Spatial and Temporal Distribution of *Mikania micarantha* Kunth in Chitwan Annapurna Landscape (CHAL) Area with Application of Satellite Imageries

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Tribhuvan University

Submitted by

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Letter of Recommendation

This is to certify that the dissertation work entitled "**Spatial and Temporal Distribution of *Mikania micarantha* Kunth in Chitwan Annapurna Landscape (CHAL) Area with Application of Satellite Imageries**" has been completed by **Ms Srijana Paudel** under our supervision. This entire work was accomplished on the basis of candidate's original research work. To the best of our knowledge, the work has not been submitted to any other academic degree. we hereby recommend for acceptance of this dissertation as a partial fulfillment of the requirement of Masters of Science in Botany at the Institute of Science and Technology, Tribhuvan University, Nepal.

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Declaration

I, Srijana Paudel, hereby declare that this dissertation entitled **"Spatial and Temporal Distribution of *Mikania micrantha* Kunth in Chitwan Annapurna Landscape (CHAL) Area with Application of Satellite Imageries"** is my original work and all other sources of the information used are duly acknowledged. I have not submitted it or any of its part to any other universities for any academic award.

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Abstract

Mikania micrantha is a fast-growing neotropical, and the most problematic terrestrial invasive plant species rapidly invading tropical parts of Nepal. Remote Sensing offers synoptic view for detecting and mapping invasive plant species and record changes in actual and potential distribution across wide region over time period. Knowledge based classification approach was used for mapping *M. micrantha* distribution in Chitwan Annapurna Landscape using multispectral Landsat and WorldView-2 imageries. For Knowledge Based classification, information on elevation, slope, aspect, maximum temperature, minimum temperature, rainfall, unsupervised classified image based on digital number (DN) value NDVI from reflectance and supervised classified image of land use that is suitable for *M. micrantha* were used as variables for rules. Results have shown increasing trend i.e. 0.1%, 0.19 %, 0.65% and 1.39% of total area of CHAL covered by *M. micrantha* in 1990, 2000, 2008 and 2018 respectively in Landsat image. WorldView 2 images of different small patch of Chitwan, Nawalparasi, Chitwan-Makwanpur, Chitwan- Tanahu, Makwanpur (Hetauda) were classified and accuracy assessment was done. WorldView-2 images with high spatial resolution than the Landsat images show higher accuracy. Overall accuracy varied from 68.75% to 76% and 79% to 82.5% in Landsat and WorldView-2 imageries respectively. Kappa coefficient varied between 0.37to 0.52 and 0.49 to 0.65 for Landsat and WorldView-2 imageries, respectively. WorldView-2 imageries of high spatial resolution are more effective than Landsat imageries in delineation of *Mikania micrantha* however Landsat imageries can also be useful in detecting the herbaceous weed.

Keywords: Invasive plant species, Knowledge based classification, Supervised classification, Accuracy assessment

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List of Acronyms and Abbreviations

AVHR	Advanced Very High-Resolution Radiometer
CHAL	Chitwan Annapurna Landscape
DHM	Department of Hydrology and Meteorology
DIP	Digital Image Processing DN: Digital Number
ETM^+	Enhanced Thematic Mapper Plus
GIS	Geographical Information System
GPS	Global Positioning System
IAPS	Invasive Alien Plant Species
IAS	Invasive Alien species
K	Kappa
LANDSAT	Land Observation Resource Satellite
MSS	Multispectral Scanner
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
No.	Number
RS	Remote Sensing
TM	Thematic Mapper
TOA	Top of Atmosphere
UTM	Universal Transverse Mercator
WGS	World Geodetic System
WV2	World View 2

1. INTRODUCTION

1.1 Background

Invasive species are those species that occur outside their natural range, spread rapidly and cause harm to other species, communities, or entire ecosystems and to human well-being. The alien invasive species impact enormously because they harm human health; pose threat to biological diversity, and cause enormous economic losses (Vitousek *et al.*, 1997). Biological invasions are recognized as a major driver of decline of biodiversity and altered ecosystem services worldwide (Pauchard *et al.*, 2009). Invasive species are of great concern because of their wide spreading capacity, high competitiveness and ability to colonization in new environment. The spread of a species in a new range is limited by propagule pressure, abiotic factors and biotic interactions with competitors, enemies and mutualists (Dietz and Edwards, 2006). The list of established introduced species grows annually, as does the number of their significant economic and ecological effects (Vitousek *et al.*, 1997). In Nepal, alien plant species that naturalized in different habitats, 26 species are recognized as invasive aliens plant species (IPAS) (Shrestha, 2016). Among 26 IAPS, four species (*Chromolaena odorata, Eichhornia crassipes, Lantana camara* and *Mikania micrantha*) are included in world's 100 worst invasive species (Lowe *et al.*, 2000). Spread of Invasive species varies spatially and temporarily and since it is the most problematic issue for native biodiversity and ecosystem, there is urgent need for new techniques enabling timely fast and precise monitoring (Humle *et al.*, 2009).

Remote sensing is the field of study to extract information about an object without requiring physical contact (Schott, 1997). This process is done by sensing and recording emitted or reflected energy and then processing, analyzing and applying that information (Sowmya *et al.*, 2017). Since the early 1960s, multispectral airborne and satellite remote sensing technologies have been used as a common source for the remote classification of vegetation (Landgrebe, 1999). Remote sensing provides a wide range of sensor systems including aerial photographs, airborne multi-spectral scanners, satellite imagery, low and high spatial and spectral resolution and ground-based spectrometer measurements (Joshi *et al.*, 2004). Multispectral systems commonly collect data in three to six spectral bands in a single observation from the visible and near-infrared region of the electromagnetic spectrum. The Multispectral satellite sensor provides digital raster images, that allow us to apply Digital Image Processing (DIP) techniques to develop thematic maps of landuse/landcover classes which are essential in many remote sensing applications like forestry, agriculture, environmental studies, weather forecasting, ocean studies, archeological studies etc. There are various sensors used that differ in spatial resolution, spectral resolution, spatial extent and temporal resolution (Bradley, 2014). On the basis of spectral resolution, two broad categories of sensors are utilized for IAPs detection that are multispectral and hyperspectral sensors. Effective use of Remote Sensing techniques for vegetation mapping and monitoring is a function of scale, resolution, season of imagery, kind of vegetation, phenology of vegetation, sensor and spectral sensitivity processing of the remote sensing product, and speed and precision of transfer of information into a map product (Jarman *et al.*, 1983). Spatial patterns of invasion can be predicted by linking current presence and absence of invasive species to spatially explicit predictor variables, like land use, geomorphology, and topography, using geographic information systems (Store and Kangas, 2001). Land use and land form characteristics related to increased probability of invasive species can then be used to inform conservation and management efforts (Bradley and Mustard, 2006).

The use of multispectral imagery offers the opportunity for automated image processing, access to recent historical data for time series analysis, and large spatial coverage. Some studies have had success even using coarse resolution (1.1 km pixel) advanced very high-resolution radiometer (AVHRR) imagery to identify weed (Underwood, 2003). The weed species distinguished from grassland using the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), due to differences in phenological activity. At higher spatial and spectral resolution Landsat 5 thematic mapper (TM) imagery (30 m pixels) was used to predict the distribution of dyers wood (*Isatis tinctoria*). Known infestations were mapped and correlated with brightness, greenness and wetness value derived from the reflectance data. However, the spatial resolution of TM, like AVHRR imagery, mean that invasive populations can often only be detected after they become dense and widespread (Carson *et al.*, 1995).

Plant species invasion can potentially be detected directly by remotely sensed data based on the reflectance properties of vegetation in certain portions of the electromagnetic spectrum (called wavelength windows) (Rocchini *et al.*, 2015). Multispectral sensors at a high spatial resolution have been used to detect tree and shrub invasive species. In general, identifying individual species reliably using satellite-based and aerial imagery is challenging due to the difficulties of choosing and detecting optimal spectral wavelengths to differentiate the target species from others (which may only be possible at certain times of year), and controlling for the effects of vegetation structural characteristics (Chopping, 2011) as well as identifying spatial associations between invasive and closely-related native species (Call and Nilsen, 2003). Remote sensing provides a great opportunity to develop predictive models for invasion risk analysis and to draft early detection strategies.

1.2 Justification of the study

Invasive plants are exotic species that threaten native species, and ecosystems, and cause economic damage. Invasive alien plant species are major threat to the biodiversity of the world including Nepal. Although some documentation work as well as impact analysis of a few species are done but the exact distribution of invasive alien species with the application of satellite images is still new in the context of Nepal. The geographical extension of Chitwan Annapurna Landscape (CHAL) area with intensive coverage of invasive species is known to below 2500 m in the southern face of the Himalayas. CHAL is a region of scenic beauty with the rain shadow of the trans-Himalayan area and snowcapped mountains of Annapurna, Manaslu, and Langtang in the north. The terrain descends southwards to the mid-hills, Churia range, and the flat lowlands of the Terai and part of CHAL falls within the Sacred Himalayan Landscape (SHL).

Remote sensing technology has received considerable interest in the field of biological invasion in the recent years. Techniques such as remote sensing offer significant opportunities for providing timely information on invasions of non-native species into native habitats (Underwood *et al.,* 2003). It is a tool offering well-documented advantages including a synoptic view, multispectral data, multi-temporal coverage and cost effectiveness. Therefore, application of satellite imageries might become a new technique to assess the alien invasive plant species.

1.3 Research questions

This research aimed to answer following questions:

- What is the distribution pattern of invasive weed *Mikania micrantha* in Chitwan Annapurna Landscape since 1990?
- Which is the best satellite data for mapping of invasive weed *Mikania micrantha* among Landsat and World view 2?

1.4 Objectives

General objective

- To access spatial and temporal distribution of *Mikania micrantha* in Chitwan Annapurna Landscape (CHAL), Nepal using satellite imageries.

Specific objectives

Following are the specific objectives of this study:

- To compare changes in distribution of *Mikania micrantha* between 1990 to 2018.
- To compare distribution and accuracy of Landsat and World view 2 imageries.

1.5 Limitations

The limitations of this study are:

- Presence of cloud cover and other atmospheric factor in satellite imageries there may be chance of fluctuation in data.
- Detection of species that are present under canopy.
- Sampling is mostly focused on road side.
- Landsat imageries of 3 years window were downloaded as lack of imageries of certain year.

2. LITERATURE REVIEW

2.1 Biological invasion

Biological invasions have been identified as a major non-climatic driver of global change (Beck *et al.*, 2008). Invasion is a dynamic process that can be fast, and after the species has spread over the landscape and achieved a high abundance it can be difficult or even impossible to stop or slow down the invasion (Rejmánek and Pitcairn, 2002; Pluess *et al.*, 2012). Invasive species can profoundly modify the structure and function of invaded ecosystems, alter biotic interactions and homogenize diverse plant and animal communities at large spatial scales, ultimately resulting in a loss of genetic, species and ecosystem diversity (Qian and Ricklefs, 2006). Along with other drivers of ecosystem degradation such as habitat change and exploitation, environmental pollution, climate change, and associated effects, including the loss of keystone species, loss of pollinators and altered ecosystem functioning, biological invasions contribute to the decline of biodiversity worldwide (Millinium, 2005; McGoech *et al.*, 2010). Plant invasions occur across a wide range of bioclimatic conditions and spreading of non-native plants often depends on humans. Human activities such as international trade and travel promote biological invasions by accidentally or deliberately dispersing species outside their native biogeographical ranges (Alpert, 2006). Biological invasion is mainly influenced by three factors that are propagule pressure, biological traits and invisibility of community (Londsale, 1999). Many invasive alien plant species have different life history trait that facilitate the invasion process; they are smaller seed size, allelopathic substances, vegetative reproduction, persistent seed bank, phenotypic plasticity and successive colonizer of the disturbed habitat (Grice, 2006). Invasive species are now viewed as a significant component of global change and have become a serious threat to natural communities (Mack *et al.*, 2000; Pyšek and Richardson, 2010). Early and fast detection is needed to make the management cost-effective (Pyˇsek and Hulme, 2005).

