MAPPING AND MONITORING SPATIAL PATTERNS OF LAND DEGRADATION USING REMOTE SENSING AND GIS IN A MOUNTAINOUS TERRAIN

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IN THE NAME OF ALLAH, THE MOST BENEFICIENT

AND THE MOST MERCIFUL

Dedicated to

My parents

Aunty (Riffat Fayaz)

Sisters

And

Wife (Naila Gohar)

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ABBREVIATIONS

AMSL	Above Mean Sea Level
B7b4	Band 7 and Band 4
ROC	Receiver Operating Characteristic
Curv	Curvature
DTM	Digital Terrain Model
ED	Explained Deviance
EGVs	Eco-geographical Variables
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GPS	Global Positioning System
L. D	Land Degradation
MAI	Mediterranean Agronomic Institute
MIR	Mid Infrared Band
NASA	American's National Space Agency
ND	Null Deviance
NDVI	Normalized vegetation Index
NIR	Near Infrared
Plan	Plan Curvature
Prof	Profile Curvature
Slf	Slope Length Factor
Spi	Stream Power Index
SRS	Satellite Remote Sensing
SWIR	Short-wave Infrared Ratio
TM	Thematic Mapper
Tpi	Topographic Position Index
Twi	Topographic Wetness Index
WRS	World Reference System

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ABSTRACT

This study describes the techniques and methods used to develop GIS data from available remote sensing data to help the identification of major types of land degradation in the study area (Palas valley). Remote sensing has high potential for land degradation data collection due to large area coverage, regular time interval, spatial and spectral resolution and which facilitates detection of degraded areas. It has long been recommended for its potential to detect, map and monitor land degradation problems including their spread and effects with time. Use of remotely sensed imagery evolved on the basis that traditional survey became expensive and time-consuming. It is especially useful in areas that are not accessible.

For respective years, models for land degradation were selected and exported in Arc View in which final land degradation maps were produced. The maps revealed that the 9.45 hectares of unaffected land has been shrunk in 2001 as compare to 1992 data. The land degradation type D1 (Degraded forests) and D2 (Shrubberies) has increased in 2001 to 1138 and 43.11 hectors respectively. The maps also show that degraded land type D3 (Degraded shrubberies) decreased by 1289.7 hectares which may be reclaimed/recovered or may be shifted in other types of land degradation. It was noticed that degraded land type D4 (No vegetation cover/ sheet erosion) and type D5 (Severe erosion and gully formation are also increased by 107.62 and 9.9 hectors respectively.

The study area is no exception to this and present exercise will be a good contribution with respect to spatially explicit information about land degradation and mediating factors such as erosion, forest cutting, over grazing etc. The study, in general, would also contribute towards understanding the main causes, monitoring and mapping of degraded areas in Pakistan.

CHAPTER 1

Introduction

Degradation refers to the deterioration in the quality of the environment for man, vegetation, animals and aquatic life (Barber, 1984). Land degradation is a "complex term", which has no single readily identifiable feature or trait, but instead it describes how one or more of the land resources (soil, vegetation, water, rocks, air, climate, relief) has changed for the worse condition. Land degradation can be defined in quite a few ways depending upon the subject that needs to be emphasized. Land degradation is defined by Wasson (1987) as a change to land quality that makes it less useful for human beings (users). A more specific definition states that the land degradation is a decrease in optimum functioning of soil in ecosystems (Kimpe and Warkentin, 1998). We can also define land degradation in terms of increase in soil loss from agricultural lands affecting crop productivity and increasing sediment loss to rivers and reservoirs. According to Scherr and Yadav (1996) land degradation is a temporary or permanent decline in the productive capacity and ability of the land or its potential for environmental management.

Another definition considers the aggregate and cumulative diminution of the productive capacity of land, including its major uses (rainfed, irrigated range land, forest) farming systems (e.g. smallholder subsistence) and worth as an economic resource. This link between degradation (which is often caused by land use practices) and its effect on land use is central to nearly all published definitions of land degradation. The emphasis on land, rather than soil, make wider the focus to include natural resources such as climate, water, land forms and vegetation, the productivity of grass land and forest resources in addition to that of crop land, is embodied in this definition (Stocking and Murnaghan, 2001).

The concept of land degradation is a multifaceted and complex because it encompasses physical, biological, and socio-economic parameters. In the context of this study, the term land degradation is used as defined in the International Convention to Combat Desertification (Interim Secretariat, 1994). According to this definition, land degradation involves and occupies the processes, practices and end results of both vegetation and soil degradation due to anthropological factors.

1.2 Types of Land Degradation

1.2.1 Chemical Degradation: Chemical degradation is mostly due to leaching and pathetic farming practices which result in the loss of nutrients and a concomitant increase in exchangeable elements, and sometimes chemical degradation can also be caused by weak farming systems which " mine" the soil, i.e. where there is a steady removal of nutrients with no, or only minimal, nutrient substitutes (Barber, 1984). Nutrient depletion in soil results when the inflow of nutrients to the soil from outside the system soil, are less than outflow due to cultivation, erosion and leaching. (Stoorvogel and Smaling, 1990).

1.2.2 Physical Degradation: Physical degradation mainly includes a negative impact on physical soil properties, such as soil structure, texture, aggregate stability, porosity, permeability (compaction) and crusting. Erosion may be considered part of this category because it physically decreases soil deepness. Besides, soil compaction is an increase in bulk density due to external load leading to the degradation of physical properties such as root penetration, hydraulic conductivity and aeration (Mitiku *et al.*, 2006).

Physical degradation consists of those processes (such as poor cultivation practices), which negatively affect soil physical property such as infiltration rate, structural stability, root penetrability, and permeability. Some of these processes, which result in the exposure of the soil surface to rain, are closely related with sheet and gulley erosion (Barber, 1984). The infiltration and water retention are very limited on hard-setting soils and plants cannot germinate in such conditions. Crusting occurs due to several factors, e.g. the destruction of aggregates in the topsoil by rainfall, which is closely linked to soil erosion, an upward movement of water and soluble salts under semi-arid conditions. Crusting reduces infiltration and promotes surface water runoff. It inhibits germination and emergence of seedlings. Poor infiltration rates reduce water retention capacity and aggravate drought stress (Mitiku *et al.*, 2006).

1.3 Processes of Land Degradation

There are broad ranges of soil degradation processes, some of which are interrelated, which have been classified in six categories (FAO, 1979). These are water erosion, wind erosion, salinisation and alkalization, physical degradation and biological degradation. The main causes of these processes are invariably a combination of natural phenomena, man's actions such as destruction of vegetation cover, overgrazing, and unsuitable agricultural practices that aren't in according to the ecological environment. It is man's actions, as a result of increasing population pressure, that extend and accelerate the processes of degradation (Barber, 1984).

Land degradation is a long-standing environmental issue and concern for the world. As a major issue concerning, environmental changes, it has recently received wide attention (Feddema, 1999; Fairhead 2005). Recent studies undertaken in many parts of the world have emphasized the need for monitoring the degree and extent of soil degradation. Soil degradation is a major environmental hazard to the sustainability and the productive capacity of agriculture and forest sector. Soil degradation is associated with long-term changes in ecosystem functions, changes physical structure and chemical component of soils, reduces soil nutrients, declines land productivity, threaten to biodiversity, and diminishes economic viability (Melegy 2005).

1.4 Factors Causing Land Degradation

Different regions have different causes of land degradation, including biophysical, socioeconomic and political factors. Natural hazards, population change, poverty, land ownership problems, political instability and maladministration, economic and social problems, health problems and inappropriate land use are among some of the key factors. (Barrow, 1991)

Depending on characteristics and the climatic conditions, lands vary from highly resistant or stable, to those which are vulnerable and highly sensitive to degradation. Fragility, acute sensitivity to degradation processes, may refer to whole land. Stable lands do not necessarily resist change. They are in a stable steady state within their environmental conditions. Under stress, fragile lands degrade to a new steady state and the altered state is unfavorable to the plant growth and less capable of performing environmental regulatory functions.

Following natural hazards (factors) can increase land degradation

- Steep slopes
- Easily damaged soils
- Dry lands, droughty soils
- Lowlands close to sea and coastal areas
- Regions of intense rainfall

- Drought-risk areas in monsoon rainfall
- Hurricane-prone areas
- Earthquake or volcanic hazard
- Areas subject to insect invasion

Anthropogenic activities can add to natural damage which may includes

- Building in floodplains or other sensitive area
- Removing vegetation
- Altering hydrology (hydrograph)
- Intensive grazing
- Draining, flooding and filling (Barrow, 1991).

1.11 Objectives of the Study

The current study focuses on the land degradation mapping and monitoring in Palas valley, Kohistan (Khyber Pakhtoonkhwa). Specific objectives of the study are

- To detect and map different types of land degradation in the study area
- To monitor land degradation in study area using satellite data and ancillary GIS data

CHAPTER 2

Literature Review

Land degradation is long-term loss of ecosystem function and services, caused by disturbances from which the system cannot recover itself. It blights a significant part of the land surface, and one-third of the world's population – poor people and poor countries suffer excessively from its effects. Reputable evidence links land degradation with loss of biodiversity and climate change (Gisladottir and Stocking, 2005). Direct effects of land degradation include losses of soil organic carbon, nutrients, soil biodiversity, soil water storage and regulation. Indirectly, it means a loss of wildlife habitat and productive capacity of land. For instance, in rangelands it disrupts wildlife migration, brings changes in forage, introduces new pests and diseases, and increases competition for food and water among the users. Water resources are diminished by disruption of the water cycle, sedimentation and off-site pollution. Threat to sustainable development posed by land degradation has been recognized and accepted for decades, including 1992 Earth Summit and the 2002 World Summit on Sustainable Development, but responses have been limited by weaknesses in available data, predominantly in relation to the distribution, degree and severity of the various facets of degradation.

Land degradation negatively affects the ecological integrity and productivity of about 2 billon hectors or 24% of landscapes under human use. Farming lands in both dry land and forest areas have been most severely affected by land degradation. They cover about one-fourth of the world's total land area and account for 94.5% of all animal and plant protein and 98% of calories consumed by people. About two-thirds of agricultural land has been degraded to some degree during the last 50 years (World Resources Institute, 2000).

The impacts of human activities and interventions on natural systems are increasingly serious issues for the future. Increasing population pressures and escalating demands for services from a fixed land base are threatening the quality and the natural regulating functions of the soil/land, air and water resources on which sustainability depends. For the first time in history, we are crossing from the threshold of new lands available for cultivation. For the first time, the sustainable management of the existing land resource is more important than land supply for development. However, land degradation and mismanagement are threatening our opportunities and flexibility for increased services from the soil/land, requiring increased investment in soil conservation and even rehabilitation/construction and reclamation. It is clear from the research that about 40% of agricultural lands are affected by human induced land degradation (Oldeman et al., 1990).

Land degradation in term of soil erosion is the most important environmental concern in the developing countries like Bangladesh, Srilanka, Pakistan etc. The eroded sediment also acts as physical and chemical pollutants. It has been become an ecological, economic and social problem. Land degradation causes decrease in productive capacity of the land. This is in fact the main reason for the dramatic decrease of prime lands where only up to 3% of the global surface is left prime or class 1 (Eswaran et al., 2001).

Land degradation is closely associated with soil degradation. The loss of vegetation covers enhances soil erosion/ land degradation and hence reduces the productive capacity of the land. The productivity of some lands has declined by 50% due to desertification and soil erosion (Hill et al., 1995a). In turn, soil degradation reduces natural vegetation and biodiversity (De Jong, 1994). Lal and Stewart (1985) stressed that soil degradation destabilize the productive capacity of the ecosystem resulting in alteration of water and energy balance.

Knowing degree and severity of the land degradation is important as a decision support system to policy makers, resource managers as well as farmers. Fifth International Conference on Land Degradation held at the Mediterranean Agronomic Institute of Bari (MAI), Italy in September 2008. Some of the conference important outcomes were following.

- Land degradation and desertification continue to threaten the livelihood of millions around the world. It is a process that is present in both rich and poor countries.
- In the dry land regions, already in 1990, about 1 billion hector were estimated to be degraded
- Environmental measures, which include investigation on land and water in range of ecosystem spanning the agricultural, forest and livestock sector, should be assessed in term of impacts on both productivity, ecological functions and on the effects have on ecosystem stability and on human livelihood.
- Much valuable research has been carried out, published and is still ongoing. However, if research results do not find their way to being implemented their impact on arresting and even reversing land degradation are marginal or none.

- Much coordination is still need between researchers and research groups on land degradation and decision makers, policy designers and implementation bodies.

In order to combat land degradation, several efforts have been made at the national and regional levels to develop monitoring and data collection methodologies and to formulate appropriate policies, programs and projects. At the national level, such measures include watershed management, soil and water conservation, sand dune stabilization, reclamation of waterlogged and saline land, forest and range management and the replenishment of soil fertility in arable lands by use of green manures and cultivation of appropriate crops.

The criteria for assessing land degradation may be physical/ biological (e.g. reduced genetic diversity, species extinction, soil erosion and pollution) and socioeconomic (e.g. farm productivity decline, increased water treatment cost, lack of infrastructure and labor scarcity) (Wasson, 1987). In practice, different indicators, such as soil erosion and soil fertility decline, Stalinization and loss of vegetation cover, are often used to assess the status of land degradation. Stocking and Murnaghan (2001) provided many indicators of soil loss and of production constraints and combined indicators for the evaluation of land degradation.

Knowledge on the spatial distribution of land degradation is as relevant as knowing the availability of a resource base. Sujatha et al. (2000) claimed that the information on the nature, extent, severity and geographic distribution of degraded lands is of paramount importance for planning reclamation strategies and setting up preventive measures for sustainable agriculture development. As such, they become a significant basis for planners in drafting and implementing development plans for sustainable use of land resources (Hill et al., 1995a) as well as for resource restoration and quality enhancement (Lal, 1998b). Particularly, reliable information on the nature, extent and magnitude of soil erosion is required in planning and implementation of soil conservation and management programs (Dwivedi et al., 1997a).

Satisfactory information on degradation changes provides satisfactory strategies for the prevention and mitigation of land degradation (Barrow, 1994). Degradation changes being monitored give a considerable attention to the planners. According to Eswaran et al. (2001) information which gives a warning indicator to degradation problems can gain a collective effort to determine mitigation measures.

Remote Sensing has high potential for land degradation data collection due to large area coverage, regular time interval, spatial and spectral resolution and which facilitates detection of degraded areas (De Jong, 1994). It has long been recommended for its potential to detect, map and monitor degradation problems (Hellden and Stern, 1980; Sujatha et al., 2000) including their spread and effects with time. Use of remotely sensed imagery evolved on the basis that traditional survey became expensive and time-consuming. It is especially useful in areas that are not accessible.

CHAPTER 3

Research methods

3.1: Study Area

The study area selected for current assessment was Moro pasture and its adjacent areas located in the Palas valley (Fig 3.1). It is one of the most important pastures in the palas valley located between 34.95° and 35.06 ° L and 73.06 ° and 73.16 ° E with highest point falling at about 3800 asl. The valley is located on the left bank of the river Indus falling under the jurisdiction of Tehsil *Palas* and *Kohistan* Forest Division. The locality of the tract fall at 34°-52' to 35°-16' NL and 72°-52' and 73°-35' EL. It is bounded on the north and north-east by *Jalkot* valley, on the east by *Kaghan*, on the south by *Allai* and on the West by the river Indus.

The tract covers an area of 1300 km^2 and is a sub-watershed of the river Indus. The area is drained by two main nullahs; via *Musha'ga* and *Sherakot,* which drain into the river Indus near *Keyal* and *Pattan* respectively.

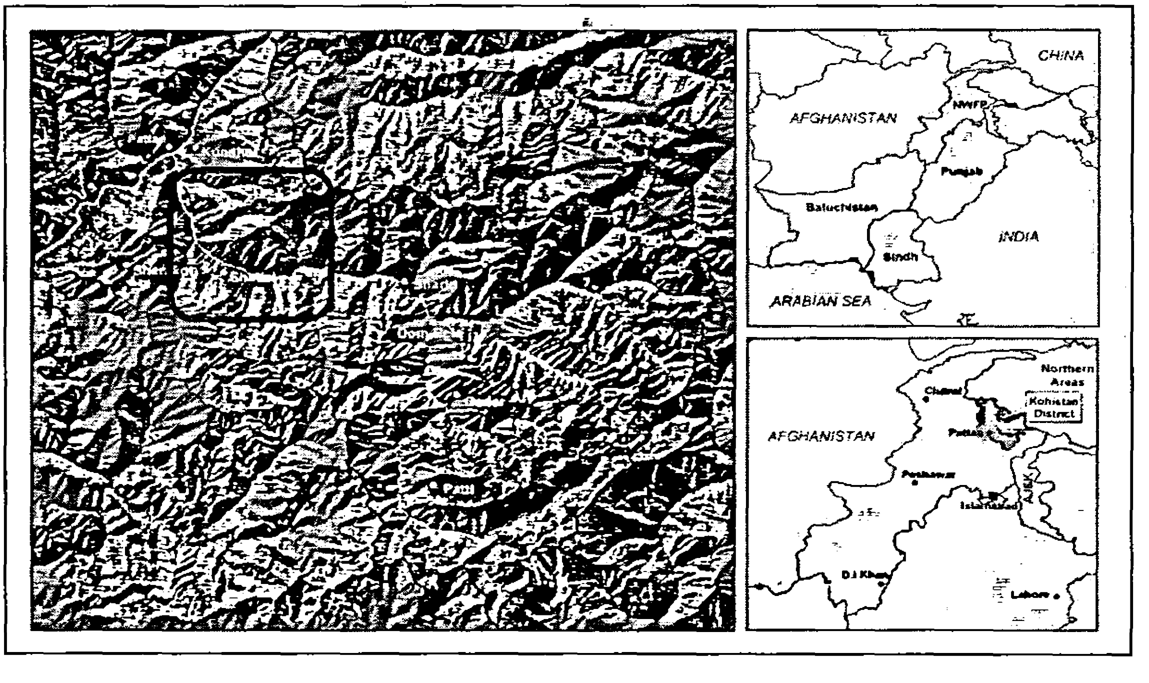


Figure. 3.1: The map of Palas Valley showing Location of Moro Pasture

The entire tract is a series of rugged mountains with elevations ranging from 600 to 5151 masl. The topography of the area is rough with bare out-crops and desolate precipitous slopes breaking the continuity of the forests. Moderate slopes and flat pans are found near the valley.

Mapping and monitoring the land degradation in Moro pasture and its surroundings involved the data collection regarding various types of land degradation, and correlating them with various remote sensing based and physical (terrain based) variables to produce a statistical model. The statistical models for individual land degradation type were then used in GIS platform to produce land degradation maps at decadal intervals for interpretation. The detailed procedures followed for mapping and monitoring the land degradation in the study area are as under:

3.2 Sampling of degraded land

The degraded land sites were identified in the field through physical survey. Each site was classified into one of 5 class scale depends upon the severity of degradation (Table: 3.1). Geographic coordinates of each site were recorded using Garmin™ GPSMAP® 60Cx global positioning system (GPS) device. Some additional points from arduous inaccessible places were identified and field condition recorded through panoramic photographs, field sketches and videos. The geographic position of these additional points (n=72; D1 and D2 only) was carefully located using 3-D visual image analysis of Landsat ETM image (captured: 2001-10-07; path 150; row 36) overlaid on 30m resolution Aster digital terrain model (DTM). A total 243 samples of various degraded land type were selected for assessment (Table: 3.1).

Table: 3.1: different land degradation categories defined in the study area

S. No	Class Code	Description	No. of Sampled Sites
1	D1	Degraded forests (logging)	117
2	D2	Shrubberies	4
3	D3	Degraded shrubberies	46
4	D4	No vegetation cover/ sheet erosion	57
5	D5	Severe erosion and gully formation	19
		Total	**243**

Figure: 3.3: some views showing different land degradation categories of the study area.

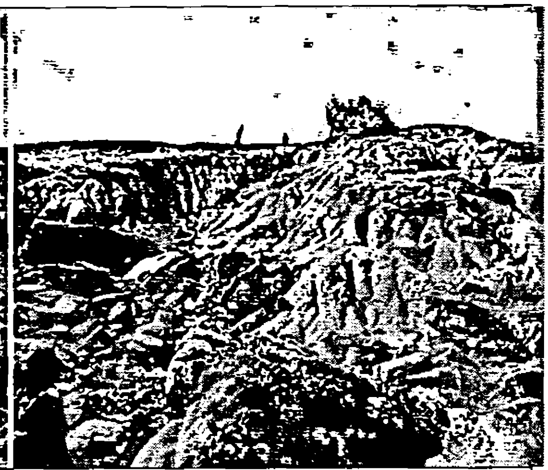
Degraded forests (logging)

Shrubberies (converted from forest)

Degraded shrubberies

No vegetation cover/ sheet erosion

Severe erosion and gully formation



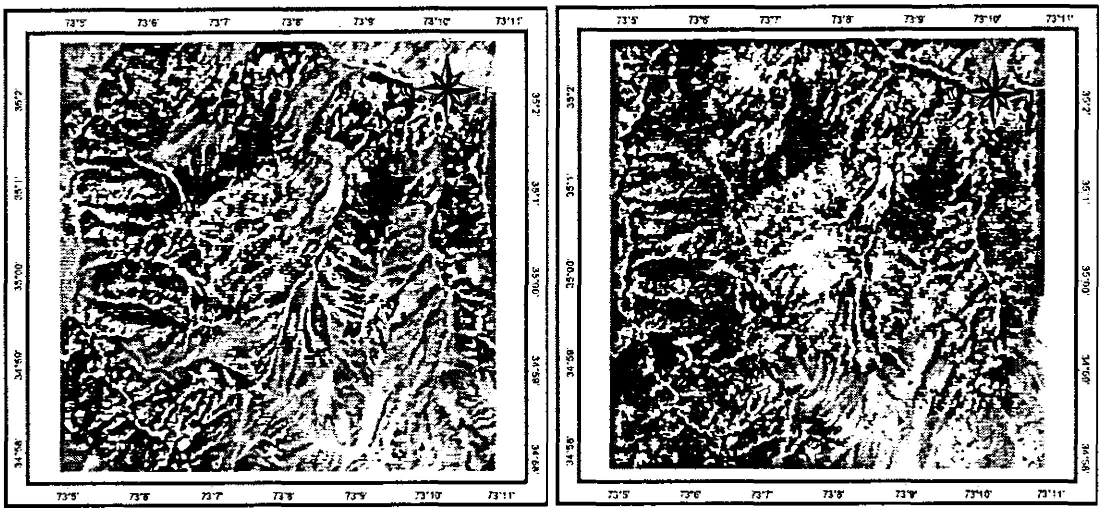
Severe erosion and gully formation

The geographic locations of the sampled degraded land sites were used to produce a GIS layer (shape file) and were intersected with SRS and GIS based layers /variables (fore-coming section) to extract their values for each degraded site. These variables were then further used in developing statistical models that were implemented in GIS to map and monitor land degradation process in the study area.

3. 3. Remote sensing Data

The main source of information extraction regarding the land degradation was through satellite remote sensing (SRS). The LANDSAT satellite imagery was used as a source of SRS data for the current assessment. It was a good choice due to the fact that data is available since 1972 holding a largest data for monitoring the global environment. The data is available at no cost from America's National Space Agency (NASA) and can be searched using World Reference System (WRS) consisting of Path and Row system for entire globe. The study area falls within path 150 and row 36 of WRS-2.

The SRS data for the current study comprised of two Landsat TM (Thematic Mapper) images at similar decadal interval anniversary dates (2001-10-07 and 1992-09-20). These imagery dates were preferred due to the fact that the vegetation in the study area is at its maximum growing phase after monsoon period and there were no problems of snow cover, a regular phenomenon at these elevations.



Landsat TM image 2001 1 0 1 2 km Landsat TM image 1992

Figure 3.4: The satellite images of study area for different years used to extract parameters for detection of land degradation

The imagery has seven spectral bands including three visible (0.45-0.69 μm, TM bands 1, 2, and 3), one near infrared (0.76-0.90 μm, TM band 4), one short wave infrared (1.55-1.75 μm, TM band 5), one thermal infrared (10.40-12.50 μm, TM band 6), and one mid-wave infrared (2.08-2.35 μm, TM band 7) band with a spatial resolution of 30 meters, and a revisit time of 16 days (Ray 1994).

3.3.1. Image processing

Both images were obtained as L1G data, which are geo-referenced and radiometrically corrected. The information that was extracted from these images was a vegetation index (NDVI) and band two band ratios all of which are sensitive to vegetation and were supposed to be helpful in detecting land degradation process.

The vegetation indices and band ratios are commonly used to normalize external effects for consistent temporal comparisons (e.g., sun angle and viewing angle), normalize internal effects (e.g., canopy background, topography, and soil), and be associated with some measurable biophysical parameter (e.g., biomass) maximize sensitivity to plant biophysical parameters (Jensen 2000). The vegetation indices and band ratios that were calculated for both satellite images include:

Normalized vegetation index: Vegetation indices particularly normalized difference vegetation index (NDVI) derived from satellite images have extensively been utilized to monitor vegetation and land use changes. NDVI is a non-linear transformation of the visible (red 0.58–0.68 μm) and near-infrared (NIR 0.75–1.1 μm) bands of satellite images (Rouse *et al.*, 1973; Tucker *et al.*, 1991) and can be considered a measure of vegetation in terms of biomass, leaf area index (LAI), and vegetation cover percentage. The values of NDVI range from -1 to +1 (0–255 in case of 8 bit data) and was calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \text{ .... (Equation 3.1)}$$

Where: NDVI = Normalized difference vegetation index
NIR = Near infrared band (TM 4)
RED = Visible red band (TM 3)

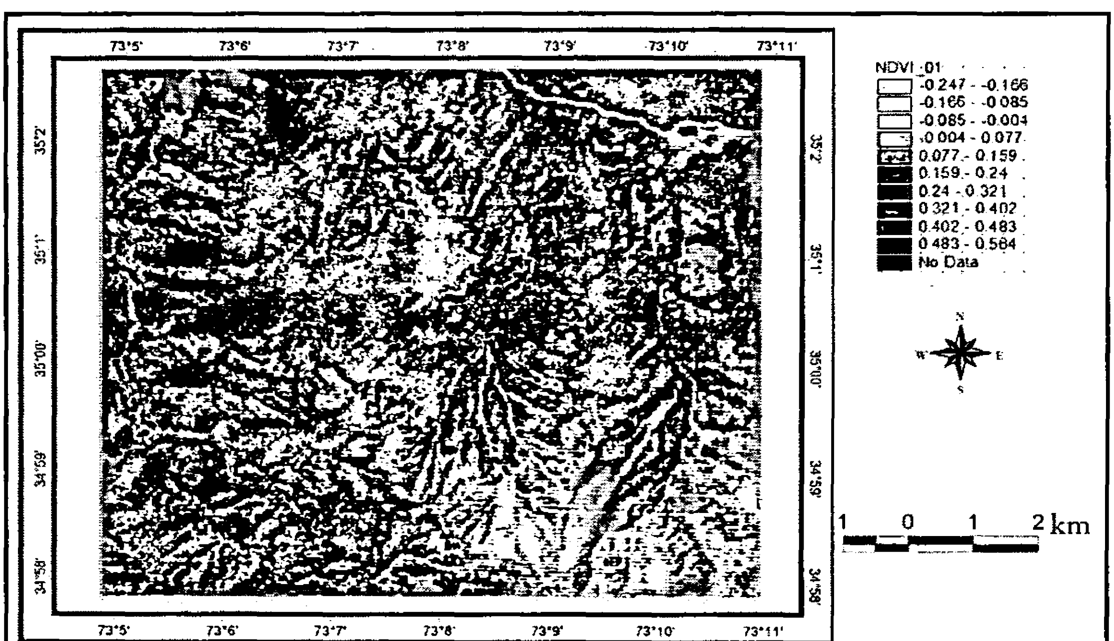


Figure 3.5: Showing the NDVI (2001) of the study area.

