Chapter 2

REVIEW OF LITERATURE
Review of Literature

2.1 Use of Remote Sensing and GIS in LULC Mapping and Change Detection

Economic development and population growth have triggered rapid changes to Earth’s land cover over the last two centuries, and there is every indication that the pace of these changes will accelerate in future. Land cover change can affect the ability of land to sustain the human activities through the provision of multiple ecosystem services and because the resultant economic activities cause feedback affecting climate and other facets of global change. Although the terms land cover and land use is sometimes used interchangeably, they are actually different. Land cover refers to what covers the surface of earth and land use describes how the land is used. Land cover is the combination of both biotic and abiotic components on the surface of Earth and is one of the basic properties of earth’s ecosystem. These components are focused in three aspects (Turner et al., 1994). The first lies in the interaction of land cover with the atmosphere, which lead to regulation of the hydrologic cycle and energy budget, and as such is needed in both for weather and climate prediction (DeFries et al., 2002). Secondly, land cover plays an important role in the carbon cycle acting both sources and sinks of carbon. Lastly, land cover provides food, fuel, timber, fiber, and shelter resources for human population, and serves as a critical indicator of other ecosystem services. Information on land cover is fundamental to many national/global applications including watershed management and agricultural productivity. Therefore the need to monitor land cover is derived from multiple intersecting needs, including the physical climate, ecosystem health, and social needs.

Land use and land cover classes are the outcome of interaction between man and environment. Some of the land uses are directly related to cultures, and social and economic conditions of the people (Vink, 1975). It changes with space and time as well as the concept of changing land use pattern is often considered a holistic approach of land surface related to the use of land within space and time. It is a geographical phenomenon caused by man and nature (Khanal and Bastola, 2005).

2.1.1 LULC Mapping

**LULC Classification System:** There are different perspectives in the classification process, and the process itself tends to be subjective, even when an objective numerical approach is used. Each classification is made to suit the need of the user. In order to address the issues
associated with classification like class definition, multiple land use on a single land parcel, minimum representable area and to standardize the LULC information that could be generated using remote sensing data. According to Anderson et al., (1976), the minimum level of interpretation accuracy in the identification of LULC categories from remote sensing data should be more than 85%, the accuracy for several LULC categories should be almost same, the classification system should be applicable over extensive areas, the categorization should permit vegetation and other types of LULC to be used as surrogates for activity, the classification system should be suitable for use with remote sensor data obtained at different times of year multiple use of land should be recognized if possible and so on. Now days, a multilevel land use land cover classification system, where in LULC information at levels I and II would be of interest to users who desire data on a nationwide interest or statewide basis was used. Also, more detailed LULC data which was categorized at Levels III and IV, will be used frequently at the intrastate, regional or municipals level.

**Conventional Approach of LULC Mapping:** In general, compilation from revenue records by the Economic and Statistics Department of the respective countries has been the conventional approach of collecting LULC information. Topographical maps from Survey Department of India and Nepal represent land use categories mapped using mainly ground information along with aerial photograph at 1: 50,000 to 1:25,000 scale. But these maps do not represent the current condition of LULC categories. There are other many different sources of information on existing LULC and changes are available. However, major problems that occurred during application and interpretation of these LULC data sets include changes in definitions of categories and data collection methods vary by different source agencies, incomplete data coverage, varying data age and employment of incomplete LULC classification system. In addition it is nearly impossible to aggregate the available data because of the different classification system used. These limitations of traditional approaches had been overcome by adopting modern approach like remote sensing.

**Remote sensing based Approach:** LULC mapping using remote sensing was developed initially using aerial photography. Remote sensing technology, because of the benefits it offer (wide area coverage, frequent revisits, multispectral, multisource, and storage in digital format to facilitate subsequent updating and compatibility with GIS technology) proved very practical and economical means for accurate LULC mapping and monitoring. However, there are several
important considerations such as purpose, thematic content, scale, kinds of satellite data to be used and processing and analysis techniques that determine the characteristics of LULC information to be derived using remote sensing data.

Remote Sensing and Global Positioning System (GPS) have given rise to the advent of more precise and geographically referenced data on land use and land cover, which in turn have created opportunities for improved assessments and analysis. With the aid of these new data, researchers have now started to unravel the processes that drive the cycle of land use change and resource degradation (Samuel and Ardey, 2007).

For the first time the Indian Survey Department had produced the topographical map including existing land use at a scale 1:63360 of using aerial photograph in 1956. Later in 1978, the land resources mapping project (LRMP) produced the land use map of Nepal based on the aerial photo 1978/79 at the scale 1:50000 and topographical survey department of Nepal has been producing the topographical map including general land use system at the scale of 1:25000 in 1998 based on 1996 aerial photo (Poudel, 2000).

Landsat images are among the widely used satellite remote sensing data and their spectral, spatial and temporal resolution made them useful input for mapping and planning projects (Sadidy et al., 2009). Over the past years, data from earth observing satellites has become vital in mapping the earth’s features and infrastructure, managing natural resources and studying environmental change (Zubair, 2006).

Schuft et al., (1999) examined sampling methods and landscape metrics to characterize the riparian stream networks. Longitudinal and lateral extents along streams of land-cover types interpreted from aerial photography were examined for incrementally wider buffers out to a maximum distance of 300 m from the stream using a process called incremental banding. The use of this technique allowed for the determination of landscape metrics, such as stream margin habitat, riparian width, and number of gaps of non-woody vegetation for use in examining relations with aquatic biota.

Fitzpatrick et al., (2001) examined environmental characteristics in relation to stream conditions at multiple scales-watersheds, segment, and reach scales. LULC information was obtained from 30-m Landsat 5 Thematic Mapper (TM) data for the watershed scale. The variable, "riparian width," for the segment and reach scales was measured from aerial photography. They
found the index of biotic integrity (IBI) for fish was related more to the adjacent land cover in a 50-m buffer along the entire stream network rather than to LULC at the watershed scale.