2.2 Invasive alien plant species in Nepal

There are over 166 species of naturalized alien plant species (Tiwari *et al.*, 2005) in Nepal. Among them Tiwari *et al.* (2005) categorized 21 naturalized species as invasive in Nepal. In addition to these, four naturalized species *Ageratum conyzoides*, *Erigeron karvinskianus, Galinsoga quadriradiata* and *Spermacoce alata* had been found to be invasive in Nepal by Shrestha, 2016 and Shrestha *et al.*, 2017 and recently *Spergula arvensis* had been added to the list of invasive species. Among them four species (*Chromolaena odorata, Eichhornia crassipes, Lantana camara* and *Mikania micrantha*) are included in world's 100 worst invasive species (Lowe *et al.*, 2000). There is high concentration of IAPS on the southern half of the country (which includes Tarai, Siwalik and Mid Hills running east-west) with tropical to subtropical climate (Shrestha, 2016).

2.3 *Mikania micrantha*: Invasive alien plant species

Mikania micrantha is native to Central and South America. It was first spread in Hongkong through sea route at the beginning of last century and from there it reached to the coast of Gaungdong province in 1980s (Zhang *et al.*, 2004). *M. micrantha* was introduced in Taiwan in 1970s for soil conservation and now it invades nurseries, orchards, lawns, plantation and disturbed forests (Zhang *et al.*, 2004). *M. micrantha* also grows in forests, along river and stream, in disturbed places and along roadsides. *M. micrantha* has now also spread in Mauritius, India, Sri Lanka, Banhladesh, south east Asia and Pacific (Deng *et al.*, 2004). It has invaded agricultural lands and plantation crops such as tea, teak, rubber, oil palm in moist tropical forest zones of Asia, particularly South east Asia (Chaudhary, 1972).

Mikania micrantha was first collected from the Jogmai-Ragapani area of Ilam district in east Nepal in 1963 by H. Hara, H. Kanai, S. Kurosawa, G. Muratta, M. Togashi and T. Tuyama (KATH) a Japanese team scientifically reported in 1966 in the Flora of Eastern Nepal (Tiwari *et al.*, 2005). The weed has been creating a serious threat in the protected areas such as Chitwan National Park and the Koshi Tappu Wildlife Reserve by suppressing the growth of native plants and preventing the regenerations of other (Siwakoti, 2007). *M. micrantha* highly invadedi in the *Dalbegia sissoo* tree in afforested land in Chitwan National Park, Nepal and the prevalent effect was observed in *Bombax ceiba* (Sapkota, 2007).

2.4 Application of remote sensing

Traditional ground-based methods for gathering distribution information are expensive and tine consuming; thus, research and management activities are often constrained by financial and/or logistical costs (Anderson *et al.*, 2003; Lawrence *et al.*, 2006). Remote sensing can provide information on the spatial and temporal distributions of plant populations (Kerr and Ostrovsky, 2003; Shaw, 2005) in an efficient and cost-effective way (Rew *et al.*, 2005). The era of global digital imagery began in 1972 when, for the first time, repeated opportunities for synoptic views of entire continents became possible. Since that time, satellite instruments have had widespread use for land cover and vegetation mapping. Historical very high spatial resolution (VHR) aerial photography provides an excellent source of information on changing landscapes over time and under certain circumstances (appropriate time of acquisition, good recognizability of target, good time series) it can be used for studying invasion process in detail (Mullerova *et al.*, 2013). Multispectral airborne and satellite systems have been employed for gathering data in the fields of agriculture and food production, geology, oil and mineral exploration, geography and urban to non-urban localities (Landgrebe, 1999). The advantage of using satellite remote sensing systems was to provide both the synoptic view space provides and the economies of scale, since data over large areas could be gathered quickly and economically from such platforms (Landgrebe, 1999).

Multispectral remote sensing allows for the discrimination of different types of vegetation, rocks and soils, clear and turbid water, and selected man-made materials (Smith *et al.*, 1990). Multispectral remote sensing technologies, collect data from three to six spectral bands from the visible and near-infrared region of the electromagnetic spectrum. The fewer number of spectral categorization of the reflected and emitted energy from the earth is the primary limiting factor of multispectral sensors. Over the past 2 decades, the development of airborne and satellite hyperspectral sensor technologies has overcome the limitations of multispectral sensors (Govender *et al.*, 2008). Although hyperspectral data are very rich in information, processing the hyperspectral data poses several challenges regarding computational requirements, information redundancy removal, relevant information identification, and modeling accuracy (Bajcsy and Groves, 2004).

2.5 Remote sensing of vegetation

Temperate landscapes offer a more manageable location for such studies, with a relatively small number of habitat types, and within each type, a greater predominance of a few, dominant species. The tropics on the other hand offer a challenge of an altogether greater magnitude, with far greater numbers of landscapes, habitats, and species, distributed across a variety of stages of growth and succession, and with far more complex canopy structures (Nagendra, 2001). Remote Sensing of herb species is possible only if the data provided enough spectral and/or spatial detail, the species is distinct from surrounding species and background, forms dense and uniform stands and/or is large enough to be detected (Müllerová *et al.*, 2005; Peterson, 2005; Bradley and Mustard, 2006; Jones *et al.*, 2011).

Remotely sensed variables, like the normalized difference vegetation index (NDVI), which is a measure of photosynthetic ‘‘greenness’’ (Tucker and Sellers, 1986), have been used to inform models predicting the occurrence of plant and animal species. Tucker *et al.* (1985) showed that it was possible to use a ‘greenness’ index, specifically the Normalized Difference Vegetation Index (NDVI), from weather satellite data to develop a consistent continental-scale map of actual vegetation, rather than a potential vegetation map based on climate.

2.6 Remote sensing of invasive alien plant species

Phenology plays a significant role in detecting and mapping the spatial distribution of invasive species in remote sensing applications (He *et al.*, 2011). Multi-date remotely sensed images have become very useful in invasion studies. Unique phenology of some invasive species provides a key for spectral differences between targeted species and co-occurring native vegetation (Evangelista *et al.*, 2009).

Huang and Asner (2009) applied remote sensing to alien invasive plant species that provides a means to detect the structure and functional properties of invasive plants of different canopy levels and finally summarize regional studies of biological invasions using remote sensing, discuss the limitations of remote sensing approaches, and highlight current research needs and future directions. Mullerova *et al.* (2013) detected the distribution of *Heracleum mantegazzianum* using remote sensing and tested effects of data resolution and image classification approach on the detection of a model plant species. Object-based image analysis of very high spatial resolution (VHR) data enabled monitoring of *Heracleum mantegazzianum* at high classification accuracies measured by various means, regardless of the spectral resolution of the data provided that the data came from the species flowering period.

Identifying individual species reliably using satellite-based and aerial imagery is challenging due to the difficulties of choosing and detecting optimal spectral wavelengths to differentiate the target species from others (which may only be possible at certain times of year), and as well as identifying spatial associations between invasive and closely-related native species (Call and Nilsen, 2003).

In general, most understory invasive species are hard to detect and map by remote sensing since they are usually hidden by overstory canopy. However, in some cases, a temporal window may exist when a clear phenology difference exists between native overstory species and understory invaders (Somers and Asner, 2012). Wilfong *et al.* (2009) effectively detected the distribution of an understory invasive shrub, Amur honeysuckle (*Lonicera maackii*), in the deciduous forests of south-western Ohio, using phenological difference between Amur honeysuckle andco-occurring native tree species in the canopy. In this case, the invading shrub leaves out earlier in the spring and retains leaves longer in the fall than native deciduous species. Therefore, the best acquisition windows for remote sensing could possibly be the early spring and late fall when native deciduous species are leafless.

The ability to accurately identify the spatial distribution of an invasive exotic plant species would enhance the efficacy of control and management efforts by enabling land managers to more accurately direct eradication programs, develop better predictive models about future dispersal, and coordinate management programs across multiple scales. Furthermore, enhancing our ability to detect plant communities that have been invaded by an exotic species and those that have not will aid research into what characteristics make ecosystems susceptible to invasion by exotic species. The identification of such characteristics has been identified as being of critical importance in the control of invasive species and in mitigating the impacts of exotic species invasion (Hobbs and Humphries,1995).

Wolter *et al.* (1995) used Landsat TM imagery of June 1987 and MSS imagery of October 1980, September 1985, February 1988 and May 1992 to map the Chequamegon National Forest in the U.S. Nineteen forest types were mapped, 11 with single species stands, and 8 with mixed species. Landsat MSS imagery was acquired to correspond with leaf flush stages of trembling aspen and black ash, and leaf-off of oak and tamarack. Landsat TM data was acquired for the period in which all species were in leaf flush. The TM image was used to separate forest from nonforest, and to stratify forest into broad categories of conifer, hardwood and mixed.

2.7 Research gap

Mikania micrantha is included in world's 100 worst invasive species (Lowe *et al.*, 2000), and is one of the 6 worst invasive alien plant species that poses the highest risk to native ecosystems in Nepal (Tiwari *et al.*, 2005). The weed has been rapidly invading the different tropical ecosystems of Nepal (forest, cropland, grassland, and wetland) by suppressing the growth of native plants and preventing the regenerations of other plants due to its high dispersal ability and adaptability to colonize in new habitat and difficult to control if once established. Remotely sensed data are cost-effective and permit fast and frequent mapping. It also presents valuable information for understanding the natural and man-made environments through quantifying vegetation cover from local to global scales at a given time point or over a continuous period. The technology of remote sensing offers a practical and economical means to study vegetation cover changes, especially over large areas (Langley *et al.*, 2001). But to date not a such type of research of remote sensing of invasive weed has not conducted in Nepal. So, this study intends to find out the distribution of invasive weed *Mikania micrantha* in CHAL area. The results from this study might be helpful for providing a great opportunity to develop predictive models for invasion risk analysis and to draft early detection strategies (Vanderlinder *et al.*, 2014).

3. MATERIALS AND METHODS

3.1 Study species

Mikania micrantha Kunth (Family Asteraceae) is an extremely fast-growing perennial vine and native to Central and South America. It is commonly known as a mile-a-minute-weed and locally known as a lahare banmara. It is included in world's 100 worst invasive species (Lowe *et al.*, 2000), and is one of the 6 worst invasive alien plant species in Nepal (Tiwari *et al.*, 2005). It is characterized by the capitulum of four flowers (disc florets) surrounded by four phyllaris, and is a multi-branched, perennial, scrambling vine with five ribbed stems, internodes pubescent or glabrous and 7.5-21.5 cm long (Tripathi *et al.*, 2012). The leaves are opposite, cordate or triangular with an acute apex and broad base, 4-13 cm long, inflorescence is axillary, panicled corymbs; capitulum is cylindrical and 1.5 mm in diameter. It has cushion like growth in open areas whereas in forests, it grows more than 20 m high and forms a heavy covering over the tree canopy (Zhang *et al.*, 2004). The weed has a vigorous vegetative and sexual reproductive capacity (Swarmy and Ramakrishnan, 1987). Seeds are dispersed long distances by wind and the plant can grow vegetatively from very small sections of stem and the weed rapidly forms a dense cover of entangled stems bearing many leaves (Holm *et al.,* 1977).

