamuna. Significant increase in impervious surface is observed in the North-West and North District. The most alarming development include exploitation of river terrace for expansion of roads, bridges and even metro depot. These are long term changes on the most pristine part of the flood plain (Pant and Mukherjee, 2017).

Chapter 5
Summary and Conclusions

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In the present work, two different areas encompassing the floodplain of two very important perennial rivers of India namely the Ganges and Yamuna were selected to test the varied objectives identified in the study. These two sites are namely, a) District Haridwar in Uttarakhand and b) River Yamuna Flood plain in Delhi. Both the areas were subjected to a plethora of analyses using computational intelligence approaches for Remote Sensing to solve Natural Resource Management problems.

Haridwar is situated in South-West of Uttarakhand, drained by river Ganga and is one of the most populated district of Uttarakhand. Land cover is dominated by rural type with agriculture, plantation and forest as prominent land cover classes. With rapid population growth, it is pertinent to assess the natural resources to ensure a sustainable future for the inhabitants.

Yamuna basin of Delhi is selected as the second site for the present work. Being densely populated with rapid urbanization, the city tends to encroach on the Yamuna flood plain. It is, therefore, important to quantitatively assess the change in land cover and ecologically sensitive areas in the flood plain. The impervious surface encroachment of the flood plain will result in loss of biodiversity, lower ground water table and increase in the vulnerability of the city to urban floods.

Remote sensing proves to be a powerful tool in natural resource management. Land cover assessment being key information required for a spatially enabled natural resource management. Traditional approaches in remote sensing employ statistical classifiers to extract information classes from spectral classes. This method is becoming inadequate due to complex information classes (those which cannot be represented by unique spectral classes). Further, the new generation sensors are providing better spectral/spatial resolution resulting in increased variance in the input data.

Present study deals with implementation of computational intelligence approaches for estimation of natural resources. These intelligence approaches includes decisions tree classifier or machine learning approaches. We further try to compare traditional method with computational intelligence approaches by assessing accuracy of either approach. We also try to assess the issue of generalization of AI approaches.

Landsat and IRS satellite data along with ancillary data including Survey of India toposheets were used. Reference data in the form of high resolution Quickbird images as well as ground truth sampling was conducted using random sampling strategy.

Traditional statistical classifiers have been around for a long time, while remote sensing and image processing has witnessed development of novel methods of classification. Artificial Neural Network and Object Based Image Analysis are a few computational intelligent approaches.

While computational intelligence approaches are recent and being proven to be more accurate. They will further grow with advancement of processing power of computers. This study also proves that the ANN compared to Segmentation with rule based classification and traditional statistical classifiers are more accurate. They are specially adapted in non-linear separation of spectral information meeting the criteria of desired information class. They however, require large set of training data and optimization of various parameters including training set, hidden layer, training threshold contribution, training rate, training momentum etc. This is one of the major hindrance in their application. While traditional classifier like MLC are not as accurate but they generalize well. Current state of AI in image processing is still using either Rule based decision or Machine learning. With a possibility of contextually adaptive algorithm, AI will be able to overcome its current limitation.

Rapid growth of Delhi and its adjoining areas will keep on building pressure on the available land resources. This can be seen by the results of this study. Yamuna flood plain has witnessed severe degradation. This has serious implications on the quality of life in Delhi. Flood plain sustain seasonal wetlands keeping the bio-diversity, ensuring ground water level and effect micro-climate. A healthy flood plain also acts as mitigation to urban floods, with increased impervious surface, the city is prone to urban floods making the population living on the flood plain more vulnerable. At most, the river terrace should be saved from long term Land Cover change as being witnessed in past couple of years.

The studies at Haridwar district deals with the performance evaluation of ANN Classifier and MLC approach. ANN outperform traditional classification methods due to their flexible approach for separation of spectral information in the n-dimensional space. They are agnostic to *a priori* distribution hence the classification focuses on the information class separation. The classification result for training site using ANN and MLC shows the former to be more accurate.

Generalization, meaning application of learning gained at one site to another site. ANN has shown to be dependent on training. Over-training might lead to accurate classification however this overfit model makes the model not be useful elsewhere with similar accuracy. The result of this study shows that the ANN while performing well at training site where the original training happened, were not as accurate at the test site owing to their overfit to the conditions at training site.

The key motivation behind the use of ANN for remote sensing is realization that human vision and brain can be a very efficient classifier processing large quantity of data from a variety of different sources. Neuron in the human brain receive inputs from other neurons and produce an output, which if higher than a threshold passes to other neurons. While it is not possible to reproduce the complexity of human brain on a computer, ANN are based on architecture of simple processing elements to solve complex problems including classification of satellite images. In a simplistic sense NN can be seen as data transformers where the objective is to associate the elements in one set of data with the elements in a second set. When applied to classification they are concerned with transformation of data from feature space to class space.

While there are many advantages of using ANN for land cover classification, they also have certain limitation. They are heavily dependent on training sample size. Larger the training sample better is their accuracy but on the other hand result in poor generalization. Thus, they are poor in abstracting knowledge and using it elsewhere.

Theoretically, these limitations can be removed if contextually adaptive artificial intelligence mechanisms to create underlying explanatory models helping them to characterize real world phenomenon. Such system will be able to learn on their own and will require a very few training samples. Future work in the direction of creating ANN with system level understanding is required. This will enable such AI to abstract information and to provide reason making them truly computationally intelligent.

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Publications

USE OF MOBILE GIS FOR QUALITATIVE AND QUANTITATIVE DATA COLLECTION FOR PUBLIC HEALTH PURPOSES IN VIETNAM

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ABSTRACT:

Geographic Information System (GIS) and Remote Sensing (RS) are a set of technologic and scientific tools that increasingly play important roles in public health surveillance and research. These tools enable data with spatial dimensions to provide a better understanding of the vulnerabilities, hazards, and risks to zoonotic disease outbreak investigations. In order to perform such analyses, data collection by surveys is a major component of these investigations in terms of resources for any health research. This article summarizes the methods used to rapidly and effectively collect and integrate health data into a GIS in order to facilitate further epidemiological analyses.

In order to better understand human-animal and animal-animal interface issues in cross-species transmission of disease, a GIS/RS based approach was used to collect high resolution household level point data in Hau My Phu and Nam Cao communes of Tien Giang and Thai Binh provinces of Vietnam, respectively. In the absence of high resolution household level qualitative and quantitative data on animals and husbandry practices, additional information was collected verbally from study participants. To add spatial dimensions and to make the surveying and data integration time shorter, mobile GIS systems were used. Remote Sensing data was used to facilitate the process of data collection and analysis. Survey forms were designed to collect information related to human, pig, chicken, and duck populations, plus various animal husbandry practices. Data collected are both qualitative and quantitative.

Based on the survey forms and expert knowledge solicitation, database schema was created using Unified Modelling Language (UML). The schema in UML was transferred to ESRI geodatabases. Further, the database schema in desktop GIS environment was transferred to mobile GIS environment of ESRI ArcPad. Customizations were introduced in the mobile GIS environment to suit the needs of surveyor's, including language, default value, and validation support. Land use maps were created from high resolution satellite images and other ancillary datasets. Emphasis was given to extract information about transportation features, agricultural land, water bodies, and household objects. This generalized information is transferred to mobile GIS to be used as a cue in data collection.

GIS and RS were rapid and effective tools for collecting, reviewing, and collating household level data from both hand-held devices and paper surveys.

KEY WORDS: GIS, Mobile GIS, RS, Satellite Image, Survey, Public Health

INTRODUCTION

Vietnam is an agrarian country, with agriculture as major land use (FAOSTAT, 2011). As common practise in south-east Asia livestock animals are reared in backyard and commercial farms (Tiensien etal. 2005, 2007).

With recent increase in influenza like disease outbreaks in various parts of world and especially in Vietnam (WHO, 2011, Phan etal. 2009), it is important to keep surveillance and monitoring for evidence based mitigation.

Epidemiology has relied on surveying to collect information to understand cause-effect relationship. It takes into consideration both quantitative and qualitative information. Quantitative information gives clues of presence or absence of an effect with statistical significance, while qualitative information provides details of causation which might not be apparent from purely quantitative perspective (Rothman, Kenneth J., 2002).

In order to ascertain information which can be used for an in-depth analysis of epidemiology of zoonotic diseases outbreak it is important to collect information at household level. In the absence of availability of such data a mobile GIS based household survey is planned. The planned survey form intends to collect information regarding poultry/livestock (chicken, ducks and pig), animal husbandry practises (John, 2005) and demography. This will help to better understand practises in light of animal-animal and animal-human interface of disease transmission (Graham etal. , 2008).

Mobile GIS is integration of traditional GIS with GPS on a mobile platform (Heywood et al. 2006, Burrough & McDonnell 1998). The GIS/GPS component helps in capturing spatial information while mobile computation device provide a movable platform with easy integration and visualization of spatial data (base map, satellite images and surveyed point etc.).

MATERIAL AND METHODS

Study Area

The household survey was carried out in two communes of Thai Binh and Tien Giang province namely Nam Cao and Hau My Phu commune. Thai Binh is situated in North-East Vietnam. It is a coastal province situated in the Red river delta (Figure 1).

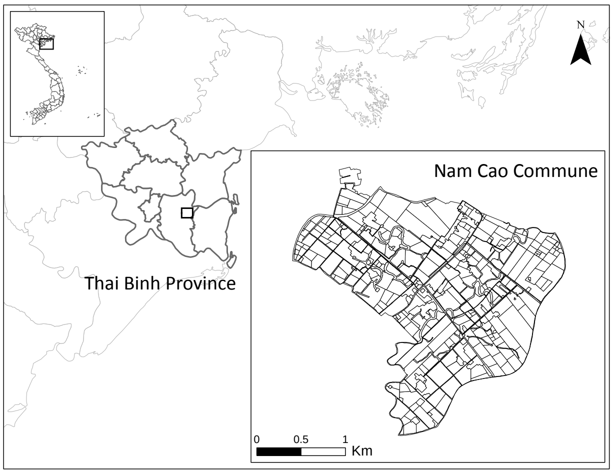

Figure 1. Nam Cao Commune Thai Binh province

Surrounded by Red, Tra Ly, Luoc and Hoa River, Thai Binh faces Gulf of Tonkin in East China Sea. Tien Giang province on the other hand is situated in South Vietnam, along Tien River north to Mekong River (Figure 2).

The landscape in both communes is predominantly flat, deltaic, and agricultural with wet rice as major crop. However one difference in landscape identified using satellite imagery was pattern of built-up area. In Nam Cao, built-up area was found to be aggregated in clusters. In Hau My Phu built-up areas were dispersed with few aggregations. This information was useful in planning and carrying out survey, as travel distance per household sampled in Hau My Phu was more than in Nam Cao.

Survey Design

It was planned to survey each and every household in both communes. Survey form consists of 60 questionnaires. It is further divided into four sections based on information collected i.e. pigs, chicken, ducks and human.

Survey forms consist of both quantitative and qualitative questionnaires. Information regarding current and past population sizes, animal husbandry practices, proximity between human-animal and animal-animal instances and observation of influenza like symptoms was prominent.

Database Design

It was planned to use a database for collection and storage of all spatial and attribute data. ESRI File Geodatabase (FGDB) was chosen to implement database schema for survey form along with secondary information extracted from satellite image.

FGDB provide large storage capacity, support to topology, relationship classes and incorporation of image data inside the geodatabase making them suitable for high resolution data survey.

While using Databases for data collection and integration, it is important to create structure (schema) (Burrough & McDonnell 1998). It works as a template for data collection and assist in its use for analysis. A database schema also helps in sharing the method of data collection without sharing data.

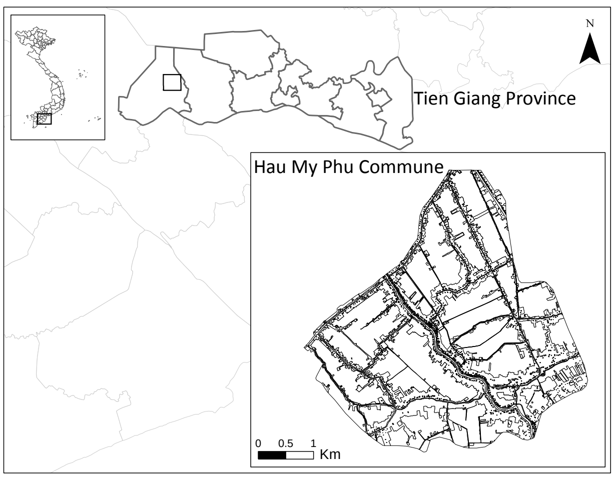

Figure 2. Hau My Phu Commune Tien Giang province

In order to create schema, Unified Modelling Language (UML) was used. UML helped in documenting the database elements, their structure and relationship. Designing databases through UML has certain advantages e.g. ease in corrective measures, sharing the schema, serve as memory documentation which can be further used and modified.

Satellite Image Data

Panchromatic images from CARTOSAT-1 (2.5m resolution) and multi-spectral images from IKONOS (1m resolution) covering Nam Cao and Hau My Phu communes respectively were procured. Satellite data thus acquired was processed for geometric and radiometric errors. The image data was mosaicked to get seamless image base map before being imported into the geodatabase.

Processed satellite images were used to prepare land use map with aquaculture, Plantation, River, Road, Settlement and Wet rice cultivation as main classes. Extraction of land use classes like settlement, rivers and roads was directly helpful in estimating and planning field work. The base map was also used for navigational purposes.

Desktop to Mobile

ArcPad™ is a GIS software providing flexibility to collect Geo-Information through mobile platform. It also help in collection of attribute information via digital forms, geocoded photos etc.

The database schema inside FGDB was replicated for the mobile GIS environment. Subsequently a project in ArcPad™ was created. Data entry forms were customized to facilitate user interaction in the field using ArcPad Studio™. Satellite image and base map were also integrated into the mobile GIS software (Figure 3). Further in order to facilitate data entry from paper based survey, database schema was exported to MS-Access. (Figure 4).

Survey

Household level Survey was conducted in both the communes with objective to collect information from each household. Each commune consists of a thousand to fifteen hundred households.

In order to complete the task with limited number of mobile GIS devices and handheld GPS two methods were adopted.

Method-1

Customized electronic survey forms integrated with mobile GIS device were used to collect data from Nam Cao commune.