Different sources of remotely sensed imagery, that is, aerial photography compared to satellite imagery, may yield varying estimates of stream ecological condition, as examined at varying longitudinal and lateral scales by Lattin et al., (2004). The ecological indicators considered in their study were fish IBI and nitrate concentration. They used a range of longitudinal and lateral scales to quantify LULC. Fish IBI correlated best with the narrowest lateral and longest longitudinal vegetation metric. Nitrate was best related to cropland classes for the widest lateral and longest longitudinal scale. Aerial photography and satellite imagery performed equally well, with each having respective advantages in terms of spatial resolution and ability to automate interpretation.

Sponseller et al., (2001) examined the influence of spatial scale and land use classified from 30-m Landsat TM data on stream macro invertebrate communities. They examined five spatial scales—the entire watershed, the riparian system for the whole stream network, and the riparian corridor for three segment lengths of 200, 1,000, and 2,000 m upstream from the sampling reach, each with a lateral extent of 30 m. Water chemistry was most strongly related to LULC patterns for the entire watershed. Stream temperature and substrate were associated with LULC for the whole stream network and for the three segment lengths. The macro invertebrate communities were most influenced by LULC at the most local scale, the 200-m segment riparian corridor.

2.1.1.1 LULC Mapping Methods using Remote Sensing

Land cover information that can be obtained from satellite images is the spectral and spatial attributes of individual cover types. LULC mapping method uses these spectral and spatial information and several methods are employed for LULC mapping remote sensing data.

**Digital classification:** The basic principle of multi-spectral classification is that the objects in the earth surfaces possess different reflectance characteristic in different parts of the electromagnetic spectrum as digital numbers. Based on this reflectance, the surface features can be categorized into specified number of classes known as land cover classes through classification software in terms of new thematic output image. Digital image classification is the popular and challenging approach of remotely sensed image analysis process. Although, there
are different classification systems in existence throughout the world, they are generally not comparable one to another and also there is no single internationally accepted land cover classification method (Latham, 2001). Therefore, determination of land cover classification method is decided considering the purpose of the study and usually it varies according to different research projects (Tateishi, 2002). There are two general classification approaches: supervised and unsupervised. In the supervised approach the useful information categories are defined and examined for their spectral separability where in the unsupervised approach, spectrally separable classes are determined and defined relative to their informational utility to form a supervised classification scheme (Kaiser et al., 2008). Supervised classification uses the independent information from spectral reflectance to define training data for determining classification categories (Ratanopad and Kainz, 2006). Among the classification procedure, supervised classification has been widely used in remote sensing applications because in supervised classification, spectral signatures are collected from specified locations (training sites) in the image to classify all pixels in the scene by digitizing various polygons overlaying different land use types (Yüksel et al., 2008). Training sites are the areas defined for each land cover type within the image. The chosen color composite image is used for digitizing polygons around each training site for similar land use/cover. Then a unique identifier is assigned to each known land cover type (Eastman, 2009). In practice, mostly maximum likely hood classifier (MLC) is performed assuming equal probability of occurrence and cost of misclassification for all classes and output stage has presented LULC map after the entire data set has been categorized (Lillesand et al., 2008).

**Manual Classification:** Manual, or visual classification of remotely sensed data is an effective method of classifying land cover especially when analyst is familiar with the area being classified. This method uses the skills that were originally developed for interpreting aerial photograph. In this scheme brain is utilized to identify features in the image and relates them to features on the ground seems to simple process. But it is tedious and slow process when compared with automated classification and it relies solely on a human interpreter which is more subjective.

**Hybrid Approach:** A hybrid approach combines the advantage of the automated and manual methods to produce a land cover map that was better than other single method. It consists of one of automated classification and manual method to refine the classification and correct
obvious error. In most cases, visually editing a classified map will improve the accuracy of the final product.

2.1.1.2 Assessment of Accuracy of LULC Mapping

The accuracy of the result is strongly dependent on the processing procedure, consisting mainly of geometric correction, image classification and spectral enhancement (Kaiser et al., 2008). A common method for accuracy assessment for a classification image is through the use of an error or confusion matrix and some important measures, such as overall accuracy, producer's accuracy, and user's accuracy can be calculated from the error matrix in the classification software. Ground truth data is used as training sample data in classification processing or as correct data in validation step. The information sources of ground truth are field survey, existing maps, satellite images with better resolution, or any pre-determined classification system. Since field survey is time consuming and needs much budget, the latter three sources are usually used (Tateishi, 2002). The testing samples are used for the establishment of the confusion matrix to assess the classification accuracy (Long-qian et al., 2009). In addition to the producer and user accuracy indices, there are other indices produced from the error matrix that involve more complex mathematical operations such as probabilities. One of these indices is called Kappa Statistic and it enables a generalization of information that allows us to compare classifications produced from different images. According to (Lillesand and Kiefer, 2000), the minimum level of accuracy in the identification of land cover categories from remote sensor data should be at least 80%.

2.1.2 Land use / Land Cover Change Analysis

Change in land use and land cover impacts both environmental quality and quality of life. Changes in habitat, water and air quality and the quality of life are some of environmental, social and economic concerns associated with land use and land cover change. Sustainable land resource management can be managed using accurate knowledge of Land Use Land Cover (LULC) features and relative risk of environmental hazards. Much of land in the earth has already been modified except for inaccessible locations (Turner II and Meyer, 1994). Approximately 25% of the earth’s land surface remains unchanged. The changing pattern in LULC reflects socioeconomic conditions. The growing population and increasing socioeconomic necessities creates a pressure on land use/land cover. This pressure results in
unplanned and uncontrolled changes in LULC (Seto, 2002). The LULC alterations are generally caused by mismanagement of agricultural, urban, range and forest lands which lead to severe environmental problems such as landslides, floods etc.

According to Riebsame, *et al.*, (1994), land use affects land cover and changes in land cover affect land use. Changes in land cover by land use do not necessarily imply degradation of the land. However, many shifting land use patterns driven by a variety of social causes, result in land cover changes that affects biodiversity, water and radiation budgets, trace gas emissions and other processes that come together to affect climate and biosphere.