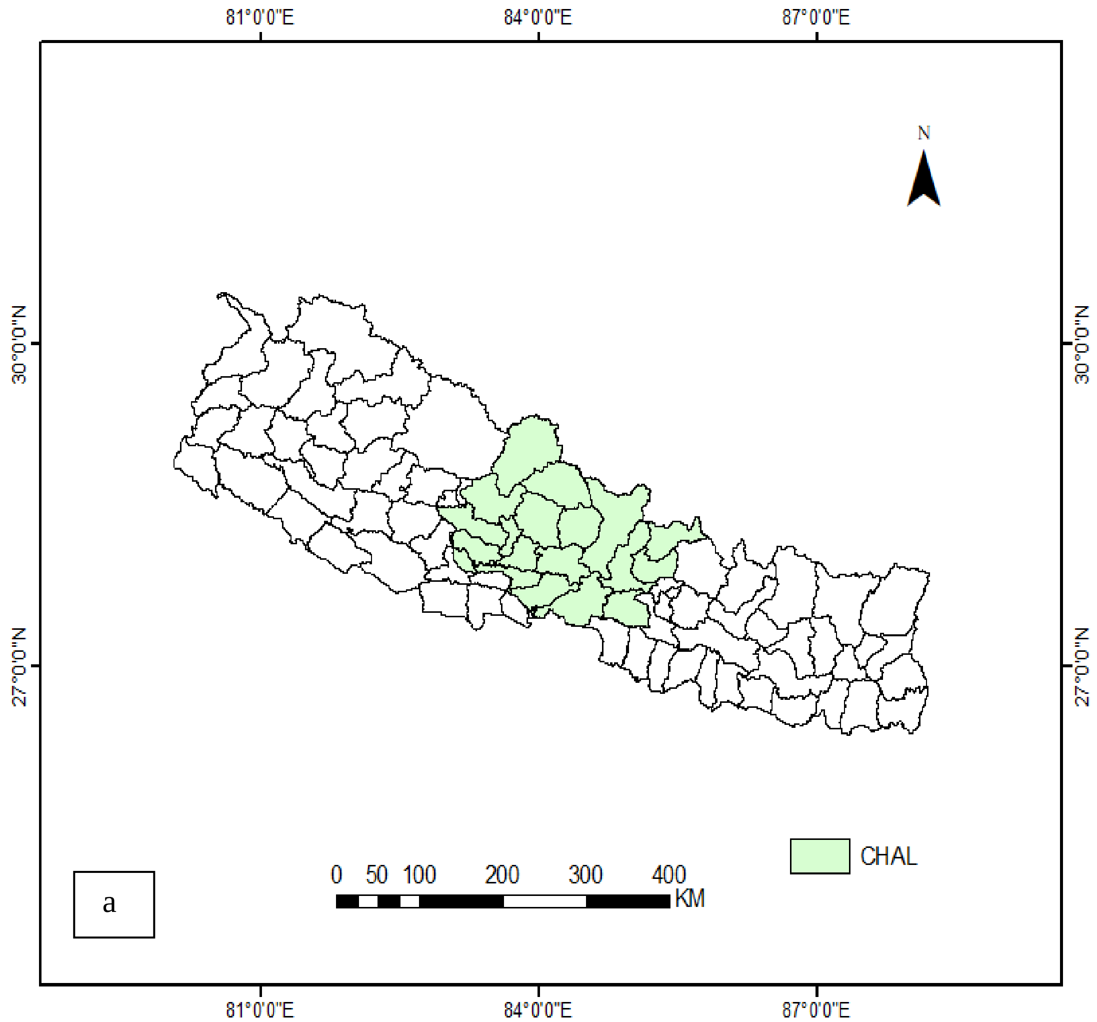
Mikania micrantha grows in orchards, forests, along rivers and streams in disturbed areas, and along roadsides. *M. micrantha* has spread extensively in the last few decades. Apart from the invasive characteristics of the invasive plant itself, this has been due to (i) a lack of natural enemies, (ii) a wide range of invasive habitats, and (iii) increased human disturbance associated with recent economic growth. The weed has been creating a serious threat by suppressing the growth of native plants and preventing the regenerations of other plants due to its high dispersal ability and adaptability to colonize in new habitat and difficult to control if once established (Siwakoti, 2007).

3.2 Study area

3.2.1 Geographic location

The study was carried out in Chitwan Annapurna Landscape (CHAL), Central Nepal. It ranges from Chitwan National Park in the south to Manaslu, Langtang and

Annapurna in the north. The CHAL covers 32,090 km^2, which is almost 22% of Nepal's land area in 19 districts (Arghakhanchi, Gulmi, Palpa, Baglung, Parbat, Myagdi, Mustang, Syangja, Kaski, Tanahun, Lamjung, Gorkha, Manang, Rasuwa, Nuwakot, Dhading, Nawalparasi, Chitwan and Makwanpur) (Fig. 1). The CHAL extends from the tropical lowland Terai (200 m above sea level) to alpine high mountains (above, 8000 m). The CHAL includes six protected areas; three national parks (Langtang, Chitwan and Shivpuri-Nagarjun and Parsa, and two conservation areas (Annapurna and Manaslu).



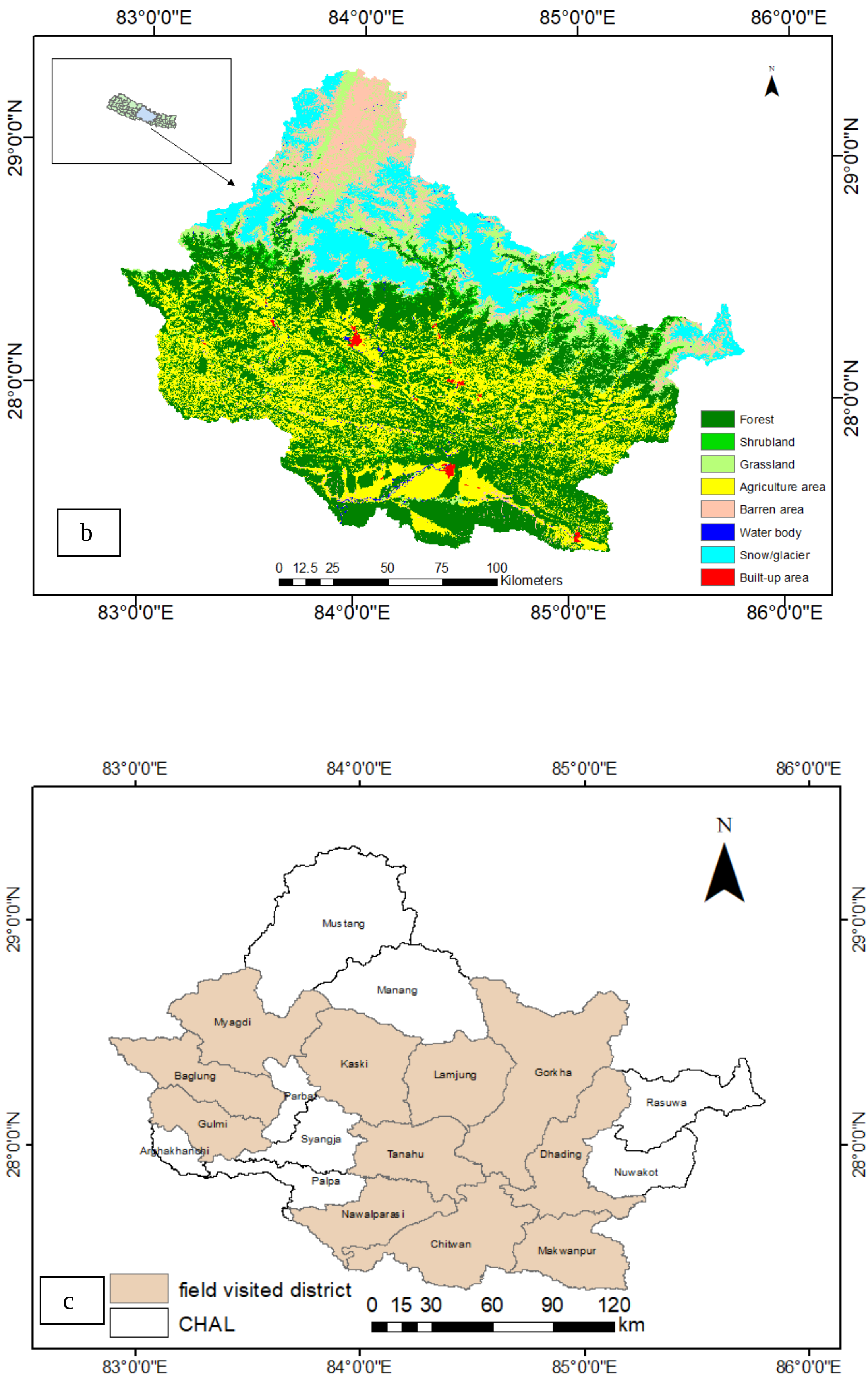


Figure 1: Study area: (a) Map of Nepal showing Chitwan Annapurna Landscape, (b) Field visited districts of CHAL and (c) Landuse map of CHAL

3.2.2 Climate

Chitwan Annapurna Landscape has a variety of climates ranging from cold alpine semi-desert (in the trans- Himalayan zone of upper Mustang), cool and warm in middle mountains and sub-tropical humid in the lowlands of the Siwaliks (WECS, 2011). CHAL has four distinct seasons: pre-monsoon (March-May), monsoon (June-September), post-monsoon (October-November), and winter (December-February). The average reported minimum and maximum temperatures are 4.9°C and 39.9°C. The mean temperature is above 25°C in the Siwaliks, about 20°C in the Middle hills, and between 10°C to 20°C in the high mountains. The average annual rainfall ranges from 165 mm at Lomanthang (Mustang) to 5,244 mm at Lumle, in Kaski, which is the highest rainfall in the country. Nearly (80%) of the total annual precipitation occurs during the monsoon season from June to September (Practical Action, 2009).

3.2.3 Biodiversity and vegetation

The CHAL area is rich in biodiversity with several flora and fauna. More than 3034 plant species were recorded from CHAL (Biodiversity Profile Project, 1995) and more than 100 species were endemic to Nepal in CHAL area. The tropical forest is mainly dominated by *Shorea robusta*, *Dalbergia sissoo, Terminalia* species, *Adina cordifolia*, *Lagerstroemia parviflora*, *Bombax ceiba*, *Albizia* species, *Eugenia jambolana*, *Anogeissus latifolia*, and *Acacia catechu* etc. The subtropical forests were dominated by *Schima wallichii* and *Castanopsis indica*, mixed with *Cedrella toona*, *Alnus nepalensis* and *Pinus roxburghii*. Temperate forests between 2,000 and 3,000 m are mainly comprised of lower temperate mixed broad-leaved forests dominated by *Quercus lamellosa*, *Castanopsis tribuloides,* and species of Lauraceae; and upper temperate broadleaved forests of *Quercus semecarpifolia*, *Acer* species, and *Rhododendron* species. Temperate conifer forests are dominated by *Pinus wallichiana*, *Abies spectabilis* and *Tsuga dumosa*, with *Larix himalaica* forest. Subalpine forests are mainly comprised of *Abies spectabilis*, *Betula utilis*, and *Rhododendron* species. The alpine ecosystems above the treeline include scrub and grasslands. Most of the alpine grasslands are rangelands, grazed by domestic livestock. The alpine scrub comprises various associations of *Juniperus* and *Rhododendron* species.

3.2.4 Population

In 2011, the total human population of CHAL was about 4.3 million and increasing at an average annual rate of (0.41%) over the last decade (CBS, 2011). The average family size was 4.21, which is lower than Nepal's average of 4.7. Twelve of the nineteen districts in CHAL had negative population growth in the last decade: Dhading, Nuwakot, Rasuwa, Lamjung, Gorkha, Manang, Mustang, Syangja, Parbat, Myagdi, Gulmi, and Argakhanchi. The main reason is likely out-migration from mountains to valleys and inner Terai in search of better livelihood opportunities.

3.2.5 Landuse pattern

The CHAL has diverse land use types. Forest covers the largest portion of CHAL, followed by agriculture, sand/bare land, snow/ice covered areas, grasslands, and alpine meadow (Table 1) (WWF, 2013).

Table 1: Areas with different landuse/landcover in 1990, 2000 and 2010

Land use class	1990		2000		2010	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Forest	1,133,621	35.4	1,137,718	35.5	1,136,709	35.6
Alpine meadow/scrub	275,518	8.6	252,863	7.9	260,682	8.1
Grasslands	329,662	10.3	334,084	10.4	276,634	8.6
Agriculture	663,505	20.7	675,475,471	21.1	677,456	21.1
Snow/ice	286,467	8.9	469,907	14.7	304,150	9.5
Sand/bare soil	484,108	15.1	303,838	9.4	517,110	16.1
Water	32,829	1.0	32,829	1.0	32,696	1.0
Total	3,205,710	100	3,206,710	100	3,205,437	100

3.3 Nature and sources of data and software

3.3.1 Primary data

The primary data was obtained by noting the Global Positioning System (GPS) location of sample points in the study area. The coordinates of the place where the *Mikania micrantha* occur were recorded using hand held GPS. All associated species where the *M. micrantha* grows was recorded. Phenology of this species as well as that of associated species were also recorded. Similarly, slope, aspect were also noted by using clinometer.