The ArcPad™ based custom forms were used to collect data from the field. Each household was mapped as a point object and attribute information collected using the form interface (Figure 3).

Method-2

In Hau My Phu commune, data collection was carried out using paper based survey forms. Along with hardcopy forms handheld GPS devices were used. These handheld GPS devices were standalone GPS's with very limited user interface to collect attribute information.

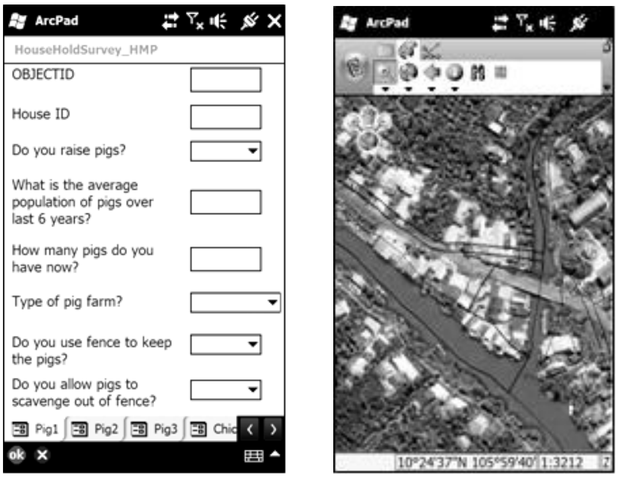

Figure 3. Survey form and base map in mobile GIS

The location of each household was captured using the GPS device which is cross-referenced with the paper based survey form.

Data Assimilation

Data collected in the field using mobile GIS and paper based survey forms were imported into geodatabase. Importing data from mobile GIS system was straight forward however data from paper based form was first imported in a MS-Access database using a custom build form (Figure 4) and subsequently imported to the geodatabase.

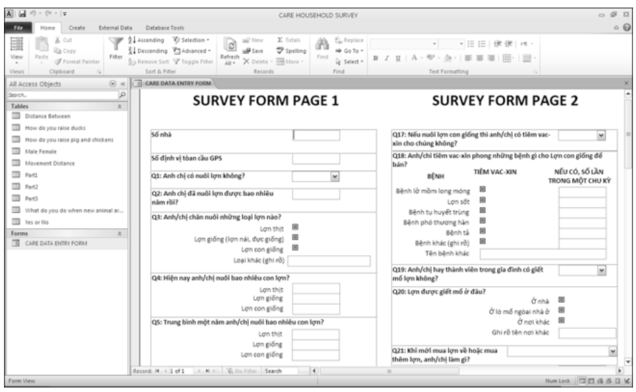

Figure 4. Data entry form in MS-Access

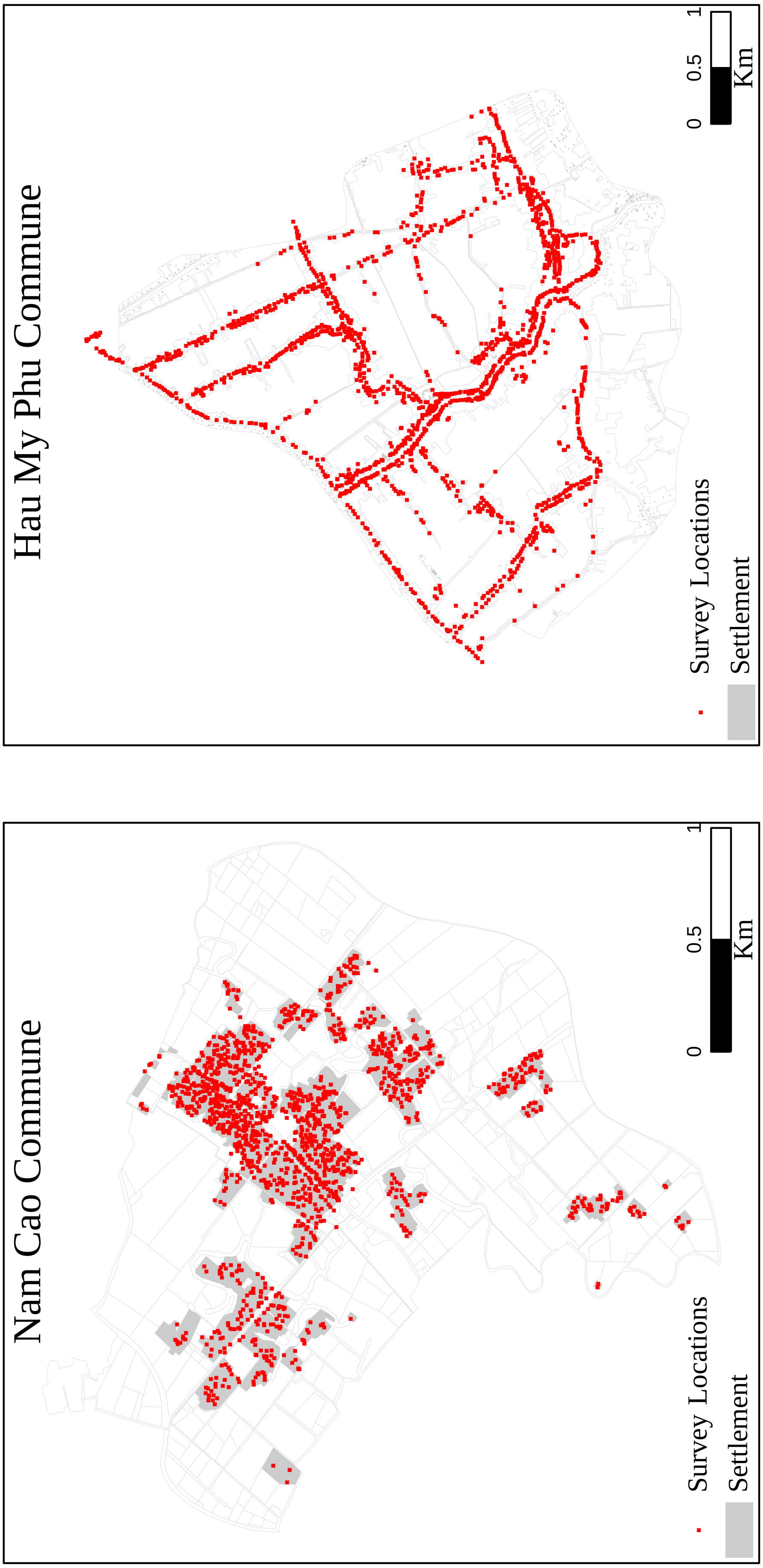

Figure 5. Household survey locations in study area

RESULTS

Results

GIS deployed in mobile phone with integrated GPS chip helped in rapid collection and update of the data to desktop GIS. It was also easy to incorporate qualitative data in survey, which can be typed in during the interview.

Updated base map created from high resolution satellite images were used to capture information like location of household, roads/streets, canals etc. The detailed land use assisted in planning and conducting survey. Pre-field digitization of households resulted in saving valuable time finding survey locations.

Survey data collected is stored in ESRI File Geodatabase in defined schema. The geodatabase created is structured to provide a 3 tiered information system. The bottom level contains satellite images of the study area. Above it is the land use and house hold survey information. Thus, one file geodatabase forms the repository of all data, stored in vector / raster and tables format.

The information stored in the file geodatabase can be readily used for various purposes including creation of thematic maps, reports, queries, visualization (Figure 5), identify spatial and non-spatial relationship between variables further it can be used for GIS based modelling.

CONCLUSION

A traditional paper based survey is one of the key methods to collect information in a public health survey; however it was observed that it is more time consuming and require far more steps to collect and assimilate the data for processing.

Advances in mobile phone technology are paving ways in which this platform can be used in conjunction with GIS to rapidly collect spatial data (Richards etal.1999). Especially mobile phones with embedded GPS chips and touch screen display are becoming important tools for collecting geocoded data. A touch screen based interface allows more data collection via digital forms which are easy to use and the whole hardware software combination package is easy to carry around in the field. Thus, as a mobile GIS system they provide solutions to collect geospatial information and also to use the same for navigation and visualization. Simple geoprocessing analysis can also be performed but this capacity is currently limited due to hardware limitations.

The mobile GIS not only assist in data collection, it helps maintain the database structure throughout the survey life cycle. This mean rapid data update back to the databases.

Because there are fewer steps in data capture and assimilation using a mobile GIS system, it has lower probability in terms of human errors as compared to paper based data collection.

Some of the limitation of mobile GIS technology is spatial accuracy. Spatial accuracy to such devices ranges from 5-10m. Although low, this accuracy is acceptable for collecting point data for household in a rural setting.

The method for data collection in this study is offline data collection i.e. data collection and data integration to the geodatabase are two separate steps. There are approaches with near real time or real time data collection and integration e.g. using mobile GIS with Server GIS where mobile functionality is part of a mobile service rendered to the client in the field from a remote server connected through internet. This will further reduce the time of data collection and visualization of results. It will also give more control over data collection strategies and will allow interventions to surveys from a central location in a timely manner. Further with recent development in cloud computing such processes will be more cost effective as users don't have to own server side infrastructure and will only pay for a mobile service hosted on cloud.

In the domain of epidemiology where we are continuously facing challenges in terms of unavailability of high resolution geocoded information of public health statistics, mobile GIS is showing promising role data collection and dissemination for preparedness and mitigation (Prasert Auewarakul, Wanna Hanchaoworakul & Kumnuan Ungchusak, 2008). Not only these methods present simple and effective data collection but they are fast enough to provide access to data for further analysis in a timely manner.

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INTEGRATED WATER RESOURCE MANAGEMENT USING REMOTE SENSING AND GEOPHYSICAL TECHNIQUES: ARAVALI QUARTZITE, DELHI, INDIA

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Information on land use patterns and changes are required for planning, utilization, and implementation of groundwater exploration and rainwater harvesting. Multispectral and multitemporal satellite data has the potential to delineate sites for water resource management. Magnetic and resistivity surveys can further confirm subsurface aquifer configuration. Due to heterogeneity of aquifer materials, it is essential to take a holistic approach that includes geological information supplemented with remotely sensed data and supported by resistivity and magnetic anomaly detection. This approach is used for locations of higher spectral reflectance and lineament density which are assumed to be areas of aquifer recharge. This investigation focussed on the Aravali quartzite terrain of Delhi, India at the Research and Referral Hospital and Jawaharlal Nehru University areas. Suitable areas are identified for construction of check dams, roof-top rainwater harvesting pits, and drilling sites in the difficult terrain of the Aravali quartzite.

INTRODUCTION

The management of a resource includes insuring a sustainable input of the resource to a place where it is in short supply from a place of excess. But to maintain the supply there should be exhaustive planning to manage the resource and at the same time consider the safety of the environment. Management includes bringing a balance to the resource availability at a place ensuring the benefit of the local population while keeping in view the well-being of the environment.

Jawaharlal Nehru University (JNU) and Research and Referral Hospital (RRH) resource management case studies invariably speak in favor of the above approach. The study area is situated in a part of the Delhi ridge, which is geologically a quartzite mass. This makes the probability of finding groundwater very small (Mukherjee, 2004). Interestingly, in such a terrain the movement and availability of groundwater depends on geological as well as structural inhomogeneity. Implementation of the project and popularizing the technique in those areas where depth of the water level is more then 25 m below ground level and have a declining trend is critical. Information on existing land use patterns, the spatial distribution and its changes is required for planning, utilization, and formulation of policies and programs for sustainable development of depleted water resources. Groundwater exploration in hardrock terrain is a challenging task. The occurrence and amount of groundwater in hard rocks is related to the complex interactions of lithological, structural, geomorphological, and pedological and climatological factors. Crystalline rocks, with little intergranular porosity, are generally impervious. Movement and storage of water can occur in the network of joints, fractures and faults and in weathered zones. The thickness and nature of the weathered layer is also related to lithological and structural characters and climatological conditions (Horton, 1945).

Remote sensing techniques using satellite images have become a powerful tool in groundwater exploration to supplement conventional methods. The importance of remote sensing in groundwater studies is based on the fact that images help in identifying morphological and structural features that influence groundwater movement and occurrence. Delineation of lineaments and fractures, drainage pattern, weathered zones, vegetation anomalies and their mutual relationships have been carried out utilizing resistivity and magnetic data (Mukherjee 1998).

DATA USED AND METHODOLOGY

Multispectral and multitemporal data merged with land use, geological, geomorphologic, hydrogeological and magnetic data have potential for identification of suitable areas for construction of check dams across drainage at appropriate locations. This is one of the successful methods of artificial recharge and selection of drilling sites for groundwater exploration.

Information derived from satellite image analysis and other collateral data were integrated together to synthesize and mark potential areas for artificial recharge.

Satellite data products inferred land use, geological, hydromorphological and ecological information. The satellite image covering the area was analyzed digitally to prepare a geomorphologic map on 1:12,500 scale. The following satellite data products were used in the analysis

1. IRS 1D PAN+LISS III merged acquired on PAN on 15 Feb. 2002 and LISS 15 Feb. 2002
2. IRS 1D PAN +LISS III merged acquired on PAN on 6 march 2004 and LISS on 23 Feb. 2004.

The Research and Referral Hospital (RRH) encompasses the western and southwestern parts of the national capital territory, Delhi, while Jawaharlal Nehru University is situated on the southern part of Delhi. The rock types of RRH and JNU are the same and are mostly Aravali Quartzite. The terrain has undulating topography with a regional slope toward the north-northwest. The low-lying area is filled with buried shallow to medium pediment plain. Due to this heterogeneity in aquifer material, water resources management in the RRH and JNU areas needed a holistic approach of geological information supplemented with remotely sensed data and detailed resistivity and magnetic surveys.

Sustainable fresh groundwater availability in the area can only be expected in the shallow fresh water aquifers, which are regularly recharged over suitable geological formations. In order to find the remedial measures it has become essential to identify suitable areas where optimum rainwater harvesting can be done.

LOCATION OF THE STUDY AREA

The JNU campus is situated on a low relief hill, northwest of Mehrauli and southwest of Hauz Khas in south Delhi, falling in topographical sheet No. 53 H/2 (SE quadrant). Latitude $28^o32'30''$ E and longitude $77^o10'00''$ N pass through the middle of the campus.