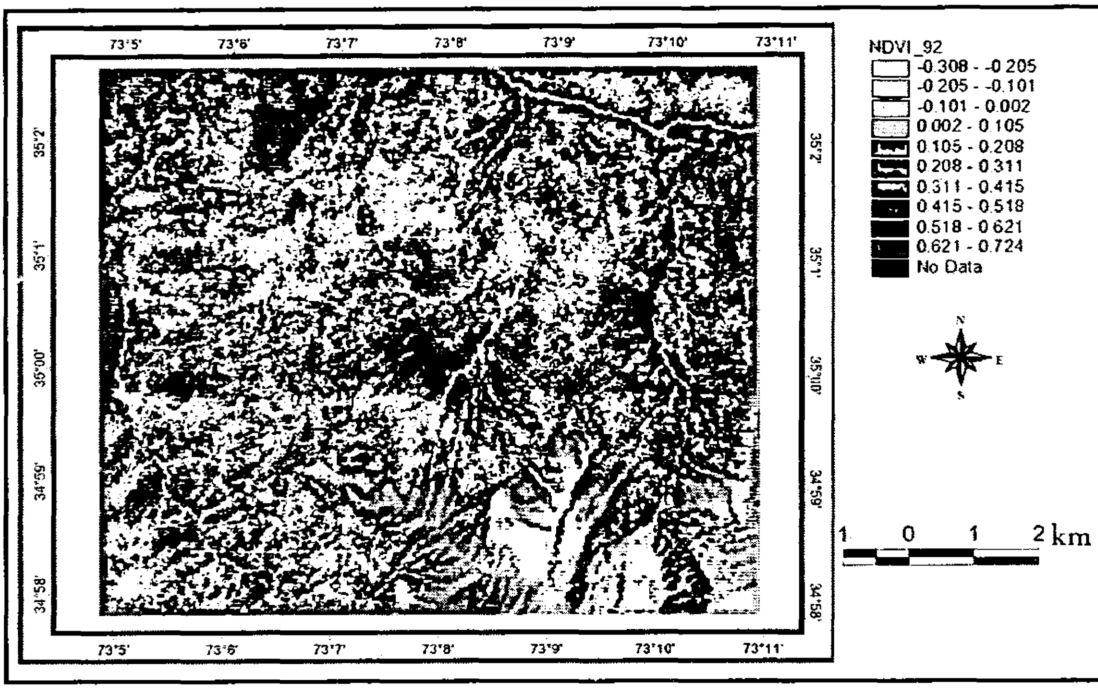


Figure 3.6: Showing the VDVI (1992) of the study area

TM Short-wave Infrared to Near Infrared ratio (Swir): Short-wave infrared (Landsat TM band 5, 1.65µm) to near infrared ratio (Swir) is well researched band ratio to detect forest vegetation (Vogelmann and Rock 1988, 1989). The SWIR ratio is influenced by the Short-wave Infrared region (MidIR; TM band 5 and Near Infrared TM band 4) where moisture content influences reflectance: ((Vogelmann 1990). Moisture differences in vegetation are known to alter the relative amplitude of spectral reflectance in the SWIR band (TM band 5, 1.65µm) and the mid-infrared band (TM band 7, 2.20 µm), providing an accurate indication of leaf water content. As a leaf becomes dryer, reflectance increases in these spectral regions. In contrast, reflectance in the NIR band (TM band 4, 0.83 µm) is relatively unaffected by changes in moisture content. Thus, the dryer a leaf becomes, the higher the SWIR/NIR ratio will become (Vogelmann and Rock 1988).

It was calculated as:

$$Swir = \frac{SW.IR}{NIR} \text{ .... (Equation 3.2)}$$

Where: Swir = Short-wave Infrared to Near Infrared ratio
SW.IR = Short wave infrared band (TM 5)
NIR = Near infrared band (TM 4)

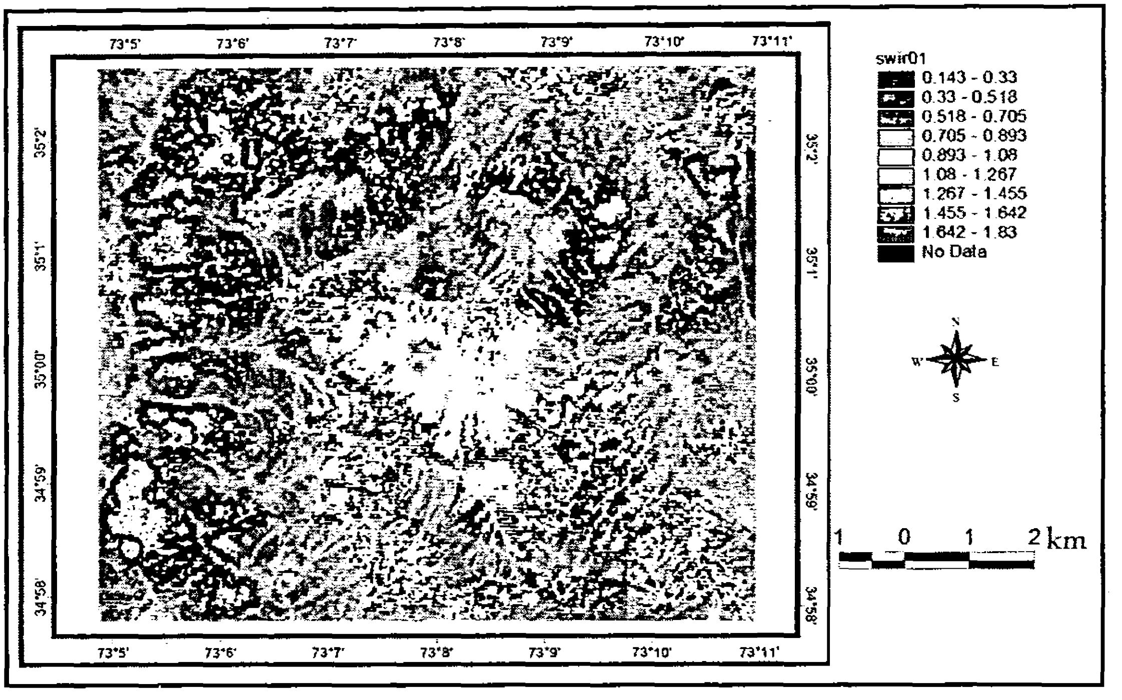


Figure 3.7: Showing TM Short-wave Infrared to Near Infrared ratio (Swir 2001) of the study area

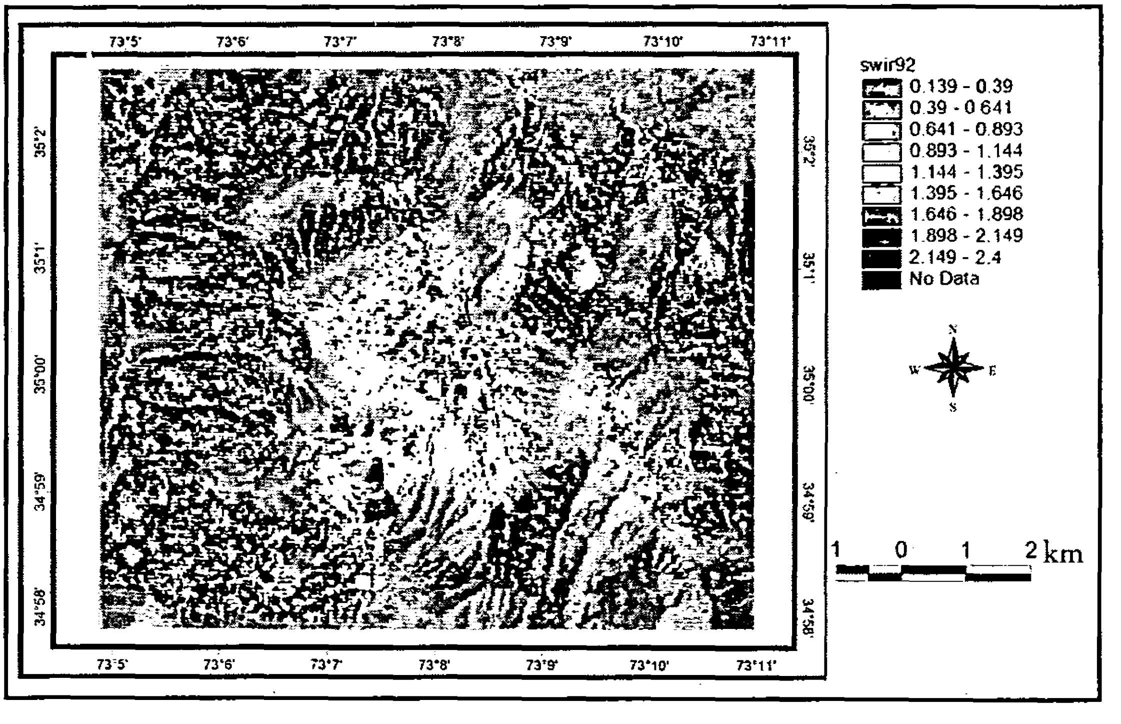


Figure 3.8: Showing TM Short-wave Infrared to Near Infrared ratio (Swir 1992) of the study area

TM Mid-Infrared to Near Infrared Band Ratio (B7B4)

It was calculated as:

$$B7B4 = \frac{M.IR}{NIR} \quad \text{(Equation 3.3)}$$

Where: B7B4 = Mid infrared to near infrared band ratio
M.IR = Mid infrared band (TM 7)
NIR = Near infrared band (TM 4)

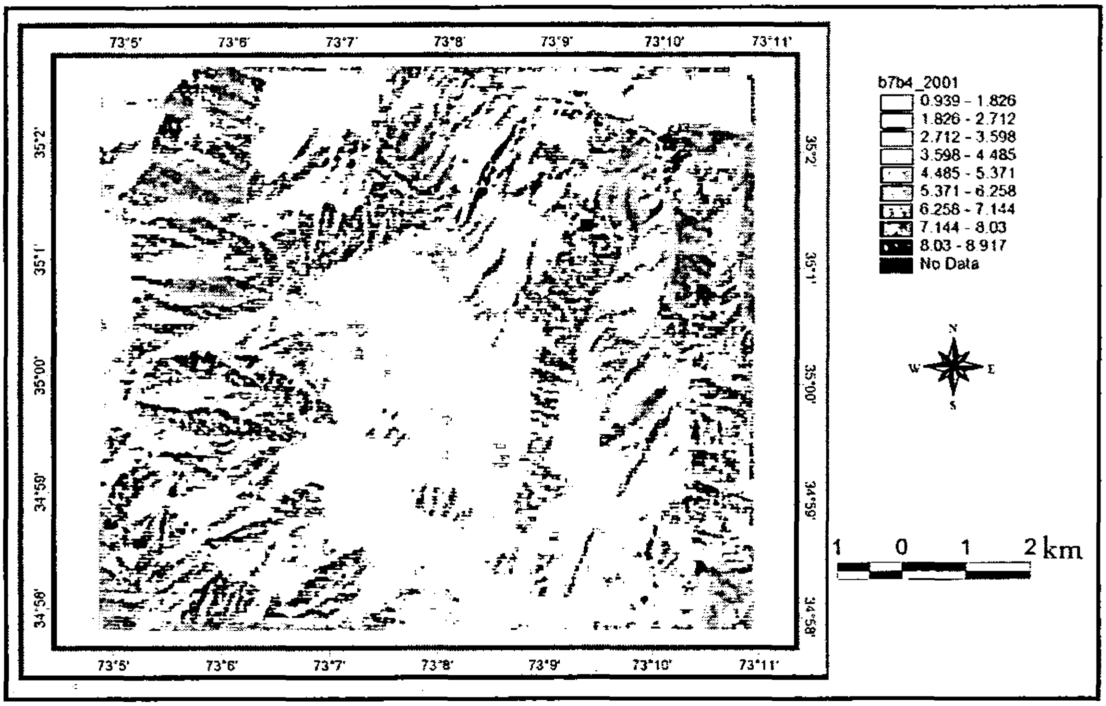


Figure 3.9: Showing TM mid-infrared to Near Infrared band ratio (B7B4) of 2001 data

3.4. GIS Data

Monitoring of landcover using SRS alone is not as powerful or accurate as when it is combined with ancillary GIS data (Green, et al, 1994). The combination of SRS data with GIS layers (such as topography, property ownership, and forest stand management information) may result in data analysis with powerful and more reliable information capabilities. The GIS data used during the present study was extracted from Digital Terrain Model (DTM) since it was assumed that topography was most important factor in explaining the land degradation process in the mountainous terrain of the study area.

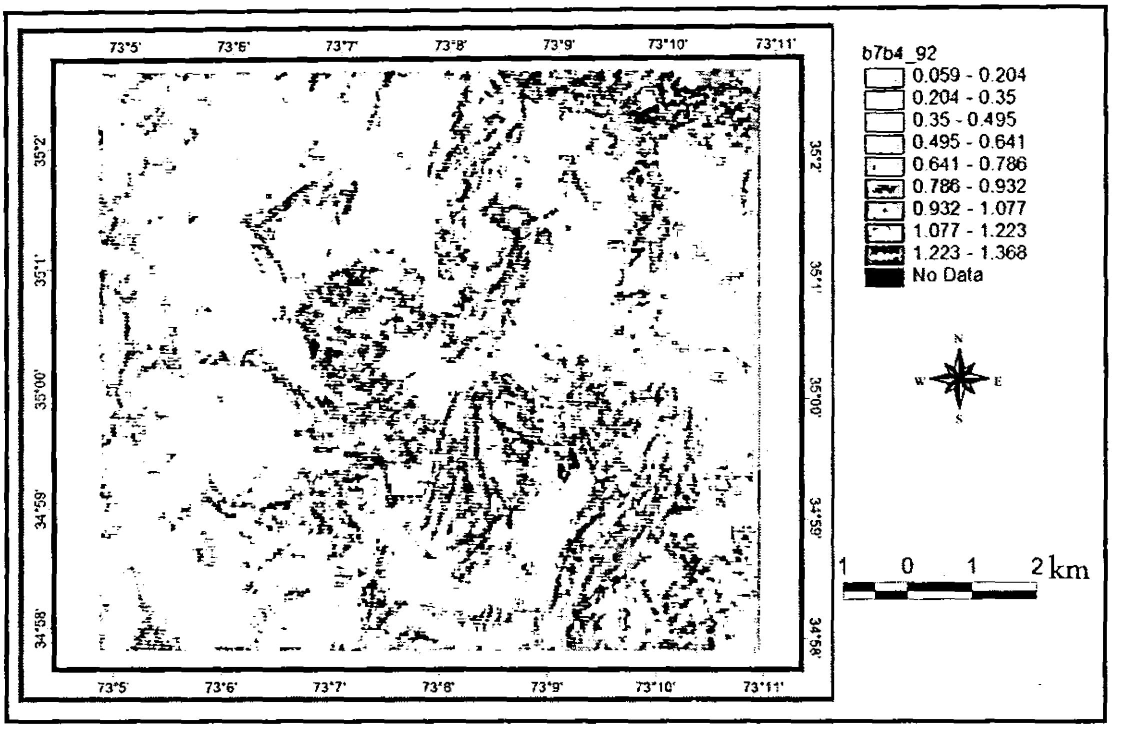


Figure 3.10: Showing TM mid-infrared to Near Infrared band ratio (B7B4) of 1992 data

3.4.1. Digital terrain model (DTM) and DTM derived data

Recently a high resolution DTM (30 m post-spacing) created through ASTER stereo model has been made available by ERSDAC (www.gdem.aster.ersdac.or.jp) and was chosen as parent GIS layer to extract various terrain related variables. The terrain related variables that were made available as GIS layers through DTM includes:

***3.4.1.1 Elevation*:** The elevation of a geographic location is its height above a fixed reference point, often the mean sea level. Since the vegetation types and subsequent landuse are known to alter along altitudinal gradient, the elevation is supposed to be one of the important variables in context of land degradation. The DTM itself represented the elevations at all locations of the study area and was available as raster layer (Figure 3.7). The rest of layers were generated through the modeling of DTM.

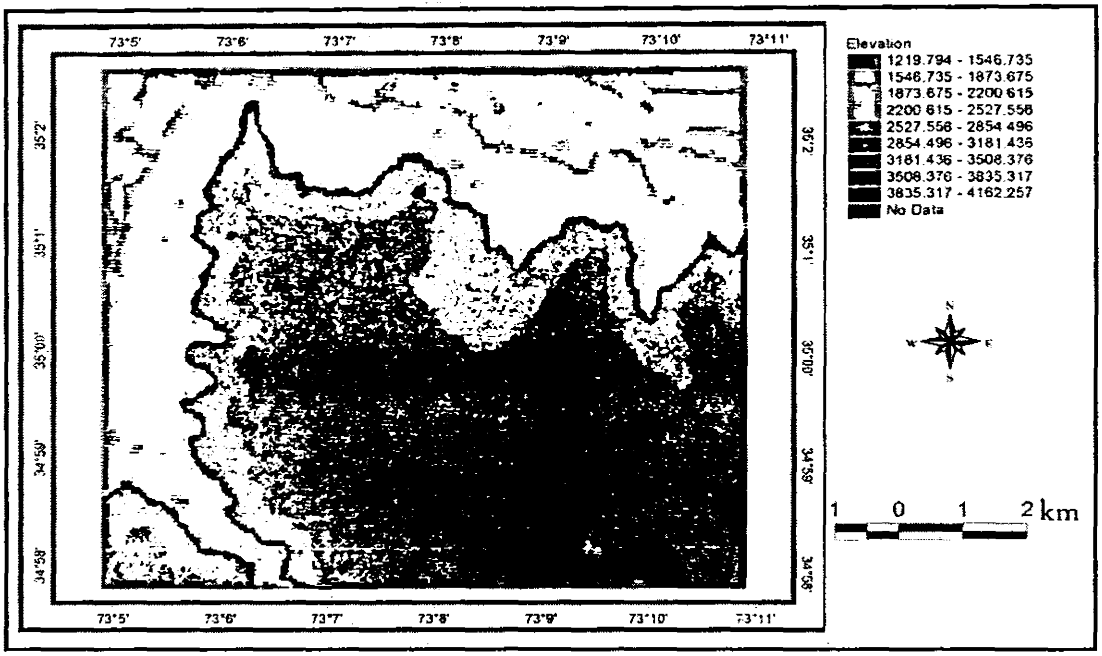


Figure 3.11: Digital elevation model of the study area showing its elevation range

3.4.1.2 Slope: It is defined as the steepest downhill descent for the cell i.e., the maximum rate of change between a cell and its eight neighbors (Figure 3.8) for example; the slope in degrees for two raster cells 5 and 6 (Figure 3.8) can be calculated using equation 3.4. Lower the value of slope, flatter is the terrain and vice versa.

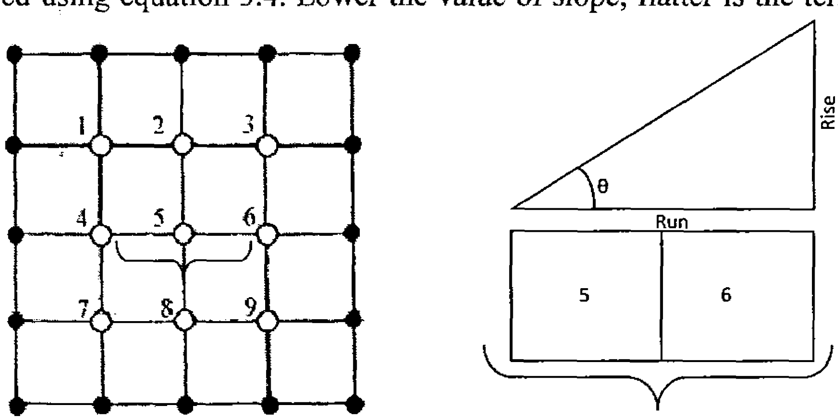


Figure 3.12: The representation of slope between two adjacent cells in a raster elevation grid

$$\tan\theta = \frac{\text{Rise}}{\text{Run}} \quad \text{(Equation 3.4)}$$

The steeper slopes may be more vulnerable to gully erosion and land sliding since the water flows faster and has more potential energy to cause severe erosion.

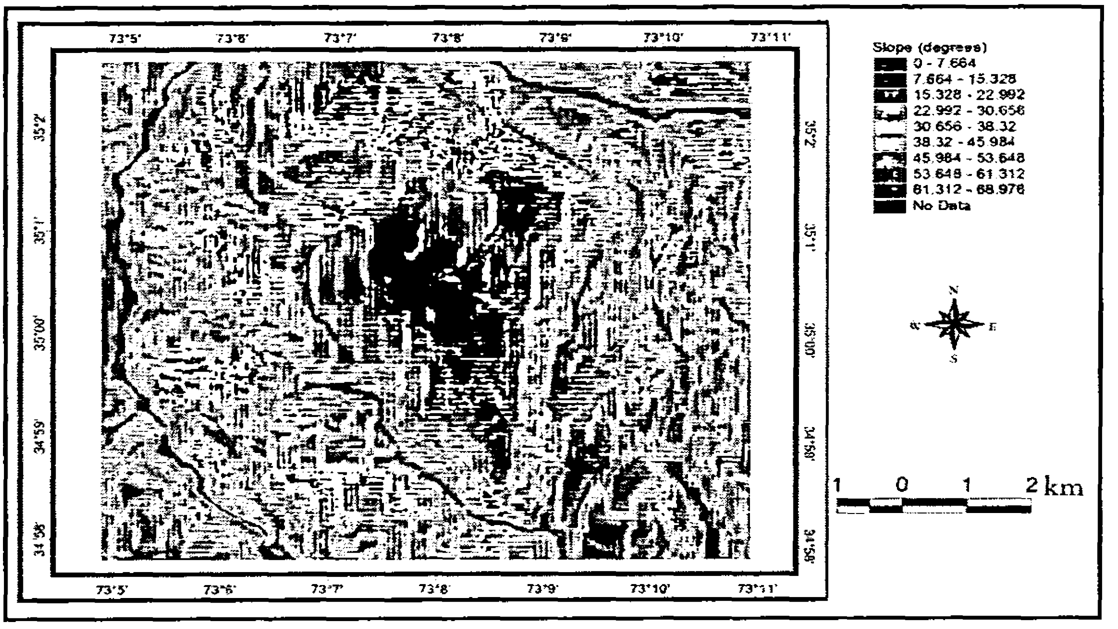


Figure 3.13: Map showing the variation of slope in the study area

3.4.1.3 Aspect: Aspect (Figure 3.10) plays a significant role regarding solar insulation, evapo-transpiration, flora and fauna distribution and abundance and can affect land use pattern.

