Tremendous developments in space technology in 21st century has provided number of satellites platform to study the complex physical processes of the earth-atmosphere system and one of the best basic characteristics of remote sensing is the extensive use of qualitative and quantitative algorithms for estimating earth’s surface variables (Liang, 2004).

2.1 Topographic Correction

Scientific studies using remote sensing data in the past were primarily focused on land-use classification and long term temporal changes in terrestrial land cover, assuming flat terrain in order to avoid complexities due to topography (Sandmeier et al. 1995). The strong variations in topographical parameters (mainly slope, aspect and altitude) in rugged mountainous terrain significantly influence the qualitative and quantitative analysis of snow physical parameters. The relief effect due to topography is neither eliminated during system correction nor during the normal geometric correction and has great significance in mountainous regions (Mishra et al. 2010). The methods for correcting the topographic effect can be grouped into three categories: (i) Band-ratio method (ii) Hyperspherical Direction Cosine Transformation (HSDC) and (iii) Digital elevation models (DEM).

2.1.1 Band-ratio method: This method was one of the earliest and simplest topographic correction method reported by Crane (1971) by using the ratio of two bands in satellite data. It does not require any additional input data and much of information is lost using this method. A major disadvantage of this method is that it becomes invalid when different land use/land cover (LULC) classes have similar reflectance as reported by Sabins 1997; Colby et al. 1998 because of the decreased radiometric resolution of the ratio image. Previous research (Metternicht et al. 2003; Cheng et al. 2004) also shows that the band ratio could partly remove the topographic effects from an image.

2.1.2 Hyperspherical Direction Cosine Transformation (HSDC): HSDC projects, measurement vectors on to hypersphere (Chen et al. 2005). Chen’s research (2005) showed that although the HSDC transformation can remove the topographic effects dramatically but it is less suitable for multispectral classification of rock types. It only improved classification accuracy of a few rock units, probably because some information was lost in the transformation.
2.1.3 **DEM based Method**: This method can be summarized as three broad types (a) Lambertian methods (b) Non-Lambertian methods and (c) Empirical approaches.

2.1.3(a) **Lambertian methods**: DEM based following Lambertian methods has been introduced by researchers:

(i) **Cosine-T** (Teillet et al. 1982): It is a simple photometric function that, attempts to correct only for differences in illumination caused by the orientation of the surface. It is commonly applied for flat to hilly terrain data to equalize illumination differences due to different sun positions in multitemporal data analysis. These models are wavelength dependent. Several authors (Duguay and LeDrew 1992; Meyer and Itten 1993) have reported that Cosine-T often results in over correction. This model does not take into account diffuse irradiance from atmosphere and terrain sources (Soenen et al. 2005).

(ii) **C-correction** (Teillet et al. 1982): It is a modified form of Cosine-T and considers non-Lambertian assumption to account for the smaller cos i regions (shadow areas). The model introduces a parameter C, which is estimated using empirical statistical approach. It assumes a linear relationship between satellites estimated spectral reflectance and terrain illumination. This method is further modified in advanced C-correction form which additionally requires satellite altitude and map coordinates for the corners of the original image. This model has not been implemented very commonly for different satellite images (Mishra et al. 2009).

(iii) **Cosine-C**: Due to the problem of overcorrection in cosine correction, an improved version has been proposed by (Civco 1989). This model is wavelength independent, since the correction is based on the same factor for all the bands. This assumption is not appropriate as far as diffuse irradiance concerns. Therefore, it should be more appropriate to propose band-dependent factors of topographic correction as reported by (Riano et al. 2003).

(iv) **SCS**: This method is proposed by Guand Gillespie (1998). It is based on sun-canopy-sensor (SCS) geometry as well as forest canopy model. It is used for SCS correction algorithm and therefore SCS model works better for forests.

(v) **Dymond-Shepherd**: This method is proposed by Dymond and Shepherd (1999). It provides a simple analytical correction for visible-light reflectance, which is applicable to grass and forest situations where there is canopy closure. Extension of this theory from visible to near-infrared light as well as analysis of accuracy of slope data from digital terrain models is still required.
(vi) Smooth C-correction: This method is reported by Riano et al. 2003 and the results of this method is obtained with a variation of C method which takes into account the overcorrection of low illuminated slopes by the original C method. A smoothed correction does not alter reflectance values significantly, whereas a more extreme correction could introduce additional errors and not provides good results in snow cover area of Himalayan terrain, especially in shady area, reported by Mishra et al. 2011.