Physiographically, Delhi is at the northeastern culmination of the Mewat branch of the Aravalli mountain system. Here, this branch of the Aravallis is called the Delhi Ridge. JNU is situated on an easterly projecting spur of this ridge and forms an undulating and dissected plateau of quartzite. The general slope is towards north to northeast.

The campus area is drained by three drainage systems, forming structurally controlled sub-dendritic to sub parallel patterns. The main streams are controlled by a formational strike (NS to NE-SW), while the minor drainages by fractures and joints. All the drainages are dry except in the rainy season and all rainwater flows out of the campus in the absence of any structure to control the runoff. There are a few shallow ponds along drainage, but they are mostly silted and remain dry.

The RRH complex is located SW of the Dhaula Kuan, and is adjacent to Indira Gandhi international airport to the west. It is located on the line joining a portion of the ridge forest area of Delhi. This linear fracture of ridge reaches Yamuna at one end which is NE from the hospital.

The area is covered by latitude 28034'30" to $28^0 35'30''$ and longitude $77^0 8'30''$ to 77010'10" (Figure 1). The RRH complex boundary consists of the RRH hospital itself as well as residential areas, a parade ground and xerophytic vegetation characteristic of arid to semiarid conditions. The complex has an area of 146 acres situated in the southwest district of the national capital territory of Delhi.

GEOLOGY OF THE AREA

The area is occupied by an alluvium buried pediment plain, comprised of sand, silt, clay and kankar (agglomeration of clay and sand) underlain by bedded, highly weathered Alwar quartzite constituting a north - south trending low ridge in the area (Table 1). A clear lineament has been observed in a north-south direction and few lineaments have a diagonal relationship with the main one. The sequence of the rock formations in the area is:

Quaternary alluvium / buried pediment plain

Post Delhi intrusive – pegmatite and basic intrusive

Delhi super group – Alwar quartzite (ferruginous / siliceous)

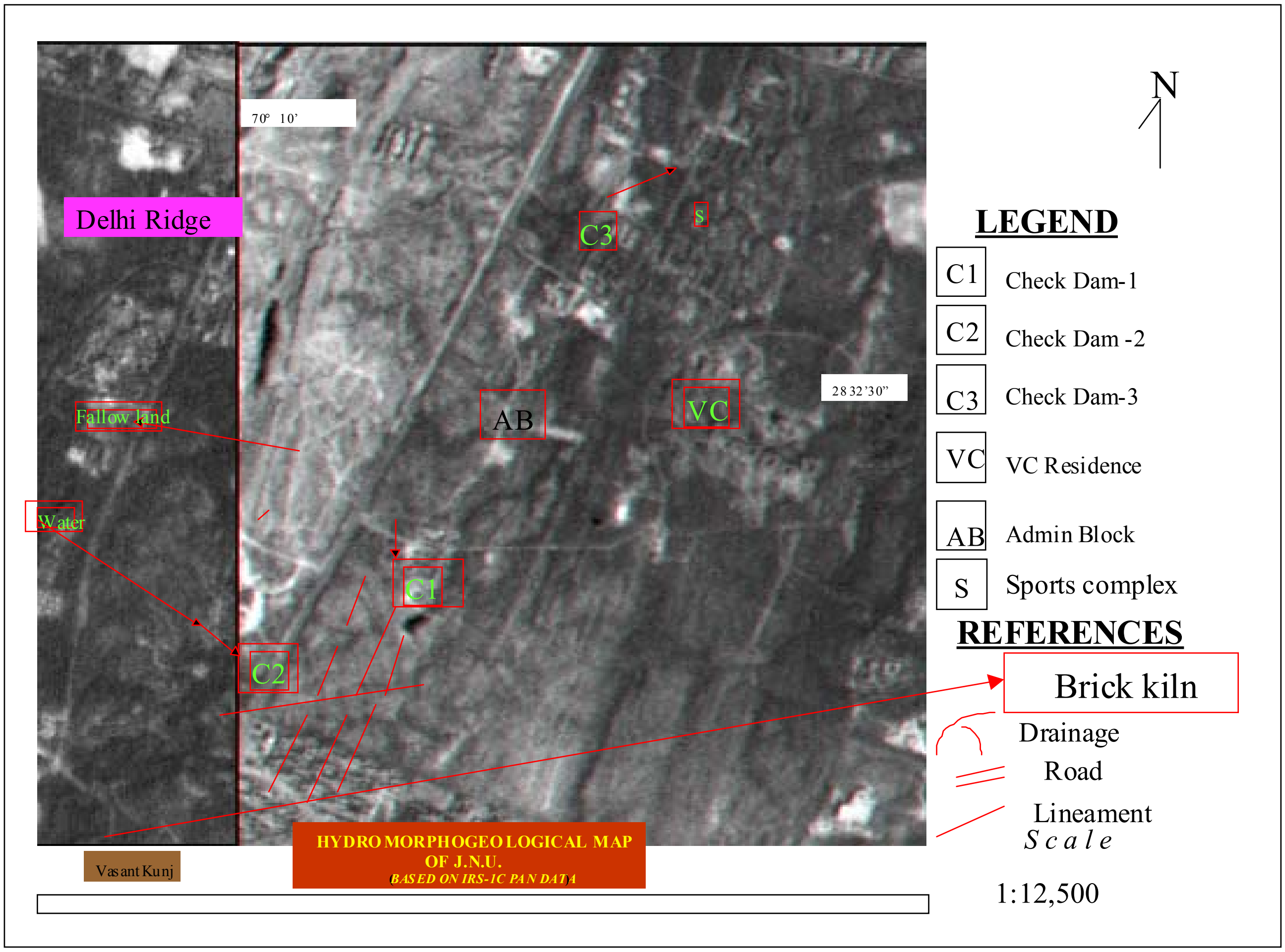

Figure 1. Hydrogeological study of JNU environs for integrated water resource management.

The Delhi region is a part of the Indo-Gangetic alluvial buried pediment plain at an elevation ranging from 198-270 m. A quartzite ridge extending roughly from north-northeast to the south-southwest transects the area. The thickness of alluvium on the eastern and western side of the ridge is variable. It generally thickens (>300 m) towards the west.

HYDROGEOMORPHOLOGY

From the hydrogeomorphological investigation of JNU and RRH of Delhi area it is clear that it includes the following features:

1) Low Residual Structural Hills: These are parts of Delhi ridge forming N-S to NS-SW trending structural ridges, tors, and mounds and composed of folded and jointed quartzite. Joints allow only limited groundwater infiltration. This unit has very poor prospects of groundwater. They are mostly barren, with scanty vegetation along joints and slopes.

2) Pediment: The undulating, eroded and dissected shallow, buried planar surface along the fringe and slopes of ridges and tors form this unit. The main drainage systems are developed in this unit. Weathering is shallow and soil thickness varies, the maximum being in the valleys near the streams. The soil is generally clay and fine silty, and partly gritty and gravelly. Drainage dissection is quite intense at places, often developing gullies. Weathering is more intense in coarse gritty or arkosic quartzite. Groundwater potential is generally low due to poor infiltration, with high runoff resulting from varying slopes and clay mantle.

Table 1. Stratigraphy of Delhi

Period	Formation	Description
Quaternary	Newer alluvium	Unconsolidated interbedded line of sand, silt, gravel and clay confined to flood plains Yamuna river
	Older alluvium	Unconsolidated interbedded, interfingering deposit sand clay and kankar, moderately sorted thickness variables, at places more then 300m
Precambrian	Alwar quartzite	Well stratified thick bedded brown to buff color, hard to compact, intruded locally by pegmatite and quartz vein inter bedded with mica sheets.

3) Buried pediment: This unit forms the almost flat terrain in the northeastern part of the RRH premises. In JNU this type of feature exists in the northeastern part mainly between the ridges where the depth of the buried pediment is shallow (Figure 1). It has a shallow to moderately thick soil cover, which is mainly silty and clayey, and at places gritty and gravelly. The surface slopes gently towards the northeast and merges with deeply buried pediment beyond the campus and with the Yamuna alluvial plain further east. This unit forms a moderate to good groundwater potential, especially along fractures and drainages.

Groundwater occurrence

Groundwater is the subsurface water that fully saturates pores or cracks in soils and rocks. Groundwater is replenished by precipitation and, depending on the local climate and geology, is unevenly distributed in both quality and quantity. When rain falls, some of the water evaporates, some is transpired by plants, some flows over land and collects in streams, and some infiltrates into the pores or cracks of soil and rocks. After the water requirements for plant and soil are satisfied, any excess water will infiltrate to the water table – the top of the zone below which the opening in rocks are saturated.

Role of remote sensing in groundwater studies

Space technology in the form of remote sensing can play a useful role in hydrological studies. Remote sensing is defined as the science of deriving information from measurements made at a distance from the object without the sensor actually coming in contact with it. Remote sensing though is a fledging phenomenon; either substituting or complementing or supplementing the conventional technology with reasonably faster, efficient and accurate methods of survey in the domain of water resource planning, conservation, development, management and utilization (Roy and Bhattacharya, 1982).

Remote sensing by virtue of its synoptic coverage, spectral behavior, repeatability, and availability, offers an effective first hand tool in mapping and monitoring resources in a reasonably short time frame. The synoptic view facilitates the study of objects and their relationships. Spectral signatures permit identification of various features, while the temporal aspect allows change detection in the environment. The real advantage is the real time measurement that facilitates constant and effective monitoring. The main advantage of the remote sensing is that the data is in the digital form and can be analyzed easily with the help of computers.

The application areas for remote sensing data are both wide and varied. Radiometric data potentially represent a very useful source of information in pedological research and in the study of water quality though remote sensing but cannot be used for groundwater studies (Sharma and Anjaneyulu, 1993). But remote sensing allows us to make indirect references regarding subsurface through sacrificial expression of the aquifer. The subsurface hydrological conditions are inferred based on identification and correlation of surface phenomenon involving geological features and structures, geomorphology, surface hydrology, soils and soil moisture anomalies, vegetation types and distribution, land use and many other indicators. The benefits that accrue in the use of remotely sensed data are usually greatest when they are applied for large-scale preliminary investigation of groundwater reserves.

Although remote sensing techniques can never replace conventional hydrologic observation network, remote sensing data have two distinct advantages. Remote sensing platforms provide data with high resolution in space and data and can be obtained for areas that has no record of measurements (e.g. remote areas). Remote sensing data, particularly satellite data can be most helpful for design and operation purposes if they are used in combination with ground truth (Usha et al., 1989). The disadvantages of satellite data are an unfavorable combination of resolution in time and space, Airborne geophysical exploration is highly used in groundwater prospects. Conventional prospecting tools viz., hydrogeological and geophysical instruments generally do not yield the relevant details and occasionally exhibit lack of resolution (Orellena and Mooney, 1966). Integration of satellite data and vertical electrical sounding (VES) data as well as magnetic intensity data, indirectly giving the potential fracture zones using other collateral data generated from the imagery as well as collected from various institutions is used to access the groundwater potential of various geomorphic units (Mukherjee, 1998).

In the present work, more thrust has been given to the detection of area which has high groundwater potential and areas which can serve as good point of recharge to groundwater. Also undertaken in this exercise is an effort to generate a model to find the trend of flow of the surface water during rainy months so that this water can be diverted toward the areas selected for recharging the groundwater. All this has been achieved using geophysical techniques viz. resistivity survey, magnetic survey, soil analysis, drawdown tests of existing pumps, and using remotely sensed data to correlate the data. New data like trends of the lineaments are also used to detect the reflectance values and to generate a model to find the trend of flow and help in locating suitable sites for check dams (Figure 1).

Electrical Resistivity Method

The electric resistivity of a rock formation limits the amount of current passing through the formation when an electric potential is applied. It may be defined as the resistance in ohms between opposite faces of a unit cube of the material. If a material of resistance R has a cross-sectional area A and a length L, then its resistivity can be expressed as

$$r=RA/L$$

Units of resistivity (r) are ohm-m.

Resistivity of rock formations vary over a wide range, depending on the material, density, porosity, pore size and shape, water content and quality, and temperature. There are no fixed limits for resistivities of various rocks. In relatively porous formations, the resistivity is controlled more by water content and quality within the formation than by the rock resistivity. For aquifers composed of unconsolidated materials, the resistivity decreases with the degree of saturation and the salinity of groundwater. Clay minerals conduct electric current through their matrix, therefore clayey formations tend to display lower resistivities then do permeable alluvial aquifers.

Actual resistivities are determined from apparent resistivities, which are computed from measurements of current and potential differences between pairs of electrodes placed in the ground surface. The procedure involves measuring a potential difference between two electrodes (potential electrode) resulting from an applied current through two other electrodes (current electrode) outside but in line with the potential electrode. If the resistivity is everywhere uniform in the subsurface zone beneath the electrodes, the current and equipotential lines will form an orthogonal network of circular arcs. The measured potential difference is a weighted value over a subsurface region controlled by the shape of the network. Thus the measured current and potential differences yield an apparent resistivity over an unspecified depth. If the spacing between the electrodes is increased, a deeper penetration of the electric field occurs and a different apparent resistivity is obtained. In general, actual subsurface resistivity vary with depth; therefore, apparent resistivities will change as electrode spacing are increased, but not in a like manner. Because changes of resistivity at great depths have only a slight effect on the apparent resistivity compared to those at shallow depths, the method is seldom effective for determining actual resistivities below a few hundred meters.

Electrodes consist of metal stakes driven into the ground. In practice various standard electrode spacing arrangements have been adopted; most common are the Wenner and Schlumberger arrangements.

The Wenner arrangement has the potential electrode located at the third points between the current electrodes. The apparent resistivity is given by the ratio of voltage to current times a spacing factor. For the Wenner arrangement, the apparent resistivity

$$r_a=2pa\ V/I$$

Where ‘a’ is the distance between the adjacent electrodes, ‘V’ is voltage difference between the potential electrodes, and ‘I’ is apparent current.

The Schlumberger arrangement used for this study has the potential electrode close together. The apparent resistivity is given by

$$r_a = (p(L/2)^{2} - (b/2)^{2}V)/\ b*I$$

Where ‘L’ and ‘b’ are current and potential electrode spacing, respectively. Theoretically L>>b, but for practical application good results can be obtained if L>=5b.