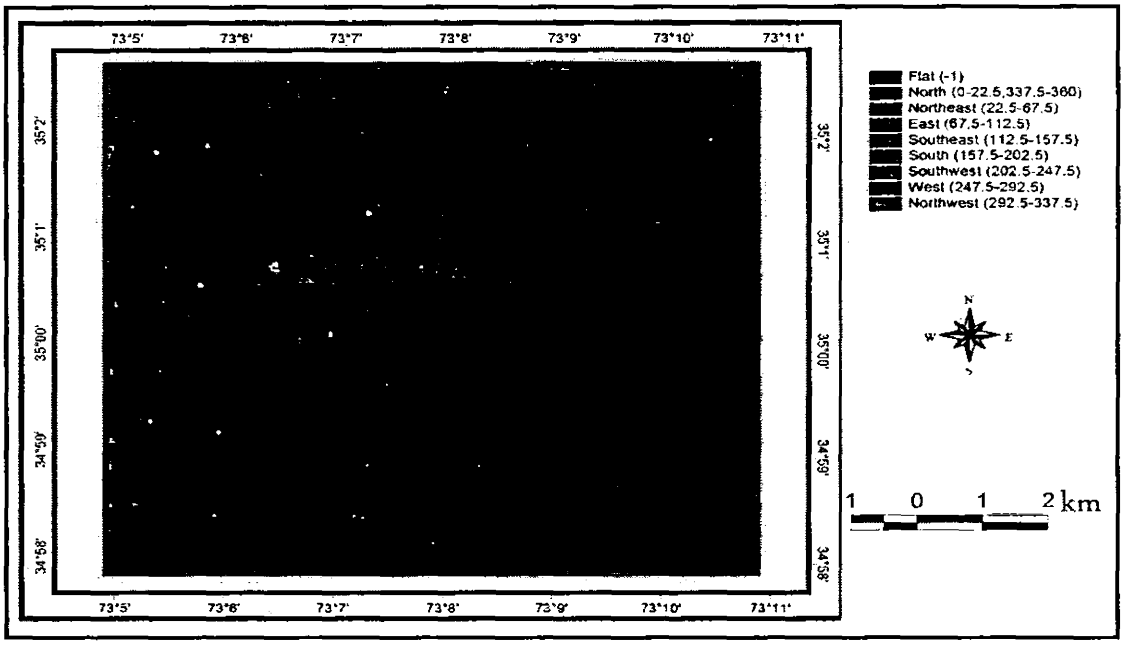


Figure 3.14: Aspect of the slope in Study Area

3.4.1.4 Stream Power Index (Spi): Stream power index (Figure 3.11) is a parameter used to describe the erosion/energy potential of Hortonian overland flow. It is calculated as the product of overland flow discharge and slope; this is referred to in the literature as mean stream power per unit length of flow (P). Simply the Stream Power Index means to calculate the power of water exerted on land to make it susceptible for erosion.

$$Spi = As \tan\beta \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Equation 3.5)}$$

where: Spi = Stream power index
As = specific catchment area
β= Slope gradient

3.4.1.5 Topographic Wetness Index **(Twi):** This variable describes the spatial distribution and extent of zones of saturation (i.e. source area) for runoff generation as function of upslope contribution area, soil transmissivity and slop gradient (Figure 3.12).

$$Twi = \ln\left(\frac{As}{\tan\beta}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Equation 3.6)}$$

where: Twi = Topographic wetness index
As = specific catchment area
β= Slope gradient
ln = natural log

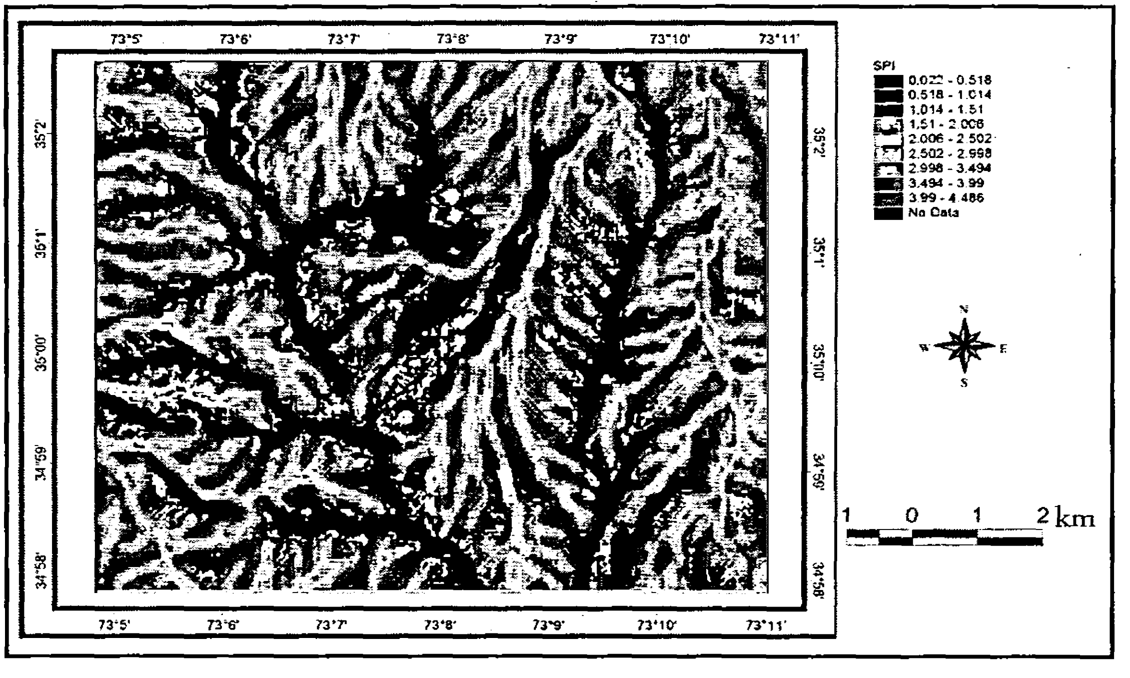


Figure 3.15: Stream Power Index for the study area

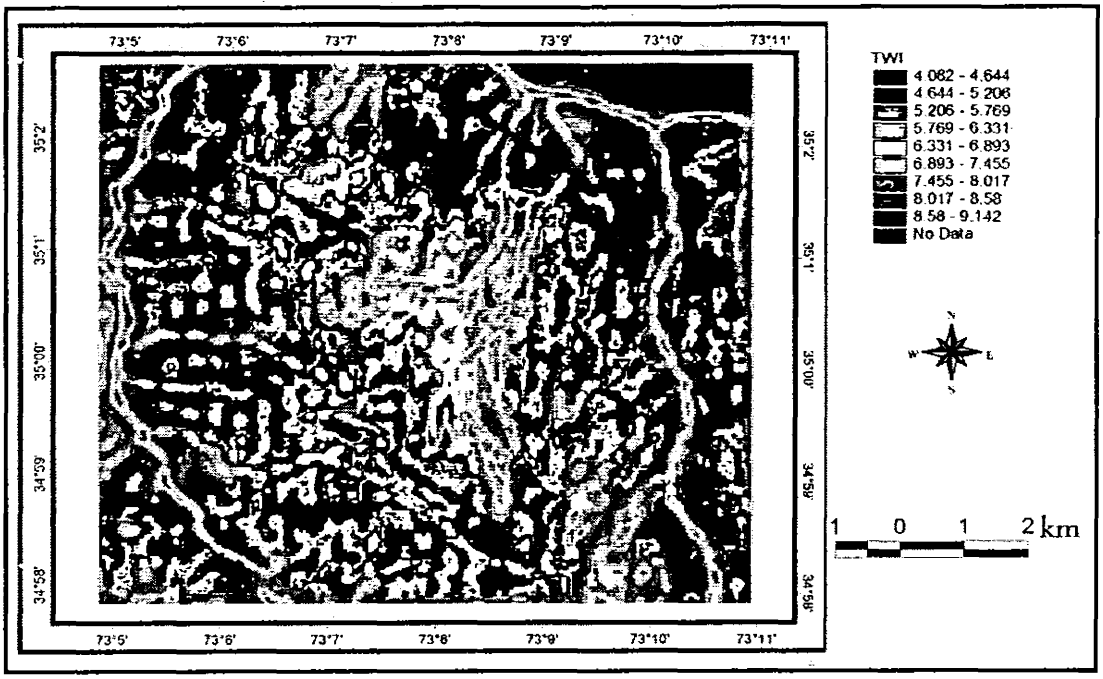


Figure 3.16: Topographic Wetness Index for the study area

3.4.1.6 Slope length Factor (Slf): It is also an important variable in land degradation as it plays a role in erosion rate, sediment yield and time concentration. The slope-length factor (Figure 3.13), accounts for increases in runoff volume as downslope runoff lengths increase.

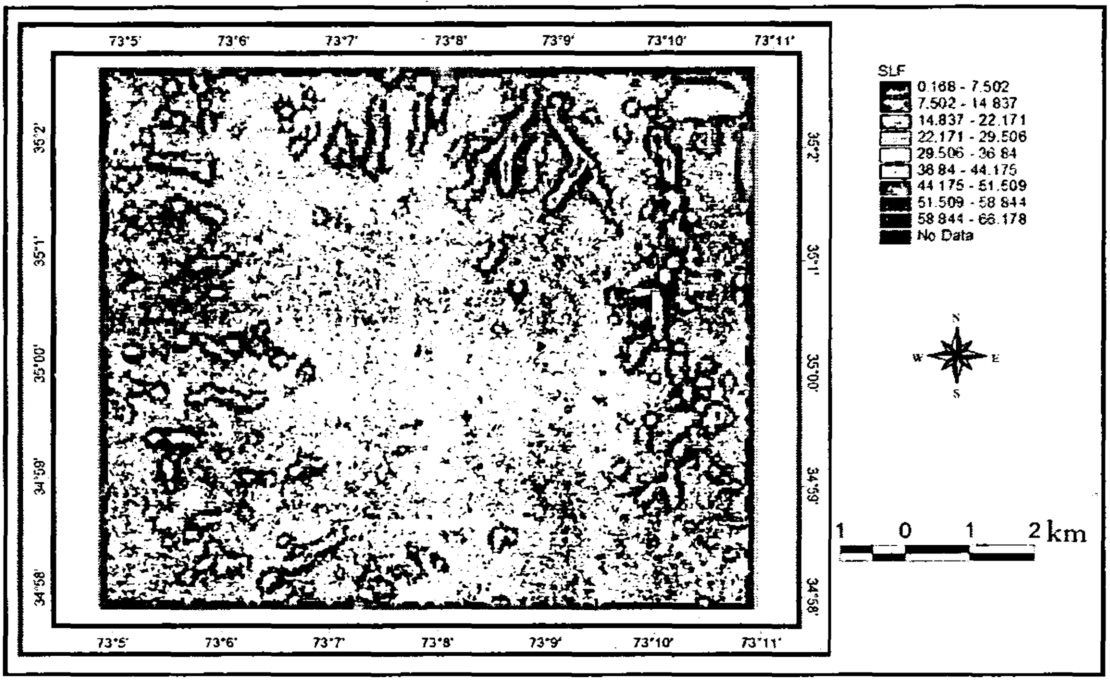


Figure 3.17: Slop length factor for the study area

3.4.1.7 Curvature (Curv): Curvature means the slope of the slope (i.e., the second derivative of the surface). It shows whether a given part of a surface is convex or concave (Figure 3.14). Convex parts like ridges, are generally exposed and drain to other areas, however, concave parts, like channels, are generally more sheltered and accept drainage from other areas.

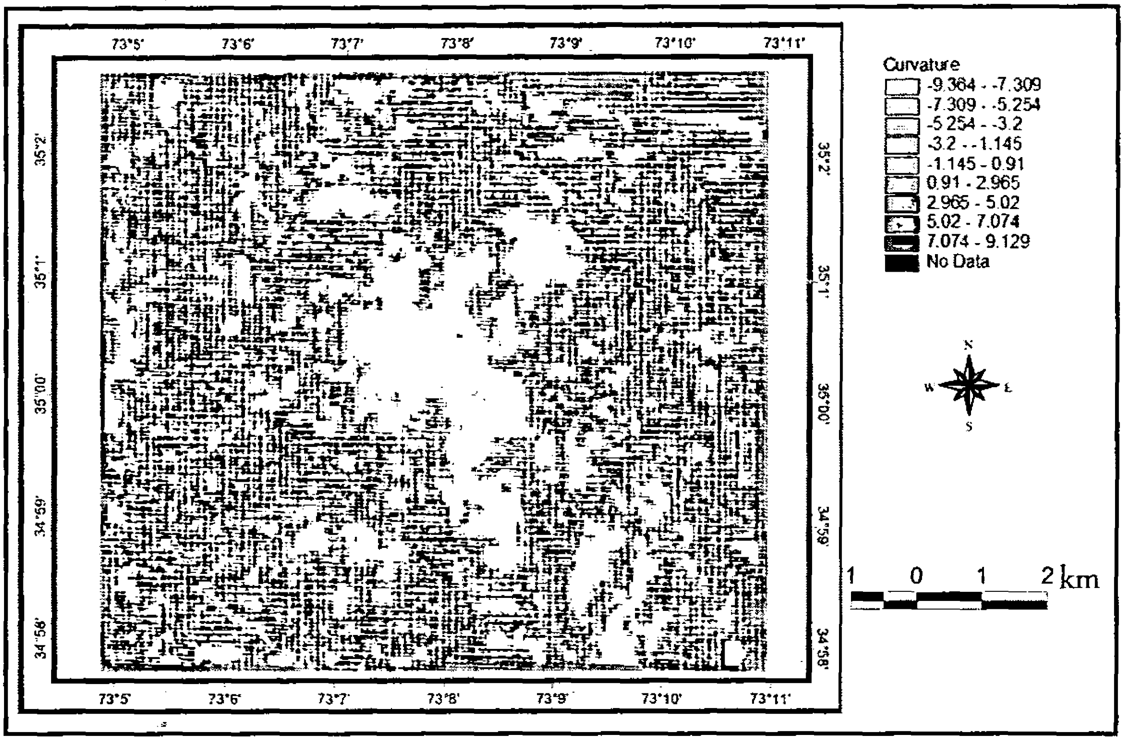


Figure 3.18: The Terrain Curvature map of the study area

3.4.1.8 Plan Curvature (Plan): It is defined as slope profile curvature and simply means contour curvature. Plan curvature has play an important role in land degradation as it affects converging and diverging of water flow, soil-water content and soil characteristics (Figure 3.15).

3.4.1.9 Profile Curvature (Prof): Profile curvature means Slop profile curvature, and it mainly affects the water flow acceleration, catchment area distribution, erosion, deposition point and geomorphology (Figure 3.16).

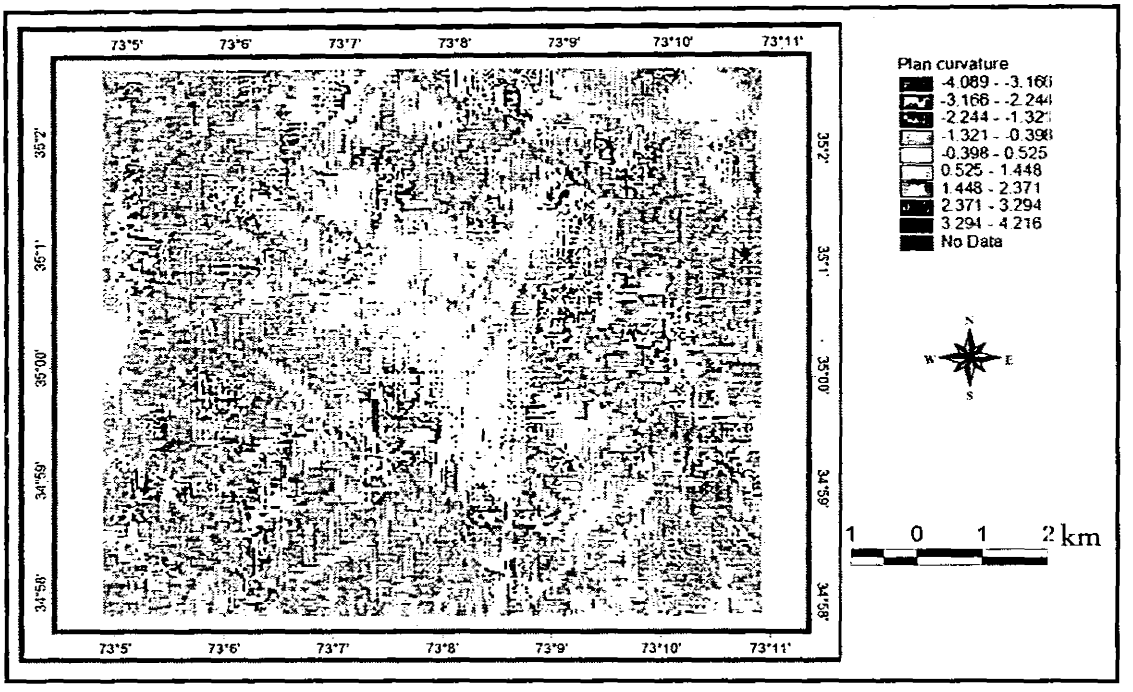


Figure 3.19: The Plan curvature for the study area

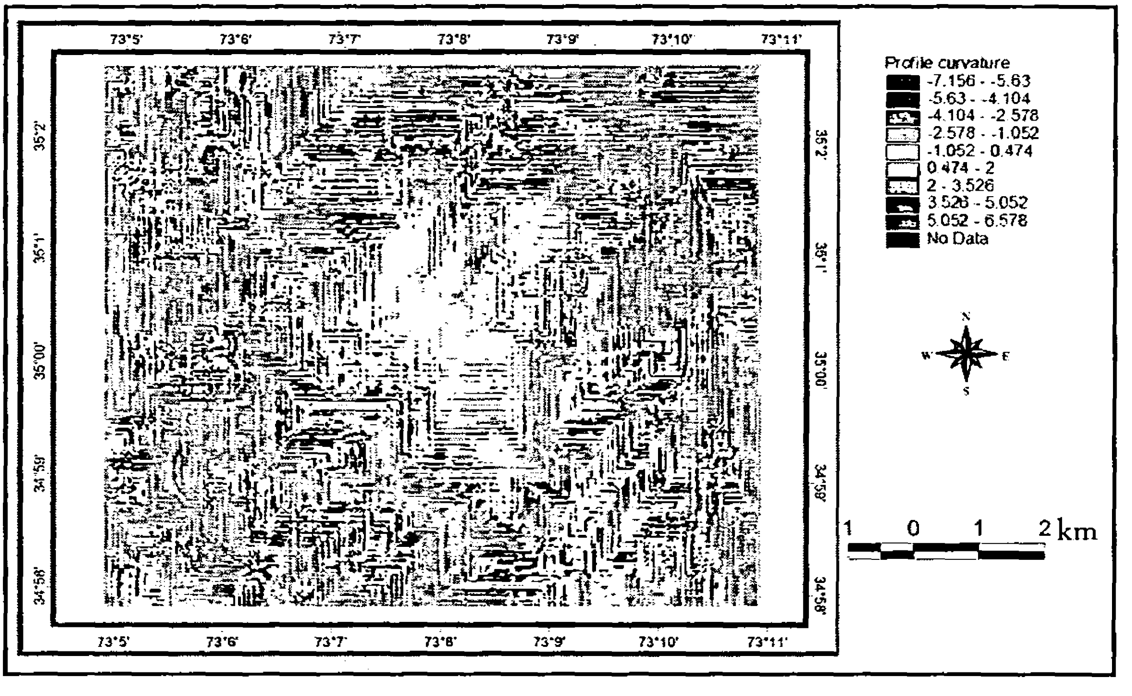


Figure 3.20: The Profile curvature of the study area

3.4.1.10: Topographic position index (Tpi): It is the difference between a cell elevation value and the average elevation of the neighborhood around that cell. Positive *Tpi* values mean the cell is higher than its surroundings and vice versa. The Tpi was calculated based upon eight neighboring grid cells (Figure 3.17).

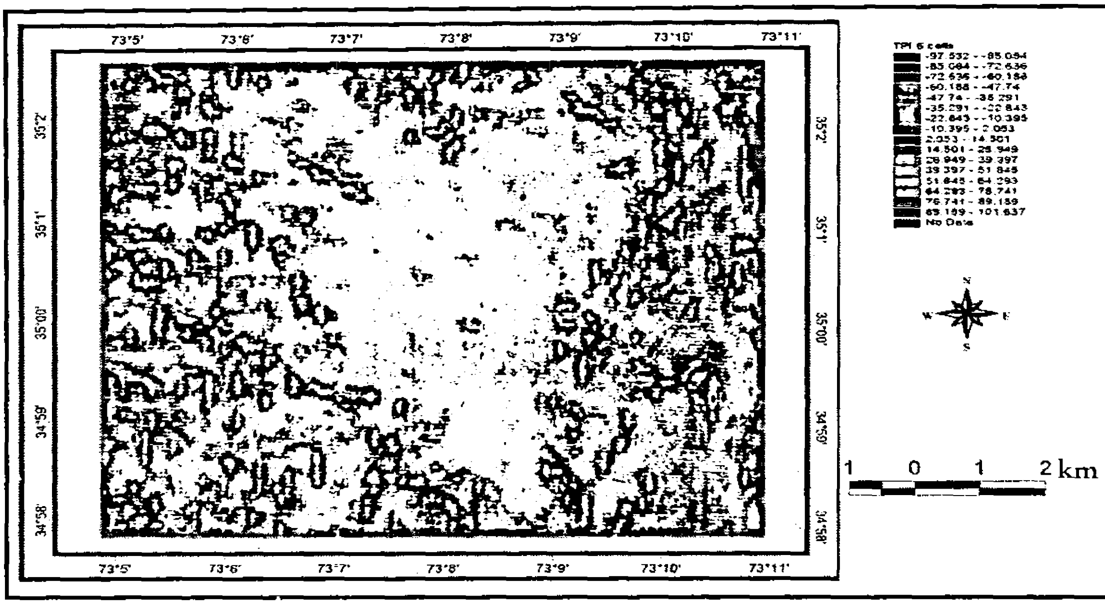


Figure3.21: Representation of the Topographic Position Index for study area

3.5 SOFTWARE

The major objective of this particular study was to carry out a "hard" classification to model land degradation in the study area occurred in pass decade. In order to achieve this, a method for statistical generalization based on land degradation samples was worked out rather than the approaches relying purely on the physical aspects of reflectance.

3.6 Conceptual Model

The conceptual background of the model was that the spectral data from satellite imaginary in combination with eco-geographical variables (EGVs) can detect the land degradation more accurately in the study area. The use of different spectral ratios is known to reduce "bad" effect of shadow on the classification (especially mountainous area), and enhance its validity. Conglomeration of eco-geographical (EGVs) such as terrain related features with spectral ratios were supposed to provide an improved, ecologically meaningful classification of the satellite data.

3.6.1 Model Selection

The point sample location and their associated variable data were exported to S-Plus ver. 8 (insightful Corp.2007) and a land degradation generalized additive model was fitted for each year (1992 and 2001) separately using GRASP (Generalized Regression Analysis and Spatial Prediction) package. The initial generalized models fitted for land degradation were:

$$\mathbf{Dn \approx NDVI._{yr} + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) \div s(Ndvi_{yr}, 4) + s(B7b4._{yr}, 4) + s(Swir._{yr}, 4)}$$

Where: D= land degradation, n = type of degradation (1-5), yr = years (92= 1992, 01= 2001), s = spline smoother, 4 = degree of freedom for spline smoother, plan = plan form curvature, profile = profile curvature, Curv = Curvature, Aspect = Slop aspect, Slf = Slop length factor, Spi = Stream power index, Twi = Topographic wetness index, Elevation = Elevation, Tpi = Topographic position index, Slop = Slop, Ndvi = Normalized, B7b4 = Band 7 and band 4, Swir = are the shortwave infrared to near- infrared band ratios of the landsat TM imagnery of the year 1992 and 2001 respectively.

A stepwise procedure was adopted for selection of a final land degradation model after backward eleminitatin of fited variables from a full model on the basis of X^2 change in deviance tested at 5% level. After first elimination all predictors were also tested for re-inclusion in the model on each iteration. The effect of dropping smooth terms was tested using an analysis of varience (ANOVA; CHI- sq- test) for the models. At each step, the less significant change was kept that served as starting point for the next step.

3.6.2 Model Validation

The adequacy of the fitted models was determined by a pseudo-coefficient D^2. The models for each year were evaluated using simple validation as well as cross-validation procedure.

Map algebra was used to calculate land degradation in thematic maps produced by statistical modeling. Post- classification pixel by pixel comparison of thematic maps was done to perceived change in land degradation during a decade.

3.6.3 Production of land degradation maps

Once the model for particular degradation type of respective year was formulated, it was exported as a "lookup table" that can be read in ArcView GIS software. The variables that were used in the modeling process were loaded in the view of ArcView GIS project with exactly the same names/codes used in the statistical model in S-Plus software. The lookup table was then loaded through an Avenue script program "GRASPIT" which interpreted the table to produce the desired map.

3.6.4 Area calculations

The map areas were calculated for each year and respective degradation type using map algebra in GIS software. The areas were then compared together to get the degradation picture in a decade.

CHAPTER 4

Results

4.1 Land degradation 1 (D1): year 1992

Predictor's Space:

The predictor's space occupied by the Land degradation 1 (D1) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.1 and 4.12.

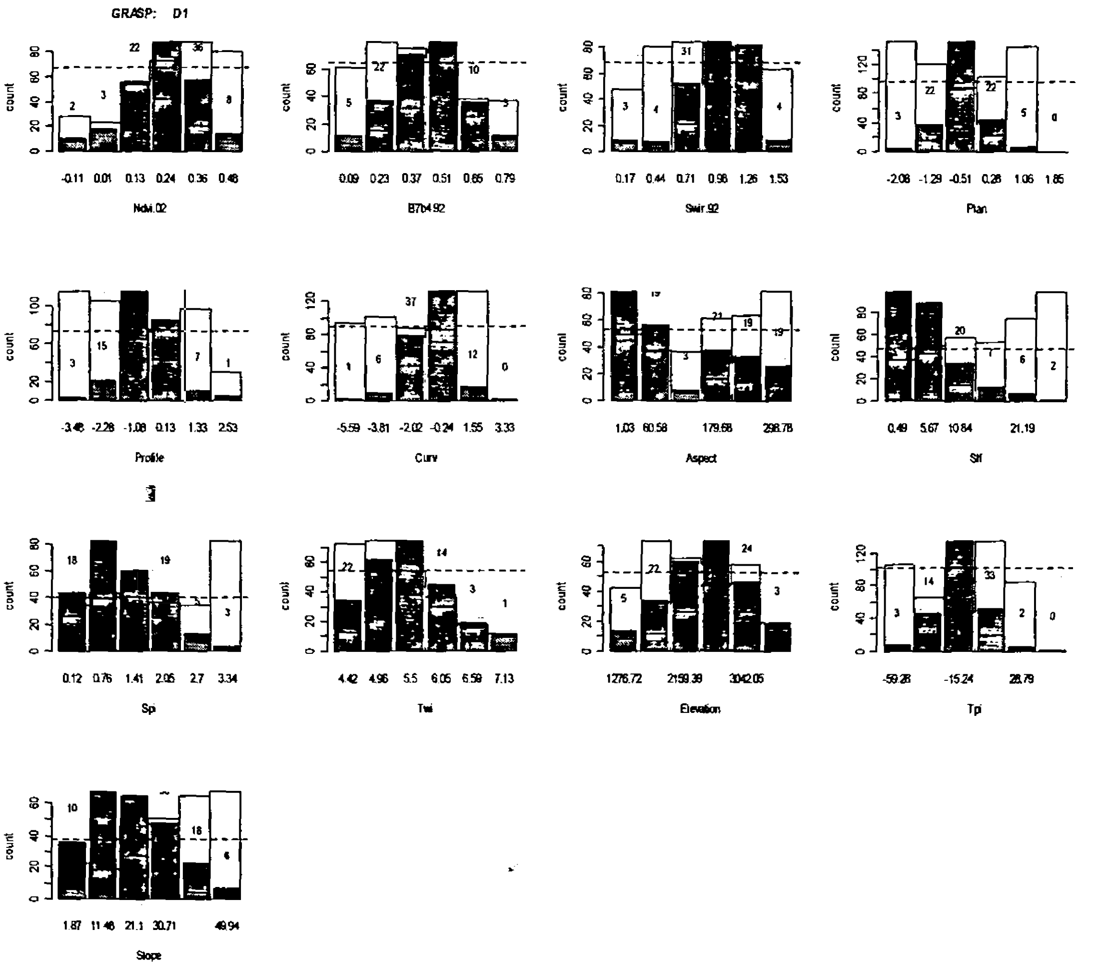


Figure 4.1: Histograms of Land degradation 1 (D1) against predictor variables

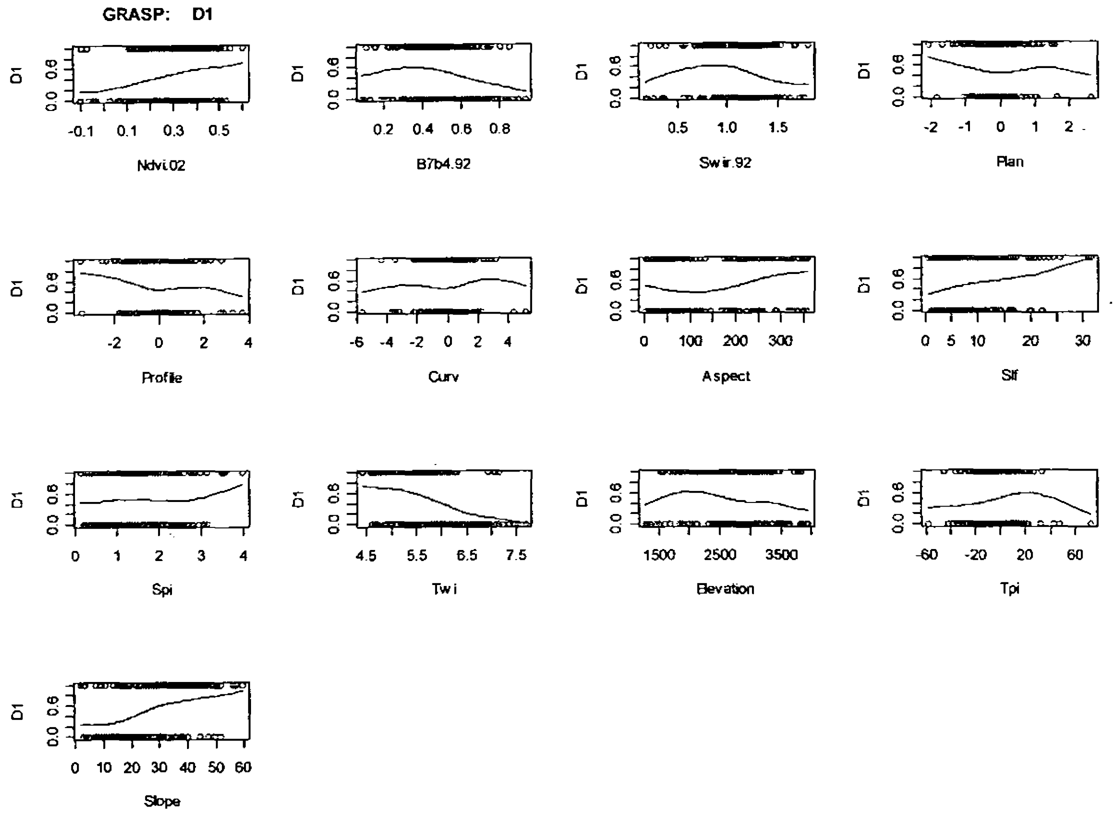


Figure 4.2: Scattergrams of Land degradation 1 (D1) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D1 was observed in 117 points (prevalence = 48%). Null Deviance of the final model resulted after stepwise selection of variables was 336.54 and the explained deviance for the model was 134.6844. The pseudo quotient D^2 for the model was 0.40 and correlation value for the model was 0.67. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:
YYY$D1 ~ s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) + s(Ndvi.02, 4) + s(B7b4.92, 4) + s(Swir.92, 4)

Final Model:
YYY$D1 ~ s(Aspect, 4) + s(Slf, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Ndvi.02, 4)

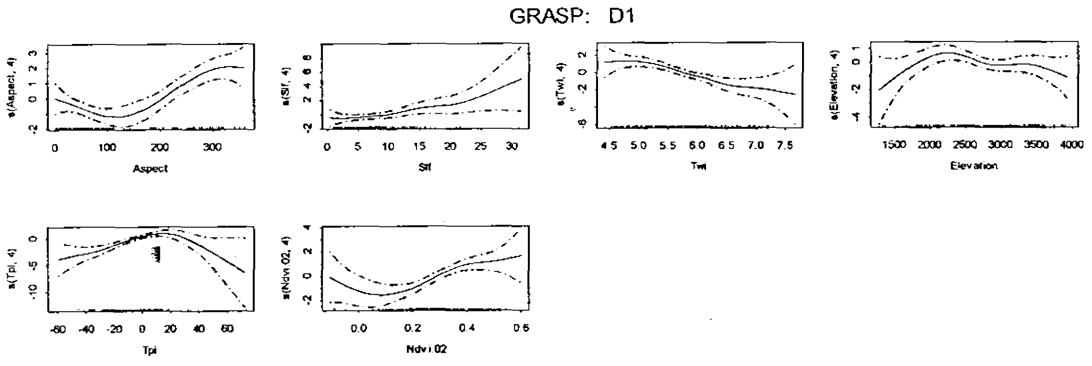


Figure 4.3: Response of Land degradation 1 (D1) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are drcpped from the model has been presented as Table 4.1.