3.3.2 Secondary data

The distribution of invasive species *Mikania micrantha* in the CHAL area was intended for study by using different multispectral satellite imageries (ETM Landsat

TM/ ETM, and World view 2). Landsat TM/ETM Imageries available in the archives of different specified years of study were downloaded from the archives. Landsat 8 OLI/TIRS data was used for mapping of *Mikania micrantha* for 2018. Landsat 7 ETM data was used for 2010 and 2000 and Landsat 5 TM Data was used for 1990. All the Landsat data used were of 30 m spatial resolution. Detailed information about Landsat data are given in Table 2. Due to cloud cover and limitation of optical sensor that all required months imageries were not available, data were taken from 2-3 years interval/buffer. Aster Dem data were also freely downloaded from archives. World view 2 imageries of resolution 2 m × 2 m of different parts of CHAL Area were purchased from the authentic sources. World view 2 imageries of Chitwan and Nawalparasi districts were used for mapping of weed (Table 2). Similarly, Toposheet maps were collected from Department of Survey and Climatic data were provided by Department of Hydrology and Meteorology.

For the Literature Review, the secondary data were collected from different articles about the mapping of vegetation and invasive species as well as studied conducted on the basis of Remote Sensing. Similarly, various books, articles published on national and international journal, reports, newspapers and documents from related literature have also been adequately consulted for relevant information.

Table 2: Data used for mapping of *Mikania micrantha* with source and acquisition date

Data source	**Year**	**Path/row**	**Acquisition date**
Landsat 5		142/040	1992/11/15
	1990	142/041	1992/11/15
		143/040	1992/11/06
		141/041	1992/11/08
		142/040	1991/11/29
Landsat 7	2000	141/040	1999/10/27
		141/041	1999/10/27
		142/041	1999/12/05
		143/040	1999/12/28
		142/040	1999/12/05
Landsat 7		142/041	2009/10/29
	2010	143/041	2009/11/05
		142/040	2009/10/29
		141/040	2009/11/23
		143/040	2009/11/05
		141/041	2009/11/23

Landsat 8	2018	141/041	2018/06/25
		141/040	2018/06/25
		142/040	2017/06/13
		142/041	2016/06/10
		143/040	2017/06/04
World view 2 (Chitwan)	2018		2018/1/22
World view 2 (Nawalparasi)	2018		2017/12/05

3.3.3 Software used

ArcGIS 10.3 and Erdas Imagine 2014 were software that had been used for mapping of *Mikania micrantha.* In ArcGIS unsupervised and supervised classification were performed. ArcGIS was used for GIS operations and map formation. Similarly, various variable that were used in knowledge-based classification (slope, aspect, elevation, Normalized Difference Vegetation Index (NDVI), Digital Number (DN) value, climatic data) were calculated in ArcGIS. Accuracy assessment with field verification points was done in ArcGIS. Whereas, Knowledge base classification was performed in ERDAS imagine. General process of methods is shown in flow diagram (Fig. 2).

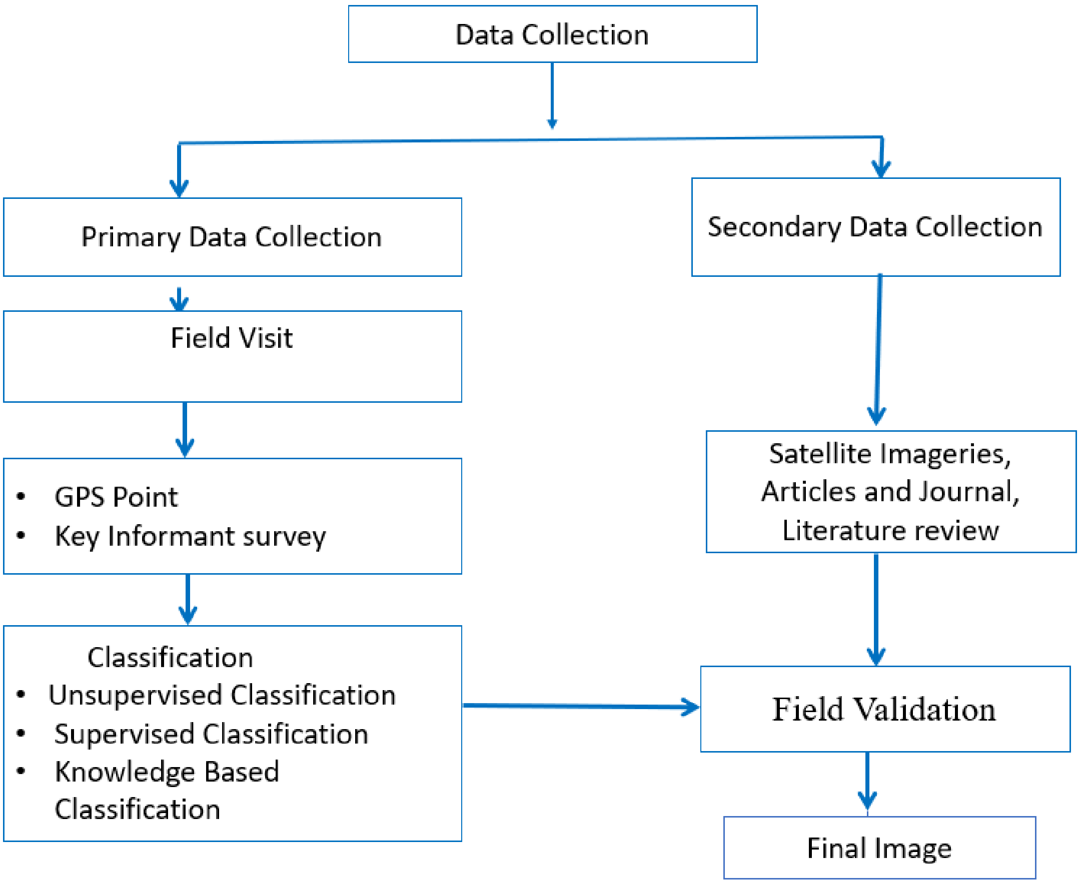


Figure 2: Flow diagram of methods in general

3.4 Image preprocessing

All the data acquired were further subjected to image processing. After downloading required data and purchase data, various image preprocessing techniques were applied.

3.4.1 Layer stacking and mosaicking satellite image

Layer stacking is the process of “stacking” multiple images from the same area together in order to form a multilayer image. For layer stacking, ortho-rectified and cloud-free images of the multispectral scanner (MSS) and Thematic Mapper (TM) with individual bands extracted and stacked respective row and path spectral bands. CHAL area (95%) is present in zone 44 of Universal Transverse Mercator (UTM) coordinate system, World Geodetic System (WGS) 84.

Mosaicking is the process of combining multiple, individual image into a single scene. Five individual layer stacked image were mosaicked into a single scene of CHAL and required boundary was clipped from the shape file of CHAL.

3.4.2 Image enhancement

Image enhancement is the technique by which the low contrast of satellite images is improved to make the image more interpretable and it improve the visual impact of remotely sensed data. It was carried out through histogram equalization and performed in ERDAS Imagine. The histogram equalization technique is a non-linear stretch. In this method, the DN values are redistributed on the basis of their frequency. More different gray tones are assigned to the frequently occurring DN values of the histogram (Sowmya *et al.*, 2017).

3.5 Normalized difference vegetation (NDVI) calculation

The Normalized Difference Vegetation Index (NDVI) is based on the difference of reflectance in the near-infrared and red bands. It was calculated by using the formula.

NDVI = (NIR-Red)/ (NIR + Red)

Where NIR and RED are the spectral reflectance in the sensor’s near-infrared and red bands, respectively.

For the calculation of NDVI, first of all DN value of Landsat image was converted to the reflectance value. This process was operated on ArcGIS.

3.5.1 Conversion of DN to radiance

For landsat TM data

The formula used in this process is as follows:

$$L_\lambda = ((LMAX_\lambda - LMIN_\lambda)/(QCALMAX - QCALMIN)) * (QCAL - QCALMIN) + LMIN_\lambda$$

Where:

L_λ is the cell value as radiance

QCAL = digital number

$LMIN_\lambda$ = spectral radiance scales to QCALMIN

$LMAX_\lambda$ = spectral radiance scales to QCALMAX

QCALMIN = the minimum quantized calibrated pixel value (typically = 1)

QCALMAX = the maximum quantized calibrated pixel value (typically = 255)

3.5.2 Conversion of radiance to ToA reflectance

$$\rho_\lambda = \pi * L_\lambda * d^2 / ESUN_\lambda * \cos\theta_s$$

Where,

ρ_λ = Unitless plantary reflectance

L_λ= spectral radiance (from earlier step)

d = Earth-Sun distance in astronmoical units

$ESUN_\lambda$ = mean solar exoatmospheric irradiances

θ_s = solar zenith angle

For ETM/OLI sensor data

Reflective band DN's can be converted to TOA reflectance using the rescaling coefficients in the MTL file.The conversion was performed using parameters provided with the metadata file of the Landsat 8 satellite images and the following formula set:

$\rho\lambda' = M\rho Qcal + A\rho$

Where,

$\rho\lambda'$ = ToA planetary spectral reflectance without correction for the solar angle (unitless)

$M\rho$ = Reflectance multiplicative scaling factor for the band

$A\rho$ = Reflectance additive scaling factor for the band

Qcal = L1 pixel value in the DN

This process does not include correction for the solar elevation angle. The following additional formula is used to obtain the true ToA reflectance:

$\rho\lambda = \rho\lambda'/\sin(\Theta_{SE})$

Where,

$\rho\lambda$ = ToA Planetary Reflectance (unitless)

Θ_{SE} = Solar Elevation Angle

After the radiometric calibration process, the ToA images are recorded as float data.

High NDVI values will result from the combination of a high reflectance in the near infrared and lower reflectance in the red band. Non-vegetated areas, including bare soil, open water, snow/ ice, and most construction materials, will have much lower NDVI values. NDVI was calculated and the suitable value ranges for the species was found to be 0.24-0.34 based on field data collected during field visit.

Along with NDVI various other variables were incorporated to knowledge-based classification (Table 2).

3.6 Imageries classification

After the acquisition of required satellite imageries from the archives different algorithms of classification was carried out based on the spectral and spatial resolution of respective imageries. The high-resolution imageries provide the details of species diversities. Based on both large spatial resolution of the latest imageries provides better spatial accuracy of the species domination. However, classification as well as delineation process was determined by the practical capability.

3.6.1 Unsupervised classification

Unsupervised classification is a means by which pixels in an image are assigned to spectral classes without the user having foreknowledge of the existence or names of those classes. Image processing software classified an image based on natural groupings of the spectral properties of the pixels, without the user specifying how to classify any portion of the image. Pixels are grouped based on the reflectance properties of pixels. These groupings are called clusters and classification was performed most often using clustering methods (Richards and Jia, 2006). These procedures were used to determine the number and location of the spectral classes into which the data falls and to determine the spectral class of each pixel. The number of clusters and bands to be generated were identified. With this information, the image classification tool generated clusters. The unsupervised classification technique was commonly used when no sample sites exist. This method was used as an initial step prior to supervised classification.

In this study, unsupervised classification was performed on ArcGIS Software. 100 clusters were given as classes for classification. The classified image obtained from unsupervised classification was used for calculation of DN value. DN value was identified in mosaicked image and then suitable classes were reclassified based on the classes on unsupervised classified image (Fig. 3).