Typical resistivities of the geological materials

Resistivity near surface materials is heavily affected by groundwater, and water is a low resistivity material. In general finer grained sediments have low resistivities, and bedrock has high resistivities. Resistivity values for different rock types are shown in Table 2. Resistivities are reduced by increasing porosity, increasing ion content of groundwater, increasing content of clay and decreasing grain size.

Magnetic anomaly studies

Magnetic anomalies can be an useful geophysical component in groundwater management (Regan et al., 1975). A magnetic survey was carried out in and around, the RRH complex, using a proton precession magnetometer modal PM - 600 manufactured by Integrated Geo Instruments and Services ltd.

The proton precession magnetometer utilizes the spinning of protons or nuclei of the hydrogen atoms in a sample of hydrocarbon fluid to measure the total magnetic field intensity. Water, kerosene, alcohol etc. are taken as samples. The protons in these fluids behave as small spinning magnetic dipoles. These magnetic dipoles are temporarily aligned (polarized) by application of strong uniform magnetic field by sending a current through a coil wound on the bottle containing the hydrocarbon fluid / water. When the current is removed i.e., when the applied field is removed, the spin of protons causes frequency of which is proportional to the ambient field intensity. The total magnetic intensity as measured by a proton precession magnetometer is a scalar measurement i.e., it gives simply magnitude of the total earth's magnetic field independent of its direction. The RRH complex is in a region with normal magnetic intensity around 47000 gamma (Figure 2).

Table 2. Typical resistivity of various geological materials of Aravalli Quartzites of Delhi

S.No.	Lithology	Resistivity (Ω)
1	Silt	10-100
2	Sand-gravel	300-8000
3	Fresh water sand	50-100
4	Argillaceous sand	25-50
5	Salt water sand	0.4-1.3
6	Pebble aquifer	100-several hundred
7	Limestone	80- several hundred
8	Clay marls	Several to 50

A lineament trespassing the hospital complex is inferred by IRS-1D PAN+LISS-III merged, acquired on 06-march-2004, LISS23-march-2004 respectively and the second data by IRS-1D PAN+LISS merged 15-feb-2002 and 15-feb-2002 respectively. It shows a strong trend in NNE-

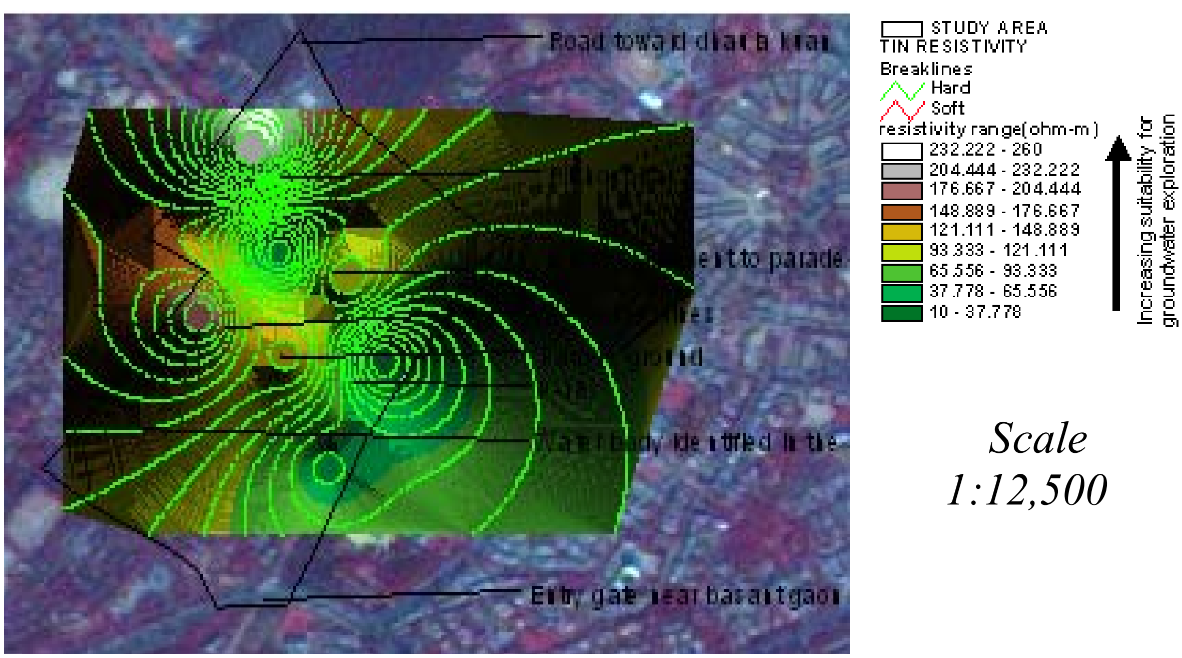

Figure 2. Hydrogeological study of RRH environs for integrated water resource management.

SSW direction, which passes directly through the hospital premises. On its NNE side from the hospital the lineament shows a water body at Subroto Park. And also on the SSW of the hospital the lineament has a water body inside the hospital premises. Measurements were taken along this lineament, which is inferred as a sudden decrease in magnetic values. Based on the spot magnetic values a contour map was made along the profile. Contour lines were been drawn at every 3000-gamma interval. Low magnetic values were noticed along lineaments and places with fractured ferruginous quartzite. Selection of check dams was based on the points inferred by magnetometer showing low magnetic values and interconnected lineaments.

DISCUSSION

Land use land cover and water resources management are directly linked with each other. It is clear that selection of the site for RRH and JNU was not done keeping this point in mind. However during that period, the latest knowledge of remote sensing as well as its integration with geophysical data was considered. The study area is on a series of parallel lineaments (Mukherjee, 1997). These lineaments are a connecting conduit of occasional surface water. In JNU the surface water is going out of the campus through seismically generated lineaments while at the RRH water logging takes place in the basement of the hospital. The JNU area has shown remarkable development (Figure 3) in its environment after the water resource management program and a similar development is expected in the RRH areas (Figure 2).

Keeping all these points in consideration a recommendation is given that can be implemented for the integrated water resource management in the terrain. Rainwater harvesting and groundwater exploration in selected areas may lead to sustainability to this area.

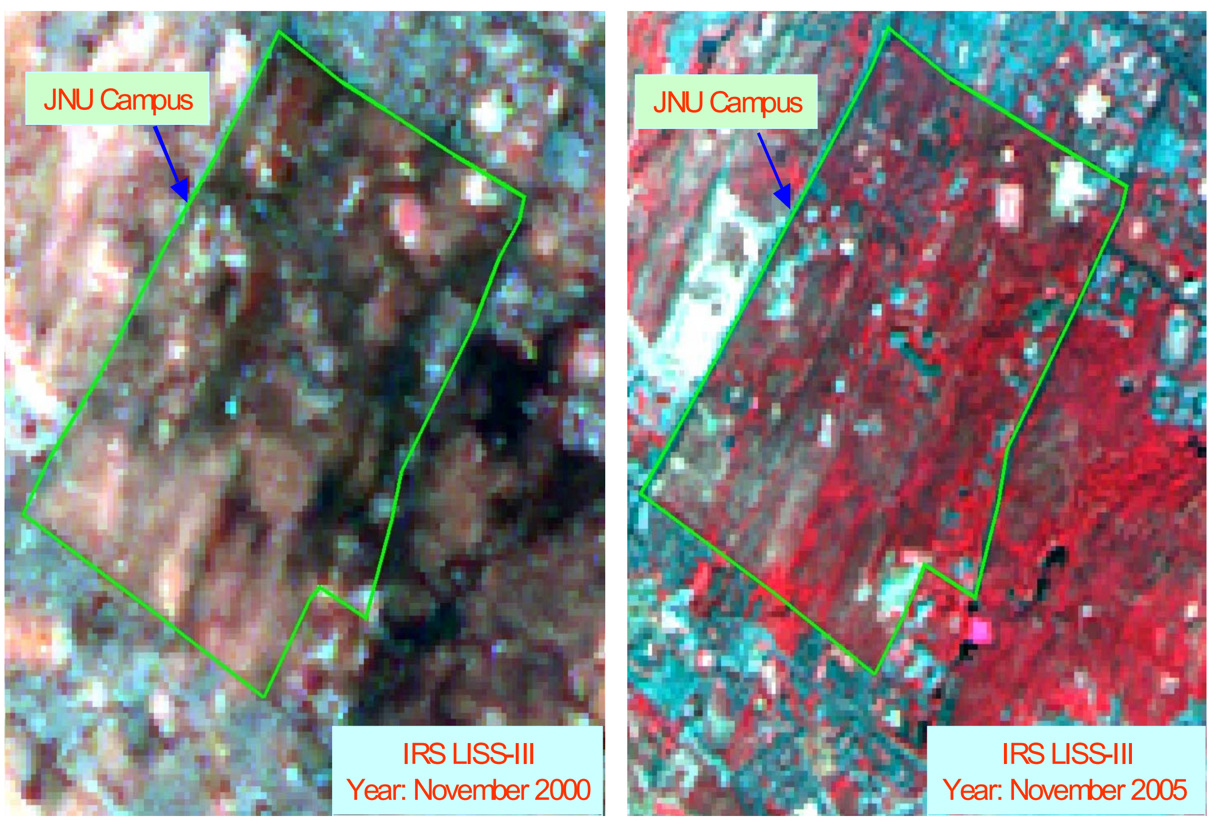

Figure 3. JNU area has shown remarkable improvement in terms of forest coverage.

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National and regional impacts of climate change on malaria by 2030

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The article reports projection of malaria by 2030 using A1B scenario of PRECIS model basically derived from HadRM3. Malaria scenario has been defined in terms of opening of months of malaria transmission based on minimum required temperature and relative humidity for baseline (1961–1990) and by 2030. Detailed analysis has been done for four vulnerable sectors, viz. Himalayan region, northeast, the Western Ghats and coastal region. Some parts of Uttarakhand, Jammu and Kashmir and Arunachal Pradesh are likely to open transmission windows in new districts with increase in 4–6 months category of transmission. In the northeastern states, intensity of transmission is projected to increase from 7–9 months to 10–12 months. The Western Ghats is projected to be affected to a minimum, whereas in the east coastal districts, reduction in transmission months is likely due to increased temperature. As malaria transmission dynamics is multi-factorial, driven by agricultural practices, water availability, urbanization, migration, socio-economic conditions and intervention measures, projections based on climatic parameters alone should not be viewed with certainty rather they are for guidelines for preparedness in vulnerable areas and strengthen health infrastructure, effective health education and use of best available tools of intervention to cope with the threat of climate change.

Keywords: Climate change, malaria, relative humidity, transmission window, temperature.

Introduction

VECTOR-BORNE diseases (VBDs) are climate-sensitive as the pathogen has to complete some part of its development in insect/arthropod vectors like mosquitoes, sand flies, ticks, etc. Since these vectors are cold-blooded creatures, their developmental stages of life cycle and the development of parasite in their body (extrinsic incubation period) are affected by climatic conditions like temperature, rainfall, relative humidity, wind velocity etc. Seasonal fluctuations in VBDs are caused by fluctuating climatic conditions and are well known. The role of climatic factors has been studied extensively in the epidemiology of malaria due to its global public health importance[1–4]. The minimum temperature required for development of *Plasmodium vivax* parasite in anopheline mosquitoes is 14.5–16.5°C, whereas for *P. falciparum* it is 16.5–18°C (refs 5, 6). At 16°C, it will take 55 days for completion of sporogony of *P. vivax* whereas at 28°C the process can be completed in 7 days and at 18°C it will take 29 days[7]. The duration of sporogony in *Anopheles* mosquitoes decreases with increase in temperature from 20°C to 25°C (ref. 7). From 32°C to 39°C, there is high mortality in mosquitoes[5] and at 40°C, their daily survival becomes zero. The interplay between temperature and mosquitoes has recently been reviewed[8]. At increased temperatures, the rate of digestion of blood meal increases, which in turn accelerates the ovarian development, egg-laying, reduction in the duration of the gonotrophic cycle and more frequency of feeding on hosts, thus increasing the probability of transmission[5,6].

Distribution of malaria in turn is the reflection of suitable climatic conditions and availability of mosquito vectors in different parts of the country. In stable malaria, transmission continues almost throughout the year as the temperature, rainfall and resultant relative humidity are suitable for all the 12 months. The states having unstable malaria experience winters during which transmission does not take place. Areas with unstable malaria are epidemic-prone depending on the favourable conditions provided by unusually high rains at the threshold of the transmission season.

Recently, climate change has emerged as a new threat which is likely to affect spatial and temporal distribution of malaria and other VBDs. Studies undertaken globally for projections of malaria are based on global climate models which provide malaria scenario by 2100 (refs 9–12). Impact assessments in various sectors, including health, have been undertaken under the aegis of the National Communication Project I (refs 13, 14). Initial assessments were based on the HadRM2 model using IS92a scenario wherein the projections were made for 2050 (ref. 14).

In view of transmission dynamics of malaria depending on various factors like agricultural practices, urbanization, water scarcity, socio-economics, etc. long-term projections are of little value in developing preparedness plan to address the issue. In view of this, PRECIS model of A1B scenario which provided projection of climatic parameters by the year 2030 was used for assessment of

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malaria at national and regional level in India, with emphasis on the Himalayan region, northeastern states, the Western Ghats and coastal areas under the aegis of NATCOM II and the recently set up Indian Network for Climate Change Assessment (INCCA). The present assessment will elicit the most vulnerable areas of malaria due to climate change and pave the way for identifying remedial measures for addressing the potential threat in the country.

Material and methods

Extraction of data from PRECIS

A1B scenario of PRECIS model developed at Hadley Centre, UK Met Office and provided by the Indian Institute of Tropical Meteorology (IITM), Pune, provided baseline data based on 30 years average (1961–1990) and projection of temperature, rainfall and relative humidity (RH), wind velocity, surface roughness, canopy cover, etc. The model provides daily data. From the viewpoint of determining transmission windows of malaria, temperature and RH data were extracted. Data were extracted following the guidelines provided in extraction tool by IITM, Pune. Monthly temperature and RH for baseline and by 2030 were extracted for 1495 grids in the country. The grid size was $0.44° \times 0.44°$ (roughly 48.8 km × 48.8 km, covering a district). In districts with larger geographic area, there were up to six grids. The figures for average temperature provided in the model were found incorrect, which were rectified by calculating the same manually.