(vii) SCS+C: It has been reported by Soenen et al. 2005 that SCS algorithm overcorrects the topography induced effects when solar incidence angles approaching 90°. This problem is resolved by Soenen et al. 2005 after introducing an empirical parameter C into the SCS model to moderate the effect of diffuse sky illumination in a similar way to the C-correction to the Cosine-T correction, and thus the SCS algorithm was modified to the so called sun-canopy-senor with C correction (SCS +C) model.

(viii) C-Huang Wei: This method is used for topographic correction under Lambertian methods developed by Huang Wei (2005). This method does not provide well results in snow cover area of Himalayan terrain, reported by Sartajvir et al. 2011.

(ix) Cosine-b: It is reported by Yongnian et al. 2009 that Cosine-b corrections method has a problem of overcorrection because no account is taken of the contribution of indirect irradiance.

2.1.3(b) Non-Lambertian methods: The following non-Lambertian, DEM based topographic correction model has been discussed by various researchers:

(i) Minnaert Method: Initially a simply a semi-empirical equation has been proposed by Minnaert (1941) to assess the roughness of the moon’s surface. The function has been used for photometric analysis of lunar surfaces (Holben and Justice 1980) and implemented for topographic corrections. This method is further modified by Colby (1991) very effective in slightly rugged terrain but the Minneart constant is difficult to estimate according to changing Earth-Sun geometry and different spectral bands, which hinders application of the method.

(ii) Ekstrand-e: This method is reported by Ekstrand (1966). The general approach of this methods is to normalize the observed radiance from inclined surfaces to flat (horizontal) surfaces by modeling the local incidence angle to the terrain surface cos i for each pixel.

also performed similar work and considered BRDF correction. They converted slope reflectance to horizontal reflectance after accurately modeling the above three radiance components. It is necessary to consider surface target BRDF when carrying out reflectance related work. Introducing a BRDF model requires multi-angles of sun incidence and sensor observation, such as with the polarization and directionality of the earth’s reflectance (POLDER) instrument, Moderate Resolution Imaging Spectroradiometer (MODIS), Multiangle Imaging Spectra Radiometer (MISR) and Along-Track Scanning Radiometer (ATSR) data, which can provide enough angle information to calculate the BRDF model. However, in general, it is difficult to obtain a precise BRDF model from one satellite scene with one solar incident angle and one sensor observation angle (Jianguang Wen et al. 2007)

(iv) **Slope Matching Method:** Nichol et al. 2006 reported that the magnitude of the second stage Civco (1989) correction is small for very dark pixels because the extent of correction cannot be greater than the original digital number (DN) values. This model considers the mean illumination of the sunlit slopes as compared to mean illumination of the entire image considered by Civco (1989). Secondly, it considers maximum and minimum DN values as compared to mean DN value of an entire image in two stage normalization. Slope matching method has been most widely used for visual analysis on IKONOS images for vegetation analysis.

(v) **VECA:** Variable Empirical Coefficient Algorithm (VECA) method has been reported by Gao (2009) for vegetation analysis using Landsat (ETM+) and analyzed that The Cosine-T, Cosine-C, SCS and Cosine-b corrections have the problem of overcorrection because no account is taken of the contribution of indirect irradiance and the non-Lambertian nature of the surface to the incident solar flux, so they are not suitable methods for topographic correction. On the other hand Gao et al. 2009 reported the performance of Teillet-regression correction model, SCS + C, Minnaert and Minnaert-SCS corrections is worst for vegetation analysis.