The natural land cover is generally a good expression of the soil and vegetation pattern that goes with the natural environment. However, changes in the nature of land use activities often results in land cover changes, which are categorized into two types: modification and conversion. Modification is a change of condition within a cover type in which significant change in land cover can occur within these patterns of land cover change. Conversion is a change from one cover type to another (Turner II and Meyer, 1994).

2.1.2.1 Land Use and Land Cover Change Detection with Remote Sensing data

An increasingly common application of remotely sensed data is for change detection. The state of an object or phenomenon difference is identified in the process of change detection by observing it at different times. It is useful in land use change analysis, assessment of deforestation, and other environmental changes. Many change detection methods have been developed and used for various applications. Post-classification and spectral change detection approaches are the widely used methods in remote sensing endeavor (Singh, 1989).

Post-classification is a most widely applied technique and numerous studies carried out using this technique. In this classification two images from different dates are classified and labeled. The area of change is then extracted through the direct comparison of the classification results. Main advantages of post-classification include: detailed “from to information’’ (Chen, 2000). It bypasses the difficulties associated with the analysis of images acquired at different times of year or sensor. The main disadvantage of the post classification approach is the dependency of the land cover change results on the individual classification accuracies (Chen, 2000). Therefore, it is imperative that the individual classification be as accurate as possible.
According to Chen (2000), a large number of techniques are in the spectral change identification category and it rely on the principle that land cover changes result in persistent changes in spectral signature of the affected land surface. These techniques involve the transformation of the two original images into a new single band or multiband image, in which the area of spectral change is highlighted. Most of these techniques are based on image differencing or image rationing. This technique advantage is based on detection of physical changes between image dates. This avoids the errors introduced in post-classification change detection. However; the greatest challenge to the successful application of these techniques is the discrimination of “change” and “no change” pixels. For spectral change detection, an accurate image co registration is crucial.

The scientific literature shows that digital change detection is a difficult task to perform accurately and unfortunately, many of the studies concerned with comparative evaluation of this application have not supported their conclusion by quantitative analysis (Singh, 1989). Digital change detection is effected by spatial, spectral, temporal and thematic constraints.

Coppin and Bauer, (1996) pointed out that image differencing method perform more accurate than the change detection and such monitoring techniques based on the multi spectral satellite data have demonstrated potential as a means to detect, identify, and map changes in forest cover. Image differencing is the most probable change detection algorithm for the different geographical environment.

Principal Components Analysis (PCA) is another multivariate analysis technique for data reduction. Experiments showed that first component contains unchanged spectral information and later component contains changed information (Barnes et al., 1998). PCA can be used by original or standard data.

There are mainly two categories for LULC change: direct (proximate) driving forces and indirect (underlying) driving forces. Direct driving forces include the immediate actions of local people to fulfill their needs from land use (Geist and Lambin, 2002), such as agricultural expansion, wood extraction, infrastructure expansion and other causes that change the physical state of land cover (Meyer and Turner II, 1996). Driving forces mainly operate at the local level (i.e. individual farms, householders, or communities). In contrast, indirect driving forces are fundamental socioeconomic and political processes that ‘push’ direct causes into immediate
action on LULC (Geist and Lambin, 2002). These ‘underlying’ driving forces include demographic pressure, economic status, technological and institutional factors, and can influence LULC in combination (Geist and Lambin, 2002). Land use constantly changes in response to the dynamic interaction between direct and indirect causes it is non-static (Lambin et al., 2001).

Awasthi et al., (2002) used aerial photographs of 1978 and 1996 for the measurement of land use land cover and watershed analysis based on GIS in Mardi and Phewa lake watershed. In these watersheds, there was a net increase in forest cover with a corresponding decrease in shrub and rain-fed agriculture. A significant area under agriculture in 1978 was found abandoned in 1996 in both watersheds most likely due to increased out migration of the labor force.

Loppiso (2010) studied the impact of LULCC on soil loss in Shashugoworeda, Southern Ethiopia by analyzing LULCC during 1973-2005 using Landsat images of 1973, 1984 and 2005 and found that land use land cover classes viz. bare land, cultivated land and water body were increasing on the expense of decrease in wet grass land, bush land and grazing land.

Nikhil and Azeez (2010) has also studied the spatial and temporal change in land use and land cover using RS and GIS and analyzed the LULC of Bharathapuzha river basin south India using Landsat images of 1973-2005 time period. During this period 31 percent depletion in the natural vegetation cover and 8.7 percent depletion in wetland agriculture area in the basin were observed. On the other hand, the urban area in the basin increased by 32 percent.

The study of land use and land cover change detection in the western Egypt using four periods Landsat images (1984, 1999, 2005, and 2009) had shown the recent and historical LULC changes in the study area. Approximately, 28%, 14%, and 9% of barren lands were changed into agricultural land in the study periods. In addition to these LULC changes, evidence of land degradation due to human activities was also observed (Kawy et al., 2011).

The study of Influence of land use/land cover (LULC) changes on atmospheric dynamics over the arid region of Rajasthan state, India examines the long-term effects of land use/land cover (LULC) changes by comparing the satellite data of Landsat MSS (1972–73) and IRS-P6 AWiFS (2006–07). The result of this study revealed that crop-land and vegetation areas increased by 57% and 68% respectively. However, the overall analysis shows that the variability in precipitation is much more influenced by the general monsoonal circulation and partly can be associated with local phenomena, such as LULC changes (Kharol et al., 2013).
The study of land use/land cover dynamics and their driving forces in the Hirmi watershed and its adjacent agro-ecosystem, highlands of Northern Ethiopia showed by using aerial photographs (1964 and 1994) and SPOT 5 satellite image (2006). The results of their study revealed that cultivated and rural settlement land increased by 24.6% and grassland decreased by 20% to 11.3% from 1964 to 2006. Also the forest cover increased by 0.9% to 1.8% during 1964 to 2006. It was concluded that expansions of cultivated and rural settlement and forestland leading to reduction of grassland and scrubland (Gebrelibanos and Mohammed, 2013).