Extraction of regions of India

The extent of Himalayan, northeastern, Western Ghats and coastal areas was deduced from the website of Encarta (http://encarta.msn.com) in general; and http://www.uttaranchal.ws/him.htm (for the Uttarakhand details) http://gbpihed.gov.in/envis/ihr.png (for the Himalayan region), http://www.northeastindiadiary.com/map.htm/ (for the northeastern region), http://www.india9.com/i9show/Western-Ghats-13531.htm (for the Western Ghats) and http://en.wikipedia.org/wiki/Geography_of_India#Coasts3 (for coastal areas) in specific.

Determination of transmission windows of malaria

Transmission windows (TWs) of malaria were determined keeping in view the lower cut-off temperature as 18°C and upper as 32°C (ref. 15) and RH from > 55% (ref. 3). Keeping in view the climatic suitability for the number of months transmission is open, TWs were categorized into I–V (category I, not a single month is open; category II, 1–3 months open; category III, 4–6 months; category IV, 7–9 months open and category V, 10–12 months open continuously for malaria transmission) for country level. Indigenous transmission of malaria is possible if TW is open for 3 months continuously[15], therefore, for analyses at regional level, more categories, i.e. TW open for 1–2 month and 3 months were also made. TWs open for more than 6 months indicate stability of malaria transmission. TWs were determined for baseline (1961–1990) and for the projection year 2030, based on temperature alone, as well in combination with temperature and RH to compare the effect of just temperature rise with combined effect of temperature and RH, which affects the longevity of the mosquitoes.

Generation of maps in GIS format

Based on the data derived from PRECIS model and exported to excel, TWs were determined and categorized. The inputs were fed in ArcGIS 9.3 software for generation of region/area-wise maps with district boundaries.

Results

Impacts of climate change at the national level

Based on minimum required temperature for ensuing transmission of malaria, a district-wise map of India was generated to show the distribution of different categories of TWs under baseline and projected scenario by 2030 (Figure 1 *a*). Details of the number of pixels under different categories are given in Table 1. Data for 42 pixels were not available. In the baseline scenario, 140 pixels are totally closed for transmission while by 2030, there is opening of five pixels. In all the categories from II to IV there is increase in the number of pixels by 2030, while under category V there is reduction. When the map of baseline TWs determined based on temperature alone (Figure 1 *a*) is compared with reported incidence of malaria in 2009 (Figure 2), there is mismatch in endemicity level, particularly in the southwestern part of India.

TWs determined based on minimum required temperature and RH (Figure 1 *b*) show overall lesser number of pixels for categories IV and V in the baseline as well as the projected scenario (Table 2). Detailed analysis of four regions of India, viz. the Himalayan region, northeastern states, the Western Ghats and the coastal region was also done to find the vulnerability at district level and the additional population at risk.

Impacts at the regional level

Himalayan region: Under the Himalayan region, states like Jammu and Kashmir, Himachal Pradesh, Uttarakhand, Sikkim, West Bengal and Arunachal Pradesh are included

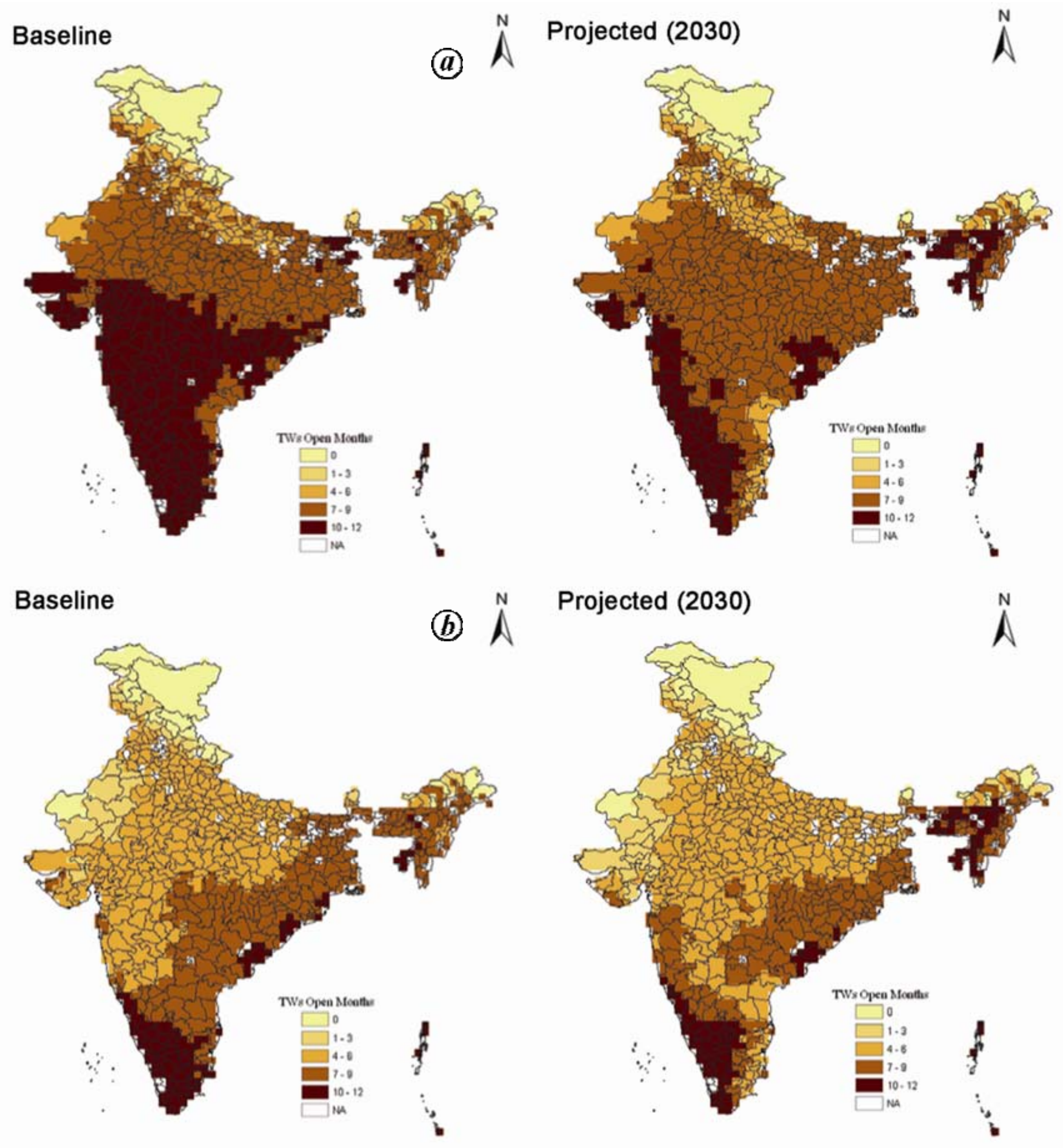

Figure 1. Transmission window (TW) of malaria, based on temperature (***a***) and temperature and relative humidity (RH) (***b***) using A1B scenario for baseline and by the year 2030.

Table 1. Pixel of transmission windows of malaria under different categories in India (based on temperature)

Scenario	Class I (0)	II (1–3)	III (4–6)	IV (7–9)	V (10–12)	Remarks (Data not available)
Baseline	140	16	132	602	563	42
Projection (by 2030)	135	23	188	857	250	42

with altogether 55 districts. Details of TWs based on temperature alone are given in Figure 3 *a* and Table 3. Under the Himalayan region, two districts show opening of TWs from 0 to 3 months in Jammu and Kashmir and Uttarakhand, i.e. Anantnag and Uttarkashi districts respectively. The population of these districts is 11.7 lakh and 16,220 respectively. There is projected increase in TWs from 3 to 4–6 in Uttarakhand, Sikkim and Arunachal Pradesh. In Una District, Himachal Pradesh and some districts of Jammu and Kashmir, reduction in the

Table 2. Pixel of transmission windows of malaria under different categories in India (based on temperature and relative humidity (RH))

Scenario	Class I (0)	II (1–3)	III (4–6)	IV (7–9)	V (10–12)	Remarks (Data not available)
Baseline	160	118	593	456	126	42
Projection (by 2030)	155	152	652	363	131	42

Table 3. Transmission windows of malaria in the Himalayan region based on temperature (A1B scenario, projection by 2030)

State	District showing change in TWs	Number of open months of TWs: Baseline	Projected	Additional/ affected month
Arunachal Pradesh (9)	East Kameng (Seppa)	5	6	September
	Upper Subansiri (Dap.)	1	2	August
	Upper Subansiri(Ziro)	2	3	September
	West Kameng (Bomdila)	3	4	September
	West Siang	3	4	September
Himachal Pradesh (12)	Una	8	7	June
Jammu and Kashmir (15)	Punch	5	4	May
	Rajauri	5	4	May
	Udhampur	4	3	May
	Anantnag	0	2	July, August
Sikkim (4)	East District	4	5	September
	West District	3	4	September
Uttarakhand (13)	Champawat	5	6	April
	Garhwal	7	8	March
	Hardwar	5	7	March, May
	Uttarkashi	1	3	July, August
West Bengal (2)	Darjeeling	8	9	November
	Jalpaiguri	8	9	November

Figures in parenthesis denote the number of districts in the state. Of the total 55 districts, data of five districts were not available.

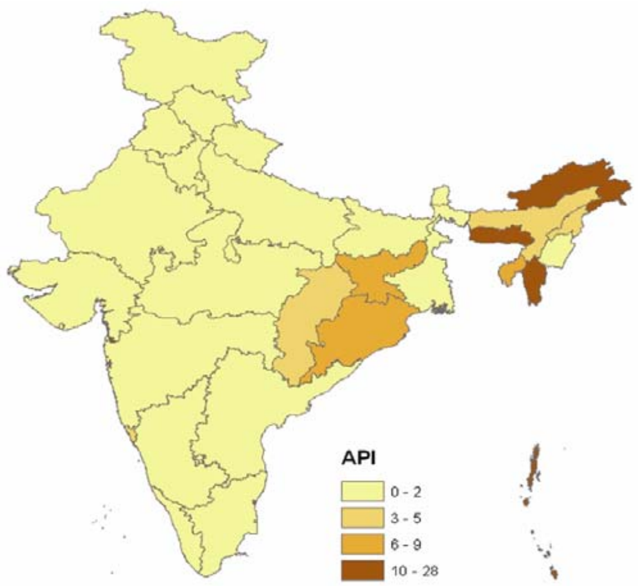

Figure 2. Endemicity of malaria in India (2009). (Source: data from NVBDCP.)

number of open months for malaria transmission is visible. There is no district with 10–12 month TW category under the Himalayan region.

TWs were also determined based on both temperature and RH (Figure 4 *a* and Table 4), which show lesser number of pixels in category IV. The seasonality of malaria in the representative district of Uttarakhand, i.e. Dehradun (Figure 5) corroborates with the baseline map (Figures 3 *a* and 4 *a*).

Northeastern region: This region consists of seven states, namely Assam, Meghalaya, Arunachal Pradesh, Nagaland, Manipur, Tripura and Mizoram. The region is characterized by mountainous and plains. Due to steep mountain slopes inaccessibility is a problem and most parts of the states are not utilized properly for land use and other developmental activities. There is diversity in terms of physical, ecological, ethnic and socio-cultural aspects. The region is rich in water resources and biodiversity, particularly evergreen forest and medicinal

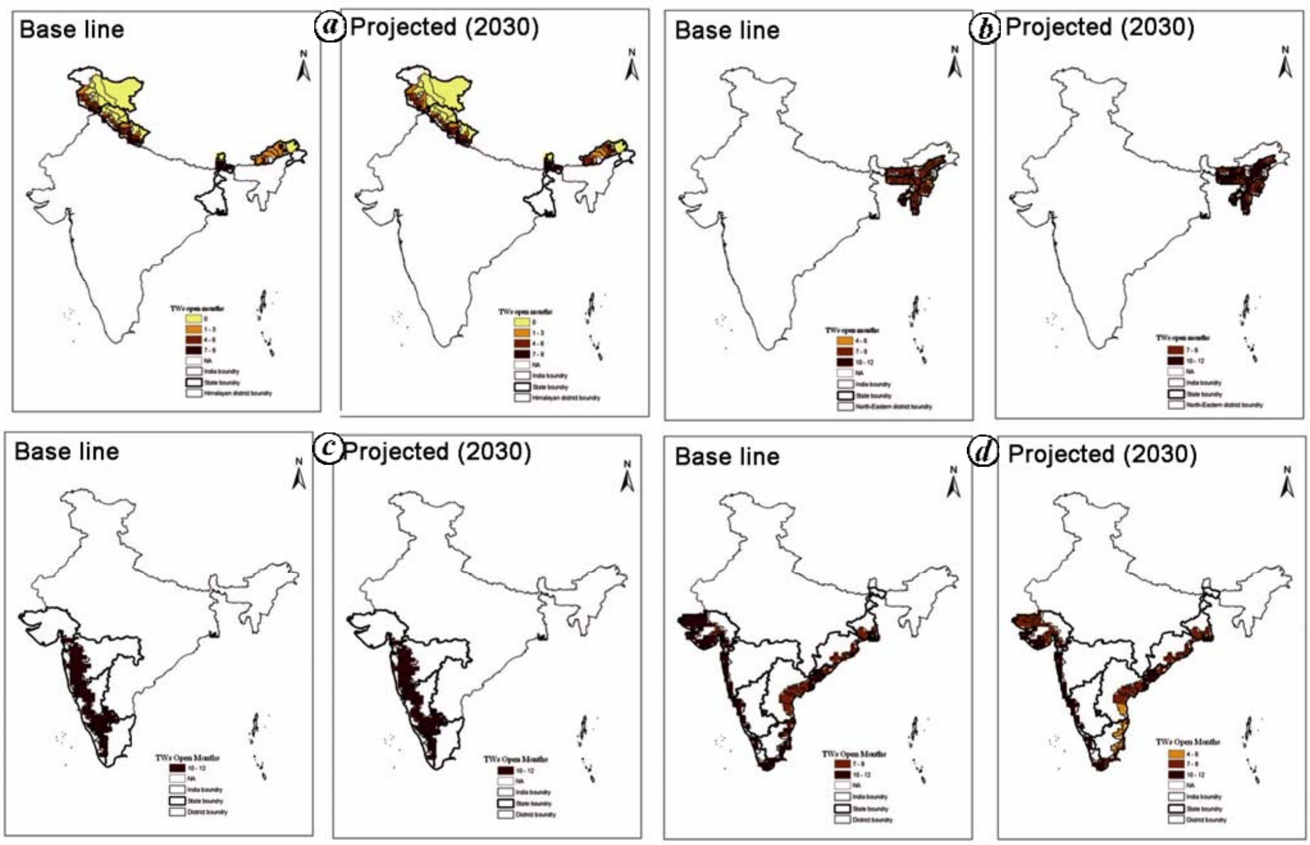

Figure 3. Transmission windows of malaria based on temperature in the Himalayan region (***a***), northeastern region (***b***), the Western Ghats (***c***) and coastal region (***d***) using A1B scenario for baseline and by 2030.