Table 4.1: Analysis of deviance for dropping of terms in D1 model for year 1992

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				190.73	180.08	0.05
2	s(Spi, 4)	3.94	1.17	194.67	181.25	0.87
3	s(Swir.92, 4)	3.97	1.47	198.64	182.73	0.82
4	s(Curv, 4)	3.90	1.54	202.55	184.279	0.80
5	s(Profile, 4)	3.85	2.54	206.41	186.81	0.61
6	s(Slope, 4)	3.95	3.39	210.35	190.21	0.48
7	s(Plan, 4)	3.99	4.71	214.35	194.92	0.32
8	s(B7b4.92, 4)	3.95	6.93	218.30	201.85	0.13

Analysis of variance (ANOVA) for the selected terms in the model are shown as Table 4.2

Table 4.2: ANOVA for the selected terms in model for degradation D1 for year 1992

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Aspect, 4)	-3.91	-34.39	5.53
[2,]	-s(Slf, 4)	-4.16	-14.57	0.01
[3,]	-s(Twi, 4)	-4.30	-23.89	0.000116
[4,]	-s(Elevation, 4)	-3.93	-9.63	0.044966
[5,]	-s(Tpi, 4)	-3.89	-32.18	1.55E-06
[6,]	-s(Ndvi.02, 4)	-4.01	-25.16	4.74E-05

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.3.

Table 4.3: ANOVA for the selected terms in model for degradation D1 for year 1992

	Drop	Alone	Model
s(Aspect, 4)	34.39657	18.77014	3.266358
s(Slf, 4)	14.5735	11.93197	5.46E+00
s(Twi, 4)	23.89029	42.32275	3.842958
s(Elevation, 4)	9.632395	20.56558	2.722026
s(Tpi, 4)	32.1858	9.832647	7.488353
s(Ndvi.02, 4)	25.16268	17.42403	3.20E+00

Model validation:

The validation parameters for the degradation D1 for year 1992 are as follows (Figure 4.4):

cv ROC auc: 0.82
cv COR: 0.549
ROC auc: 0.891
COR: 0.676

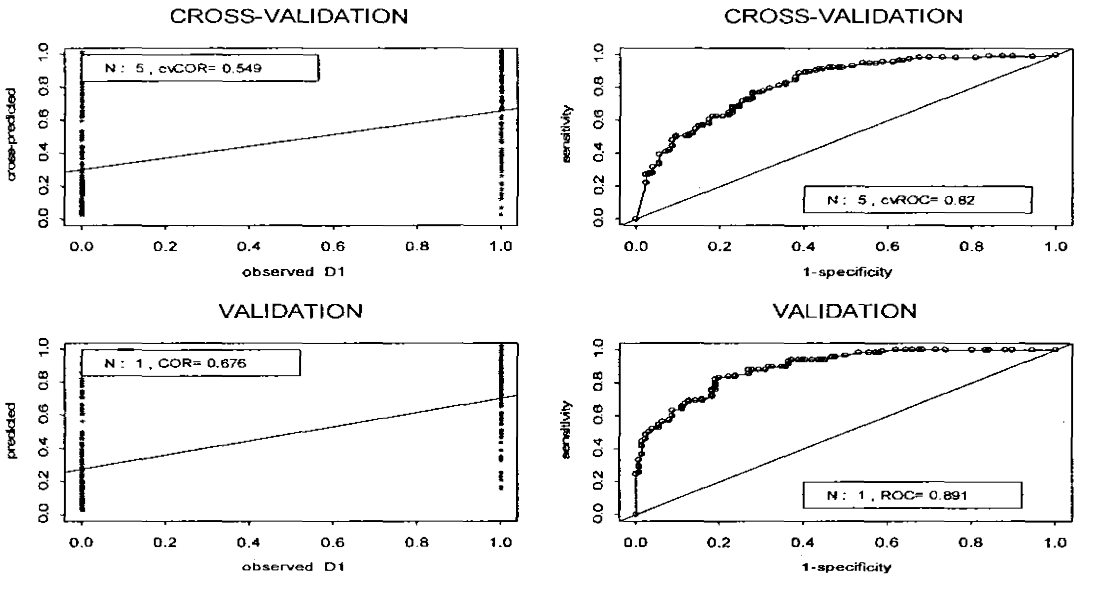


Figure 4.4: Cross-validation of predictive model of land degradation D1 for year 1992

4.2 Land degradation 2 (D2): year 1992

Predictor's Space:

The predictor's space occupied by the land degradation type 2 (D2) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

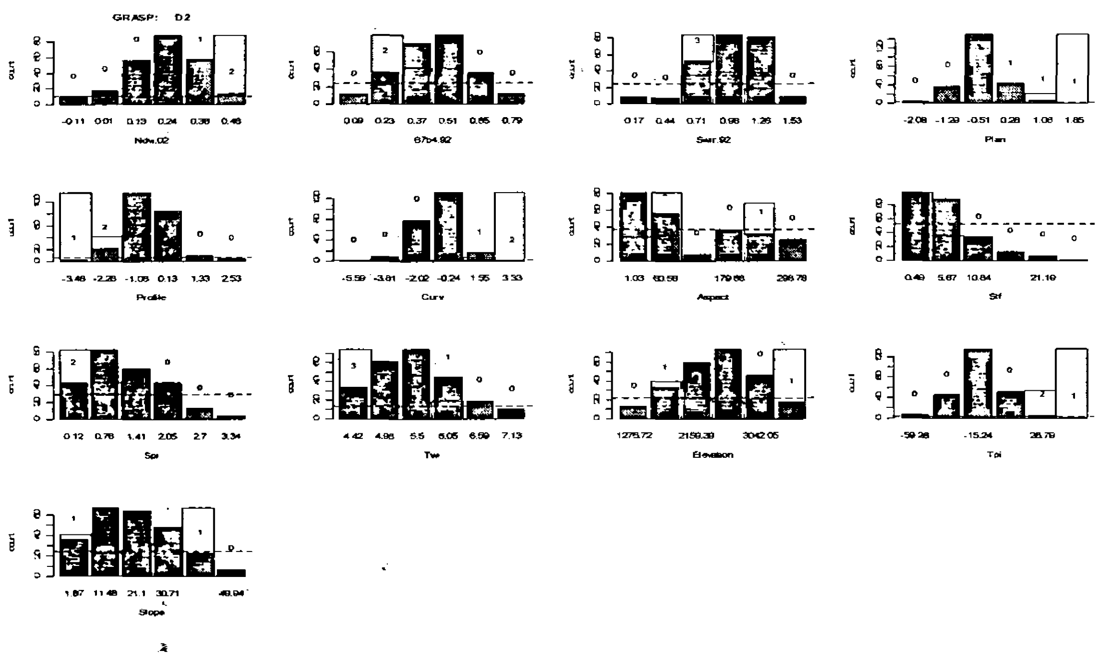


Figure 4.5: Histograms of 1992 *Land degradation (D2)* against predictor variables

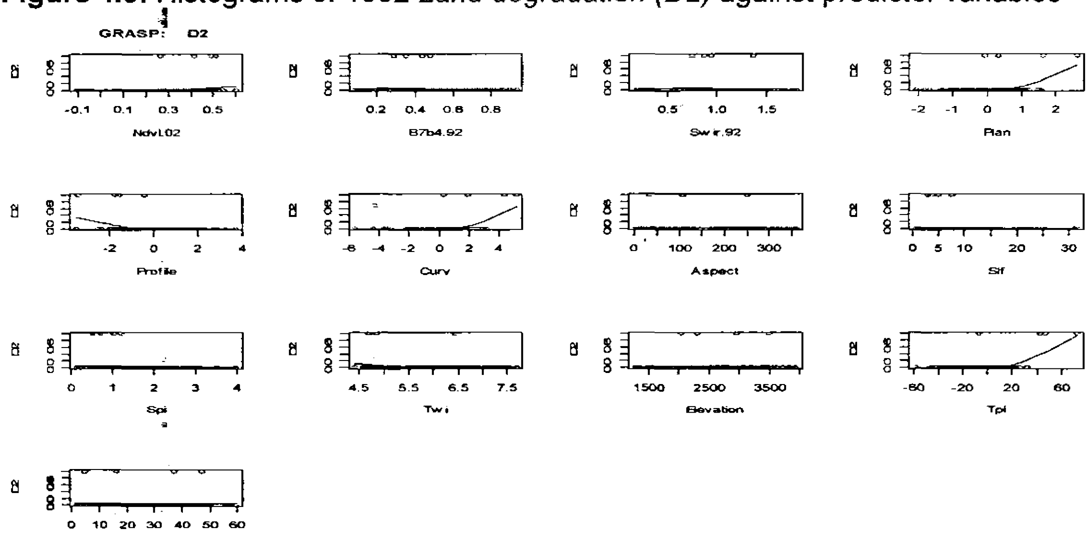


Figure 4.6: Scattergrams of 1992 *Land degradation (D2)* response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D2 was observed in only 4 points (prevalence = 1.6%).Null Deviance of the final model resulted after stepwise selection of variables was 40.78 and the explained deviance for the model was 33.35. The pseudo quotient D^2 for the model was 0.87 and correlation value for the model was 0.67. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D2 ~ s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) + s(Ndvi.02, 4) + s(B7b4.92, 4) + s(Swir.92, 4)

Final Model:

YYY$D2 ~ s(Tpi, 4)

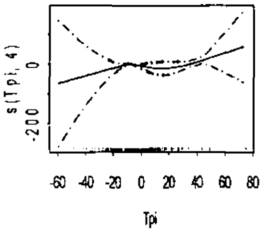


Figure 4.7: Response of 1992 *Land degradation (D2)* against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.4.

Table 4.4: Analysis of deviance for dropping of terms in 1992 D2 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				199.7002	0	0.05
2	s(Plan, 4)	3.341847	0	203.0421	0	1
3	s(Profile, 4)	3.261486	0	206.3036	0	1
4	s(Curv, 4)	3.645067	0	209.9486	0	1
5	s(Aspect, 4)	3.158218	0	213.1069	0	1
6	s(Ndvi.02, 4)	2.944772	0	216.0516	0	1
7	s(Slope, 4)	2.538604	0	218.5902	0	1
8	s(Slf, 4)	3.036513	0	221.6267	0	1
9	s(Twi, 4)	3.403643	0	225.0304	0	1
10	s(Elevation, 4)	3.100944	0	228.1313	0	1
11	s(Spi, 4)	2.965083	0.00001	231.0964	0.000011	1
12	s(Swir.92, 4)	3.702216	2.373122	234.7986	2.373132	0.621122
13	s(B7b4.92, 4)	3.476596	5.065004	238.2752	7.438136	0.218669

ANOVA for the selected terms in the model are shown as Table 4.6

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Tpi, 4)	-3.72477	-33.3498	7.18E-07

Table 4.5: ANOVA for the selected terms in 1992 D2 model

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.6.

Table 4.6: ANOVA for the drop contribution of selected terms in 1992 D2 model

	Drop	Alone	model
s(Tpi, 4)	33.34979	33.34979	123.5375

Model validation:

The validation parameters for the degradation D2 for year 1992 are as follows (Figure 4.8):

cv ROC auc: 0.866
cv COR: 0.851
ROC auc: 0.997
COR: 0.877

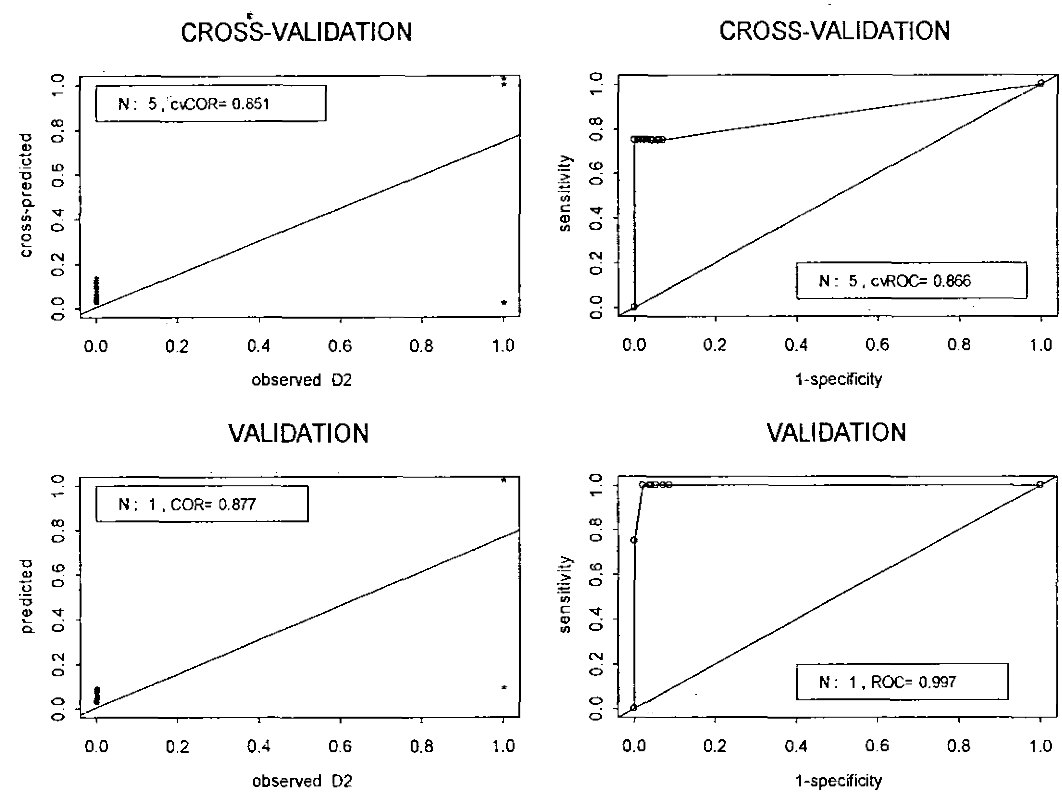


Figure 4.8: Cross-validation of predictive model of 1992 D2 model

4.3 Land degradation 3 (D3): year 1992

Predictor's Space:

The predictor's space occupied by the Land degradation 3 (D3) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

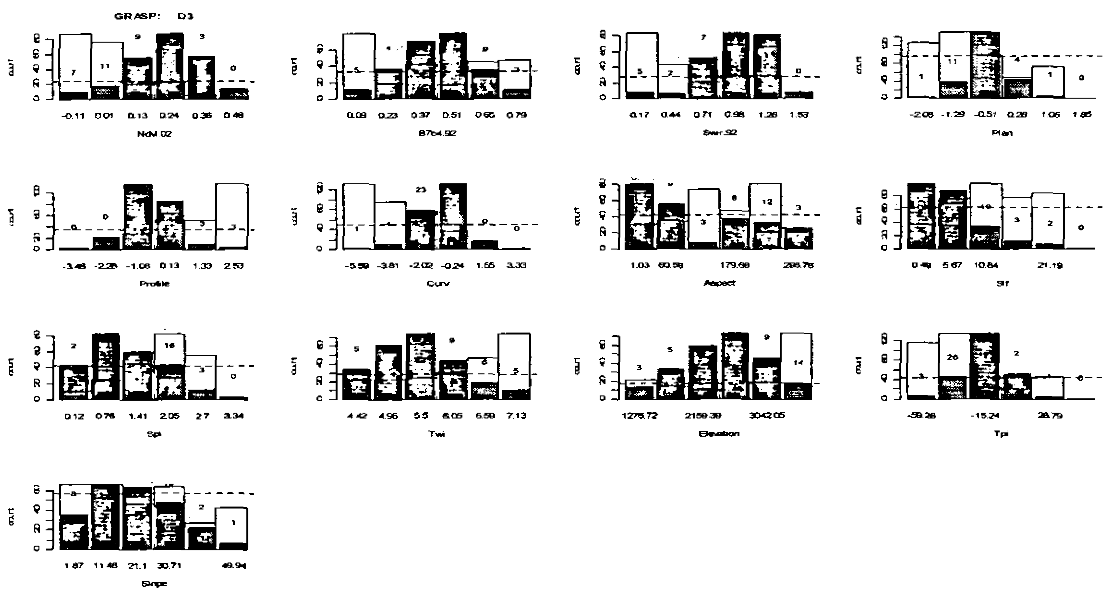


Figure 4.9: Histograms of 1992Land degradation (D3) against predictor variables

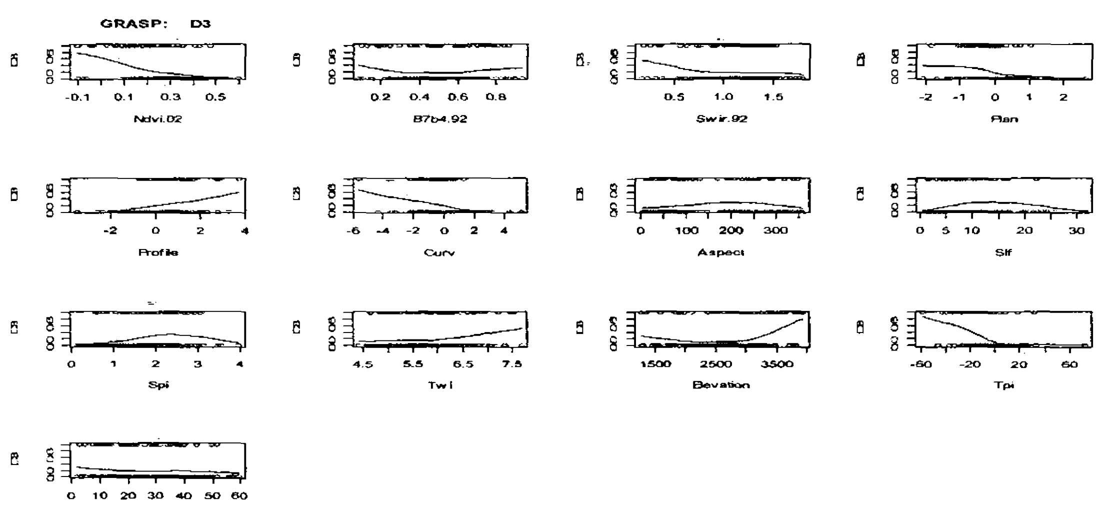


Figure 4.10: Scattergrams of 1992 Land degradation (D3) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D3 was observed in only 46 points (prevalence = 18.9%).Null Deviance of the final model resulted after stepwise selection of variables was 235.81 and the explained deviance for the model was 166.87. The pseudo quotient D^2 for the model was 0.71 and correlation value for the model was 0.85. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D3 ~ s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) + s(Ndvi.02, 4) + s(B7b4.92, 4) + s(Swir.92, 4)

Final Model:

YYY$D3 ~ s(Aspect, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(B7b4.92, 4) + s(Swir.92, 4)

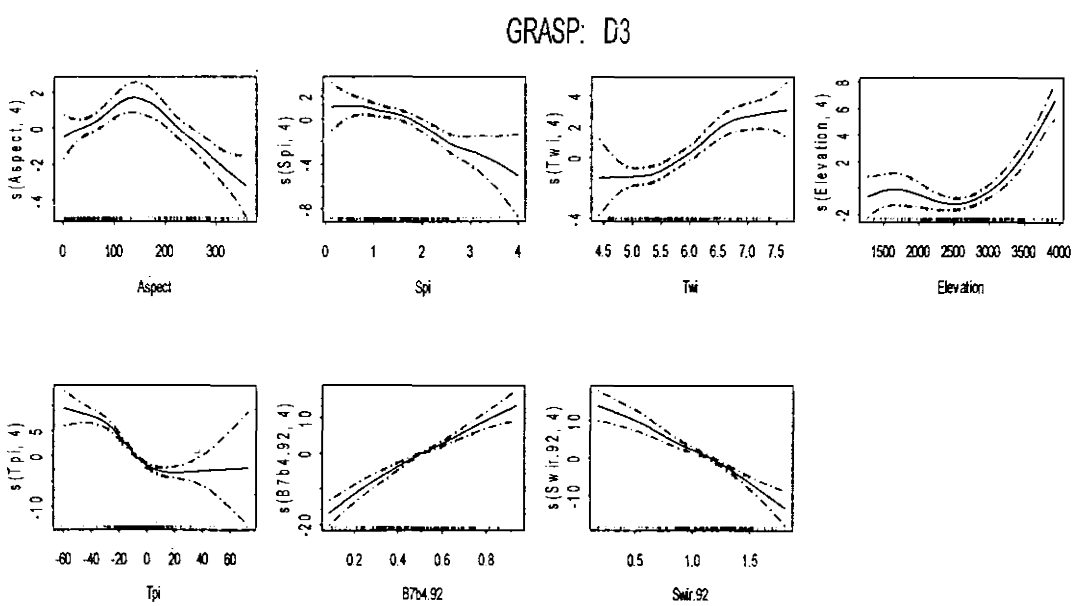


Figure 4.11: Response of 1992 Land degradation (D3) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.7.

Table 4.7: analysis of deviance for dropping of terms in 1992 D3 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				190.8409	35.08565	0.05
2	s(Ndvi.02, 4)	3.826262	2.393466	194.6671	37.47912	0.637126
3	s(Slope, 4)	3.866672	2.421154	198.5338	39.90027	0.638369
4	s(Curv, 4)	3.82563	4.390923	202.3594	44.29119	0.331531
5	s(Profile, 4)	4.548205	7.022644	206.9077	51.31384	0.178580
6	s(Plan, 4)	4.291269	9.625177	211.1989	60.93901	0.057144
7	s(Slf, 4)	3.550772	7.998011	214.7497	68.93702	0.068806

ANOVA for the selected terms in the model are shown as Table 4.8.

Table 4.8: ANOVA for the selected terms in 1992 D3 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Aspect, 4)	-3.66485	-12.4694	0.010811
[2,]	-s(Spi, 4)	-3.57079	-12.0938	0.011799
[3,]	-s(Twi, 4)	-3.46187	-18.5309	0.000567
[4,]	-s(Elevation, 4)	-3.3781	-32.0762	8.43E-07
[5,]	-s(Tpi, 4)	-4.00308	-61.6573	1.31E-12
[6,]	-s(B7b4.92, 4)	-3.48727	-26.406	1.45E-05
[7,]	-s(Swir.92, 4)	-3.56018	-17.427	0.001045

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.9.