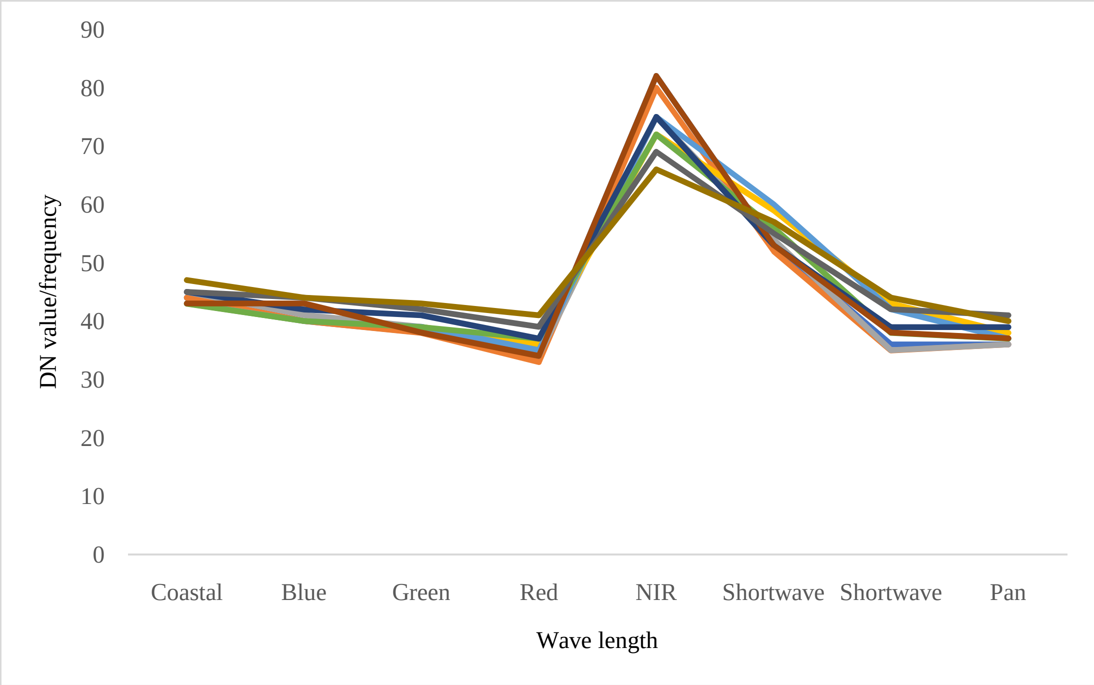


Figure 3: Reflectance curve for *Milkania micrantha*

3.6.2 Supervised classification

In supervised classification spectral signature was defined in the training samples. It was done with sample pixels in an image that are representative of specific classes. Then these training sites were used as reference for the classification of all other pixels in the image. Representative samples of each land cover were used for supervised classification. Maximum likelihood classification algorithm was performed for the landuse classification. Pixel belongs to a specific class were assigned to the class having the highest probability (Richards and Jia, 2006). Classified image was then reclassified according to area that was suitable for *Mikania micrantha*.

3.6.3 Knowledge based classification

Essential in knowledge-based image classification was a knowledge base that may contain variables, a hierarchical tree of decision rules, and output classes of interest (Gao *et al.*, 2004). The variety and number of variables stored in the knowledge base depends on the type of knowledge considered in mapping the distribution of species. For the mapping of *Mikania micrantha*, the most effective variables were incorporated so that rules formed were able to use for knowledge-based classification. Knowledge gained from various literature and observations were utilized to form variables. The knowledge base was constructed from the satellite image and the DEM data and was performed in ERDAS Imagine 2014. The knowledge-based classifier executes the knowledge rules created in the Knowledge Engineer module and classify the image and image obtained from this method was binary. All variables used were reclassified into a binary form that one class was suitable for *Mikania micrantha* and another was not suitable (Fig. 4). All used variables in Knowledge Based Classification is presented in Table 3 and detailed process of Knowledge based classification was in flow diagram (Fig. 4).

Table 3: Variables used for generating rules in knowledge based classification

Rules	Calculation	Suitable criteria	Source
Elevation	Reclassifying DEM file	60-600 m	Field observation and database prepared from TUCH
Aspect	Reclassifying DEM file	All Aspect except North	Field observation
Slope	Reclassifying DEM file	1-26	Field observation
Temperature (max)	DHM data	24°C-34°C	Average analysis
Temperature (min)	DHM data	17°C-24°C	Average analysis
Precipitation	DHM	500-3000 mm	Field observation
NDVI	(NIR - Red)/ (NIR + Red)	0.24-0.34	NCAR, 2018
Landuse	Supervised classification	Degraded forest, Dense forest, Agriculture	Field observation
Spectral value (Digital Number-DN)	Band 5 isoclustering	72-82	From coordinates

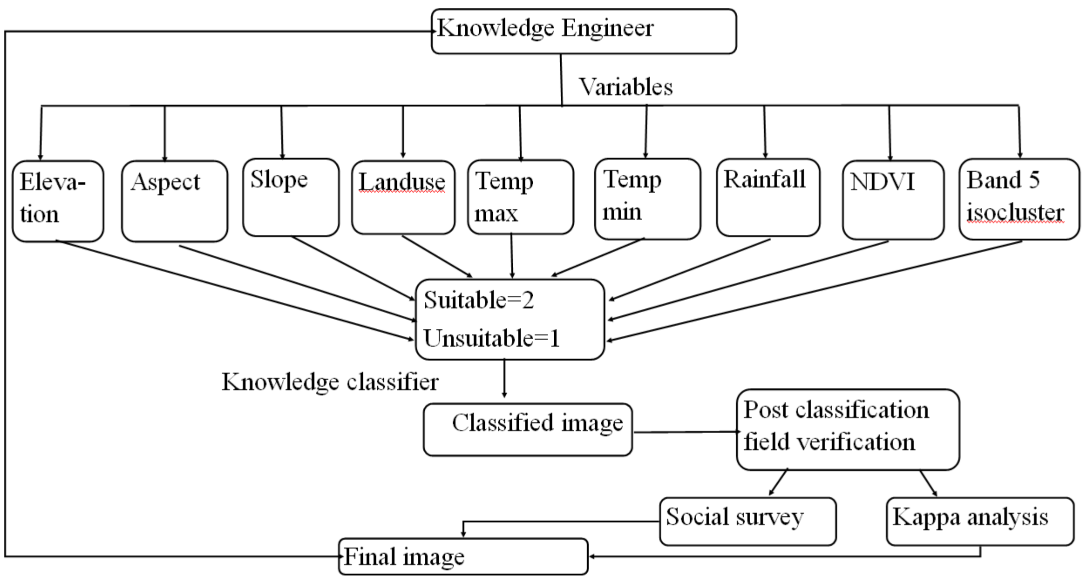


Figure 4: Flowcharts of method used in knowledge based classification

3.7 Accuracy assessment

Accuracy assessment was performed by comparing the map created by remote sensing analysis to a reference map based on a different information source such as GPS coordinates. Accuracy assessment was able to permit quantitative comparisons of different interpretations. Classifications done from images acquired at different times, classified by different procedures, or produced by different individuals were evaluated using a pixel-by-pixel, point-by-point comparison (Congalton, 1991).

Verification of sample points with field visits was an integral part of this study. First of all, the sample points of two categories of binary image that are presence point and absence point of *Mikania micrantha* were identified. The set of data was distributed to an internal expert for more careful visual interpretations. The outcomes from those independent visual interpretations of the same sample points were arranged as a confusion matrix/error matrix (Table 4) and the overall consistency of the interpretation was calculated. In this study a total of 200 presence points and 200 absence points of *Mikania micrantha* were collected and used for field verification in total area of CHAL in Landsat imageries. Likewise, in patch of Chitwan district of World view 2, 100 presence and 100 absence points were used and in patch of Nawalparasi district of World view 2 were used. The set of data was distributed to an internal expert for more careful visual interpretations.

Overall accuracy was calculated by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. In error matrix, all nondiagonal elements of the matrix represent errors of omission or commission. Omission errors correspond to nondiagonal column elements and commission errors are represented by nondiagonal row elements. The accuracies of individual in each category was calculated by either the total number of pixels in the corresponding row or column. Similarly, producer and user accuracy of both presence and absence class of *Mikania micrantha* were calculated from the error matrix.

Producer Accuracy was calculated by dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of reference pixels known to be of that category (the column total). This value represents how well reference pixels of the ground cover type are classified. Users accuracy was calculated by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total) (Table 4). This accuracy represents the probability that a pixel classified into a given category actually represents that category on the ground.

Table 4: Error matrix table for accuracy assessment

	Reference data			
Classified data	**Presence**	**Absence**	**Row total**	**User accuracy**
Presence				
Absence				
Column total				
Producer acccuracy				

Overall accuracy = correctly classified pixels/total no. of pixel

Producer's accuracy = No. of correctly classified in reference data/ total no. actually in reference data (the column total)

User's accuracy = No. of correctly classified in reference data/ total number of pixels that were classified in that category (the row total)

The kappa statistic was used to control only those instances that may have been correctly classified by chance. This can be calculated using both the observed (total) accuracy and the random accuracy. The formulae for calculation of kappa coefficient is given below:

Kappa coefficient = (n * SUM Xii) - SUM (Xi+ * X+i)/ n2 - SUM (Xi+ * X+i)

Where,

SUM = sum across all rows in matrix

Xii = diagonal

Xi+ = marginal row total (row i)

X+I = marginal column total (column i)

n = number of observations

The value of Kappa Coefficient reflects the how accurate the produced map. Interpretation of Kappa Coefficient was given in Table 5.

Table 5: Value range of kappa coefficient and its interpretation

Values	**Interpretation**
Smaller than 0.00	Poor agreement
0.00 to 0.20	Slight agreement
0.21 to 0.41	Fair agreement
0.41 to 0.60	Moderate agreement
0.61 to 0.80	Substantial agreement
0.81 to 1.00	Almost perfect agreement

4. RESULTS

4.1 Current status of distribution of *Mikania micrantha*

The results from this study show the current status of distribution of *Mikania micrantha* in Chitwan Annapurna Landscape Area. *M. micrantha* covers 435.86 km^2 which is equivalent to 1.39% of total area of CHAL. Chitwan, Nawlparasi, Makwanpur, Dhading, and Gorkha districts of CHAL were invaded by *M. micrantha*. It has been proliferated rapidly in forest trees, grasslands and wetland areas. Invasion by *M. micrantha* has been found along the roadside, open fallow land, forest canopy and grassland of CHAL. With the use of different suitable variables from observations as well as secondary data (elevation, slope, aspect, NDVI from reflectance rainfall maximum temperature and minimum temperature) result show the distribution of invasive weed in CHAL (Fig. 5).

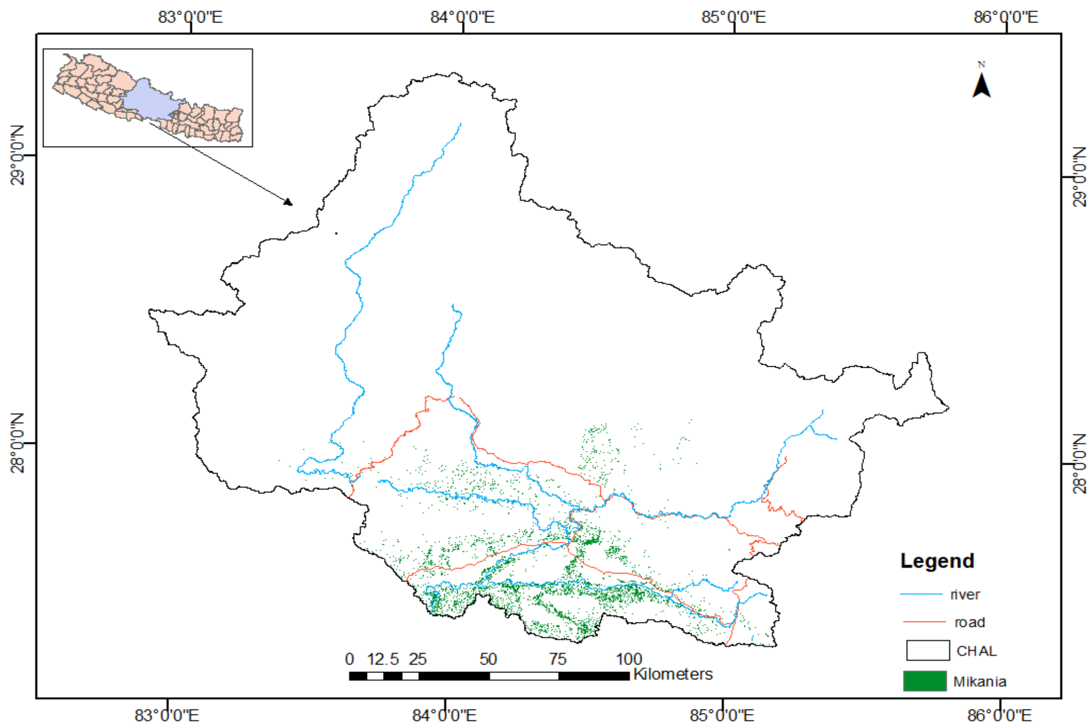


Figure 5: Distribution of *Mikania micrantha* in CHAL in 2018

4.2 Trend of invasion by *Mikania micrantha* since 1990

Results show 31.29 sq km (0.1%) of total area of CHAL was covered by *M. micrantha* in 1990. Similarly, 59.07 sq km (0.19%) and 208.65 sq km. (0.65%) of total area of CHAL was covered by *M. micrantha* in 2000 and 2008 respectively. This shows the increasing trend of invasion since 1990 to 2018 (Fig. 6). Area covered by *M. micrantha* was increased from 31.29 sq km to 435.86 sq km from 1990 to 2018.