The study of analysis of LULC changes using remote sensing data and GIS at an Urban Area, Tirupati, India was carried out by using the Survey of India topographic map and the remote sensing data (LISS III and PAN of IRS ID 2003). The results of this study indicated that LULC classes such as built-up area, open forest, plantation increased while agriculture land water spread area, and dense forest area decreased significantly. Rapid increase in urban area led to decrease in other LULC (Mallupattu and Reddy, 2013).

LULC change analysis was carried out over a period of 39 years (1973–2012) by using Satellite images of Landsat MSS (1973), TM (1986), ETM+ (2000), and Rapid Eye (2012) and following Object-Based classification approach in the Munessa - Shashemene Landscape of the Ethiopian Highlands. The change analysis results showed a rapid reduction in woodland cover of 81.8%, 52.3%, and 36.1% between the first (1973–1986), second (1986–2000), and third (2000–2012) study periods, respectively. Similarly, natural forests cover decreased by 26.1% during the first, 21.1% during the second, and 24.4% during the third periods. Grasslands also declined by 11.9, 17.5, and 21.1% during the three periods, respectively. On the contrary, croplands increased in all three periods by 13.1, 31.5, and 22.7%, respectively (Kindu et al., 2013).

### 2.2 Land Use Land Cover Prediction Modeling

Several different approaches are used to project future Land use/Land cover. These can be divided into two broad categories: 1) models that predict total land use change for a region, and 2) models that predict land use for specific parcels or grid cells. The first type of model is useful for knowing the total amount of land use change especially in large area like a state while second type of model is appropriate in smaller area at a specific place. Several LULC prediction models are described in following section:
**Equation - Based Model:** The most common mathematical models are sets of equations based on theories of population growth and diffusion that specify cumulative land use land cover change over time (Sklar and Costanza, 1991). A variant of this model is based on linear programming and linked to GIS information on land parcels (Cromley and Hanink, 1999). A major drawback of this model is that a numerical or analytical solution to the system of equations must be obtained, limiting the level of complexity that may practically be built into such models.

**System Models:** System models represent stocks and flows of information, material, or energy assets of differential equations linked through intermediary functions and data structures. Time is broken into discrete steps to allow feedback. Human and ecological interactions can be represented within these models, but they are dependent on explicit enumeration of causes and functional representation, and they accommodate spatial relationship with difficulty (Sklar and Costanza, 1991).

**Statistical Techniques:** Statistical techniques are the common approach to modeling the LULC change, given their power, wide acceptance, and relative ease of use. They include a variety of regression techniques applied to space and more tailored spatial statistical methods. Successful examples of combining theory and statistics are provided by spatial econometrics (Leggett and Bockstael, 2000).

**Expert Models:** Expert models combine expert judgment with probability techniques such as Bayesian probability. These methods express qualitative knowledge in a quantities fashion that enables the modeler to determine where given land uses are likely to occur (Lee et al., 1992). However these models provide qualitative knowledge in quantity through which the modelers determine the occurrence of land use. All the aspects of problem cannot include in these models leaving space for gaps and inconsistencies.

**Evolutionary Models:** Within the field of artificial intelligence, symbolic approaches such as expert systems are complemented by this model. Example of this field are artificial neural networks and evolutionary programming, are finding their way into LULC models (Balling et al., 1999).

**Cellular Models:** Cellular models (CM) include cellular automata and Markov models. Each of these models operates over a lattice of congruent cell. CA is defined as: “Cellular automata are simple mathematical idealizations of physical systems in which space and time is
discrete, and physical quantities take on finite set of discrete values “CA operates on a grid based cells and transition rules that are applied to determine the state of a cell. CA system consists of five elements – cell (lattice), cell state, neighborhood, transition rule and time (Barredo et al., 2003). The rapid development of GIS helps to foster the application of CA in land use land cover simulation. CA can be extended and integrated with GIS to help planners to search for better land use land cover forms for sustainable development (Li and Yeh, 2000). Cellular Automata Markov (CA-Markov) is a combined cellular automata and Markov Chain prediction procedure that adds element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov change analysis. These two are termed as the geo-simulation techniques used to produce land use predictions (Sun et al., 2007). However, a CA procedure specifies the context of predicted land cover change modeling. CA-Markov takes land cover map from which changes should be projected as input; the transition area file produced by Markov from analysis of that image and an earlier one and a collection of suitability images (which is produced from MCE or fuzzy logic or any GIS analysis) that express the suitability of a pixel for each class of the land cover type under consideration. Then, it begins an iterative process of reallocating land cover until it meets the area total predicted by the Markov process (Eastman, 2009). The logic of CA-Markov is that; the total number of iterations is based on the number of time steps set by the user. Within each iteration process, every land cover class will typically lose and gain some of its land to one or more of the other classes. Thus, within the consideration of each host within each iteration, claimant classes select land from the host based on the suitability map for the claimant class. CA-Markov can predict any number of land use land cover change classes (Li and Reynolds, 1997; Wu and Webster, 1998; Pontius and Malanson, 2005).

Cellular models are for modeling ecological aspects of LULC change, but it has constraints for incorporating human decision making. It is necessary to use the complex hierarchical rules sets to differentiate between the kinds of decision making that applied to group of cells (Li, 2000). CA has become especially, useful tool for modeling urban spatial dynamics and encouraging results have been documented. CA model is built within a grid - GIS system to facilitate easy access to GIS databases for constructing the constraints. The essence of the model is that constraint space is used to regulate cellular space. Local, regional and global constraints play important roles in affecting modeling results (Li and Yeh, 2000). Spatial information and
more realistic definition of transition rule in CA and state changes has simulated easier to visualize for decision making with the combination of GIS, CA and MCE.