Table 4. Transmission windows of malaria based on temperature and RH in the Himalayan region (A1B scenario, projection by 2030)

State	District showing change in TWs	Number of open months of TWs		Additional/ affected month open
		Baseline	Projected	
Arunachal Pradesh (9)	East Kameng (Seppa)	5	6	October
	Upper Subansiri (Dap.)	1	2	August
	Upper Subansiri (Ziro)	2	3	September
	West Kameng (Bomdila)	3	4	September
	West Siang	3	4	September
Himachal Pradesh (12)	Hamirpur	4	5	April, May
	Kangra	3	4	May
	Sirmaur	4	5	May, October
	Una	4	6	March, May
Jammu and Kashmir (15)	Anantnag	0	2	July, August
	Jammu	4	6	March, May
	Udhampur	3	2	June
Sikkim (4)	East District	4	5	September
	West District	3	4	September
Uttarakhand (13)	Almora	4	5	May
	Bageshwar	0	1	June
	Garhwal	5	4	June
	U S Nagar	4	5	November
	Uttarkashi	1	2	July, August
West Bengal (2)	Darjeeling	7	9	March, November
	Jalpaiguri	8	9	November

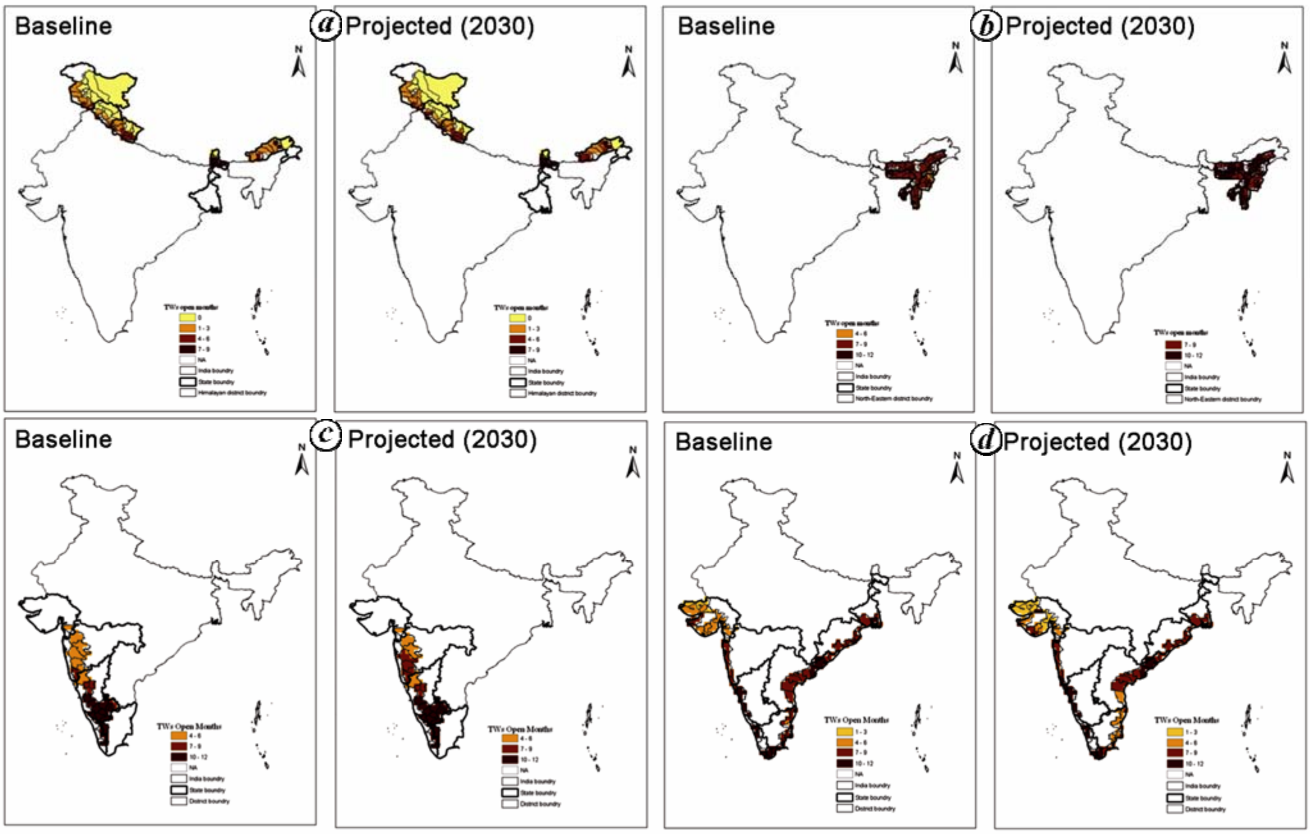

Figure 4. Transmission windows of malaria, based on temperature and RH in the Himalayan region (***a***), northeastern region (***b***), the Western Ghats (***c***) and coastal region (***d***) using A1B scenario for baseline and by 2030.

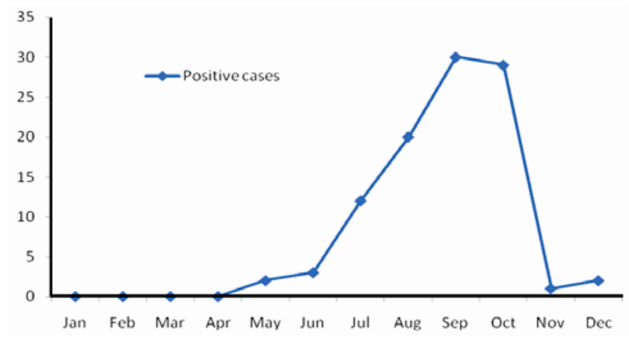

Figure 5. Seasonality of malaria transmission in Dehradun (Uttarakhand). (Source: State Programme Office, Uttarakhand.)

plants. Jhum cultivation is a characteristic feature of the region, which entails the farmer community to stay in the jungles for weeks together. Heavy rainfall leads to high humidity throughout the year. Temperature is moderate for most part of the year, with mild winters. These climatic characteristics make the region highly conducive for mosquito breeding, survival and transmission of VBDs. Six states of India covering 59 districts have been discussed under this region, except Arunachal Pradesh which has been dealt under the Himalayan region.

Under this region there are 59 districts in six states. There is not a single pixel in the 0–3 months TW open category (Figure 3 *b* and Table 5). By 2030, there is sharp increase in category V, indicating stability of malaria transmission. Meghalaya, Mizoram and Assam show more stability of malaria transmission. The category of TWs open for 4–6 months also disappears in the projected scenario. TWs determined based on temperature and RH also reveal almost similar projections (Figure 4 *b* and Table 6). The seasonality of malaria cases in Karbi Anglong (Assam), a representative district of the north-eastern states, also shows transmission of malaria for seven or more months (Figure 6).

Western Ghats: The Western Ghats runs along the western coast of India comprising 30 districts from the states of Maharashtra, Goa, Karnataka, Kerala and Tamil Nadu. The average elevation is around 900 m and the highest point is reached at Anamudi peak (2695 m). Konkan coast comprises of the northern portion of the Ghats and Malabar, the southern part. The hilly region east of the Ghats in Maharashtra is Desh, whereas the eastern hills of central Karnataka are known as the Malnad region. Scrub jungles, grasslands, dry and moist deciduous forests, semi-evergreen and evergreen forests are the

Table 5. Transmission windows of malaria in the northeastern region based on temperature (A1B scenario, projection by 2030)

			Number of months open for malaria transmission						
State	Number of districts		0	1–2	3	4–6	7–9	10–12	Data not available
Assam	23	Baseline	0	0	0	0	18	1	4
		Projection	0	0	0	0	5	14	4
Mizoram	8	Baseline	0	0	0	0	6	1	1
		Projection	0	0	0	0	3	4	1
Manipur	9	Baseline	0	0	0	1	6	0	2
		Projection	0	0	0	0	6	1	2
Meghalaya	7	Baseline	0	0	0	0	7	0	0
		Projection	0	0	0	0	3	4	0
Nagaland	8	Baseline	0	0	0	1	4	0	3
		Projection	0	0	0	0	5	0	3
Tripura	4	Baseline	0	0	0	0	0	3	1
		Projection	0	0	0	0	0	3	1
Total	59	Baseline	0	0	0	2	41	5	11
		Projection	0	0	0	0	22	26	11

Table 6. Transmission windows of malaria in the northeastern region based on temperature and RH (A1B scenario, projection by 2030)

			Number of months open for malaria transmission						
State	Number of districts		0	1–2	3	4–6	7–9	10–12	Data not available
Assam	23	Baseline	0	0	0	0	17	2	4
		Projection	0	0	0	0	5	14	4
Mizoram	8	Baseline	0	0	0	0	6	1	1
		Projection	0	0	0	0	3	4	1
Manipur	9	Baseline	0	0	0	1	6	0	2
		Projection	0	0	0	0	6	1	2
Meghalaya	7	Baseline	0	0	0	0	6	1	0
		Projection	0	0	0	0	3	4	0
Nagaland	8	Baseline	0	0	0	1	4	0	3
		Projection	0	0	0	0	5	0	3
Tripura	4	Baseline	0	0	0	0	0	3	1
		Projection	0	0	0	0	0	3	1
Total	59	Baseline	0	0	0	2	39	7	11
		Projection	0	0	0	0	22	26	11

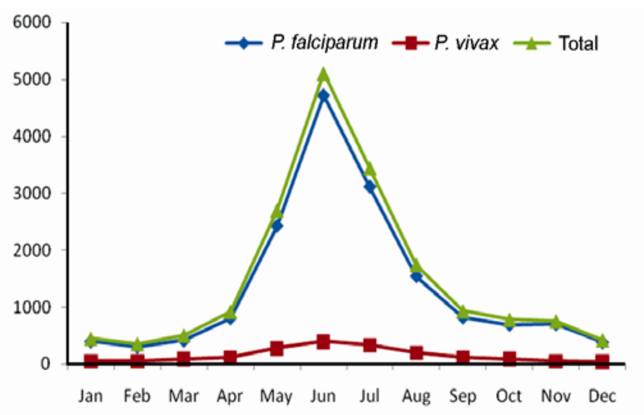

Figure 6. Seasonality of malaria transmission in Karbi Anglong (Assam). (Source: Office of DMO, Karbi Anglong.)

vegetation along the Ghats. Agasthyamalai Hills and the Silent Valley are the two main centres of diversity. The only Biodiversity reserve in the Western Ghats is the Nilgiri Biosphere Reserve.

The rainfall is heavy, which has preserved the flora and fauna in this region. The Sahyadri Mountains absorb monsoon rains and release them gradually over the rest of the year, thus keeping the regions of South India sufficiently wet. Perennial rivers like the Godavari, Krishna, Kaveri and their tributaries flow into the Bay of Bengal.

Under this region, all the districts show TWs open for 10–12 months and none of the 30 districts is affected by projected rise in temperature (Figure 3 *c* and Table 7). When TWs were determined based on both temperature and RH, the category of 4–6 months and 7–9 months

Table 7. Transmission windows of malaria in the Western Ghats based on temperature (A1B baseline and projected scenario by 2030)

State	Number of districts		Number of months open for malaria transmission: 0	1–2	3	4–6	7–9	10–12	Data not available
Gujarat	2	Baseline	0	0	0	0	0	1	1
		Projection	0	0	0	0	0	1	1
Maharashtra	6	Baseline	0	0	0	0	0	6	0
		Projection	0	0	0	0	0	6	0
Karnataka	15	Baseline	0	0	0	0	0	15	0
		Projection	0	0	0	0	0	15	0
Kerala	5	Baseline	0	0	0	0	0	4	1
		Projection	0	0	0	0	0	4	1
Tamil Nadu	2	Baseline	0	0	0	0	0	2	0
		Projection	0	0	0	0	0	2	0
Total	30	Baseline	0	0	0	0	0	28	2
		Projection	0	0	0	0	0	28	2

Table 8. Transmission windows of malaria in the Western Ghats based on minimum required temperature and RH (A1B scenario, projection by 2030)

State	Number of districts		Number of months open for malaria transmission: 0	1–2	3	4–6	7–9	10–12	Data not available
Gujarat	2	Baseline	0	0	0	1	0	0	1
		Projection	0	0	0	1	0	0	1
Maharashtra	6	Baseline	0	0	0	5	1	0	0
		Projection	0	0	0	0	6	0	0
Karnataka	15	Baseline	0	0	0	1	4	10	0
		Projection	0	0	0	1	3	11	0
Kerala	5	Baseline	0	0	0	0	0	4	1
		Projection	0	0	0	0	0	4	1
Tamil Nadu	2	Baseline	0	0	0	0	0	2	0
		Projection	0	0	0	0	0	2	0
Total	30	Baseline	0	0	0	7	5	16	2
		Projection	0	0	0	2	9	17	2

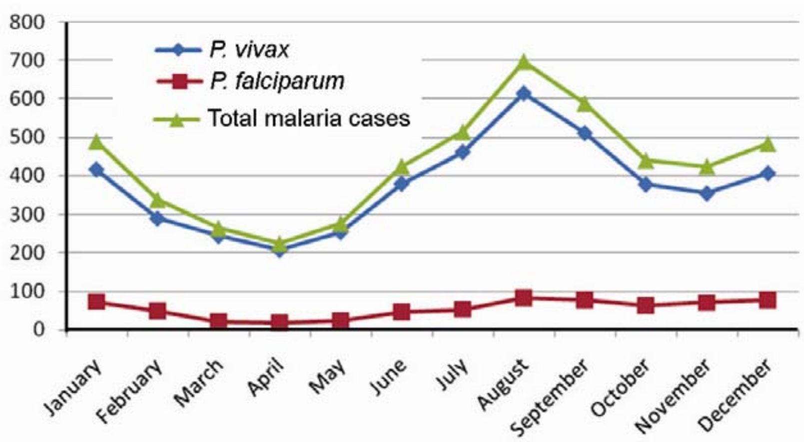

Figure 7. Seasonality of malaria transmission in Mangalore (Karnataka). (Source: Office of DMO, Mangalore.)

open TWs are visible in the baseline as well as projected scenario (Figure 4*c* and Table 8). If we compare the existing seasonal occurrence of malaria cases in a representative district of the Western Ghats, Mangalore (Karnataka), transmission continues for more than 7–9 months (Figure 7).