Tanahau, Kaski, Gorkha were new districts that were invaded in 2018. Distribution maps show that invasion extended from lower belt (low elevation) to upper belt (high elevation).

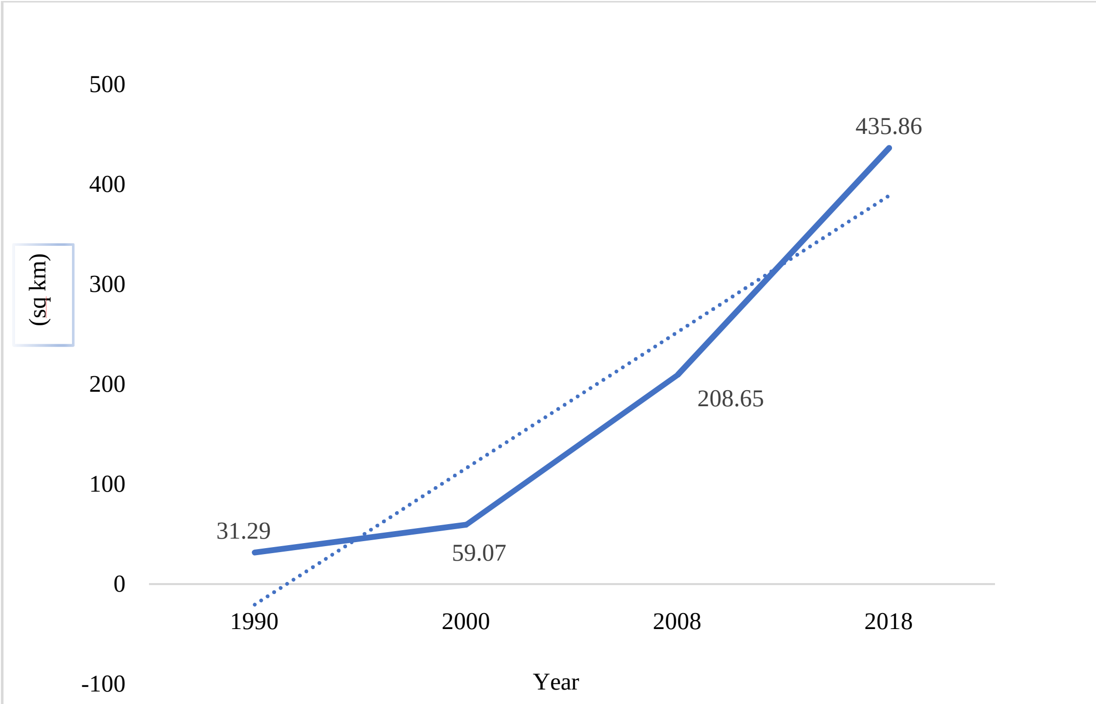


Figure 6: Trend line showing the invasion by *M. micrantha*

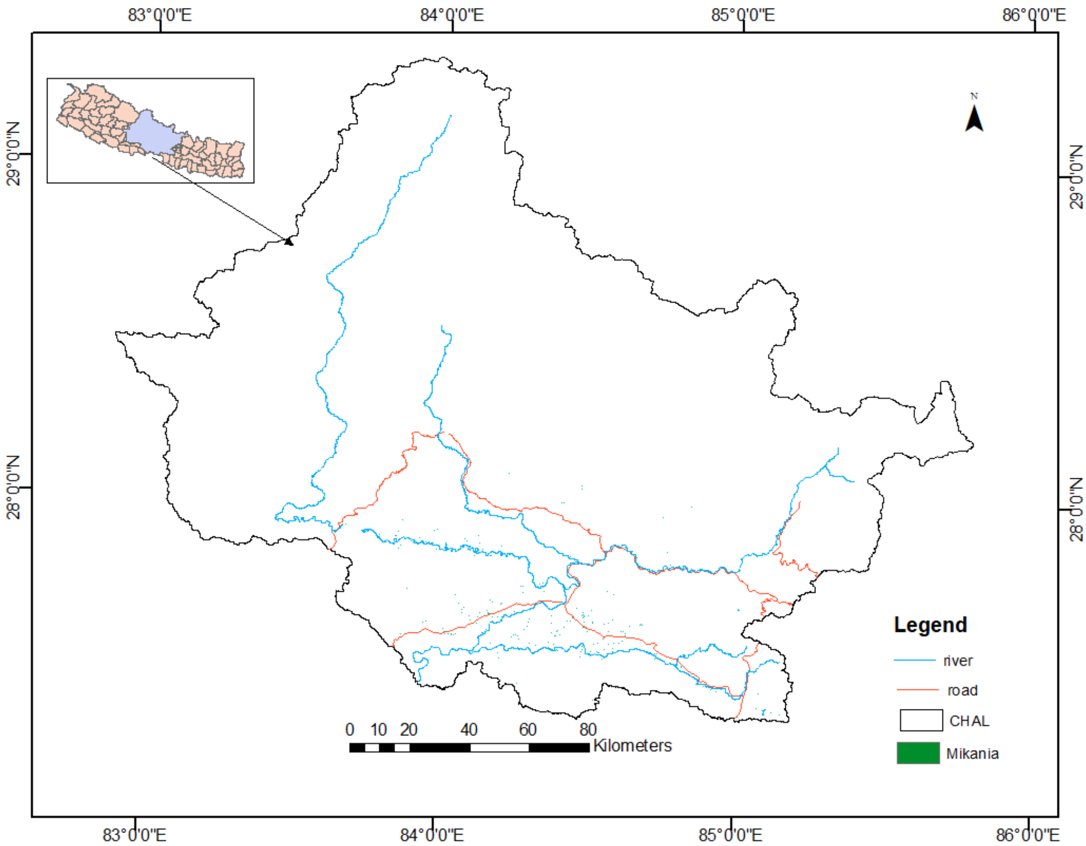


Figure 7: Distribution of *Mikania micrantha* in CHAL in 1990

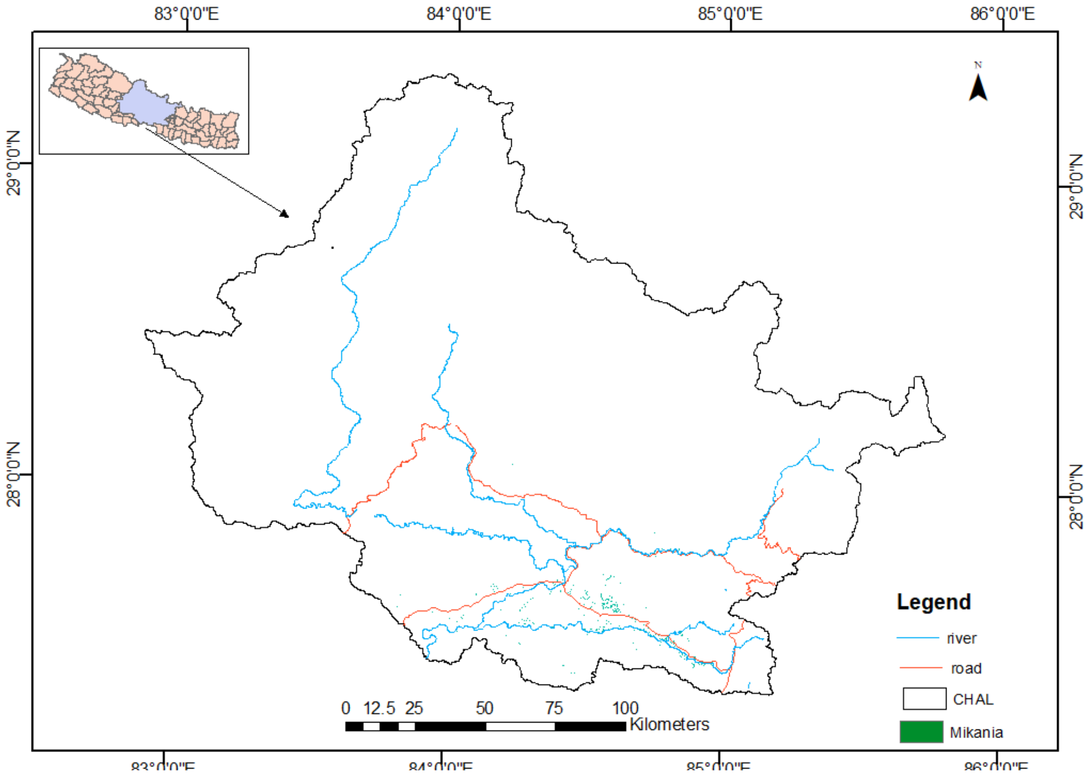


Figure 8: Distribution of *Mikania micrantha* in CHAL in 2000

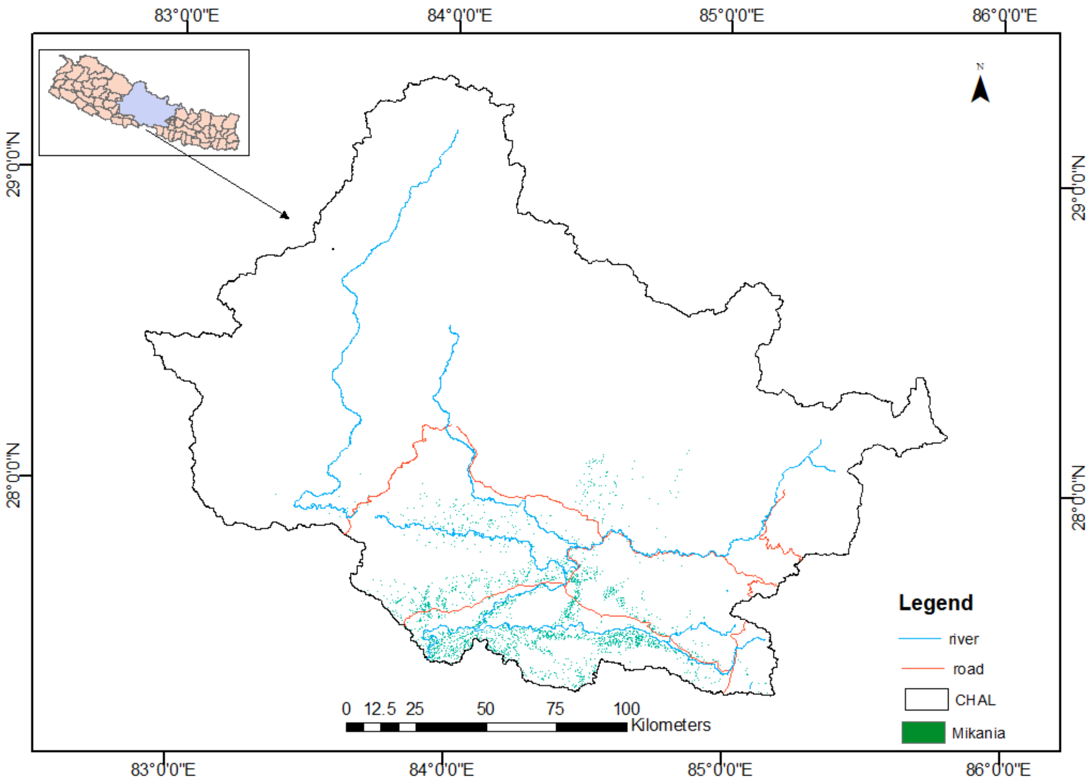
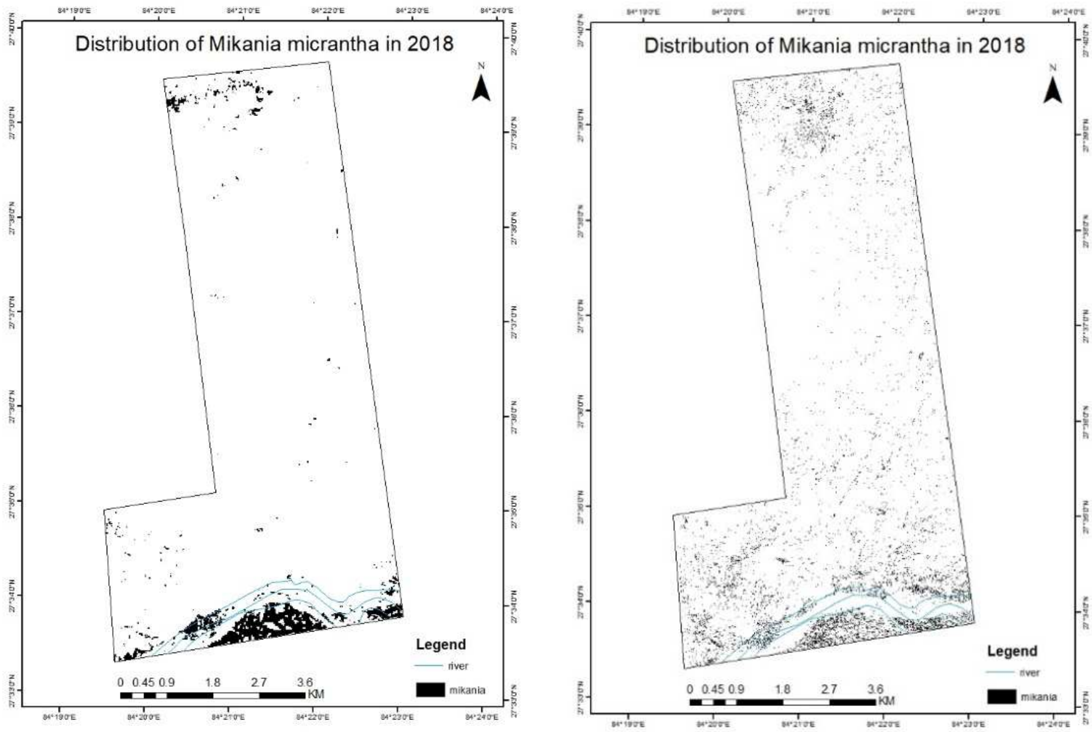


Figure 9: Distribution of *Mikania micrantha* in CHAL in 2008

4.3 Distribution of *Mikania micrantha* in Landsat and World view 2 Data

4.3.1 Distribution of *Mikania micrantha* in Chitwan

In Chitwan district, small portion (42.764% sq km) of Landsat data shows 3.34% of total area invaded by *M. micrantha* in 2018 (Fig. 10a). Likewise, 2 m × 2 m spatial resolution of World view satellite data of same area shows 2.10% of total area was invaded by this weed (Fig. 10b). In the field observation, it was highly dominated at the Rampur area and map also shows the distribution is high in Rampur area. In the distributed area it was mainly found along the road side, edges of agricultural land, fallow land and grassland.

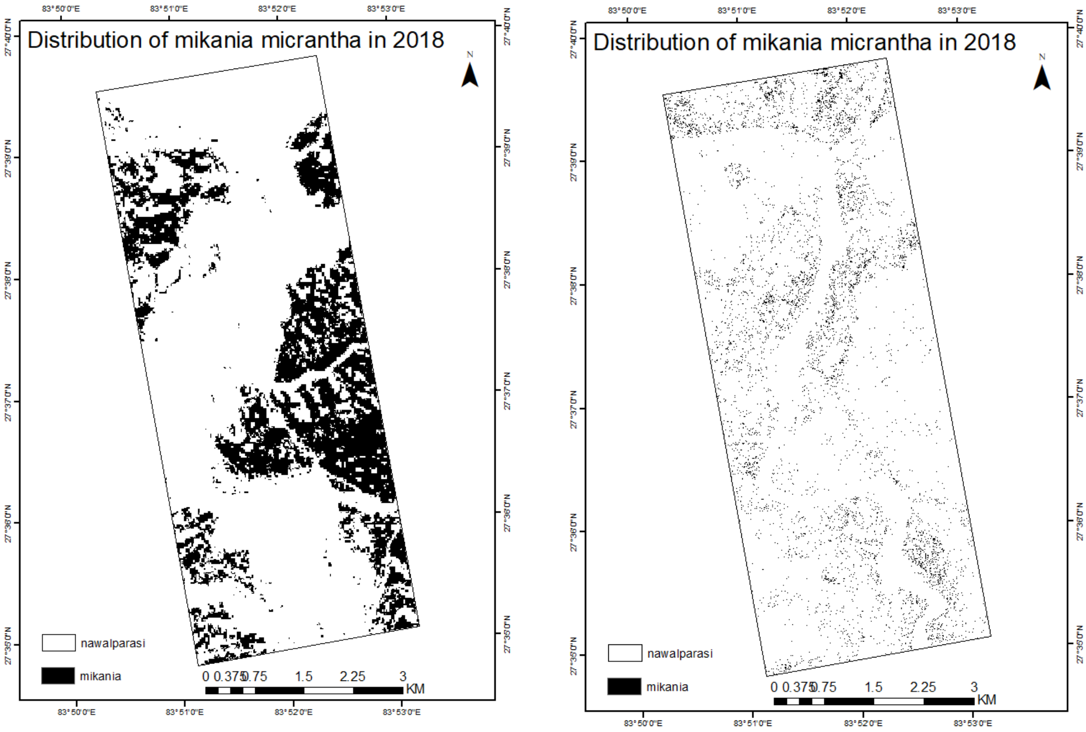


(a) (b)

Figure 10: Distribution of *Mikania micrantha* in Chitwan in 2018 (a) Landsat data and (b) World view 2 data

4.3.2 Distribution of *Mikania micrantha* in Nawalparasi