Table 4.9: ANOVA for the drop contribution of selected terms in 1992 D3 model

	Drop	Alone	model
s(Aspect, 4)	12.46942	7.61438	4.835701
s(Spi, 4)	12.09384	21.6443	6.205504
s(Twi, 4)	18.53087	8.978809	4.390728
s(Elevation, 4)	32.0762	35.89654	7.751968
s(Tpi, 4)	61.6573	62.48787	1.27E+01
s(B7b4.92, 4)	26.40604	8.07085	3.00E+01
s(Swir.92, 4)	17.42695	8.369644	27.32258

Model validation:

The validation parameters for the degradation D1 for year 1992 are as follows (Figure 4.12):

cv ROC auc: 0.89
cv COR: 0.644
ROC auc: 0.981
COR: 0.857

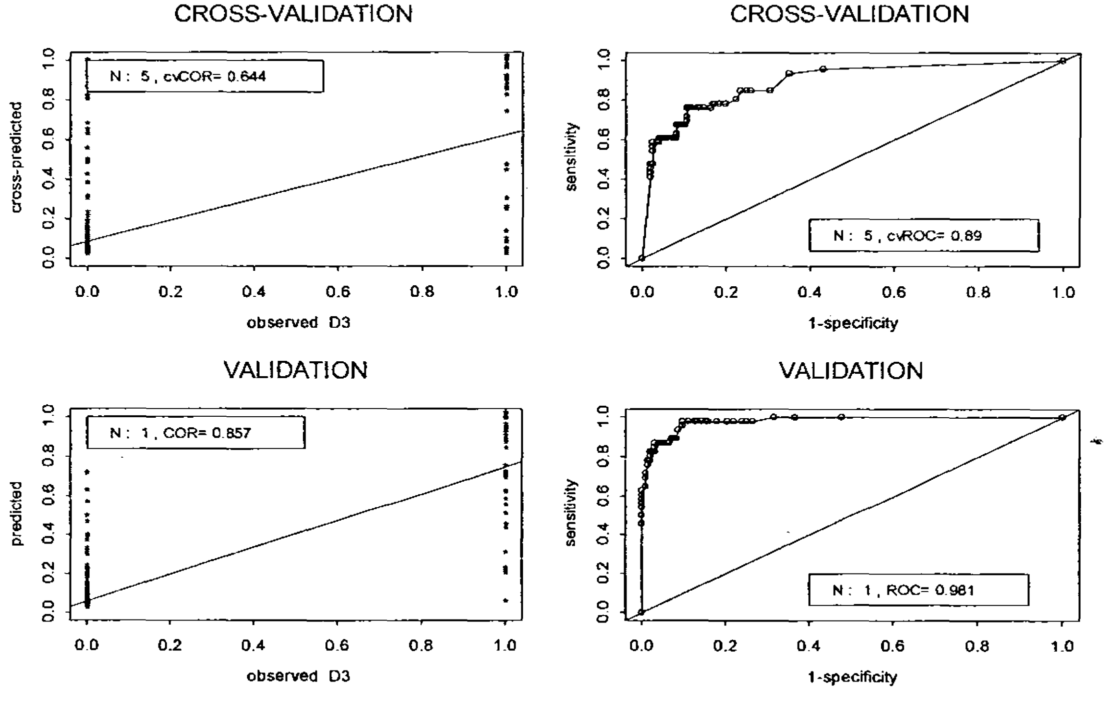


Figure 4.12: Cross-validation of predictive model of 1992 D3 model

4.4 Land degradation 4 (D4): year 1992

Predictor's Space:

The predictor's space occupied by the Land degradation 4 (D4) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

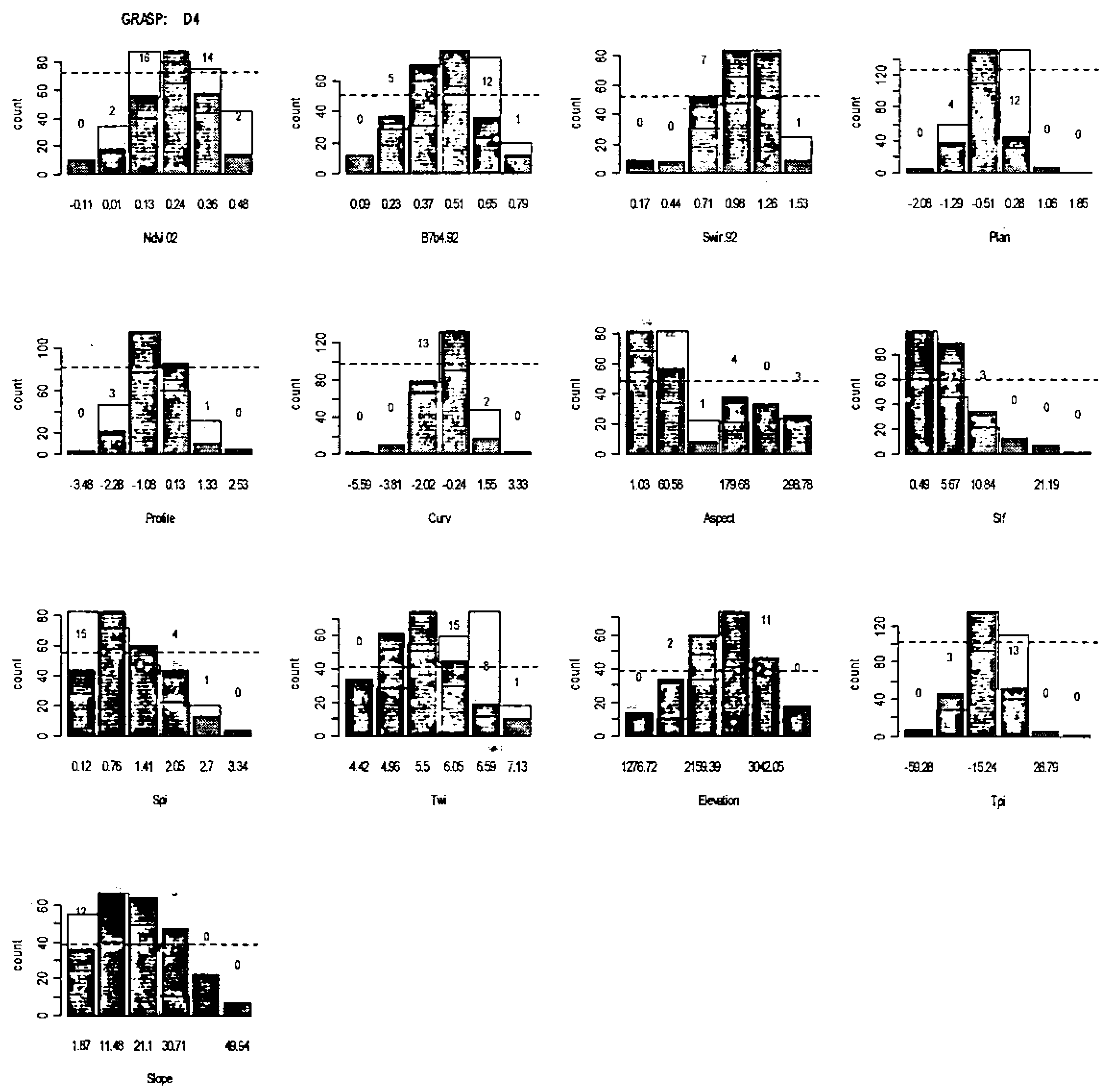


Figure 4.13: Histograms of 1992Land degradation (D4) against predictor variables

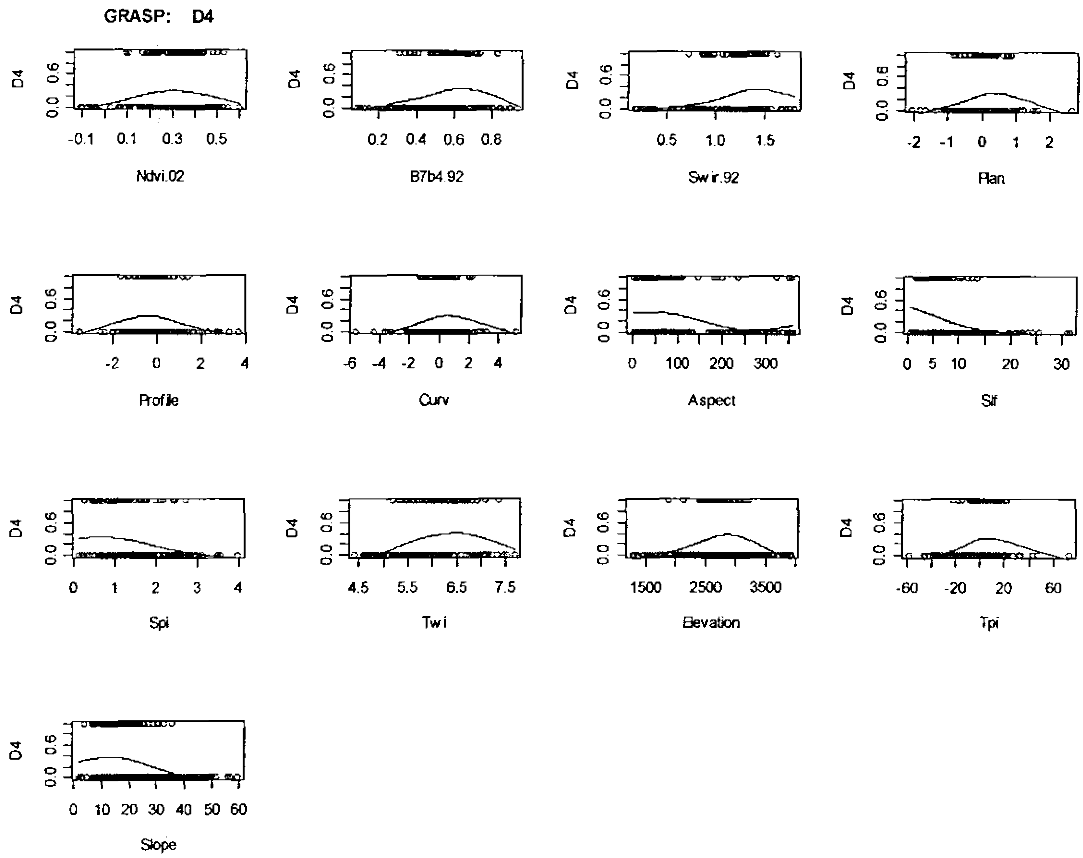


Figure 4.14: Scattergrams of 1992 Land degradation (D4) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D4 was observed in only 57 points (prevalence = 23.4%).Null Deviance of the final model resulted after stepwise selection of variables was 264.7 and the explained deviance for the model was 134.8 The pseudo quotient D^2 for the model was 0.51 and correlation value for the model was 0.72. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:
YYY$D4 ~ s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) + s(Ndvi.02,4) + s(B7b4.92, 4) + s(Swir.92, 4)

Final Model:
YYY$D4 ~ s(Aspect, 4) + s(Slf, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4)

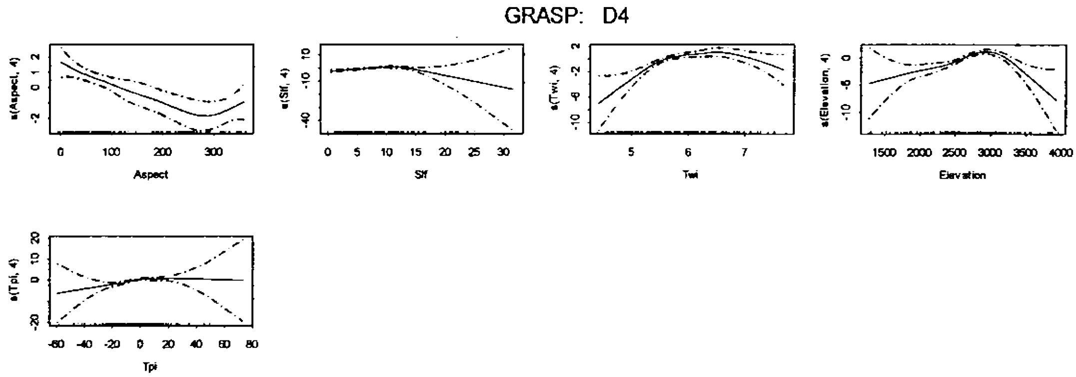


Figure 4.15: Response of 1992 Land degradation (D4) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.10.

Table 4.10: analysis of deviance for dropping of terms in 1992 D4 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				191.3498	98.0225	0.05
2	s(Ndvi.02, 4)	3.907305	2.532377	195.2571	100.5549	0.624534
3	s(Spi, 4)	3.944174	3.298144	199.2013	103.853	0.500490
4	s(Slope, 4)	3.827729	4.066953	203.029	107.92	0.371923
5	s(Profile, 4)	3.932731	3.727618	206.9618	111.6476	0.433916
6	s(Curv, 4)	3.799398	1.149551	210.7612	112.7971	0.867527
7	s(Plan, 4)	3.897627	2.20506	214.6588	115.0022	0.683002
8	s(B7b4.92, 4)	3.82623	6.37406	218.485	121.3763	0.157676
9	s(Swir.92, 4)	3.990437	8.477811	222.4755	129.8541	0.075111

ANOVA for the selected terms in the model are shown as Table 4.11.

Table 4.11: ANOVA for the selected terms in 1992 D4 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Aspect, 4)	-3.8188	-20.9786	0.000266
[2,]	-s(Slf, 4)	-3.72163	-13.7328	0.006478
[3,]	-s(Twi, 4)	-3.78436	-22.1185	0.000151
[4,]	-s(Elevation, 4)	-3.79365	-40.9284	2.11E-08
[5,]	-s(Tpi, 4)	-3.8558	-11.3523	0.020519

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.12.

Table 4.12: ANOVA for the drop contribution of selected terms in 1992 D4 model

	Drop	Alone	model
s(Aspect, 4)	20.9786	35.15773	3.47269
s(Slf, 4)	13.73275	33.92891	16.98438
s(Twi, 4)	22.11849	41.44061	8.090756
s(Elevation, 4)	40.92843	55.18379	8.89E+00
s(Tpi, 4)	11.35227	32.53056	7.008311

Model validation:

The validation parameters for the degradation D4 for year 1992 are as follows (Figure 4.16):

cv ROC auc: 0.886
cv COR: 0.604
ROC auc: 0.939
COR: 0.72

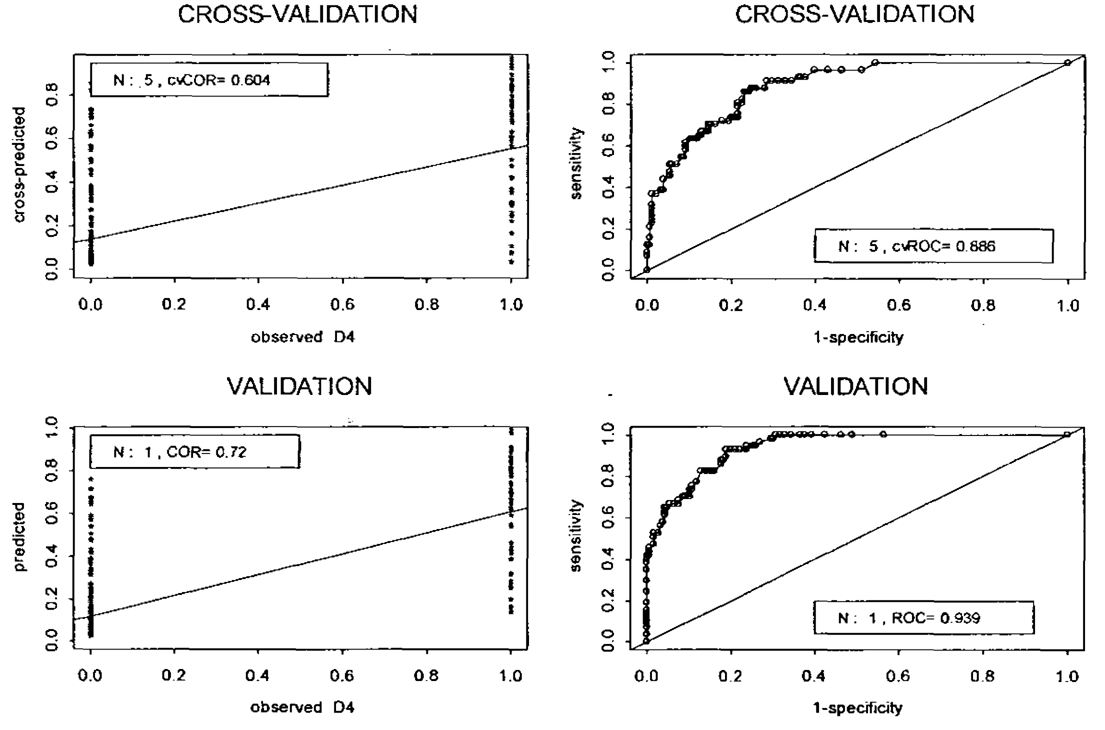


Figure 4.16: Cross-validation of predictive model of 1992 D4 model

4.5 Land degradation 5(D5): year 1992

Predictor's Space:

The predictor's space occupied by the Land degradation 5 (D5) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

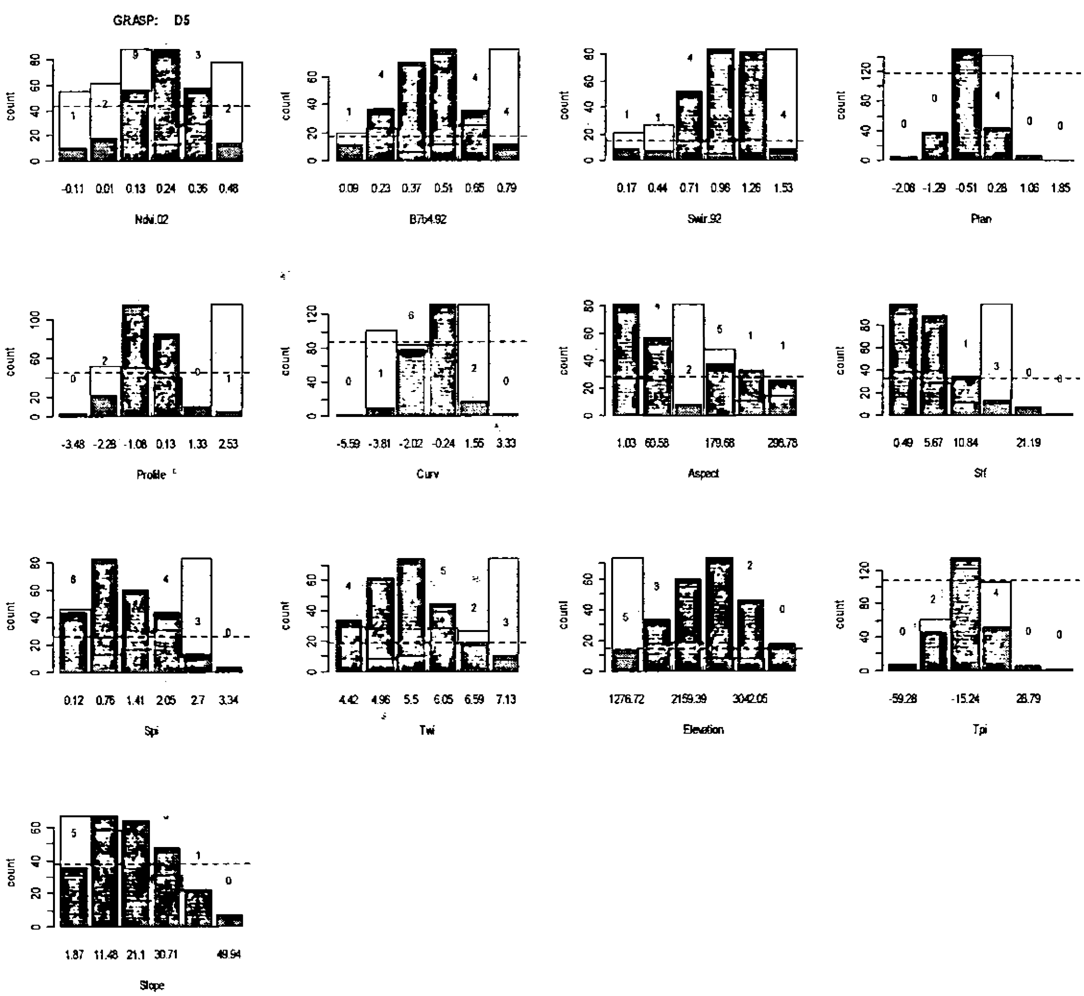


Figure 4.17: Histograms of 1992 *Land degradation (D5)* against predictor variables

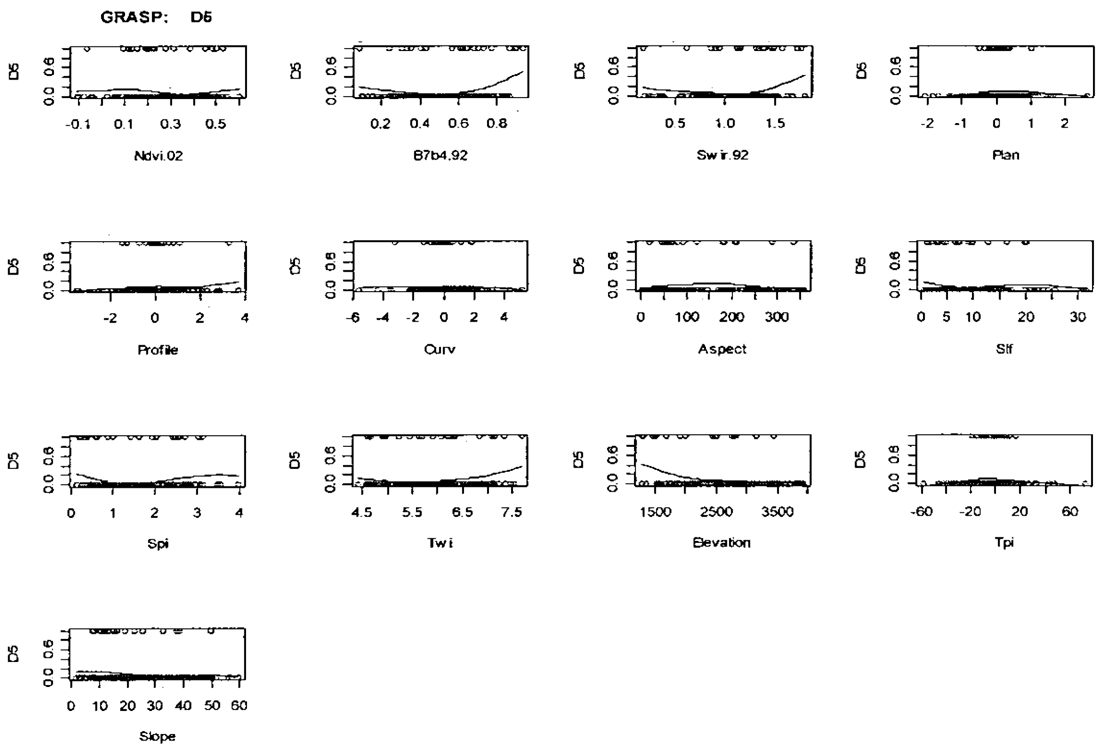


Figure 4.18: Scattergrams of 1992 Land degradation (D5) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D5 was observed in only 19 points (prevalence = 7.8%).Null Deviance of the final model resulted after stepwise selection of variables was 133.3 and the explained deviance for the model was 85.0 The pseudo quotient D^2 for the model was 0.64 and correlation value for the model was 0.78. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D5 ~ s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) + s(Ndvi.02,4) + s(B7b4.92, 4) + s(Swir.92, 4)

Final Model:
YYY$D5 ~ s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4) +

s(B7b4.92, 4)

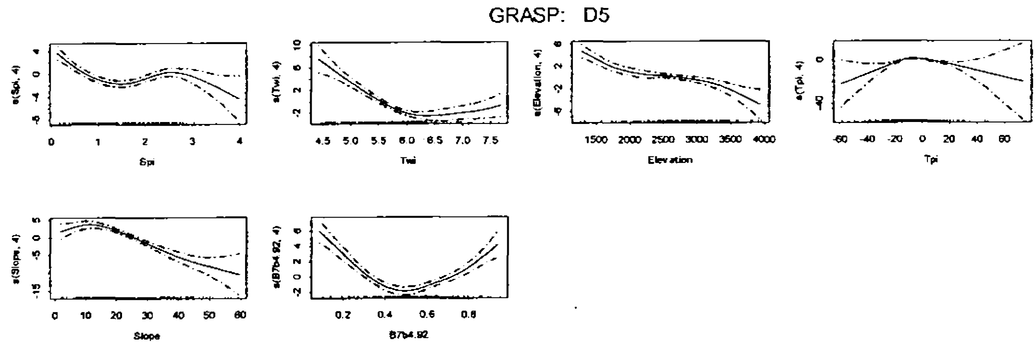


Figure 4.19: Response of 1992 Land degradation (D5) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.13.

Table 4.13: analysis of deviance for dropping of terms in 1992 D5 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				191.0381	21.64688	0.05
2	s(Swir.92, 4)	3.853675	1.143831	194.8917	22.79071	0.873848
3	s(Slf, 4)	4.357091	2.429172	199.2488	25.21988	0.70855
4	s(Curv, 4)	3.475451	2.27483	202.7243	27.49471	0.602194
5	s(Profile, 4)	4.053093	3.330594	206.7774	30.8253	0.512347
6	s(Ndvi.02, 4)	3.794326	6.591785	210.5717	37.41709	0.142222
7	s(Plan, 4)	3.782007	5.333287	214.3537	42.75038	0.229928
8	s(Aspect, 4)	3.940469	5.569043	218.2942	48.31942	0.227225

ANOVA for the selected terms in the model are shown as Table 4.14.

Table 4.14: ANOVA for the selected terms in 1992 D5 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Spi, 4)	-4.27872	-16.3385	0.003317
[2,]	-s(Twi, 4)	-4.35793	-12.3538	0.019506
[3,]	-s(Elevation, 4)	-4.1677	-12.8021	0.014003
[4,]	-s(Tpi, 4)	-4.05997	-25.4049	4.45E-05
[5,]	-s(Slope, 4)	-4.22782	-20.3099	0.000542
[6,]	-s(B7b4.92, 4)	-4.12585	-19.9762	0.000571

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.15.