Table 9. Transmission windows of malaria in coastal areas based on minimum required temperature (baseline and projected scenario 2030)

State	Number of districts		Number of months open for malaria transmission						
			0	1–2	3	4–6	7–9	10–12	Data not available
Gujarat	14	Baseline	0	0	0	0	1	12	1
		Projection	0	0	0	0	7	6	1
Maharashtra	5	Baseline	0	0	0	0	0	4	1
		Projection	0	0	0	0	0	4	1
Goa	2	Baseline	0	0	0	0	0	2	0
		Projection	0	0	0	0	0	2	0
Daman and Diu	2	Baseline	0	0	0	0	0	0	2
		Projection	0	0	0	0	0	0	2
Dadra and Nagar Haveli	1	Baseline	0	0	0	0	0	1	0
		Projection	0	0	0	0	0	1	0
Karnataka	3	Baseline	0	0	0	0	0	3	0
		Projection	0	0	0	0	0	3	0
Kerala	9	Baseline	0	0	0	0	0	6	3
		Projection	0	0	0	0	0	6	3
Tamil Nadu	13	Baseline	0	0	0	0	4	9	0
		Projection	0	0	0	7	4	2	0
Andhra Pradesh	9	Baseline	0	0	0	0	7	2	0
		Projection	0	0	0	1	6	2	0
Puduchery	3	Baseline	0	0	0	0	0	0	3
		Projection	0	0	0	0	0	0	3
Orissa	7	Baseline	0	0	0	0	6	1	0
		Projection	0	0	0	0	7	0	0
West Bengal	3	Baseline	0	0	0	0	2	1	0
		Projection	0	0	0	0	3	0	0
Andaman and Nicobar Islands	2	Baseline	0	0	0	0	0	2	0
		Projection	0	0	0	0	0	2	0
Lakshadweep Islands	1	Baseline	0	0	0	0	0	0	1
		Projection	0	0	0	0	0	0	1
Total	74	Baseline	0	0	0	0	20	43	11
		Projection	0	0	0	8	27	28	11

Coastal areas: Coastal areas in India are quite long consisting of 74 districts in 14 states on the eastern and western parts in the south. The Western Coastal Plain is a narrow strip of land ranging from 50 to 100 km in width. It extends from Gujarat in the north and extends through Maharashtra, Goa, Karnataka and Kerala. Numerous rivers and backwaters inundate the region. Originating in the Western Ghats, the rivers are fast-flowing and mostly perennial, leading to the formation of estuaries. Major rivers flowing into the sea are the Tapi, Narmada, Mandovi and Zuari. The coast is divided into three parts, namely Konkan, which is situated in Maharashtra, Goa and northern parts of Karnataka; the Kanara in Karnataka, and the Malabar coast in Kerala. Vegetation is mostly deciduous, but in the Malabar coast moist forests constitute a unique ecoregion.

The Eastern Coastal Plain extends from West Bengal in the north to Tamil Nadu in the south. The Mahanadi, Godavari, Kaveri and Krishna are the rivers that drain into the area and their deltas occupy most of the area. The temperature in the coastal regions exceeds 30°C coupled with high humidity. The region receives both the north-east and southwest monsoon rains. Annual rainfall in this region averages between 1000 and 3000 mm. The width of the plains varies between 100 and 130 km. The plains are divided into six regions – the Mahanadi delta, the southern Andhra Pradesh plain, the Krishna–Godavari delta, the Kanyakumari coast, the Coromandel coast and sandy coastal.

The Andaman and Nicobar Islands is located in the Indian Ocean. It has over 570 islands, out of which only 38 are permanently inhabited. Lakshadweep is the smallest island in India and is located in the Arabian Sea. It consists of twelve coral atolls, three coral reefs, five banks and numerous islets. Tall, green coconut palms turn this land into a tropical paradise. Moderate temperatures not exceeding 36°C and high humidity make the island suitable for almost perennial transmission of malaria.

Under coastal areas in India, a total of 71 districts in 12 states are included. PRECIS data for Daman and Diu,

Table 10. Transmission windows of malaria based on minimum required temperature and RH (baseline and projected scenario 2030)

			Number of months open for malaria transmission						
State	Number of districts		0	1–2	3	4–6	7–9	10–12	Data not available
Gujarat	14	Baseline	0	0	2	9	1	1	1
		Projection	0	1	4	4	2	2	1
Maharashtra	5	Baseline	0	0	0	0	4	0	1
		Projection	0	0	0	0	3	1	1
Goa	2	Baseline	0	0	0	0	1	1	0
		Projection	0	0	0	0	0	2	0
Daman and Diu	2	Baseline	0	0	0	0	0	0	2
		Projection	0	0	0	0	0	0	2
Dadra and Nagar Haveli	1	Baseline	0	0	0	1	0	0	0
		Projection	0	0	0	0	1	0	0
Karnataka	3	Baseline	0	0	0	0	0	3	0
		Projection	0	0	0	0	0	3	0
Kerala	9	Baseline	0	0	0	0	0	6	3
		Projection	0	0	0	0	0	6	3
Tamil Nadu	13	Baseline	0	0	0	1	6	6	0
		Projection	0	0	0	7	4	2	0
Andhra Pradesh	9	Baseline	0	0	0	0	7	2	0
		Projection	0	0	0	1	6	2	0
Puduchery	3	Baseline	0	0	0	0	0	0	3
		Projection	0	0	0	0	0	0	3
Orissa	7	Baseline	0	0	0	0	6	1	0
		Projection	0	0	0	0	7	0	0
West Bengal	3	Baseline	0	0	0	0	2	1	0
		Projection	0	0	0	0	3	0	0
Andaman and Nicobar Islands	2	Baseline	0	0	0	0	0	2	0
		Projection	0	0	0	0	0	2	0
Lakshadweep Islands	1	Baseline	0	0	0	0	0	0	1
		Projection	0	0	0	0	0	0	1
Total	74	Baseline	0	0	2	11	27	23	11
		Projection	0	1	4	12	26	20	11

Lakshadweep and Puducherry were not available. Not a single district had closed or 1–3 month or 4–6 month open TWs (Figure 3 *d* and Table 9). Districts of Andaman and Nicobar Islands, Maharashtra, Dadra and Nagar Haveli, Goa, Karnataka and Kerala under this region remain unaffected in the projected scenario. There is reduction in months of TWs of 10–12 in Gujarat, Tamil Nadu, Orissa and West Bengal due to increase in temperature by the year 2030. In the western coast there is no change from Gujarat downwards.

TWs determined based on both temperature and RH (Figure 4 *d* and Table 10) show reduction in the number of months of TW the same way as shown in Figure 3 *d* and Table 9. However, in districts of Gujarat falling under this region, baseline TWs show even 3 months and 4–6 months open TWs. It does not seem to match with the seasonality of malaria in Gujarat as reflected by epidemiological data from a representative coastal district of the state, i.e. Surat which show transmission for more than 4–6 months (Figure 8), indicating that the transmission in microniche. Projected scenario for districts falling under this region shows reduction in even 4–6 months category and shifting towards lower categories (Table 10).

Discussion

Projections for malaria based on different methodologies have been made earlier[13,14]. The current projections are for near time, i.e. by 2030 and are almost at the district level (48.8 km $\times$ 48.8 km) for the whole of India, with emphasis on four sectors.

The projections based on temperature alone, and both temperature and RH differ in the number of months of transmission opening. When we compare Figure 1 *a* and *b*, we find that the western side of India, particularly the central and southern parts exhibit TWs open for 10–12 months, while in Figure 1 *b* this category is drastically reduced to 7–9 months. Current malaria endemicity as

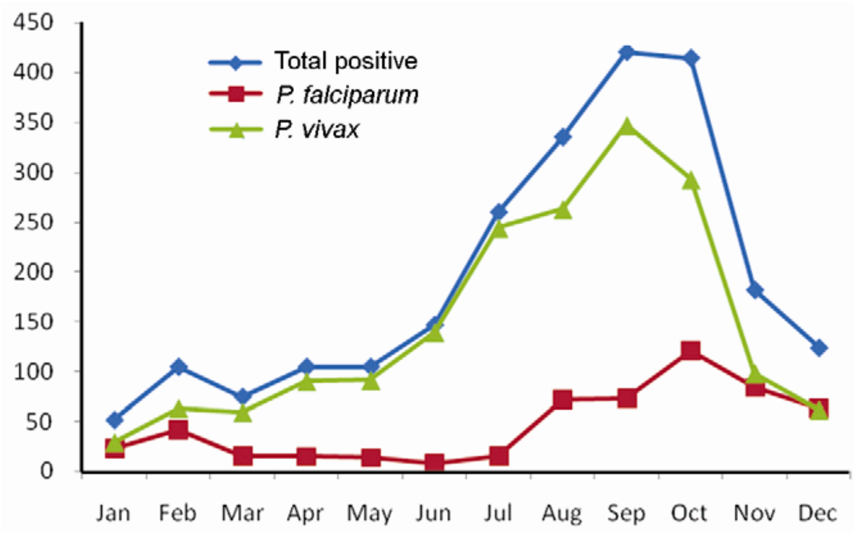

Figure 8. Seasonality of malaria transmission in Surat (Gujarat). (Source: Joint Director, Malaria and Filaria, Government of Gujarat.)

seen in Figure 2 also shows low intensity of the disease in western and southern parts of India, which corroborates with Figure 1 *b*. It shows that TWs determined using both temperature and RH are closer to the reported distribution of malaria.

Projections based on temperature reveal introduction of new foci in Jammu and Kashmir, Uttarakhand, increased intensity in Arunachal Pradesh, and increase in the opening of more transmission months in the districts of the Himalayan region, northeastern states and the Western Ghats. The northeastern states are projected to show a rise in transmission intensity.

Districts under the Western Ghats are not likely to experience any change by 2030 as all the 28 districts show opening of TWs for 10–12 months in the baseline as well as projected scenario. But TWs based on both temperature and RH show reduced intensity in the number of open months for transmission in the baseline and slight increase by 2030.

The eastern coastal areas are projected to experience reduction in the number of months open for transmission, which is basically due to increased temperature cutting off the upper limit of transmission suitability. However, it has been seen in Rajasthan that at even at higher temperature transmission of malaria may continue[16], indicating that mosquitoes have adapted to micro-niche to the avoid higher temperature. In view of this, there may be no reduction in transmission months due to increased temperatures.

When the projections based on temperature alone and both temperature and RH are compared with occurrence of malaria cases, there is mismatch between findings of temperature and RH and current seasonality in the Western Ghats and coastal areas. This indicates that there is dissimilarity in the outside climatic conditions and resting habitats of mosquito vectors, and they seek a micro-niche for their resting to get the required RH for survival. Therefore, for the western part of India which experiences dry spell, determination of TWs based on temperature and RH is desirable.

The reason of almost similar projections with temperature and both temperature and RH in the northeastern states may be due to heavy rainfall and prevalent high RH, where the windows of transmission are not closed due to low RH.

Malaria transmission dynamics is multi-factorial, driven by agricultural practices, water availability, urbanization, migration, socio-economic conditions and intervention measures. Therefore, projections based on climatic parameters alone should not be viewed with certainty rather they are for guidelines for preparedness.

Current impacts of climate change on malaria are based on climatic parameters only. In view of various determinants, viz. developmental, sociological and ecological aspects of malaria[15], assessments need to be refined attributable to climate change alone. Expanding the region of impact assessments at district level, development of capacities to detect abrupt changes in climate and hence disease detection and prevalence, capturing all cases by improving surveillance and assessing the cost of adaptation are desired. It has been amply cited by the IPCC[12] that it will be economical to undertake adaptation measures before hand, than the loss caused due to threat of climate change. Unless we know the economics of climate change, it is difficult to convince policymakers for allocation of resources. Well-planned intervention measures for malaria control are already in place with supervision from a central body, i.e. NVBDCP. The assessment provided in the present study should help programme managers to keep a vigil on the occurrence of cases in vulnerable areas and strengthen health infrastructure, effective health education and use of best available tools of intervention to cope with the threat of climate change.

Uncertainties and limitations of PRECIS model and data

- The data on temperature and RH provided by the model are at the resolution of 48 km × 48 km, which cannot delineate differences in hills and valleys in the Himalayas and some parts of the northeastern region and even in the plains.
- Analyses have been done using mean temperature, studies are warranted using diurnal temperature[17].
- Mitigation measures can change the scenarios.
- The projections made for transmission windows may be affected drastically by intervention measures, ecological changes and socio-economics of the communities.

Knowledge and research gaps

- In some geographic areas, TWs show suitability for less number of months while the occurrence of cases reflects transmission for longer periods. This suggests the presence of a micro-niche which needs to be studied in detail, particularly in areas like Gujarat and Rajasthan.
- Based on the outputs of open months for malaria transmission, validation is needed at the district level to determine cut-off limits of transmission for temperature, RH and rainfall.
- The study should be expanded to other VBDs in India.
- The outcome of projections is based on only climatic parameters alone, which if integrated with intervention measures, socio-economics and immunity of the population would provide a holistic projection.

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EVALUATION OF PUBLIC HEALTH ASSET FOR BETTER MANAGEMENT - A GIS BASED APPROACH

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ABSTRACT:

A new expansion of technological innovation is permitting us to capture, storage, retrieval, analysis, and display an extraordinary amount of information about the health GIS. It is a computer relieved database management, and mapping technology that organizes and stores, large amounts of multi-purpose information, and have the ability to integrate, manipulate, and analyses the spatial and non-spatial information in high speed. It provides mean of analyzing epidemiological data, revealing trends, dependencies and inter-relationships that would be more difficult, and very problematic to discover in tabular format as manual methods.