In Nawalparasi district, small portion (30 sq km) of Landsat data that cover Dumkibas area shows 4.46% of total area invaded by *M. micrantha* in 2018 (Fig. 11a). Likewise, 2 m × 2 m spatial resolution of World view satellite data of same area shows 3.66% of total area was invaded by this weed (Fig. 11b). It was highly dominated at the highway area of Hongshi Gate to Dumkibas area. In the distributed area it was mainly found along the road side.



(a) (b)

Figure 11: Distribution of *Mikania micrantha* in Nawalparasi in (a) 2018 in Landsat data and (b) 2018 in World view 2 data

The portion that covers the highway area from Pragatinagar to Rajahar of Nawalparasi (44.22 sq km) district shows the infestation by *M. micrantha* in 2018 and 2008 in both Landat and World view 2 data. Map shows 3.94% of total area invaded by *M. micrantha* in 2018 (Fig. 12) in Landsat data and 2.27% in World view 2 data. Similarly, in World view 2 data of 2 × 2 data of 2008, 1.23% of total area was invaded and 1.38% area was invaded by weed in Landsat data in 2008. Weed was mainly distributed along the highway, fallow land and grassland.

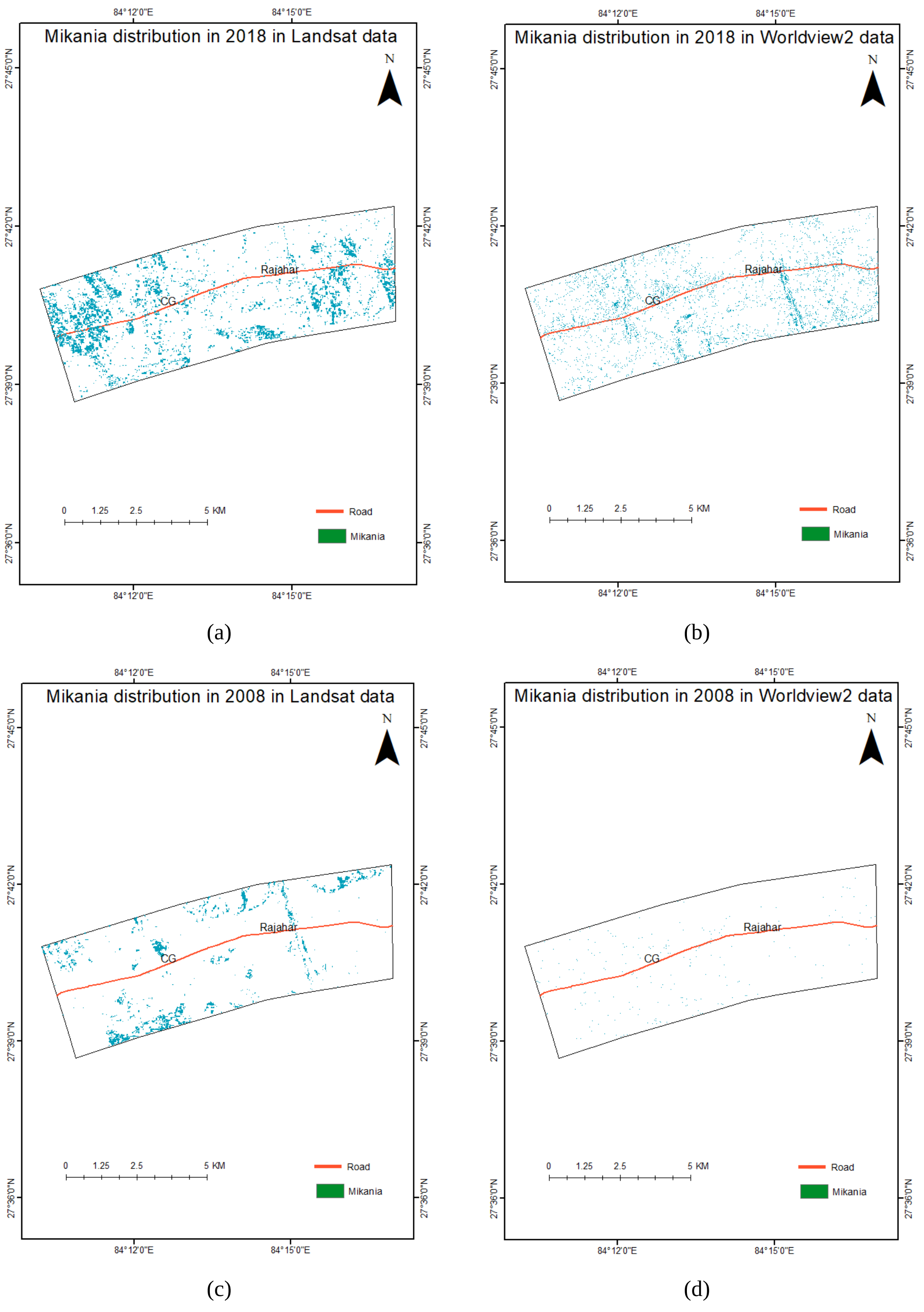


Figure 12: Distribution of *Mikania micrantha* in Pragatinagar of Nawalparasi in (a) 2018 in Landsat data, (b) World view 2 data in 2018 and (c) Landsat data in 2008 and (d) World view 2 data in 2008

4.3.3 Distribution of *Mikania micrantha* in Chitwan-Tanahu (Muglin)

In map that connects Chitwan and Tanahau district, small portion (39.85 sq km) of Landsat data shows 1.67% of total area invaded by *M. micrantha* in 2018 (Fig. 13).