**Hybrid Models:** Hybrid models combine any of the above mentioned techniques, each of which is a fairly discrete approach into itself. An example is estuarine LULC transition modeling that has an explicit cellular model tied to a system dynamics model (Costanza et al., 1986). A distinct variation of hybrid models is a dynamic spatial simulation (DSS), which portrays the landscape as a two dimensional grid where rules represents the action of land managers based on factors such as agricultural suitability (Lambin, 1994). Dynamic spatial simulation typically does not represent heterogeneous actors, institutional effects on decision making, or multiple production activities. However, due to their ability to represent individual decision making and temporal and spatial dynamics, they represent an important advance over previous models (Lambin, 1994)

**Agent – Based Models:** While cellular models are focused on landscape and transition, agent based models focus on human actions. Agents are the crucial component in these models. Several characteristics define agents as are autonomous, they share an environmental through agent communication and interaction, and they make decisions that tie behavior to the environment. Agents have been used to represent a variety of entities, including atoms, biological cells, animals, people and organizations (Conte et al., 1997; Janssen and Jager, 2000). The advantage of these models is that they rely on the emergent or synergistic idea which characteristics are understood by examining subcomponent relationship. But it exists complex system which are characterized by nonlinear relationship between changing phenomenon while system theories studies static entities linked by linear relationship defined by flow and stocks of energy, information or matter.

**Multi – Agent System MAS Model:** It consists of both cellular and agent based models. In this model cellular model represent biophysical and ecological aspects and agent based models represent human decision making. The cellular model is a part of the agent’s environment, and the agents in turn act on simulation environment. In this way, the complex interaction among the agents and between the agents and their environment can be simulated in a manner that assumes equilibrium condition. Most of the limitations are reduced by the MAS/
LULC models. In particular these models may be feasible for representing socioeconomic and biophysical complexity.

**GEOMOD Model**: GEOMOD is the model that has been used frequently to analyze baseline scenarios of deforestation for carbon offset projects, as called for by the international agreements on climate change, such as the Kyoto Protocol (Pontius and Chen, 2006). It is a grid-based land-use and land-cover prediction model, which simulates the spatial pattern of land change forwards or backwards in time. It simulates the change between exactly two land categories denoted as 1 and 2 for “non-developed” and “developed” respectively, but 1 and 2 could represent any two categories for any particular application (Eastman, 2009). Single beginning land-use map is sufficient for calibration in GEOMOD, while some algorithms for other popular models require four times for the same (Silva and Clarke, 2002).

GEOMOD has its ability to model land use change spatially but it requires exogenously defined the deforested area. Brown *et al.*, (2007) compared the Forest Area Change (FAC) model, the Land Use and Carbon Sequestration (LUCS) model and GEOMOD for simulating deforestation trends at the regional scale. Only GEOMOD provided results that could be used for dynamic deforestation determination under different driving factors, but GEOMOD only predicts the location of land-use change and not the quantity. Additionally, the model has been applied to more than 50 countries in Europe, Asia, and Latin America.

Nowadays, land use change has become one of the major issues in a developed region. Therefore, it is always important to monitor land use change within a certain period of time and predict patterns of future land use change on a spatial basis. Baja, and Arif (2014) showed Built-up area is predicted to increase and other LULC such as agricultural land, water bodies etc are predicted to decrease in the year 2029. This information of change in LULC for future period will become more beneficial and sustainable situation in terms of land use decision making process, and thus their study highlighted the simulations of LULC the land use land cover change can be predicted for the future land use change using CA-MARKOV model.

Rimal, (2011) used supervised classification system to classify the images of different land use categories. Six land use classes were identified: Urban (Built-up), water body, open field, forest cover, cultivated land and sandy area. Urban land use change for the year 2021 was modeled using a Markov chain based approach showed a growing tendency in urban land use,
which might threaten the areas that are currently reserved for forest and agricultural lands (Rimal, 2011). Keshkamat et al., (2009) reported trend of LULC change of wood land and bare land area will be maximum in the predicted years 2030 by using Markov-cellular automata model. Land use land cover change prediction and development planning successfully achieved using RS and GIS data with spatial matrices and CA modeling (Yikalo et al., 2010). The change in agricultural area has closely related with the increase in population (Ye and Bai, 2008). The method is based on probability that a given piece of land will change from one mutually exclusive state to another (Thomas and Laurence, 2006). While GEOMOD is also able to take those past changes, compare them with a wide range of geophysical and socio-economic data, and derive a statistically robust correlation between past patterns of land use and land cover change and the most likely future continuation of those patterns. The rate and location of recent conversions of forest to non-forest cover, detected by modern interpretation of satellite imagery, can be used not only but the past but to visualize possible future conditions by the use of GEOMOD (Tyrrell, et. al., 2004). Parent et al., (2007) showed that forest cover and agricultural land are predicted to decline by 3.0% and 5.6%, respectively between 2002 and 2036 while urban and turf areas are predicted to increase by 17.9% in the Northeast United States by using MCE-AHP process in GEOMOD. The data of socio-economic drivers are major drawback in land use modeling because of its availability at spatial scales and the difficulty in their integration with environmental data. Bhandari, (2010) showed that the urban growth will have significant effects in Kathmandu Valley by the prediction of LULC classes using CA Markov and GEOMOD.

The study of land use land cover change modeling using Cellular Automata (CA) Markov in Choudwar watershed, India using satellite-derived maps of 1972, 1990, 1999 and 2005 highlighted the biophysical and socio-economic drivers including residential/industrial development, road–rail and settlement proximity have influenced the spatial pattern of the watershed LULC dynamics showed the increase of agricultural and settlement areas. The annual rate of increase from 1972 to 2004 in agriculture land and settlement were 181.96, 9.89 ha/year while decrease in forest, wetland and marshy land were 91.22, 27.56 and 39.52 ha/year respectively. The predicted LULC scenario for the year 2014 by CA Markov, with acceptable accuracy would give useful inputs to the LULC planners for sustainable management of the watershed (Behera et al., 2012).
The study of spatio-temporal urbanization processes in the megacity of Mumbai, India by using Markov chains-cellular automata model was conducted to examine past urban land use changes on the basis of remote sensing data collected between 1973 and 2010 to predict city expansion for the years 2020 and 2030. The results show that the highest urban growth rates, 142% occurred between 1973 and 1990. In contrast, the growth rates decreased to 40% between 1990 and 2001 and decreased to 38% between 2001 and 2010. The area’s most affected by this degradation were open land and croplands. Strong evidence is provided for complex future urban growth, characterized by a mixture of growth patterns (Moghadam and Helbich, 2013).