Table 4.15: ANOVA for the drop contribution of selected terms in 1992 D5 model

	Drop	Alone	model
s(Spi, 4)	16.33845	14.02523	8.060557
s(Twi, 4)	12.35384	8.292852	10.06738
s(Elevation, 4)	12.80208	15.25448	9.395848
s(Tpi, 4)	25.40494	8.655559	23.34499
s(Slope, 4)	20.30992	8.806655	14.23759
s(B7b4.92, 4)	19.97622	19.49526	7.738553

Model validation:

The validation parameters for the degradation D1 for year 1992 are as follows (Figure 4.20):

cv ROC auc: 0.861
cv COR: 0.404
ROC auc: 0.979
COR: 0.786

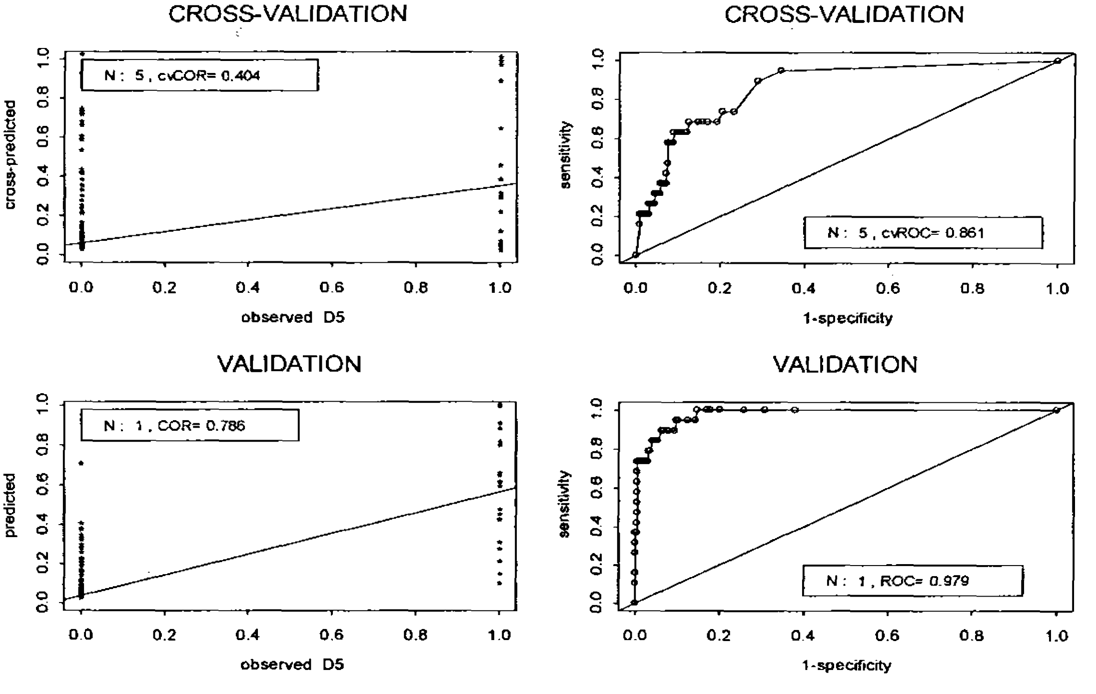


Figure 4.20: Cross-validation of predictive model of 1992 D5 model

4.6 Land degradation 1 (D1): year 2001

Predictor's Space:

The predictor's space occupied by the Land degradation 1 (D1) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

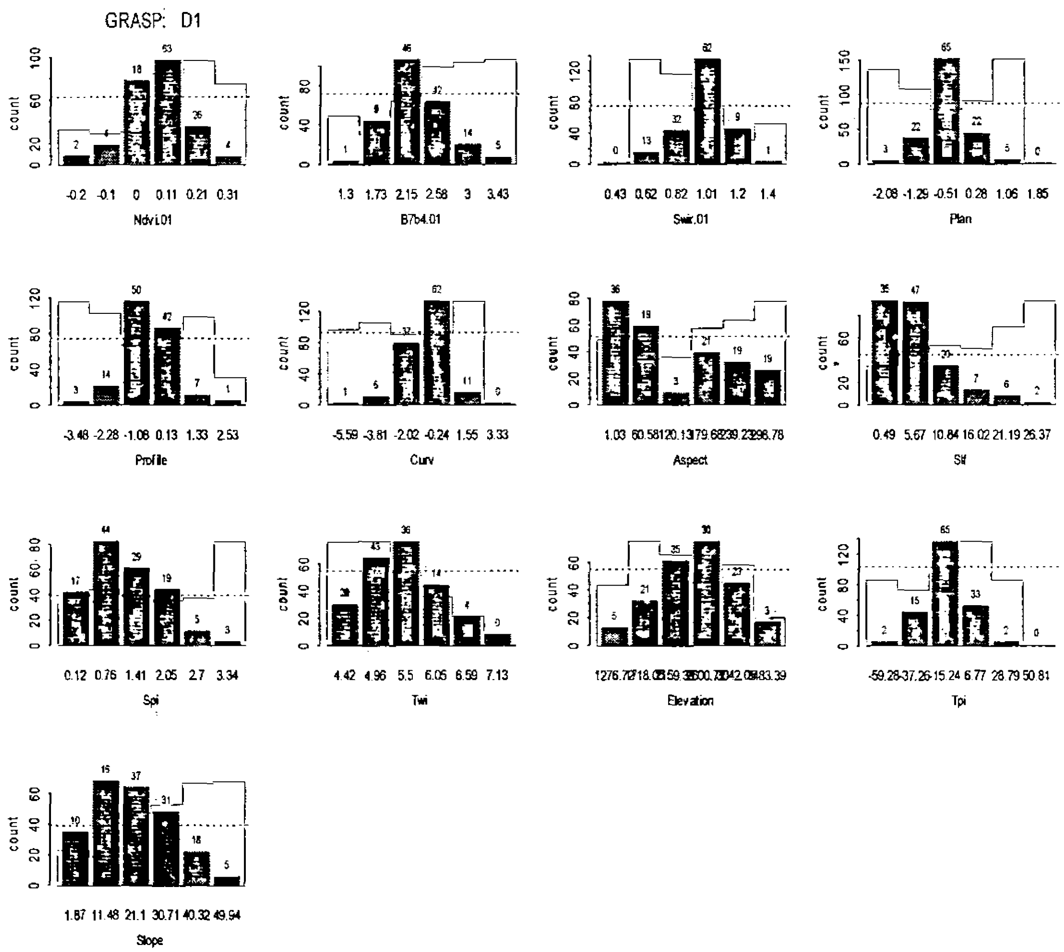


Figure 4.21: Histograms of 2001 *Land degradation (D1)* against predictor variables

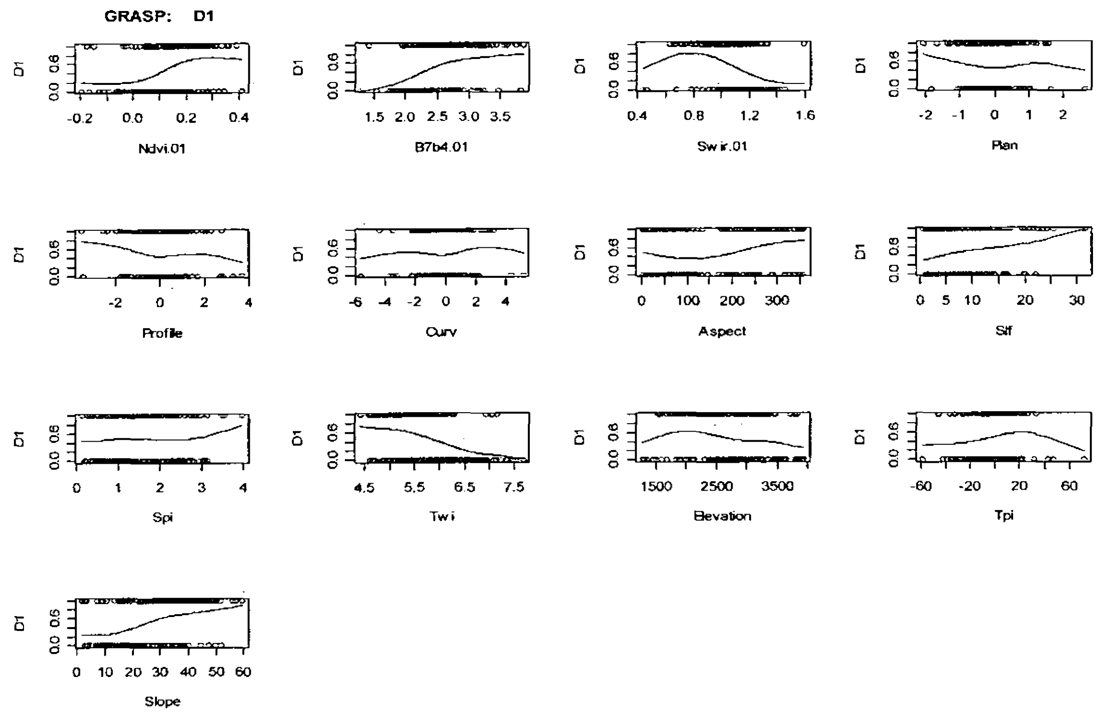


Figure 4.22: Scattergrams of 2001 *Land degradation (D1)* response against predictor variables

<u>*Model Selection*</u>:

Out of total 243 observation points land degradation of category D1 was observed in 117 points (prevalence = 48.1%).Null Deviance of the final model resulted after stepwise selection of variables was 336.54 and the explained deviance for the model was 173.59. The pseudo quotient D^2 for the model was 0.51 and correlation value for the model was 0.77. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:
YYY$D1 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Swir.01, 4) + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect,4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

Final Model:
YYY$D1 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Aspect, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

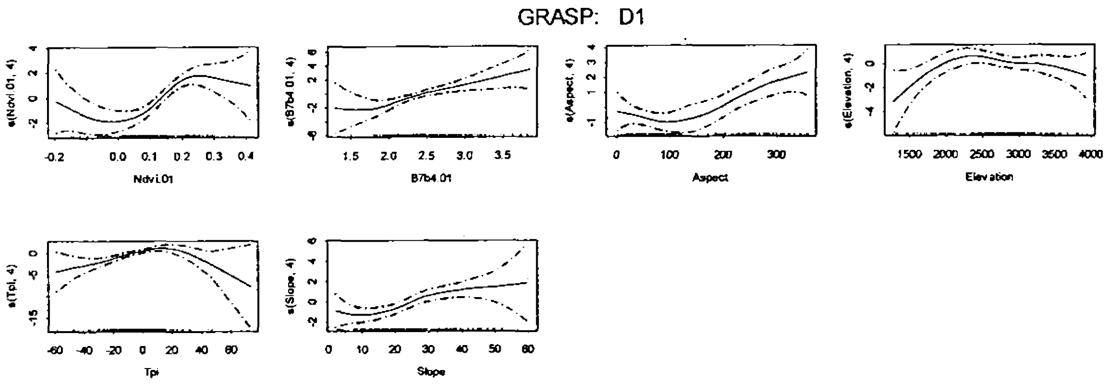


Figure 4.23: Response of 2001 Land degradation (D1) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.16.

Table 4.16: analysis of deviance for dropping of terms in 2001 D1 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
1				191.2474	143.0949	0.05
2	s(Spi, 4)	3.87	0.51	1.95	143.60	0.96
3	s(Curv, 4)	3.72	0.79	198.85	144.40	0.92
4	s(Twi, 4)	3.94	2.66	202.79	147.06	0.60
5	s(Plan, 4)	3.94	3.45	206.73	150.52	0.47
6	s(Swir.01, 4)	4.05	4.08	2.11	154.60	0.40
7	s(Slf, 4)	3.83	4.04	214.62	158.65	0.37
8	s(Profile, 4)	3.70	4.28	218.32	162.93	0.32

ANOVA for the selected terms in the model are shown as Table 4.17.

Table 4.17: ANOVA for the selected terms in 2001 D1 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Ndvi.01, 4)	-3.99	-4.72	1.34
[2,]	-s(B7b4.01, 4)	-3.90	-25.82	3.10
[3,]	-s(Aspect, 4)	-3.90	-23.58	8.67
[4,]	-s(Elevation, 4)	-4.09	-11.06	0.027
[5,]	-s(Tpi, 4)	-3.74	-3.22	1.28
[6,]	-s(Slope, 4)	-3.72	-22.46	0.00

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.18.

Table 4.18: ANOVA for the drop contribution of selected terms in 2001 D1 model

	Drop	alone	Model
s(Ndvi.01, 4)	47.21	46.02	3.65
s(B7b4.01, 4)	25.82	35.84	5.72
s(Aspect, 4)	23.58	18.78	3.32
s(Elevation, 4)	11.07	20.56	3.77
s(Tpi, 4)	32.18	9.84	8.92
s(Slope, 4)	22.46	42.03	3.16

Model validation:

The validation parameters for the degradation D1 for year 2001 are as follows (Figure 4.24):

cv ROC auc: 0.884

cv COR: 0.673

ROC auc: 0.934

COR: 0.773

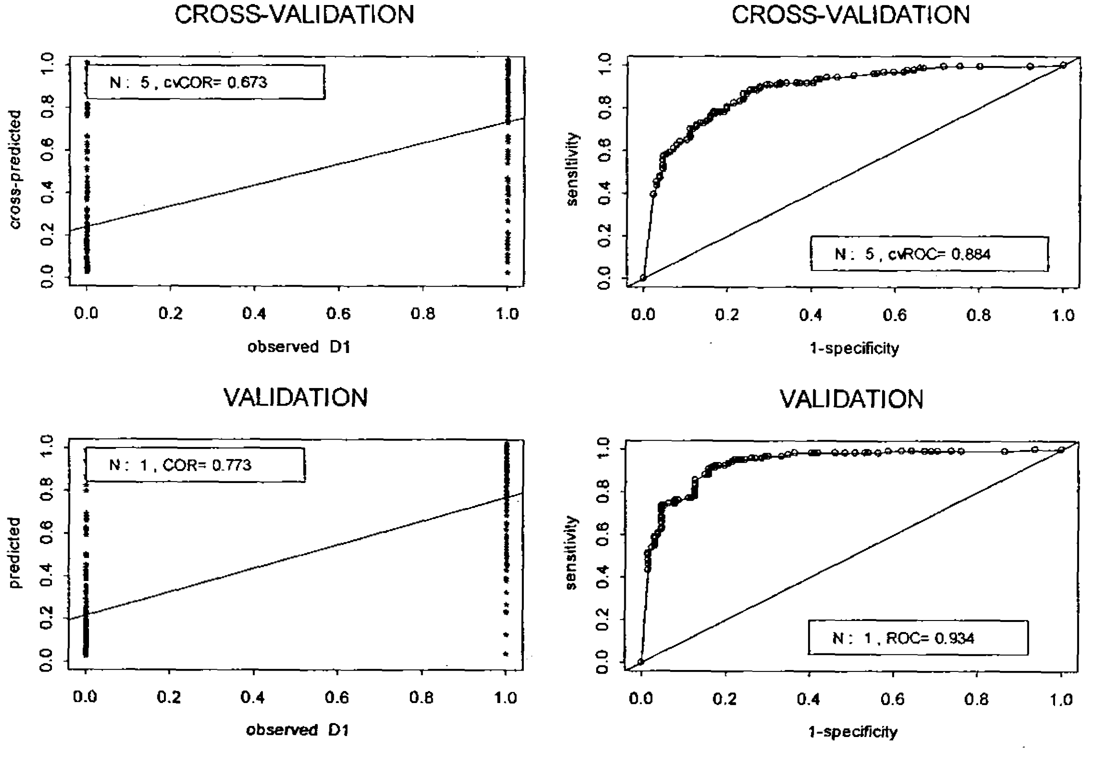


Figure 4.24: Cross-validation of predictive model of 2001 D1 model

4.7 Land degradation 2 (D2): year 2001

Predictor's Space:

The predictor's space occupied by the Land degradation 2 (D2) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

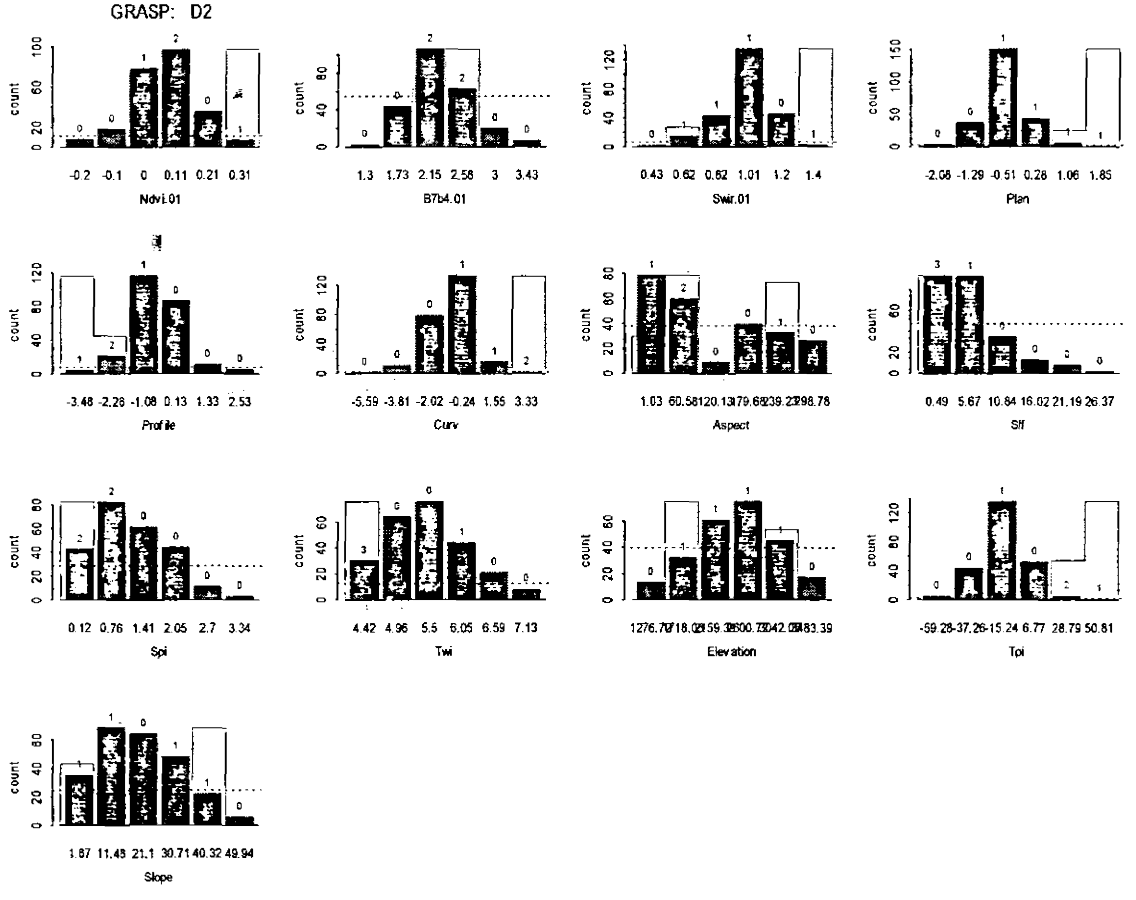


Figure 4.25: Histograms of 2001 Land degradation (D2) against predictor variables

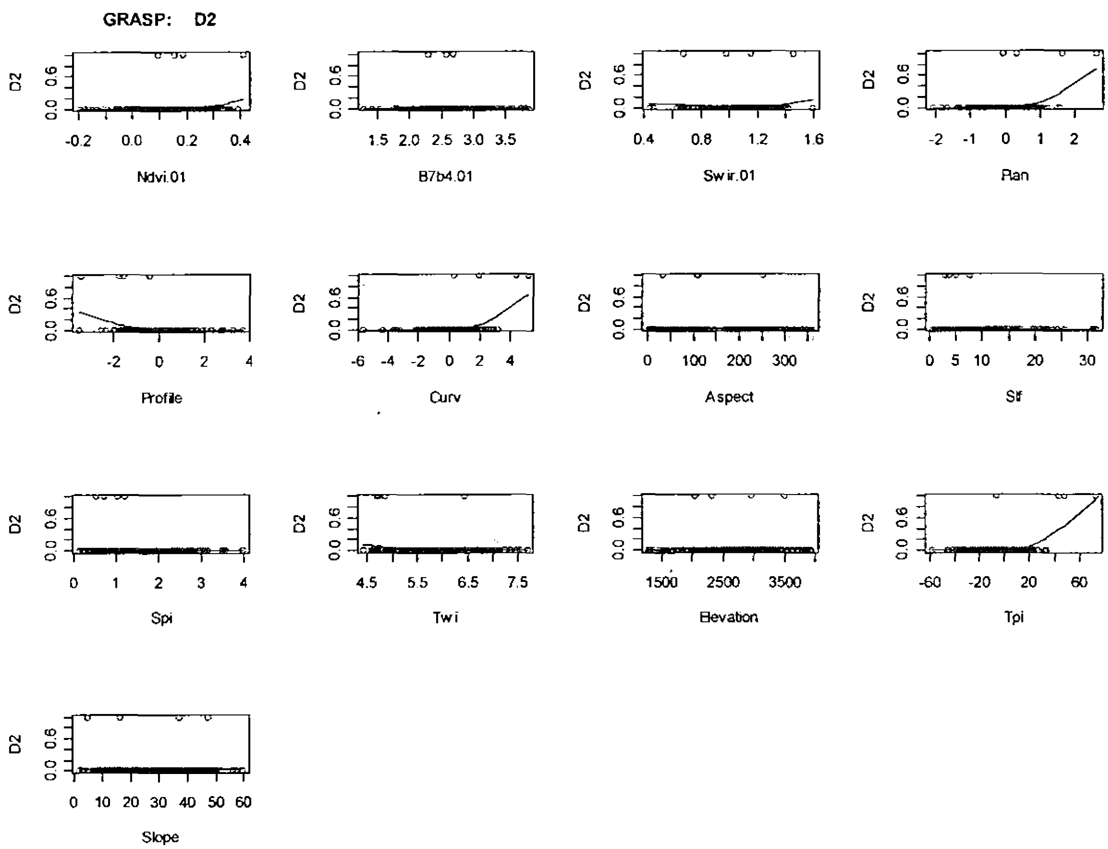


Figure 4.26: Scattergrams of 2001 Land degradation (D2) response against predictor variables

Out of total 243 observation points land degradation of category D2 was observed in 4 points (prevalence = 1.6%).Null Deviance of the final model resulted after stepwise selection of variables was 40.78 and the explained deviance for the model was 33.34. The pseudo quotient D^2 for the model was o.82 and correlation value for the model was 0.88. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:
YYY$D2 ~s(Ndvi.01,4) +s(B7b4.01,4) +s(Swir.01,4) +s(Plan,4) +s(Profile,4) +s(Curv,4) +s(Aspect,4) +s(Slf,4) +s(Spi,4) +s(Twi,4) +s(Elevation,4) +s(Tpi,4) +s(Slope,4)

Final Model:
YYY$D2 ~s(Tpi,4)

GRASP: D2

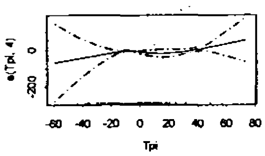


Figure 4.27: Response of 2001 Land degradation (D2) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.19.

Table 4.19: analysis of deviance for dropping of terms in 2001 D2 model

	Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance
			199.44	0	0.05
s(Ndvi.01, 4)	3.06	0	202.50	0	1
s(B7b4.01, 4)	3.36	0	205.86	0	1
s(Plan, 4)	3.90	0	209.76	0	1
s(Profile, 4)	2.70	0	212.45	0	1
s(Aspect, 4)	3.21	0	215.66	0	1
s(Slf, 4)	3.19	0	218.86	0	1
s(Spi, 4)	3.19	0	222.05	0	1
s(Elevation,	3.05	0	225.13	0	1
s(Slope, 4)	3.05	0	228.16	0	1
s(Twi, 4)	2.95	0	231.11	0	1
s(Curv, 4)	3.00	0.09	234.11	0.09	0.99
s(Swir.01, 4)	4.16	7.34	238.27	7.43	0.12

ANOVA for the selected terms in the model are shown as Table 4.20.

Table 4.20: ANOVA for the selected terms in 2001 D2 model

	Test	Df	Deviance	Pr(Chi)	
[1,]			-3.72	-3.33	7.18

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.21.