Health is one of the major aspects of socio-economic development. GIS play a major role in all areas of health research, which provide description and explanation of spatial variation of disease, illness or planning and use of health services. In India, healthcare data is regularly collected at health facilities and passed to different levels, which need to be integrated and analyzed, so that it can act as a useful decision support tool in formulating health schemes in a more realistic and to providing better health to all.

GIS can used to estimate the best and optimal location for a new clinic or hospital to minimize distances potential patients need to travel taking into account existing facilities, transport provision and population density. This act combines an efficient health service delivery includes the situation of these receivers, their socio economic status, the facilities that they currently have access. In the absence of a comprehensive understanding of all these variables, planning for interventions often end up not attaining the optimum results. GIS with its capabilities of mapping, integration of spatial and non-spatial data, and analysis, therefore, becomes an essential companion for health administration.

KEY WORDS: Public health, GIS, database management, spatial analysis, planning

1. INTRODUCTION

Geographic information system is a tool, which is used for data collection with geographic reference, and it supports to spatial analysis of attribute information. It is not only providing standard statistical evaluation methods but provides various geo-statistical methods to analyze the data. GPS, a network of satellites and handheld devices (GPS receivers) giving precise information of location, GIS can be a very fast method to capture geo-spatial information, which can be eagerly used for analysis, and thematic representation. With the exception of GPS based primary spatial information, GIS can incorporate secondary source information, which can be mapped as spatial thematic data consisting of socio-economic, epidemiological and demography. It provides possibility of additional analysis based on secondary data and provides a better overall picture of the healthcare facilities. GIS not only facilitate collection and storage of geo-spatial information, but also assists in better management, visualizing and presenting the data as tabulated, graphed, maps & hybrid maps. Thus, it provides stakeholder and decision maker a better environment for planning and decision making process.

2. OBJECTIVES

The main objective of this study is to evaluation of public health asset for better management with mapping and survey method for collection of baseline status of public health facilities. The survey and data collection has to be performed at various health facility levels. GIS can be used for analyzing spatial and non-spatial trend of information and to critically evaluate the public health at various levels with respect to the standards described in Indian Public Health Standards (IPHS) norms. The specific objectives of the study are:

1. To evaluate the health facility and household survey method
2. To evaluate the GIS mapping method for health facilities
3. To better management of public health care services
4. To better identification and tracking of beneficiaries
5. To more informed decision making
6. To improved coordination with private service providers as well as donor agencies, and NGOs
7. To optimum utilization of available health infrastructure

3. INFORMATION NEEDS FOR PUBLIC HEALTH ASSET

The focus on good health information has never been greater. Good health information is essential to informing the delivery of health care. Health has mostly struggled to help the effective use of information to manage services on a day-to-day basis. Many managers, particularly clinical managers, need little training in information management and are regularly apprise as to what information they actually need to manage their service. In addition to the existing culture, health reporting is vulnerable by having different information systems, which are mostly poorly integrated. Information is regularly uneven and not sufficiently timely to be of real value.

3.1 Key Factors for Linking of Health Information

Table 1: Key Factors for Linking of Health Information

Items	Description
Management Culture	The leadership needs to place a value on information, incorporating information and accountability for performance into how the organization works
Information Culture	Organizations need to be driven by data and grow their awareness and capability, by recruiting staff who have the right skills, and developing those skills in those who do not
Information Management	All staff has a role to play in managing the flow of information. Staff engagement and robust data quality framework that focuses on accuracy, relevance, representation and accessibility will ensure the availability of timely and meaningful data

3.2 Recommendations

1. Identify the key staff with the capability to integrate the use of data into practice, and training new staff in data extraction and statistical methodology
2. Ensure all departments will support to newly trained staff members, who largely filled business manager roles
3. Establish a new forum by which information needs will discussed and addressed across the organization
4. Maintain accountability at department level while closely support to trained staff in order to establish a consistent working relationship
5. Improve the system capability and performance
6. Identify and streamline the data flow streams within the organization
7. Broadening the scope of data collected to include all patient settings for all services to ensure relevance for all users

Health information needs to be seen as an asset. To fully appreciate the value of information, health facilities need to recognize the importance of a clear vision for information management and how it can support the overall transformation of health.

4. METHODOLOGY

The environmental factors i.e. socio-demographic, economic, political, & physical variables and health are the complex undertaking and suggest concerns are ranging at different levels. GIS can act as a facilitating mechanism to allow proper integration and presentation of the databases that includes these variables. GIS can used to explore statistical relationships, which are varying from one place to another place. It is valuable for recognizing the important relations with variables that effect health outcomes. GIS can also use to re-present results from the analysis and pattern of data in the form of thematic map, high-impact hybrid maps. These maps can tell powerful stories and communicate relationships in a way that otherwise may not be possible with other techniques (Mullner, Chung, Croke, & Mensah, 2004; Parchman, Ferreer, & Blanchard, 2002). GIS software provides the functions and tools designed to easily capture, store, update, manipulate, analyse, and display all forms of geographically referenced information efficiently (Bernardi, 2001; Riner, Cunningham, & Johnson, 2004; S. E. Thrall, 1999). GIS can quickly gaining recognition as an effective means to answer complex, ecological questions in health promotion, public health, medicine, and epidemiology (Clarke, McLafferty, & Tempalski, 1996; Cromley & McLafferty, 2002; Foody, 2006; Goldman & Schmalz, 2000; McLafferty, 2003; Melnick & Fleming, 1999; Miranda et al., 2005; Riner et al., 2004; Yasnoff & Sondik, 1999). GIS is an enabling technology that allows for the integration of multiple data sources, visual representations of complex geographic data, and the application of various spatial analytic techniques to people with a range of expertise in a variety of settings to integrate and analyse spatial data to answer pertinent questions in a vivid and meaningful way.

With the use of GIS, disease mapping and disease modelling applications can provide a systematic way of spatial pattern of epidemiologic data on disease systems with relevant features. In the GIS environment, we can develop a model that can use to predict the risk of disease over broad geographical areas where data are not available. By the use of that method, it is possible to re-present the spatial distribution of disease that allows discovery and exploration of the relationship between the variables that may not be possible by using traditional tools and techniques (Bavia et al., 1999). From a social determinants of health lens, modelling disease transmission could also play a critical role in the geography of human rights and social inequalities, and in demonstrating how processes such as climate change interact with human rights to favour disease emergence e.g., related to health equity of vector-borne disease (Winch, 1998). Interactive mapping of epidemiological data with geographic and environmental features can use to develop the hypotheses and identify relationships regarding the spatial patterns of disease.

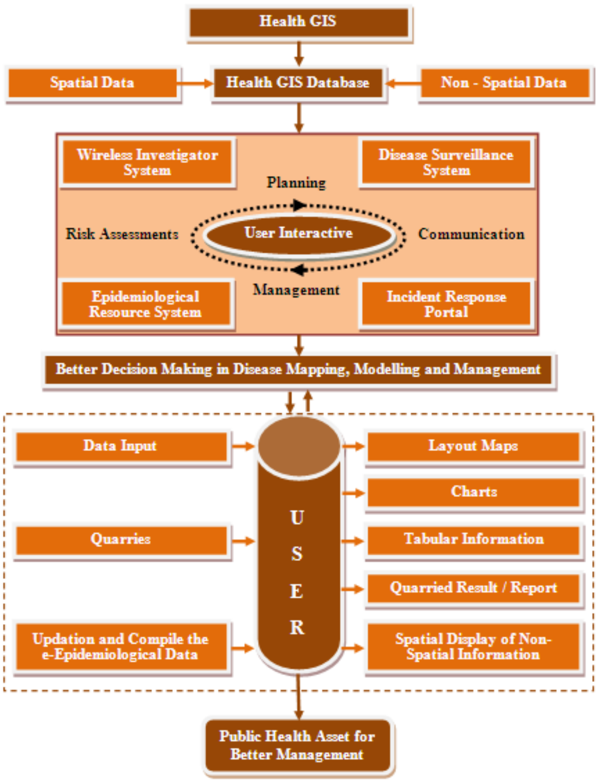

Figure 1: Flow Chart of Public Health Asset for Better Management

4.1 Public Health Database Structure

Health refers to a state of physical, mental and social well-being that allows the specific to achieve their full potential. Alternatively, health can be seen as the absence of illness. Health data in the developing countries is non-existent because no one collects it. In its place is data on illness, which is incorrectly referred to as health data. A database is a collection of related data, which are organized so that useful information may be extracted. The efficiency of databases derives from the fact that from one single, comprehensive database much of the information relevant to a variety of organizational purposes may be obtained. In health care, the same database may be used by medical personnel for patient care recording, for surveillance of patient status, and for treatment advice; researchers in assessing the effectiveness of drugs and clinical procedures may use it; and it can be used by administrative personnel in cost accounting and by management for the planning of service facilities.

4.2 Type and Sources of Information Required

4.2.1 Sources of Health Data: Two main sources i.e. census data and survey data are used as a basis for health planning in the developing countries, which generally obtained directly from the health system. Censuses are periodic and complete head counts, which usually produce general demographic data such as the age-sex composition and spatial dissemination of a population. Health data is simply one by-product; surveys are used to collect census-like information from a sample of the population. They are regularly worked to collect specific information such health data or family planning information. Both censuses and surveys yield data based on the everyday understanding of the word sickness or illness because they are based on self-reporting of illness.

The second source of data is data obtained directly from the health system. This takes the form of systematic administrative reports from hospitals, doctors, clinics and other health staff. In this source of data, the medical concept of disease is what is reported. The data is used as a basis for resource allocation, planning and management purposes.

4.2.2 Types of Health Data: Five main types of data (i.e. demographic, epidemiological, mortality data, information on the utilization of health services, and data on supply of health services) are extracted from the above sources of health data. Demographic data, which is achieved from censuses and surveys, includes information on the number of births, deaths, migrants and the age-sex opus and spatial dissemination of the population. Epidemiological, morbidity and mortality data is generated from both sources of information. Morbidity data takes the form of incidence and prevalence rates of disease, which is refers to the number of cases occurring in a population at a particular point in time, regardless of the time of onset. Mortality data refer to the number of deaths from various causes.

Data on the utilisation of health services is determined by the pattern of illness in a population and the size, age-sex composition and spatial dissemination of the population, which includes the numbers of people who utilise health facilities like hospitals, clinics and the medical personnel for preventing or curing disease and other services. Data on the supply of health services normally takes the form of the numbers of doctors, nurses and hospitals available, workers and staffing requirements, data on costs of providing services and the demand for resources to construct physical facilities. It is the responsibility of the health system to provide this data.

4.3 Limitations of the Sources and Type of Data

4.3.1 Limitations of the Sources of Data: Censuses and national surveys have a tendency to be of limited value for detailed health planning because of the difficulties of obtaining valid and reliable data on the pattern of illness. As already mentioned, self-reported illness have a tendency to be different from the medically defined concept of disease. Data from censuses and surveys is, consequently, likely to be undependable in the medical sense because self-reported illness is what is stimulated. Both censuses and surveys frequently collect only prevalence and not incidence data. This is a major limitation because incidence data is more useful as a basis for health planning due to its representation of the trends and patterns of disease.

Data obtained directly from the health systems is also normally of poor quality. It only yields data on medically disease and none data based on the everyday understanding of illness. The people who collect the masses information, without any thought of what it will be used for, have an incentive to manipulate it because it is the basis on which resources are allocated.

4.3.2 Limitations of the Types of Data: Demographic data - It is characterised by inaccuracy and incompleteness, which affect its use as a basis for planning, and it often provides only macro-level data, not detailed age & sex data at the local level, and does not for instance, show the age and sex and the distribution of people at village level. Due to the lack of small-scale area data, health systems have to use illogical rules of thumb to estimate.

Epidemiological and mortality data - There are very few developing countries, which collect data on sickness. Most of the so-called morbidity data is derived either from causes of death data or from information on reasons for hospital admittance, which often incomplete and unreliable. In India, for instance, thousands of people get malaria every day but none of them shows up in morbidity data because most of them do not go to hospitals for treatment and many deaths appear in official statistics because not all people die in hospitals.

Information on the utilization of health services - This information is mainly available only for government sponsored health services and not for private clinics and the traditional healers. Data on the willingness and ability of patients to pay for particular medical services would be more useful for planning purposes than data on the use of health services.

Data on supply of health services - Data on the supply of health services is not readily available. It normally includes only data on the supply of public health services, excluding the private sector.

4.4 General Issues on Health Data and Planning

Health planning in the developing countries, like elsewhere is dependent on broad policy decisions about the kinds of health services required and the available resources. The problem is that it tends to be over centralized in most countries leading to the misallocation of resources. As a result of proximity to planners, most health services are found principally in the urban areas. There is also the problem of lack of resources, which makes both data collection and planning difficult. Most of the available data is about disease prevalence because it is easier and cheaper to collect. Most of the health plans are therefore based on this data and the system is too rigid to adjust to seasonality of disease.

5. CONCLUSIONS AND RECOMMENDATIONS

GIS represent a powerful tool that supports health situation analysis, operations research, and surveillance for the prevention and control health problems. Moreover, these systems provide analytical support for the planning, programming, management, and evaluation of activities and interventions in the health sector. Thus, GIS can be considered part of the decision-support systems for people who formulate and follow health policy. GIS represents a new technology in the field of public health, which offers many applications and can strengthen the managerial capacity of health services.

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Water resource management in Delhi and Punjab by landuse studies by GIS technique

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Using IRS 1D and Resourcesat satellite data it was possible to infer the landuse pattern of parts of Delhi and Punjab India. In hard rock areas of various parts of Delhi for example JNU, RR Hospital and IGNU shows that interconnected fractures should be tapped for ground water exploration. In case of alluvial terrain of Punjab the spectral reflectance were one of the prime factor to infer the ground water potentiality. The buried pediment plains of Delhi were compared with the alluvial plains of Yamuna in Delhi and Beas basin in Punjab areas.Besides, the resistivity, magnetic and soil moisture field investigations were carried out in all these locations. A key is expected to be generated for water resource management in all these areas for a holistic water resource management. Texture analysis of representative soil of locations with similar spectral reflectance in all these places shows point locations of interactive GIS based water resource management.

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