The studies of Integration of logistic regression, Markov chain and cellular automata models to simulate urban environmental and socio-economic variables dealing with urban sprawl were to create a probability surface of spatio-temporal states of built-up land use for the years 2006, 2016, and 2026. The methods were calibrated for 2006 by cross comparing of actual and simulated land use maps. The achieved outcomes represent a match of 89% between simulated and actual maps of 2006, which was satisfactory to approve the calibration process. Thereafter, the calibrated hybrid approach was implemented for forthcoming years. Finally, future land use maps for 2016 and 2026 were predicted by means of this hybrid approach (Arsanjani et al., 2013).

The study of the transparency, reliability and utility of tropical rainforest land-use and land-cover change models in Amazon, the Congo basin and South-East Asia highlighted the Land use and land cover (LULC) change is one of the largest drivers of biodiversity loss and carbon emissions globally by investigating spatial predictive models of LULC change and validation. Finally their study suggested tropical LULC change models have an equally high potential to influence public opinion and impact the development of land use policies based on plausible future scenarios, but to do that reliably may require further improvements (Rosa et al., 2014).

2.3 Soil Erosion Modeling

Soil erosion is the one of the environmental crises which brings the food crisis (Bewket and Sterk, 2003; Lal, 2001). Severe problems for human sustainability have recognized the adverse influences of widespread soil erosion on soil degradation, agricultural production, water quality, hydrological systems, and environments (Lal, 1998). Many factors, such as climate, land
cover, soil, topography, and human activities make complex for soil erosion loss. In addition to the biophysical parameters, social, economic, and political components impede soil erosion (Ananda and Herath, 2003). Accurate and timely estimation of soil erosion loss or evaluation of soil erosion risk has become an urgent task.

Erosion models play critical roles in soil and water resource conservation and nonpoint source pollution assessments, including sediment load assessment and inventory, conservation planning and design for sediment control, and for the advancement of scientific understanding. Soil Erosion model try to simplify the complexity of natural processes of soil erosion (Shrestha, 2007). Model is built by relating the essential factors to the erosion and soil loss through the methodology of the field observation, measurement, experiment and statistical analysis. Several models are available for assessment of soil erosion (Gebrekirstos, 2003). Scientists have been involved in soil erosion research for a long time, and many models for soil erosion loss estimation have been developed (Wischmeier and Smith, 1978). Fullen, (2003) summarized some keynote papers about soil erosion in northern Europe, and Lal, (2001) highlighted major empirical models for predicting the soil loss.

2.3.1 Empirical Models

Empirical models describe the erosion statistically relationship between assumed important variables (Kadupitiya, 2002). Empirical models are based on the important factors field observation, measurement, experimentation and statistical technique relating erosion factors to soil loss. Empirical model can predict soil erosion quick but it needs long term data (Elirehema, 2001). The mostly used empirical model is USLE. Other models include RUSLE, SLEMSA, MMF, and RMMF etc. that are modified.

**Universal Soil Loss Equation (USLE):** United States Department of Agriculture (USDA) developed this model in 1970’s. This model was used widely in USA and worldwide (Merritt et al., 2003). This model is developed by using statistical analysis of the data from 10,000 plots years from natural runoff and 2000 plots year’s artificial rainfall simulators in USA (Wischmeier and Smith, 1978). Sheet and rill erosion can be predicted by RUSLE using the factors R-Climatic erosivity, K-soil erodibility, L and S topography, C, and P land use. It is also upgraded to put additional information, since the development of the USLE (Renard et al., 1997). Long term erosion cannot be calculated because of some limitation. It can predict only inter rill
erosion but not gully, channel or stream bank erosion. It can only estimate soil movement particle but ignore sedimentation. Short-term rainfall biases the accuracy of the equation (Merritt et al., 2003). The factors in USLE are calculated as follows:

\[ A = R \times K \times L \times S \times C \times P \]  

(1)


The USLE has another concept of experimental importance, the unit plot concept. The unit plot is defined as the standard plot condition to determine the soil's erodibility. These conditions are when the LS factor = 1 (slope = 9% and length = 72.6 feet) where the plot is fallow and tillage is up and down slope and no conservation practices are applied (CP=1) where, \( K = A/R \).

A simpler method to predict \( K \) was presented by Wischmeier et al., (1971) which includes the particle size of the soil, organic matter content, soil structure and profile permeability. The soil erodibility factor \( K \) can be approximated from a nomograph. The LS factors can easily be determined from a slope effect chart by knowing the length and gradient of the slope. The cropping management factor (C) and conservation practices factor (P) are more difficult to obtain and must be determined empirically from plot data. They are described in soil loss ratios (C or P with / C or P without).

It is the standard model for most erosion assessment and conservation planning. There is a considerable interdependence between the variables. One important factor to which soil loss is directly related is runoff which is not dealt explicitly but is incorporated within \( R \) factor is the major drawback of Universal Soil Loss Equation (USLE). USLE has followed a continuous development. It was first published in 1958 (USDA Agriculture Handbook 282) and the refined and improved in 1978 (Agriculture Handbook 537). Williams and Brendt, (1977) modified the USLE equation to estimate stream sediment yield for individual storms with its rainfall factor (R) replaced by a runoff factor and called it the modified universal soil loss equation (MUSLE) (Sadeghi et al., 2007). As a result of experience, a number of changes were made that are now incorporated in Revised Universal Soil Loss Equation (RUSLE).
Revised Universal Soil Loss Equation (RUSLE): This model has also the same factors as in USLE but it is revised in some factors from scattered research reports and professional journals. However, it has same limitation with USLE (Gebrekirstos, 2003). It estimates sheet and rill erosion as a function of 6 major factors. It maintains the basic structure of USLE and computes annual soil loss in t/ha/yr as follows:

\[ A = R \times K \times L \times S \times C \times P \]  

(2)