Table 4.21: ANOVA for the drop contribution of selected terms in 2001 D2 model

	Drop	alone	model
s(Tpi, 4)	33.35	33.35	123.68

Model validation:

The validation parameters for the degradation D2 for year 2001 are as follows (Figure 4.28):

cv ROC auc: 0.865
cv COR: 0.855
ROC auc: 0.997
COR: 0.877

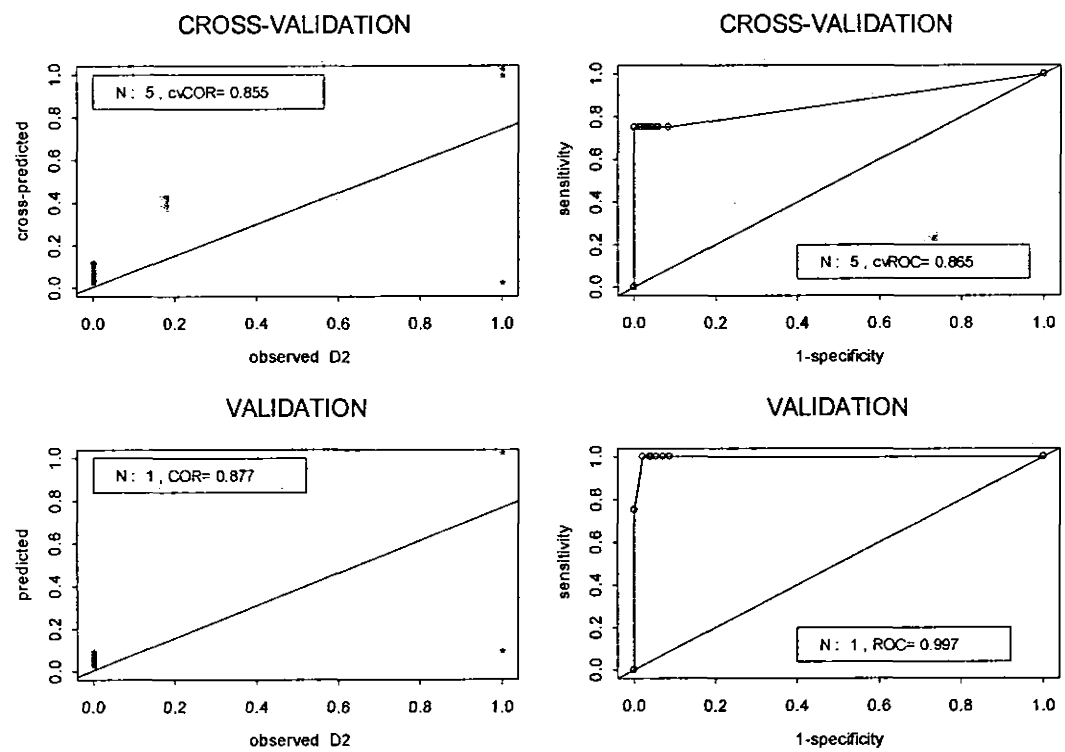


Figure 4.28: Cross-validation of predictive model of 2001 D2 model

4.8 Land degradation 3 (D3): year 2001

Predictor's Space:

The predictor's space occupied by the Land degradation 3 (D3) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

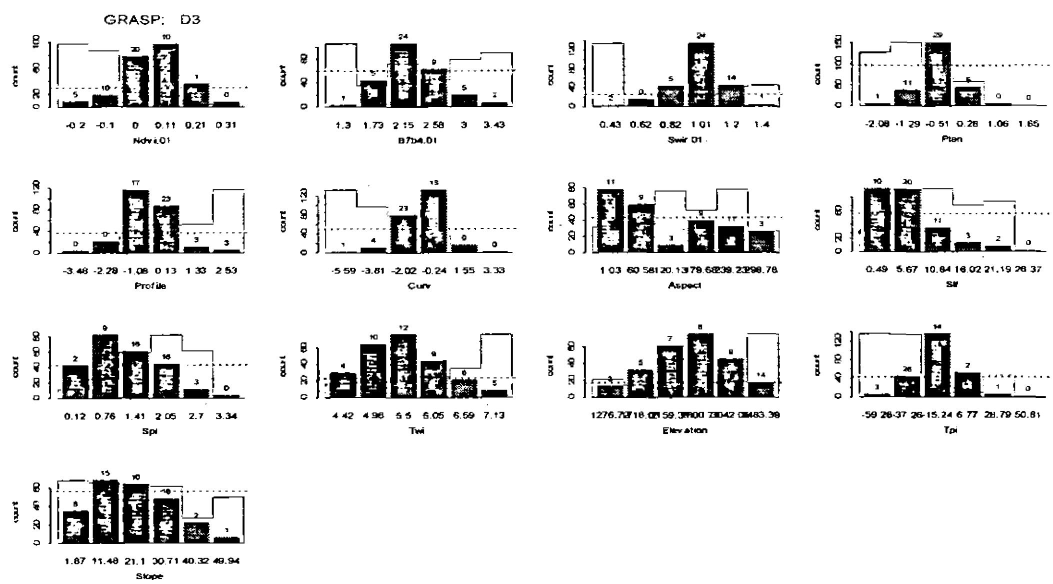


Figure 4.29: Histograms of 2001 Land degradation (D3) against predictor variables

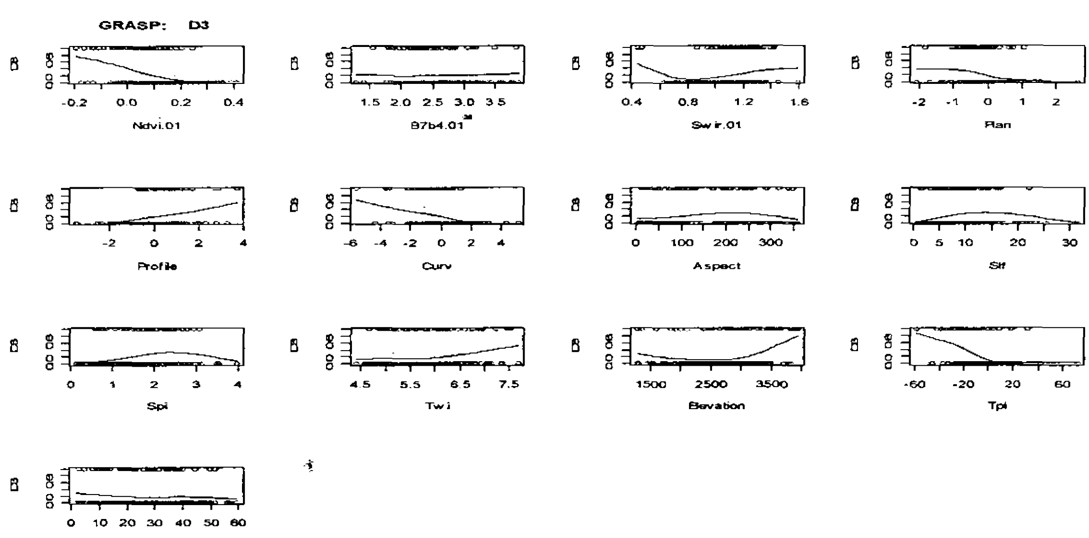


Figure 4.30: Scattergrams of 2001 Land degradation (D3) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D3 was observed in 46 points (prevalence = 18.93 %).Null Deviance of the final model resulted after stepwise selection of variables was 235.82 and the explained deviance for the model was 183.87. The pseudo quotient D^2 for the model was 0.78 and correlation value for the model was 0.90. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D3 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Swir.01, 4) + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

Final Model:

YYY$D3 ~ s(Ndvi.01, 4) + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4)

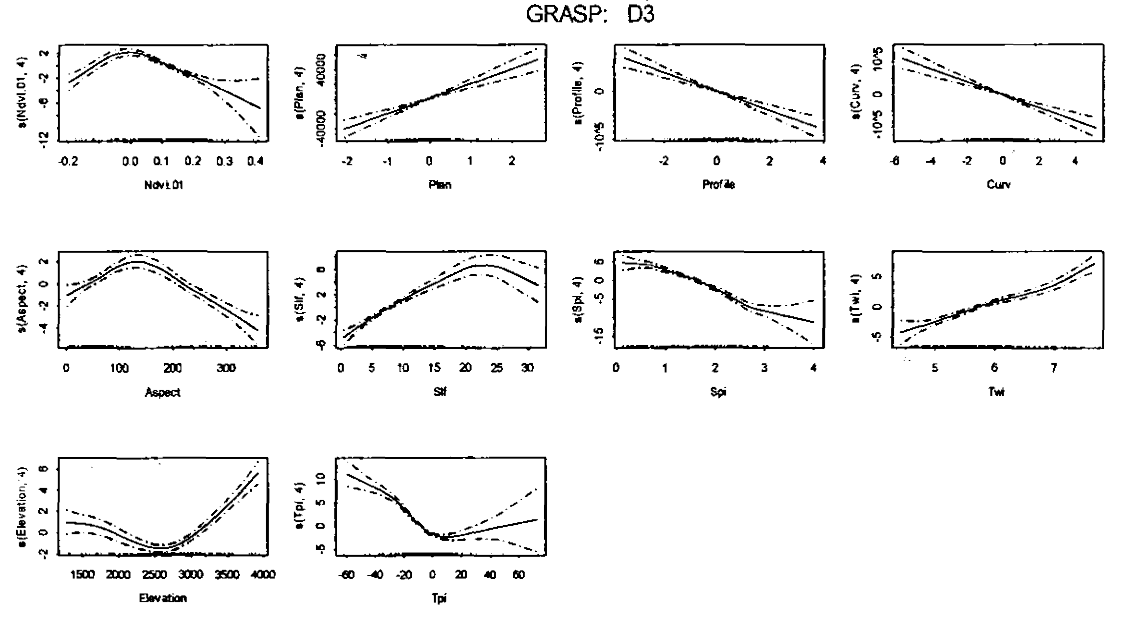


Figure 4.31: Response of 2001 Land degradation (D3) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.22.

Table 4.22: analysis of deviance for dropping of terms in 2001 D3 model

Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
s(Slope, 4)	3.91	2.69	194.72	44.91	0.59
s(B7b4.01, 4)	4.12	2.40	198.85	47.32	0.67
s(Swir.01, 4)	3.85	4.60	202.69	51.93	0.31

ANOVA for the selected terms in the model are shown as Table 4.23.

Table 4.23: ANOVA for the selected terms in 2001 D3 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Ndvi.01, 4)	-4.14	-29.46	7.41
[2,]	-s(Plan, 4)	-4.37	-16.50	0.02
[3,]	-s(Profile, 4)	-4.32	-10.10	0.04
[4,]	-s(Curv, 4)	-4.24	-1.05	0.03
[5,]	-s(Aspect, 4)	-4.22	-2.07	0.02
[6,]	-s(Slf, 4)	-4.32	-11.73	0.02
[7,]	-s(Spi, 4)	-4.26	-17.38	0.01
[8,]	-s(Twi, 4)	-4.24	-17.25	0.01
[9,]	-s(Elevation, 4)	-4.12	-28.49	1.13
[10,]	-s(Tpi, 4)	-3.89	-42.24	1.28

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.24.

Table 4.24: ANOVA for the drop contribution of selected terms in 2001 D3 model

	Drop	alone	model
s(Ndvi.01, 4)	29.46	44.25	8.99
s(Plan, 4)	16.50	17.29	9.36
s(Profile, 4)	10.10	16.42	1.43
s(Curv, 4)	10.52	21.27	2124
s(Aspect, 4)	20.68	7.61	6.20
s(Slf, 4)	11.73	12.00	11.42
s(Spi, 4)	17.38	21.64	15.94
s(Twi, 4)	17.25	8.97	11.00
s(Elevation, 4)	28.49	35.89	7.08
s(Tpi, 4)	42.24	62.48	13.50

Model validation:

The validation parameters for the degradation D2 for year 2001 are as follows (Figure 4.32):

cv ROC auc: 0.881
cv COR: 0.662
ROC auc: 0.993
COR: 0.902

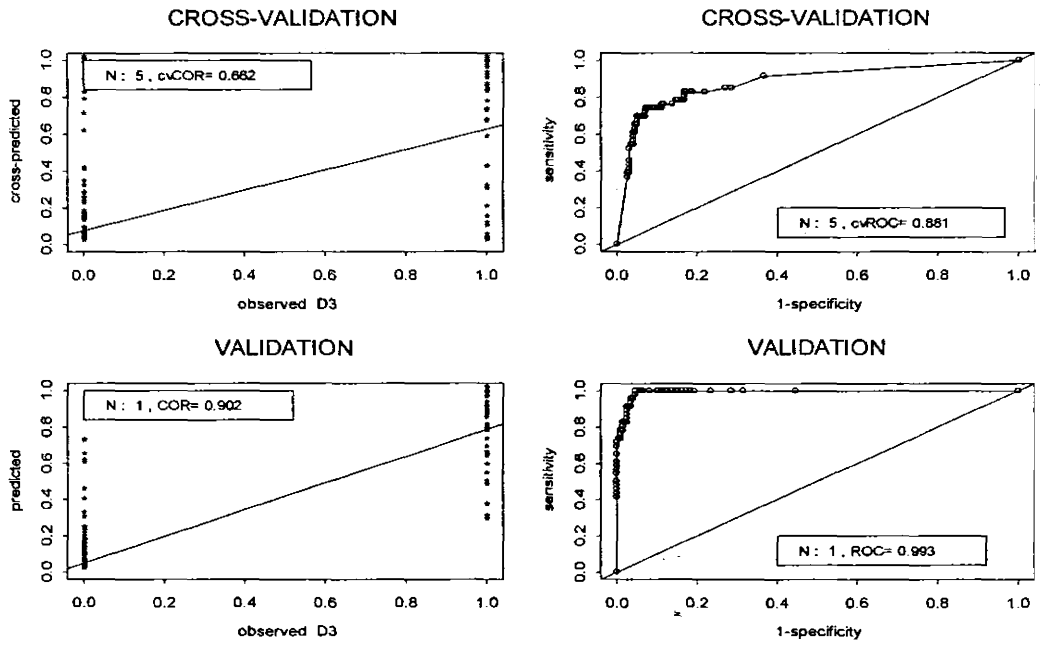


Figure 4.32: Cross-validation of predictive model of 2001 D3 model

4.9 Land degradation 4 (D4): year 2001

Predictor's Space:

The predictor's space occupied by the Land degradation 4 (D4) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

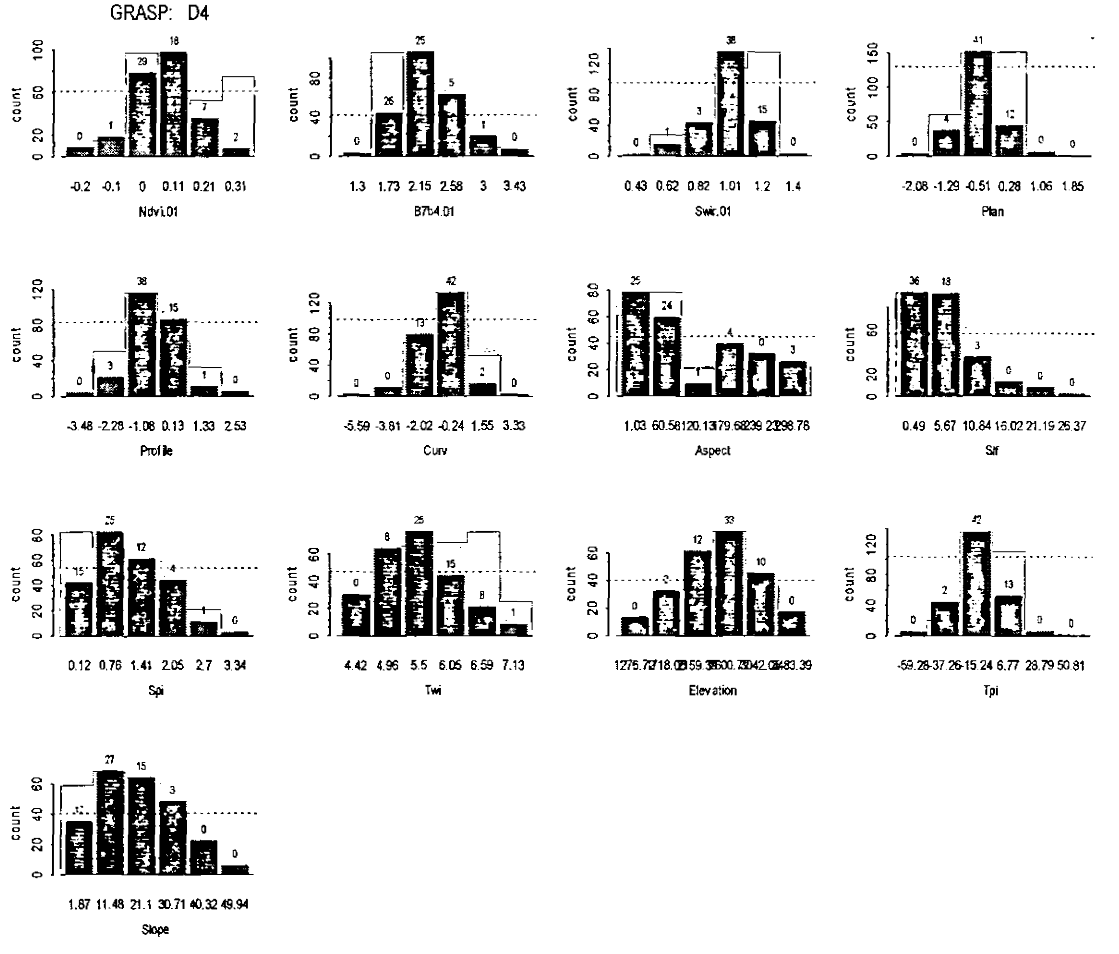


Figure 4.33: Histograms of 2001 *Land degradation (D4)* against predictor variables

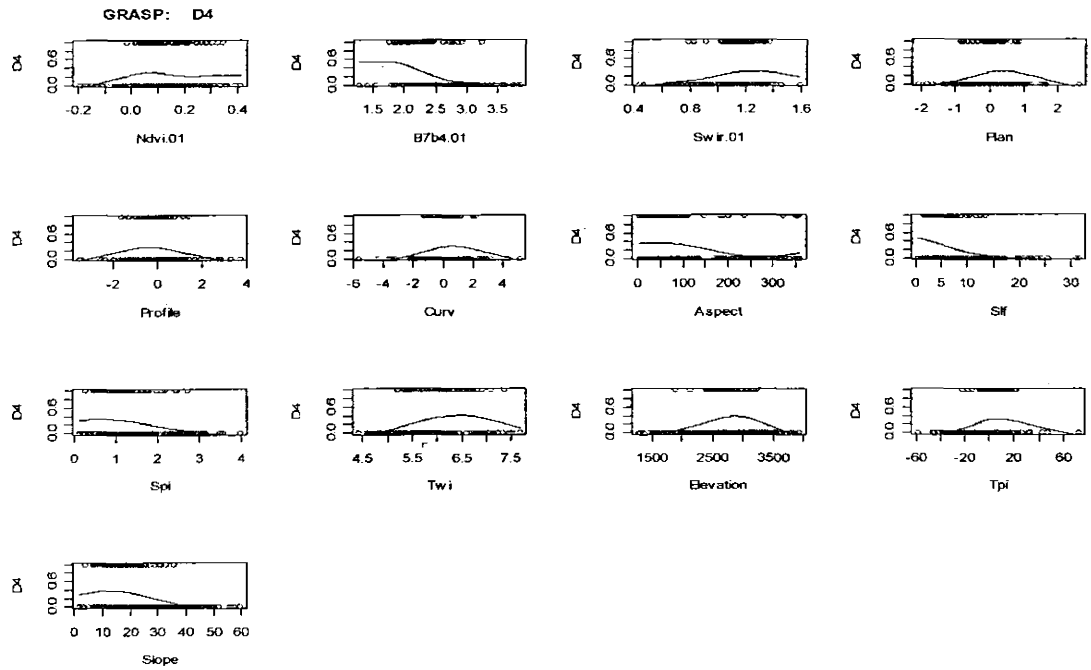


Figure 4.34: Scattergrams of 2001 Land degradation (D4) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D4 was observed in 57 points (prevalence = 23.46%).Null Deviance of the final model resulted after stepwise selection of variables was 264.74 and the explained deviance for the model was 148.78. The pseudo quotient D^2 for the model was 0.56 and correlation value for the model was 0.76. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D4 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Swir.01, 4) + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

Final Model:

YYY$D4 ~ s(Ndvi.01, 4) + s(Aspect, 4) + s(Slf, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4)

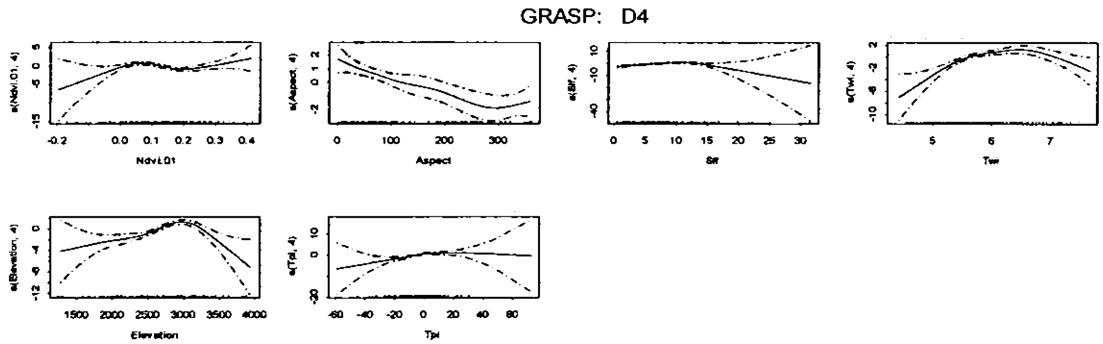


Figure 4.35: Response of 2001 *Land degradation (D4)* against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.25.

Table 4.25: analysis of deviance for dropping of terms in 2001 D4 model

Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
			191.46	82.49	0.05
s(Spi, 4)	3.86	2.09	195.32	84.58	0.69
s(Swir.01, 4)	3.79	5.18	199.12	89.77	0.24
s(Slope, 4)	3.76	7.46	202.88	97.23	0.09
s(Profile, 4)	3.86	6.76	206.75	104.00	0.13
s(Curv, 4)	3.83	1.24	210.58	105.25	0.85
s(Plan, 4)	4.06	2.62	214.64	107.87	0.63
s(B7b4.01, 4)	3.89	8.08	218.56	115.96	0.08

ANOVA for the selected terms in the model are shown as Table 4.26.

Table 4.26: ANOVA for the selected terms in 2001 D4 model

	Test	Df	Deviance	Pr(Chi)
[1,]	-s(Ndvi.01, 4)	-3.93	-1.39	0.00
[2,]	-s(Aspect, 4)	-3.97	-20.39	0.00
[3,]	-s(Slf, 4)	-3.72	-14.03	0.03
[4,]	-s(Twi, 4)	-3.72	-23.30	8.17
[5,]	-s(Elevation, 4)	-3.90	-37.21	1.44
[6,]	-s(Tpi, 4)	-3.86	-11.75	0.017

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.27.

Table 4.27: ANOVA for the drop contribution of selected terms in 2001 D4 model

	Drop	alone	model
s(Ndvi.01, 4)	13.89	19.23	8.40
s(Aspect, 4)	20.38	35.15	3.53
s(Slf, 4)	14.03	33.92	17.23
s(Twi, 4)	23.30	41.44	8.34
s(Elevation, 4)	37.21	55.18	8.40
s(Tpi, 4)	11.75	32.53	7.53

Model validation:

The validation parameters for the degradation D4 for year 2001 are as follows (Figure 4.28):

cv ROC auc: 0.897
cv COR: 0.639
ROC auc: 0.953
COR: 0.769

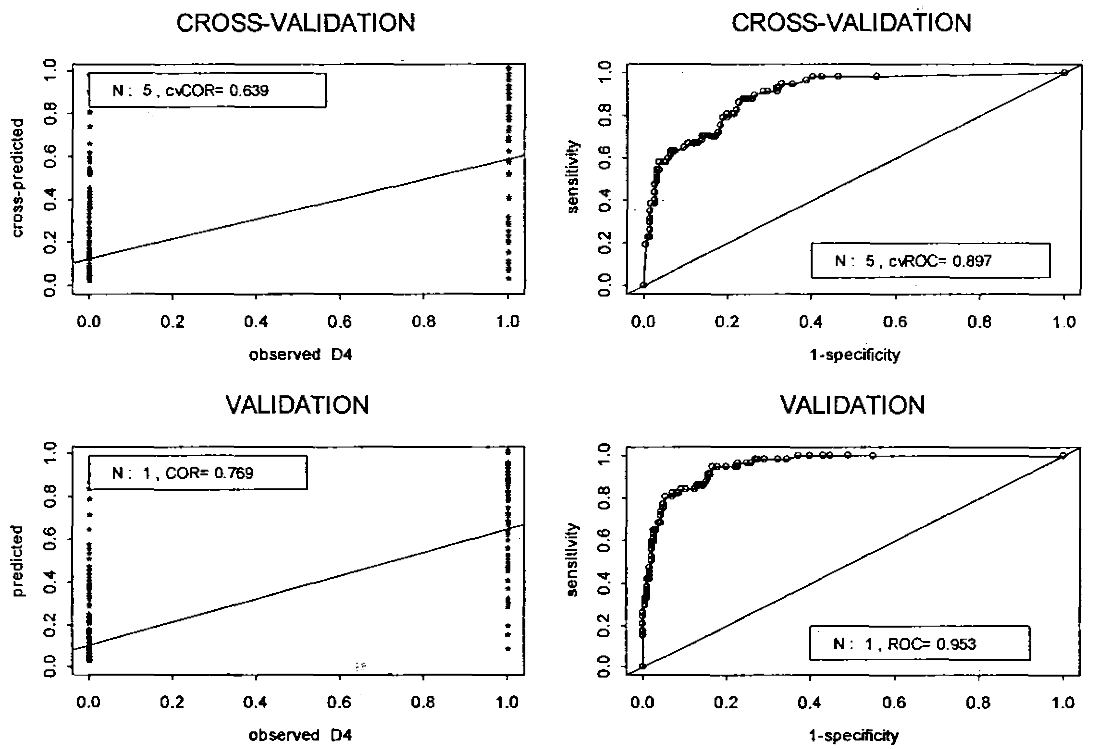


Figure 4.36: Cross-validation of predictive model of 2001 D4 model

4.10 Land degradation 5 (D5): year 2001

Predictor's Space:

The predictor's space occupied by the Land degradation 5 (D5) represented as histograms and scattergrams of response vs. predictors is shown in Figures 4.5 and 4.6.

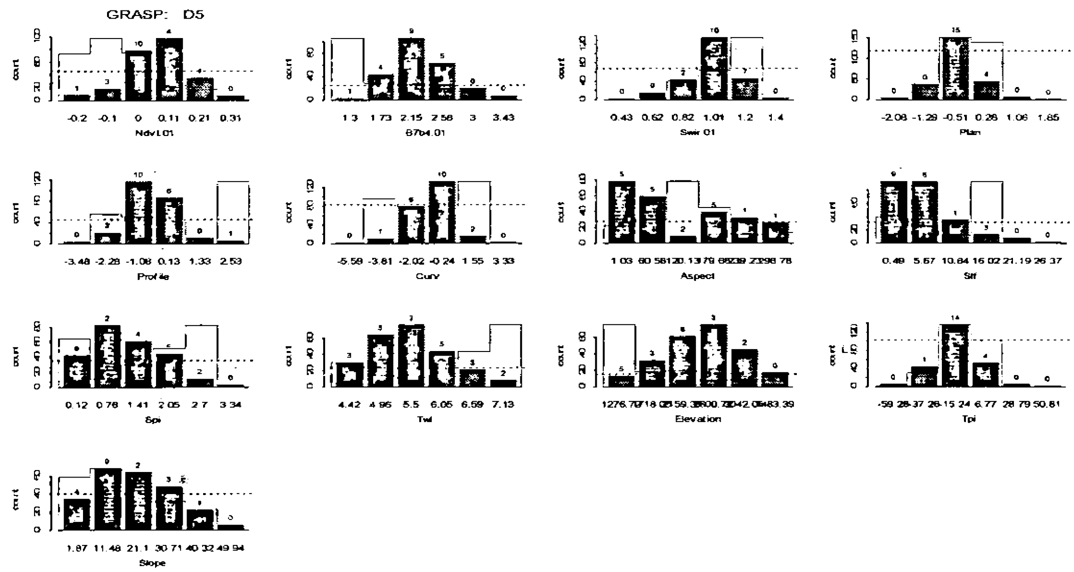


Figure 4.37: Histograms of 2001 Land degradation (D5) against predictor variables

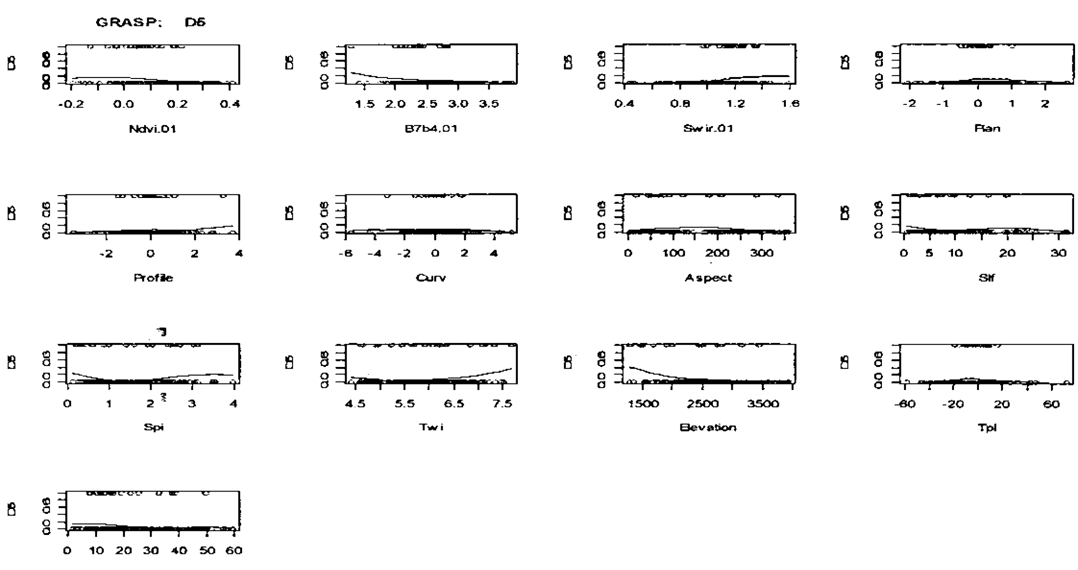


Figure 4.38: Scattergrams of 2001 Land degradation (D5) response against predictor variables

Model Selection:

Out of total 243 observation points land degradation of category D5 was observed in 19 points (prevalence = 8.00%).Null Deviance of the final model resulted after stepwise selection of variables was 133.32 and the explained deviance for the model was 104.03. The pseudo quotient D^2 for the model was 0.78 and correlation value for the model was 0.89. The initial model and final model after stepwise removal of insignificant terms are as follows:

Initial Model:

YYY$D5 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Swir.01, 4) + s(Plan, 4) + s(Profile, 4) + s(Curv, 4) + s(Aspect, 4) + s(Slf, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

Final Model:

YYY$D5 ~ s(Ndvi.01, 4) + s(B7b4.01, 4) + s(Spi, 4) + s(Twi, 4) + s(Elevation, 4) + s(Tpi, 4) + s(Slope, 4)

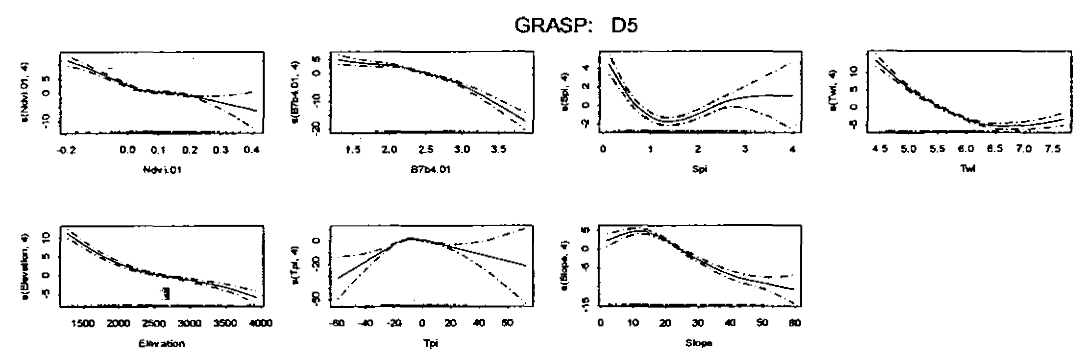


Figure 4.39: Response of 2001 Land degradation (D5) against predictor variables

Predictor's Contribution:

The contribution of explanatory variables in terms of change in residual deviance, when they are dropped from the model has been presented as Table 4.28.