2.1.3(c) **Empirical approaches:** Out of various topographic correction methods with DEM data, following empirical approaches has been introduced by researcher:

(i) **b-Correction:** This method is based on the empirical observation and proposed as an empirical normalization method. It suggests that for anisotropic reflection, a linear function of radiance logarithm tends to be more effective than Teillet regression methods but more significant for the specific band and image (Vincini et al. 2002).
(ii) **Two-stage normalization**: In this method topographic normalization is reported by Civco (1989) two stages. In the first stage, shaded relief models, corresponding to the solar illumination conditions at the time of the satellite image are computed using the digital elevation model (DEM). This requires the input of the solar azimuth and altitude provided by the metadata of the satellite image. The computed illumination values ranging from -1 to +1 are scaled to 0-255. The image DN values are then normalized using the illumination model. This provides most satisfactory results in terms of visual effect and has been tested for forest cover mapping (Law et al. 2004). It is reported that topographic effects have not been not completely removed and the low illumination areas remained dark relative to sunny slopes. In order to reduce the topographic effects further, a second stage normalization involving an empirically determined calibration coefficient was introduced. The coefficient was calculated using first stage normalization.

### 2.2 Surface parameters extraction

More than forty percent (40%) of the Earth’s land surface covers with snow during Northern Hemisphere winter (Robinson et al. 1985). Therefore it becomes one of the essential components on earth’s surface and directly influences the surface radiation, energy balance and hydrologic budgets. It is also one of the key factors to consider in the atmospheric circulation, runoff modeling, numerical weather forecasting and climate change studies (Peter Romanov et al. 2000). The snow cover analysis in mountainous regions is also needed for other applications such as snow mapping, avalanche forecasting and improvement of snow depth maps (Mishra et al. 2009). As on today various methods and models have been implemented for surface parameters extraction namely Normalized Difference vegetation index (NDVI) by Justice et al. 1985, visible band reflectance (Kazama and Sawamoto 1995; Asaoka et al. 2002), Normalized Difference Snow Index (NDSI) (Hall et. al. 1995;Salomonson et al. 2004), S3 index considering NIR band (Saito and Yamazaki 1999), Normalized Difference Glacier Index (NDGI) and Normalized Difference Snow Ice Index (NDSII) (Keshri et al.2009). The accurate estimation of surface variable using medium and coarse resolution satellite sensor is challenging task due to mixing of various heterogeneous land features in a pixel. To overcome this problem, a number of techniques for mapping the land cover at sub-pixel level have been developed. These include maximum likelihood (MLH) classifier reported by Richards (1999), Spectral angle mapper (SAM) reported by Kruse et al. 2003 and Support Vector machine (SVM) reported by reported
by Hsu et al. 2007, artificial neural network (ANN) (Foody et al., 1997), decision tree classification (Friedl et al. 1997; Ghose et al. 2010) etc. However, not all these techniques have yet been explored for snow-cover sub-pixel mapping (Foody et al. 1997; Tiwari et al. 1999). The literature suggests the use of empirical relationships (Kaufman et al. 2002; Salomonson et al. 2006), Linear mixture model (LMM) (Rosenthal et al. 1996; Painter et al. 2003; Foppa et al. 2004) and ANN (Simpson et al. 2001) for snow cover mapping at sub-pixel level. The application of these models has yet not been explored for Himalayan snow cover as complex topography influences the results and inability to map snow in mountain shadows (Sharma J.K et.al 2010).

2.3 Change detection analysis

Surface change detection analysis is important for managing environment resources. Various techniques such as unsupervised change detection (Dale et al. 1996, Bruzzone 2000), change vector analysis (Johnson et al. 1998), digital change detection using principal component analysis (Singh 1989), image classification (Song 2001), and write function memory insertion (Price et al. 1992; Jensen et al. 1993) have been reported on multispectral images in literature to determine the changes between two or more time periods of a particular area of study. A few work on change detection with hyperspectral data (Stein 2002; Manolakis 2002; Schaum 2004; Meola 2007) has been reported. Most of these methods are used for environmental monitoring (Chavez 1996), agricultural surveys (Bruzzone et al. 1997), urban studies (Merril et al. 1998) and forest monitoring (Hame et al. 1998; Jakubauskas et al. 1990; Gopal et al. 1996), vegetation analysis (Meola 2007) etc. An attempt has been made with improved change vector analysis on western Himalayas (usually snow covered area) using multispectral coarse spatial resolution MODIS at 250 m special resolution (Mishra et al. 2001; Negi et al. 2005; Singh et al. 2011). Moreover, the effect of topography on accuracy of land cover spectral change vector analysis has yet not been found reported in the Himalayan region using AWiFS and Hyperion satellite data.