Where R: Rainfall-runoff erosive factor, K: Soil erodibility factor, L: Slope length factor, S: Slope steepness factor, C: Cover-management factor, P: Supporting practices from USLE. RUSLE takes into consideration all major components likely to affect rill and interrill erosion; it is the most widely used soil loss equation (Mathews et al., 2007). It includes revision of R factor, the development of a seasonally variable K factor, modification to the LS factor to the account of the susceptibility of soils to rill erosion; and new method for the calculating the C factor value through the multiplication of various sub factor values by taking the prior land use, crop canopy, surface cover and surface roughness. However, RUSLE has great practical value but its limitations should be recognized. The main limitations of the RUSLE are that 1) it does not provide explanation of the effects of the sub-processes involved on soil erosion, i.e. effects of annual variation of runoff, soil moisture and evapo-transpiration; 2) It only predicts sediment entrained in the erosion process but doesn’t predict sediment yields into particular basins; 3) It predicts average annual soil loss but does not provide annual soil loss distribution according to the precipitation occurrence neither predict soil loss in a particular storm event. It is effective for erosion through sheet and rill flow only on short slopes (<300 ft) and not for concentrated flow or long slopes; 5) It does not adequately take into account soil dispersibility in assessment of the K-factor (Mathews et al. 2007). Caution should be taken into account in areas where processes of gully and channel erosion are present. These can contribute more than 50% of the sediment produced (Blong, 1985; Quinton, 2004).

The Morgan Morgan Finney Model (MMF): This model can predict the annual soil loss from field size area from the slope. It has USLE factors and covers the understanding of erosion processes (Morgan et al., 1984). This model is physical based empirical model. It is divided into two phases i.e. water phase and sedimentation phase. It can be easily applied on raster based
Geographic information system (Shrestha, 2007). This model can predict the annual soil loss from field size area from the slope.

**Revised Morgan-Morgan–Finney (RMMF):** Changes have been made to the way soil particle detachment by raindrop impact is simulated, which now takes into account of plant canopy height and leaf drainage, and a component has been added for soil particle detachment by flow. The model has been proved to be sensitive to changes in annual rainfall and soil type. Thus, good information in context of rainfall and soil is required for successful prediction (Morgan et al., 1984). Differences from the MMF model are soil particle detached by rain drop and takes account of plant canopy height and leaf drainage is also added for soil particle detachment flow (Morgan, 2001). Like USLE, the RMMF model cannot be applied to predict soil loss from individual storm or from gully erosion. The prediction obtained by the model are most sensitive to changes in annual rainfall and soil parameter when erosion is transport- limited and to change in rainfall interception and annual rainfall when erosion is detachment limited. Morgan, Morgan and Finney Model (MMF) is frequently selected by the researcher because of its simplicity, flexibility and strong physical base. (Morgan et al., 1984) presented a simple empirical model for predicting annual soil loss from field-sized areas on hill slopes. The MMF model used the concepts proposed by (Meyer and Wischmeier, 1969) and (Kirkby, 1976) to provide a stronger physical base than the Universal Soil Loss Equation (Wischmeier and Smith, 1978). The model was designed to separate the erosion process into a water phase and a sediment phase.

In specific condition, Universal Soil Loss Equation, (USLE) (Wischmeier and Smith, 1965), allows assessing soil loss from agricultural fields. Modified versions have been adapted to other model, such as MUSLE (Williams and Brendt, 1977) and RUSLE for sediment yield estimation. SLEMSA, the Soil Loss Estimation Equation for Southern Africa (Stocking, 1981) was developed in Zimbabwe based on the USLE model. There are some other models such as ANSWERS (Arial Non-point Source Watershed Environment Response Simulation, and AGNPS (Agricultural Non-Point Source Pollution Model, these models are based on grid cells and were developed to estimate runoff quality, with primary emphasis on sediment and nutrient transport.

USLE has been widely used through various modified versions; its application in mountainous terrain with steep slopes is still questionable. Some models, such as AGNPS or
ANSWER, may not be suitable in the Nepalese context because of very high data demand and AGNPS in particular is not adapted well enough to the Nepalese mid-hill belt mountain conditions (Shrestha, 1997). The RMMF soil erosion modeling was chosen in the present study due to its simplicity, flexibility and strong physical base.

Svorin (2003) carried out of the application of three soil erosion models, USLE/RUSLE, SLEMSA and the Morgan, Morgan and Finney (MMF), to the Simeto catchment in Sicily, and studied the differences in the results using these three models. The models are incorporated with a grid-based geographical information system, and the results are validated qualitatively and quantitatively.

Saavedra and Mannaerts (2005) tested five erosion models (USPED, USLE, RUSLE-3D, SPL and MMMF) with modest data input requirements in Bolivian semi-arid mountains, to overcome the data limitations which are a common limitation in Bolivia and the rest of the Andean region. The results of the models were validated with remote sensing imagery, which provides a spatially explicit background for indirect model validation overcoming the lack of erosion measurements to model calibration and validation. The model validation showed that none of the five models accurately predicts soil erosion across the catchment. It is therefore concluded that although the spatial patterns of predicted erosion by the different models seem reliable, quantitative prediction should be interpreted with caution.

Many researchers have conducted research in this field by applying different models and approaches. Survey methodology for the rill was used to study soil erosion in cultivated field of watershed in Ethiopia (Bewket and sterk, 2003). Some decision support system, such as the erosion prediction information system (EPIS) is led by the integration of basic soil erosion equation USLE, GIS and RS (Millward and Mersey 2001). Slope length factors were calibrated using a Win Grid system.

The several empirical models based on geomorphologic parameter were developed in the past for assessing the soil erosion and sediment yield (Jose and Das 1982; Misra et al., 1984). Major vulnerability of the erosion is the semi-arid and semi-humid areas of the world, especially in china, India, western USA central Russia and Mediterranean lands. The problem of soil erosion in these areas is compounded by the need of water conservation and the ecological sensitivity of the environment so that removal of vegetation cover for cropping or grazing results
in rapid declines in organic content of the soil, followed by soil exhaustion and the risk of desertification. Other areas of high erosion rates include mountain terrain such as Andes, Himalayas, Karkoram, and Rocky Mountains etc.