Table 4.28: analysis of deviance for dropping of terms in 2001 D5 model

Dropped term	d.f. Residual	Δ Residual Deviance	d.f.	Δ Deviance	P(>|Chi|)
			191.36	8.24	0.05
s(Curv, 4)	3.58	0.53	194.95	8.78	0.95
s(Aspect, 4)	3.83	0.67	198.78	9.45	0.94
s(Profile, 4)	4.26	3.61	203.05	13.07	0.50
s(Plan, 4)	4.07	5.85	207.13	18.93	0.21
s(Slf, 4)	3.46	4.44	210.59	23.37	0.27
s(Swir.01, 4)	3.95	5.91	214.55	29.28	0.20

ANOVA for the selected terms in the model are shown as Table 4.29.

Table 4.29: ANOVA for the selected terms in 2001 D5 model

	Variables	Df	Deviance	Pr(Chi)
[1,]	-s(Ndvi.01, 4)	-3.76	-18.46	0.00
[2,]	-s(B7b4.01, 4)	-3.99	-22.98	0.00
[3,]	-s(Spi, 4)	-4.03	-14.60	0.02
[4,]	-s(Twi, 4)	-3.70	-19.51	0.00
[5,]	-s(Elevation, 4)	-3.92	-33.25	9.65
[6,]	-s(Tpi, 4)	-4.25	-27.37	2.20
[7,]	-s(Slope, 4)	-3.73	-19.63	0.001

The contribution of the predictors in terms of drop, alone and model contribution has been documented in Table 4.30.

Table 4.30: ANOVA for the drop contribution of selected terms in 2001 D5 model

Variables	Drop	alone	model
s(Ndvi.01, 4)	18.46	9.30	17.77
s(B7b4.01, 4)	22.98	8.63	22.14
s(Spi, 4)	14.60	14.02	6.04
s(Twi, 4)	19.51	8.29	18.64
s(Elevation, 4)	33.25	15.25	17.01
s(Tpi, 4)	27.37	8.65	33.53
s(Slope, 4)	19.63	8.80	15.49

The validation parameters for the degradation D2 for year 2001 are as follows (Figure 4.40):

cv ROC auc: 0.825
cv COR: 0.495
ROC auc: 0.996
COR: 0.893

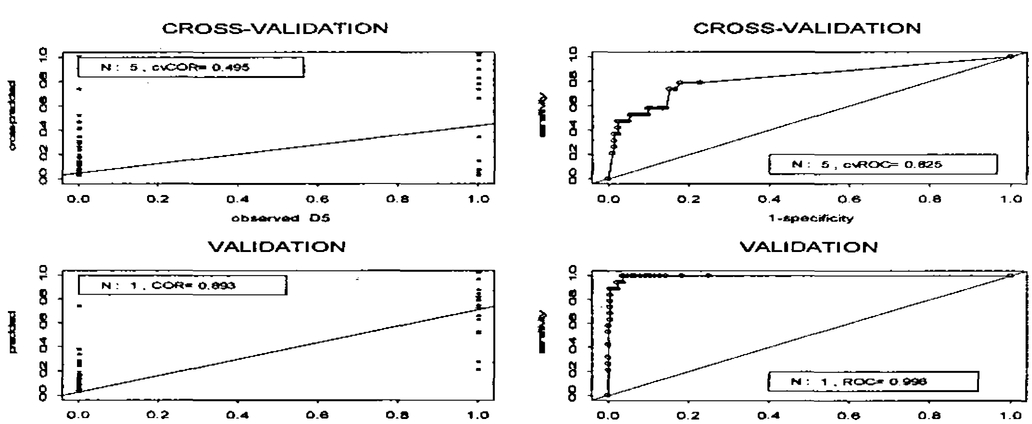


Figure 4.40: Cross-validation of predictive model of land degradation D5 for year 2001.

4.11 Final Land degradation maps and map calculations

After the final models for each of the land degradation, for respective years, were selected and exported as lookup tables in Arc View (version 3.2) to produce land degradation maps (figure 4.41 and 4.42). The maps revealed that the 9.45 hectares of unaffected land has been shrunk in 2001 as compare to 1992 data. The land degradation type D1 (Degraded forests) and D2 (Shrubberies) has increased in 2001 to 1138 and 43.11 hectors respectively. The maps also show that degraded land type D3 (Degraded shrubberies) decreased by 1289.7 hectares which may be reclaimed/recovered or may be shifted in other types of land degradation. It was noticed that degraded land type D4 (No vegetation cover/ sheet erosion) and type D5 (Severe erosion and gully formation are also increased by 107.62 and 9.9 hectors respectively.

A comparison of status of land degradation types between years 1992 and 2001 in study area has been presented in Table 4.31 and respective land degradation maps have been presented as Figures 4.41 and 4.42.

Table 4.31: Comparison of (1992 and 2001) land degradation types in the study area.

S. No	Class Code	Description	1992	2001	Change
0	Nil	Unaffected	1629.36	1619.91	-9.45
1	D1	Degraded forests (logging)	1982.52	3121.02	1138.5
2	D2	Shrubberies	14.04	57.15	43.11
3	D3	Degraded shrubberies	1989.9	700.2	-1289.7
4	D4	No vegetation cover/ sheet erosion	535.05	642.69	107.64
5	D5	Severe erosion and gully formation	100.26	110.16	9.9
		Total	**8243.13**	**8252.13**	

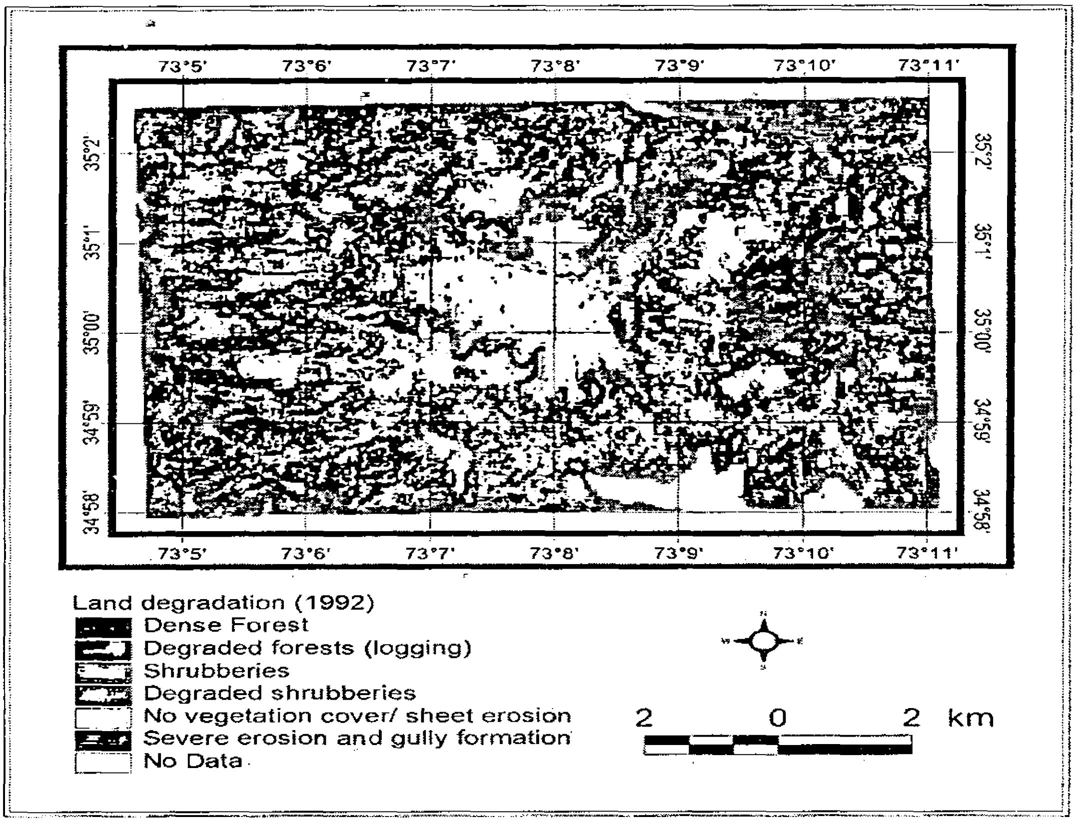


Figure 4.41: Final Land degradation map for the study area (1992)

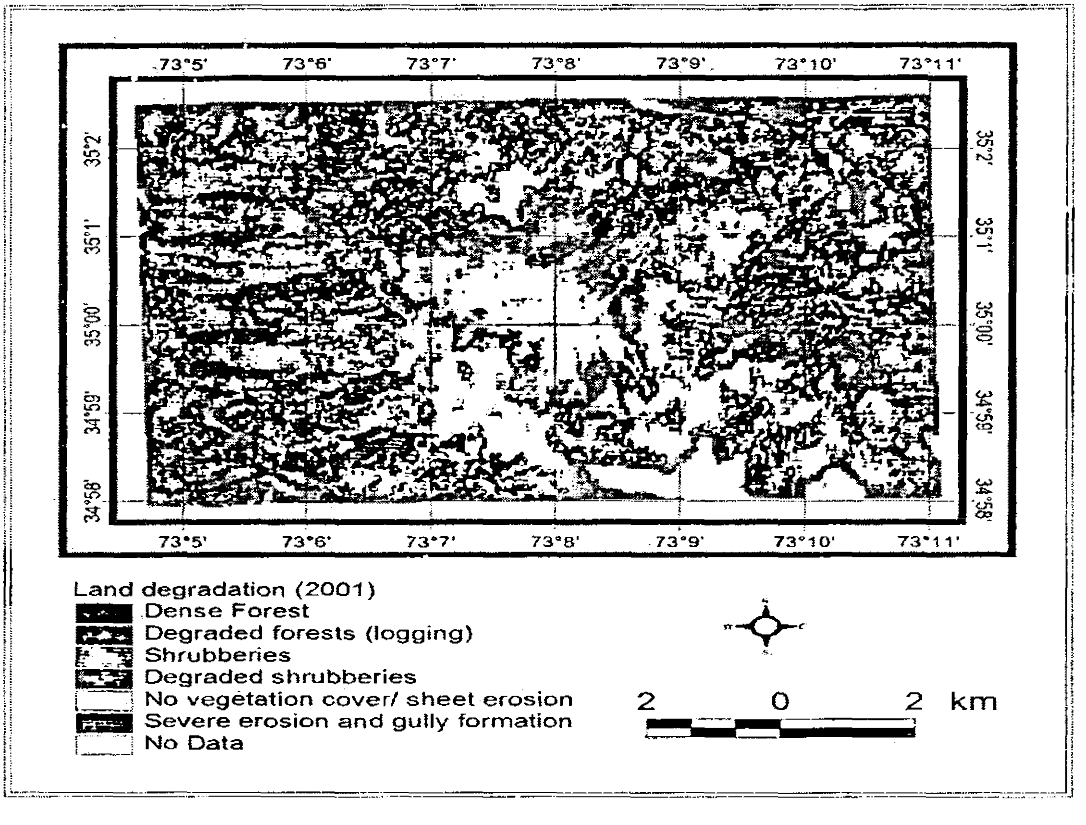


Figure 4.42: Final Land degradation map for the study area (2001)

4.12 Discussion

The present study employed predictive statistical modeling approach to map the land degradation in study area. The model predicts complex information on land degradation using a set of selected predictor variables. The modeling approach used during the current assessment was presence/absence based generalized additive models (GAMs). The GAMs are used extensively in predictive modeling for their strong statistical foundation and ability to realistically model ecological relationships (Austin, 2002; Elith et al., 2006). These models use non-parametric, data-defined smoothers to fit non-linear functions (Yee and Mitchell, 1991). Encouraging results have been achieved from other studies using GAMs for predictive mapping (Leathwick et al., 1998, Lehmann and Austin, 1999.) with respect to fitting and stability of the models as well as accuracy of the predictions at varying spatial resolutions.

Model fitness

The results showed that the fitness of the predictive models for all land degradation types varied as shown by their D^2 statistic. This statistic represents the deviance explained and its lowest values were offered by the models of land degradation type D1 year 1992 (0.40), type D2 year 1992 (0.51), type D5 year 1992 (0.64) and type D1 year 2001 (0.51), which is likely to be a result of low number of observations as well as due to missing possible predictors (Miller and Franklin, 2002). These values further suggest that the models were not 'over fit' by an excess of predictors (Hastie, 2001). The D^2 values are often very low in large binomial data sets, thus during present exercise to predict and map land degradation in the study area, GAM can be identified as robust method, which is in arrangement with many previous studies using GAMs (Zaniewski *et al.*, 2002).

Model Errors, Predictability and Validation

Nevertheless, whenever be the statistical tool be used for the modeling, there is always some disagreement of predicted and actual values. Error assessment and validation are the crucial parts of the modeling process and a variety of approaches are available for that. Fielding and Bell (1997) categorized prediction errors into: "biotic" and "algorithmic". The biotic errors are due to lack of information on biotic

controls within a predictor dataset e.g., grazing and other disturbances, that might be leading to low D^2 for land degradation type D4 year1992 and 2001, etc.
The "algorithmic" errors could be overcome through more sampling to gain a better understanding of processes and responses for better predictions. The sampling methodology employed grad-sect approach (Gillison and Brewer, 1985) that contradicts with unbiased estimation of samples; however, there is no other choice than to stratify the study area, keeping in view its extra ordinary difficult terrain. The complete GIS database was not available when the fieldwork was being carried out so as to improve the procedure through including samples in areas where there is rapid topographic variation (Pfeffer *et al.*, 2003).

The ROC (Receiver Operating Characteristics) depicts the stability and predictability of developed models (Maggini *et al.*, 2006). An ROC statistic of 0.5 corresponds to a random comparison between observed presences–absences and predicted probabilities (Lehmann *et al.* 2002[a]), and ROC statistics greater than 0.7 are considered good, with values over 0.9 as very good (Michel *et al.* 2010).

There was a small difference between simple validation and cross-validation of AUC-values which suggest that there was good model stability (Lehmann *et al.*, 2002; Maggini *et al.* 2006). The level of accuracy achieved by the GRASP methodology implemented during the present study can be regarded as very good (cross-validation ranging from 0.8 - 1.0 ROC and 89.10 - 99.79% of correlation in the models), directly related to the amount of information used to define the relationships between the components (predictors) in the models and land degradation.

Environmental Predictors

The predictive modeling and GIS based mapping of depends upon the availability of spatial information that can be mapped within a GIS (Franklin, 1995; Vogiatzakis and Griffiths, 2006). Austin *et al.* (1995) concluded that it was more important to have the right combination of ecological expertise, local knowledge and statistical skills than using the current "best method". The choice of modeling predictors also depends upon scale at which the predictions are made (Franklin, 1995). The extent of a study area influences the number and relative contribution of the variables used in predictive modeling. Generally the number of significant variables decreases as the scale of the study becomes coarser (Mentemeyer and Box, 1987). At coarse scales abiotic factors take over (e.g. drainage system, hurricane-prone areas etc) that prevail at finer scales (Greig- Smith, 1983; Olsvig-Whitakker *et al.* 1992). The precipitation data has also been utilized in modeling of land degradation studies (Brzeziecki *et al.* 1995; Huntley *et al.* 1995), but not used in present assessment due to its non availability. Other significantly contributing variables to the land degradation models were 'building in floodplains or other sensitive area, altering hydrology (hydrograph), Earthquake or volcanic hazard, dry lands/ droughty soils (Barrow, C. 1991).

Missing Predictors

Winter snow accumulation may influence land degradation as soil types, erosion by snow avalanches, water runoff/ water erosion from snow fall areas etc, can accelerate the land degradation (Burrows 1990; Barrio *et al.*, 1997; Wesche and Ronnenberg, 2004). Other predictors such as soil maps, geomorphic processes (Howard and Mitchell, 1985; Kruckenberg, 2002) would surely increase model performance and predictability.

CHAPTER 5

5.1 Conclusions

The limited knowledge about land degradation, its monitoring and modeling is one of the major constraints for land use planners, policy makers and natural conservatives. The statistical predictive modeling and mapping is particularly useful practice to obtain such information, especially for remote and inaccessible areas of the world where critical datasets are either not available or of poor quality. The study area is no exception to this and present exercise will be a good contribution with respect to spatially explicit information about land degradation and mediating factors such as erosion, forest cutting, over grazing etc.

The present study, in general, would contribute towards understanding the main causes, monitoring and mapping of degraded areas in Pakistan. The resolution of the predicted land degradation maps is ~30×30 metres and this will provide a widely applicable approach since the predictor datasets used during this study were extracted from the sources that are available free of charge worldwide. These predictive models can provide a basis for land degradation monitoring and mapping, and facilitate decision makers and land use planners for effective land management.

5.2 Recommendations

1. *Policies:* Appropriate national policies and programms should be formulated and implemented to reduce land degradation. And there should be proper mechanism for the monitoring and evaluation of these policies and programms.
2. *GIS and RS techniques:* The application of GIS and remote sensing techniques has helped in the acquisition of useful information and in the identification of land degradation types and severity. Government should establish RS and GIS labs at national and regional level as to facilitate the researchers and students to acquire precise and accurate data on land degradation to support the decision makers.
3. *Watershed management:* The government departments such as WAPDA, forest department and national and international NGOs should initiate watershed project in the areas like Palas Valley which is more water erosion prone. These types of projects can control the water erosion and ultimately

land degradation. The government and NGOs should also motivate and encourage the local communities' participation in these types of projects.

4. *Engineering Measures:* Land degradation in the form of land sliding can be mitigated by engineering measures so that the resulting damages can be minimized. Depending on topography, geology, ground water and other condition the engineering measures may be surface drainage, pile works, anchor works, gabion wall and retaining walls etc.
5. *Soil Bio-engineering Techniques:* The soil on the landslide is loose and without any vegetation cover. Planting on such loose soil on steep slops is not successful because the planted seedlings at the head of the landslide are uprooted and seedlings planted at the toe of the landslides are buried with moving mass from above. Some engineering structures are needed for temporary fixing the loose soil on the slide before a successful plantation is established. The soil bio-engineering is the use of living plant material to do some engineering work. Brush layering, hedge layering, brush wattles, brush wood fences and brush wood check dams etc.
6. *Afforestaton and Reforestation:* The most important treatment for the control of land degradation is aforestation and reforestation. The role of the trees is very important in the stabilizing the land sliding/land degradation on steep slops. Due to their high evapo-transpiration components, forests keep the soil dry and do not allow the soil to reach the saturation point. The surface root system, have soil binding quality. The anchoring role of the root system is quite useful in resisting the mass movement.
7. *Slope stabilization through grass cover:* The uses of grasses and leguminous cover crop are common practice and effective measure for the control and protection of land degradation. Grasses is quite effective in covering the soil and protecting it from wind and water erosion. Dry seeding, hay seeding, hydro seeding, tufting etc are the different methods of this technique.

References

Amissah-Arthur et al., 2000. Assessing farmland dynamics and land degradation on Sahelian landscapes using remotely sensed and socioeconomic data. International Journal of Geographical Information Science 14: 583–599.

Barber, R. .1984. "*An assessment of the dominant soil degradation processes in the Ethiopian highlands; their impact and hazards.*23 LUPRD, MoA and FAO.

Barrow CJ. .1991. Land Degradation: Development and Breakdown of Terrestrial Environments. Cambridge University Press: Cambridge; 295 p.

De Jong, S. M. 1994. Global desertification dimensions and costs. In: *Degradation and Restoration of Arid Lands*, ed. H.E. Dregne. Lubbock: Texas Technical University.

Dwivedi, R. et al., .1997. The Inventory and Monitoring of Eroded Lands Using Remote Sensing Data. *International Journal of Remote Sensing*, 18.1., 109-119.

Eswaran, H. .1993. Soil resilience and sustainable land management in the context of Agenda 21. In: Soil Resilience and Sustainable Land Use, eds. D.J Greenland and I. Szabolcs, 21–32. Wallingford: CABI.

Eswaran, H.et al., 2001. Land Degradation; An Overview. In: Second International Conference on Land Degradation and Desertification. Oxford Press, Khon kaen, Thailand.

Fairhead J and Scoones I .2005. Local knowledge and the social shaping of soil investments: critical perspectives on the assessment of soil degradation in Africa. Land Use Policy 22:33–41

FAO .1979. A provisional methodology for soil degradation assessment, FAO, Rome.

Gisladottir, G. and Stocking, M.A. .2005. Land degradation control and its global environmental benefits. In Land Degradation and Development 16:99-112

Hellden, U. and Stern, M., 1980. Monitoring land degradation in southern Tunisia: a test of Landsat imagery and digital data. IAFHE RSL Research Report, Remote Sensing Laboratory, Institute of Agriculture Forestry and Home Economics, University of Minnesota, 48.42.

Hill, J. et al., 1995a. Land degradation, soil erosion and desertification monitoring in Mediterranean ecosystems. Remote Sensing Reviews, 12.1-2., 107-130.

Interim Secretariat .1994. United Nations Convention to Combat Desertification. Interim Secretariat: Geneva.

Kimpe, C.R and Warkentin, B.P.1998. "Soil functions and the future of natural resources. Towards sustainable land use. Furthering co-operation between people and institutuions. Vol. 1 Advance in geoecology, 31, 3-10.

Lal, R. and Stewart, B. A. 1985. Soil Degradation: A Global Threat. In: Soil Degradation, Vol. 2 .Ed. by R. Lal and B. A. Stewart., pp. xiii-xvii. Springer-Verlag, New York. Advances in Soil Science.

Lal, R. 1987. Response of maize and cassava to removal of surface soil from an Alfisol in Nigeria. *International Journal of Tropical Agriculture*, 5, 77–92.

Melegy, A.A. 2005. Relationship of environmental geochemistry to soil degradation in Helwan catchment, Egypt. Environ Geol, 524–526

Mitiku, H. et al. 2006, Sustainable Land Management- A new Approach to Soil and Water Conservation in Ethiopia. Mekelle, Ethiopia: Land Resources Management and Environmental Protection Department, Mekelle University; Bern, Switzerland: Center for Development and Environment .CDE. University of Bern, and Swiss National Center of Competence in Research .NCCR. North-South. Pp.269.

Oldeman, et al. 1990. "World map of human induced soil degradation". ISRIC, Wageningen, The Netherlands, UNEP, Nairobi.

Ray, 1994. Impects of land degradation on human, In Land degradation and development 18: 364-368

Scherr, SJ. and Yadav, S. .1996. Land degradation in the developing world Implications for food agriculture, and the environment to 2020. International Food policy research institute Washington, D.C. USA

Sonneveld. BDJS. 2003. Formalizing expert judgements in land degradation assessment: A case study for Ethiopia. Land Degradation & Development 14: 347–361.

Stocking M, Murnaghan N. .2001. Handbook for the Field Assessment of Land Degradation. Earth scan: London.

Stoorvogel, JJ. and Smaling, EMA. .1990. Assessment of soil Nutrient Depletion in Sub-Saharan Africa: 1983-2000. Volume1: Main Report. Report 28, the Winand Staring Center, Wageningen, the Netherlands.

Sujatha, G. et al. 2000. Mapping and monitoring of degraded lands in part of Jaunpur district of Uttar Pradesh using temporal spaceborne multispectral data. International Journal of Remote Sensing 519–531

UNEP. 1994. *Land Degradation in South Asia: Its Severity, Causes and Effects upon the People*. INDP/UNEP/FAO. World Soil Resources Report 78. Rome: FAO.

Wasson, R. 1987, "Detection and measurement of the land degradation process in land degradation –problems and policies, chapter 13, physical and biological aspects of land degradation, university of Cambridge, Melbourne, Australia.

Wessels KJ. Et al. 2004. Assessing the effects of human induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sensing of Environment 91: 47–67.

World Resources Institute. 2000. World Resources 2000-2001. People and Ecosystems: The Fraying Web of Life.

WRI/UNEP/UNDP/World Bank. 1996. World Resources 1996-97. Oxford University Press. New York and London

Zaniewski, A. E., Lehmann, A., & Overton, J. M. (2002). Predicting species spatial distributions using presence-only data: a case study of native New Zealand ferns. *Ecological Modelling, 157*(2-3), 261.

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