2.3.2 Soil Erosion and Land use / Land cover

There are many factors influencing soil erosion. Researchers have pinpointed plant cover and land use as significant indicators affecting the intensity of soil erosion (Mohammad and Adam, 2010). Thus, soil erosion increases due to the changes of land use, such as deforestation, encroachment of agricultural interests, or other causes for the loss of land cover material. Comparably, the increase of forest area or other land covering material can potentially reduce the amount of soil loss. For example, vegetation controls soil erosion by means of its canopy, roots, and litter components, and erosion influences vegetation in terms of the structure, composition and growth pattern of plants (Mohammad and Adam, 2010). The Nepal government and international agencies recently quantified and mapped the severe degradation of the surface area on the middle mountain region (Ives and Messerli, 1989). Around 77% of land area is occupied by mountains and Himalayas in Nepal. Rate of deforestation is 1.6%, which is quite severe and government’s resettlement program cleared about 103,968 ha of forest in Siwaliks hill and plains from the 1950s to the mid-1980s (MPFS, 1988). The annual national rate of deforestation was 0.5 percent as identified by the comparison of the 1978-1979 maps with 1994-1996 maps, whereas it is 1.7 percent in plain areas and 2.3 percent in middle mountain region (FRI, 1999).

However, the community and the leasehold forestry program have increased in the forest cover in middle mountain region during the period of 1980s to 1990s (Gilmour and Nurse, 1991). Erosion rates in the middle mountain region were increased due to the destabilization of the fragile mountain slope through deforestation, agricultural expansion, excessive grazing and road networks without clear conservation measures (Ives and Messerli, 1989; Thapa, 1990). Agriculture was extended at the cost of forest in the marginal and sub-marginal areas with steep to very steep slopes without due consideration for the suitability of these lands for cultivation (Tiwari, 2000). Cultivation in steep lands could aggravate soil erosion process, rill and gully formation and provides in reshaping drainage pattern and drainage density. Ghimire et al., (2013) reported that rate of soil erosion decreases as the vegetation cover increases. In addition, plant roots significantly increase soil cohesion and hence increase the soil's resistance to erosion. Nonetheless, a number of studies have successfully integrated both environmental and socio-
economic factors in modeling land use change and its impact on erosion risk (Leh et al., 2013) showed increased urbanization leading to increased soil erosion risk. In the last decade due to rapid population growth and expansion of the urban region, large area is used as agricultural, commercial and residential purposes.

Shrestha (1997) analyzed that soil erosion is a crucial problem in Nepal where more than 80% of the land area is mountainous and still tectonically vulnerable. Results provided by running Morgan Morgan and Finney model in a GIS showed that annual soil loss rates were the highest (up to 56 t/ha/yr) in the areas with rain fed cultivation, which was directly related to the sloping nature of the terraces. The lowest soil losses (less than 1 /ha/yr) were recorded under dense forest. In the degraded forest, the soil loss varies from 1 to 9 t/ha/yr and in the grazing lands it was at 8 t/ha/yr.

According to Basayigit and Ural, (2010) soil erosion by water is the major cause of soil degradation in Lake Watershed showing high detachment effect of raindrop impacts was offset by the low detachment of soil particles by runoff and the low transport capacity of the runoff which induce sedimentation instead of erosion. RMMF model for soil loss assessment is reasonable and simulated soil losses are in accordance with topography, physiographic units, vegetation and morphological properties in the study area.

Ghimire et al., (2013) pointed soil erosion as one of the key environmental issues of mountain ecosystems leading to loss of top soil, decrease of soil water capacity, soil fertility and also inhibit vegetation growth. Over the past few decades Himalayas of Nepal have been the focus of numerous research studies exploring the relationships between different components of the hydrology and geomorphology particularly rainfall, runoff, soil erosion, sediment loss, land use and socio-economic impacts at a broad range of spatial and temporal scales. There has been considerable research on soil erosion issues mostly focused on the Middle Mountain region and a few in the High Himalaya.

The study of the land use/land cover change and its impact on soil erosion process in Begnas Tal, Rupa Tal watersheds Nepal showed the spatial temporal analysis of changes in land use/land cover between 1988 and 1999 with Landsat TM 1988 to 1999 using GIS tools. From the results of this study, it was concluded that from 1998 to 1999 land use such as dense mixed forest, agriculture land, water body, Sal forest and settlement area had increased; and open forest,
barren land are decreased in Begnas, Tal, Rupa Tal watersheds. There has been remarkable growth in agriculture land (40.06%) and dense mixed forest (37.44%) during this period. During same period open forest (9.17%) and barren land (1.24%) have decreased. The maximum and minimum soil loss was recorded under rain-fed agriculture and woody vegetated area respectively (Koirala and Cabral, 2008).

The study conducted in the Ozark Highland of USA by using GIS and remote sensing showed that the impact of land use change on soil erosion and sedimentation in a mixed land use watershed can be quantified by incorporating commonly available biophysical data (Leh et al., 2013).

The study held in the Central Spanish Pyrenees indicated that soil erosion and sediment yield are highly effected by land use land cover (LULC). It also revealed that the abandonment of traditional land uses was mostly by agriculture followed by other subsequent factors such as vegetation decolonization. The survey showed the reduction of about one order of magnitude in gross erosion (3180 to 350 Mg yr\(^{-1}\)) and sediment delivery (11.2 to 1.2 Mg yr\(^{-1}\) ha\(^{-1}\)) during the last decades (Alatorre et al., 2011).

Sharma et al., (2011) highlighted the influence of land use and land cover change on soil erosion potential of a reservoir catchment during the period 1989 to 2004 by using Universal soil loss equation (USLE) with the aid of geographic information system in his study over the issue. It stressed the main soil erosion potential of watershed increased slightly from 12.11 t/ha/yr in the year 1989 to 13.21 t/ha/yr in the year 2004. It eventually concluded that the spatial location of LUC parcels with respect to terrain and associated soil properties should be an important consideration in soil erosion assessment process.