Similarly, 0.9% of total area was covered in 2018 in World view data of 2 m × 2 m spatial resolution. In 2008, 1.02% of total area was invaded in landsat data and in World view 2 data of 2008 0.57% of total area was invaded. Weed was mainly distributed along the highway, fallow land and grassland.

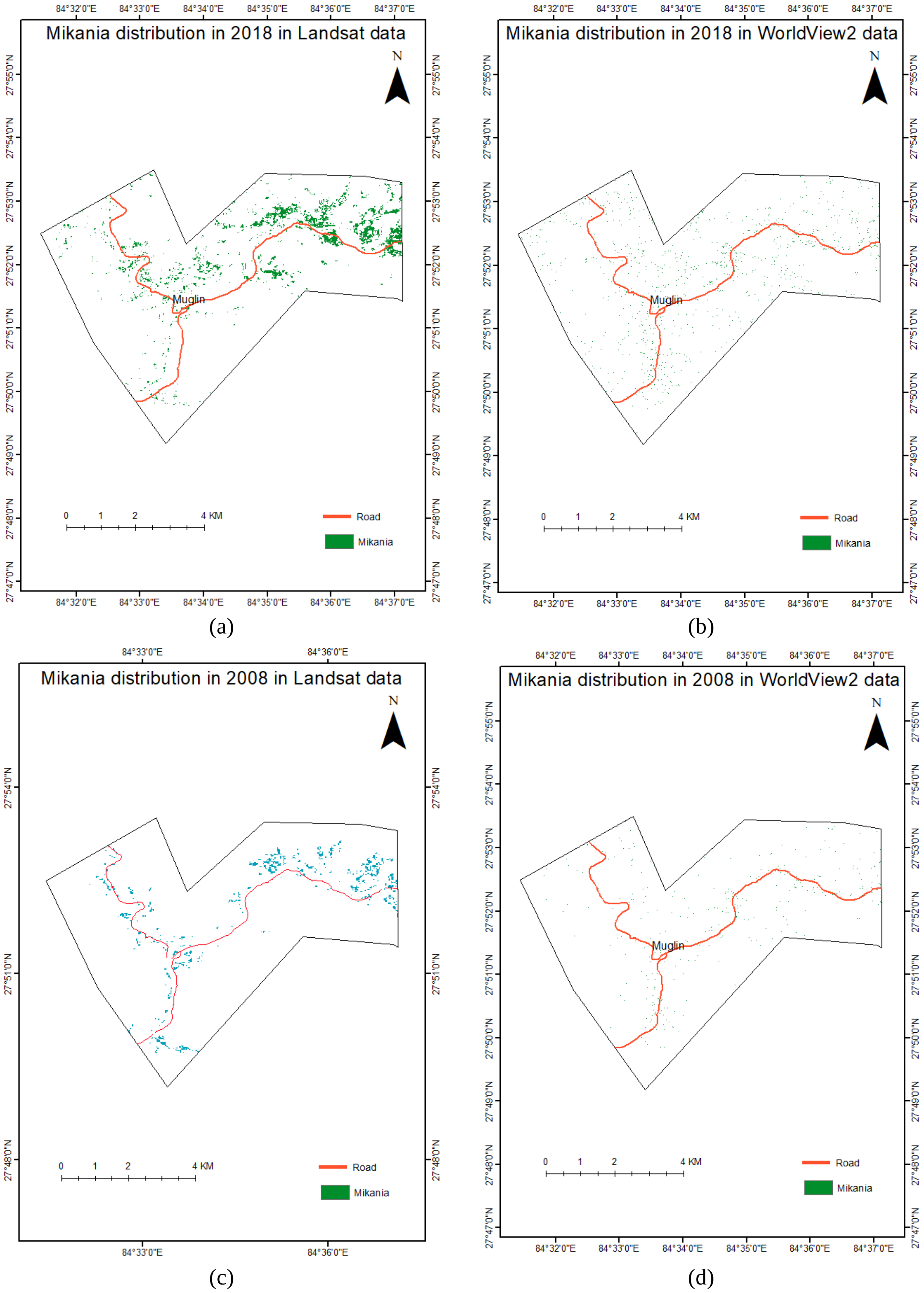


Figure 13: Distribution of *Mikania micrantha* in Chitwan-Tanahu in (a) 2018 in Landsat data, (b) World view 2 data in 2018 and (c) Landsat data in 2008 and (d) World view 2 data in 2008

4.3.4 Distribution of *Mikania micrantha* in Chitwan-Makwanpur

In map that connects Chitwan and Makwanpur district, small portion (107.2 sq km) of Landsat data shows 2.31% of total area invaded by *M. micrantha* in 2018 (Fig. 14). Similarly, 1.26% of total area was covered in 2018 in World view data of 2 m × 2 m spatial resolution. Weed was mainly distributed along the highway. fallow land and grassland.

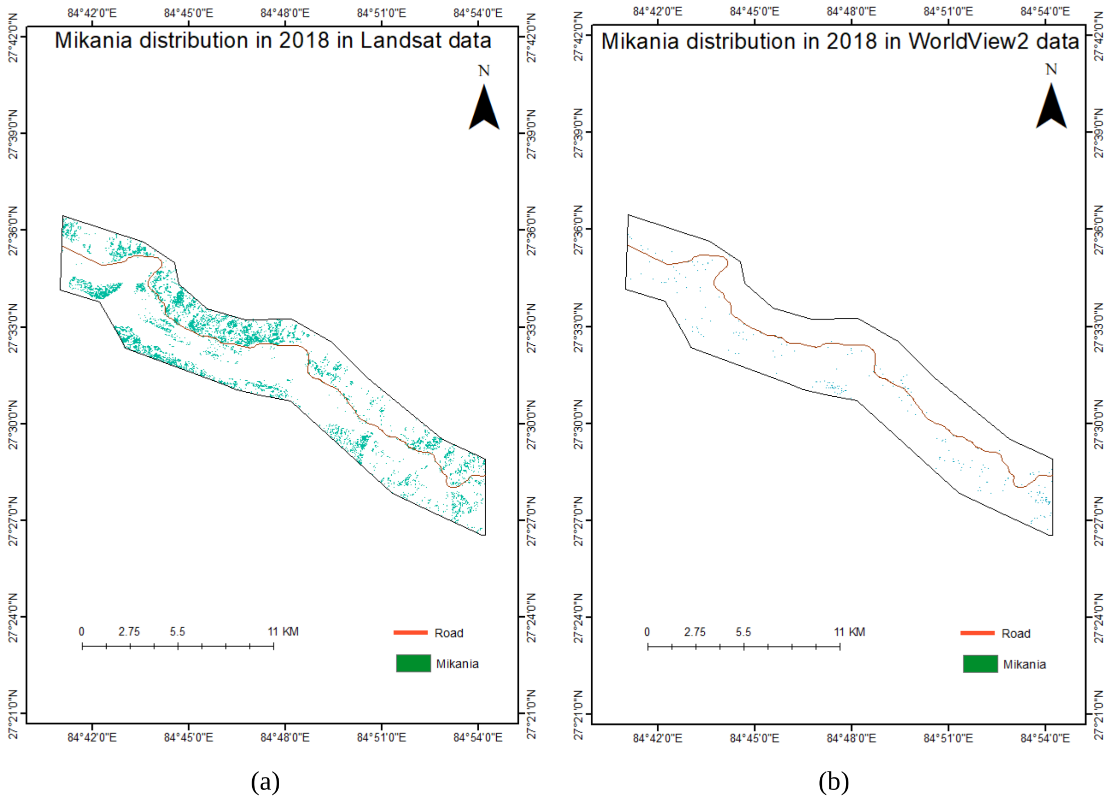
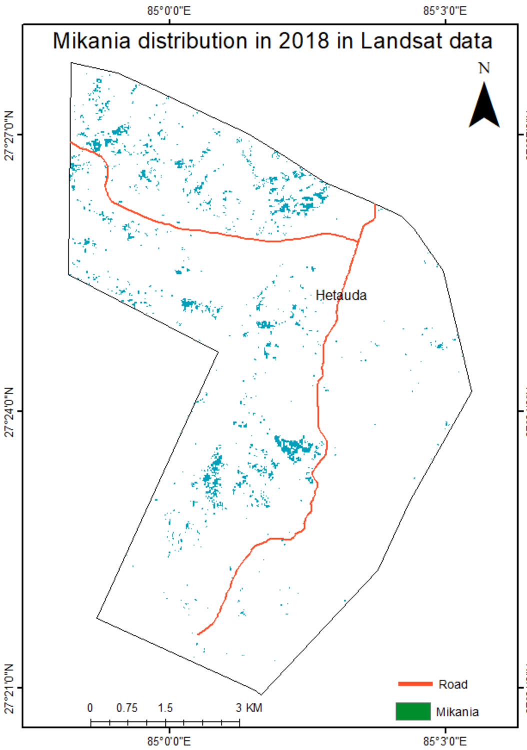


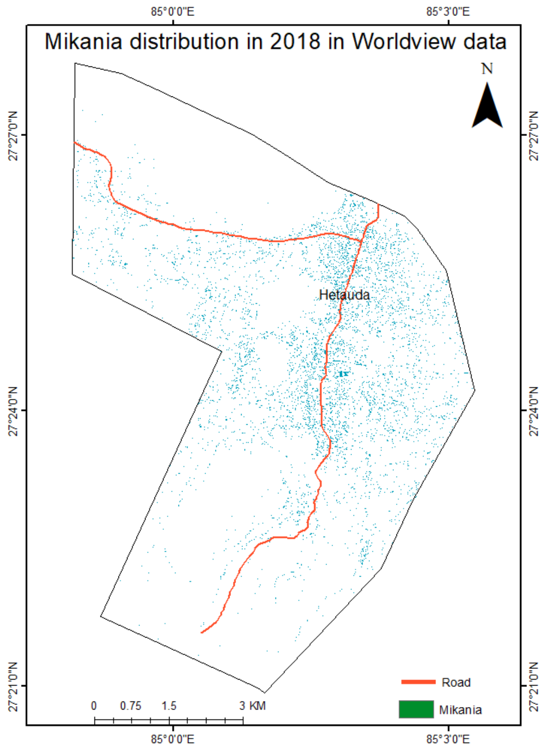
Figure 14: Distribution of *Mikania micrantha* in Chitwan-Makwanpur in (a) Landsat data, (b) World view 2 data

4.3.5 Distribution of *Mikania micrantha* in Makwanpur (Hetauda)

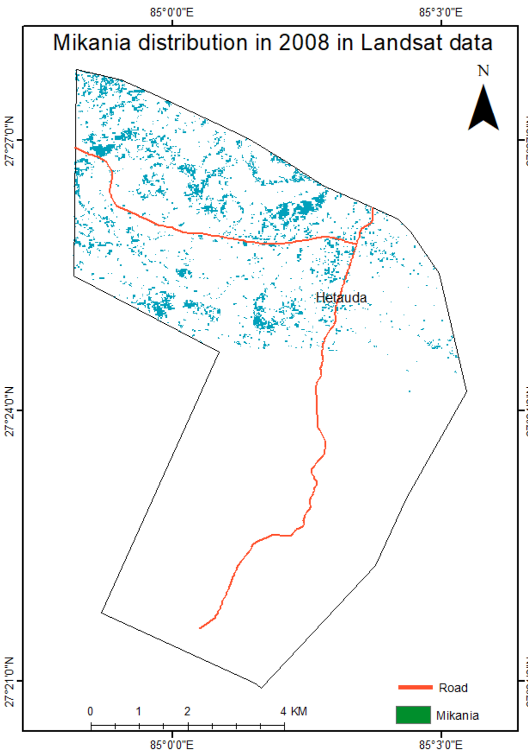
Distribution map of Makwanpur district, small portion (54 sq km) of Landsat data that cover Hetauda shows 3.31% of total area invaded by *M. micrantha* in 2018. Similarly, 2.79% of total area was covered in 2018 World view 2 data. Similarly, in 2008 in Landsat data 2.04% area was invaded by this weed and in 2008 in World view data of 2 m × 2 m spatial resolution 1.73% area was covered. Weed was mainly distributed along the roadside, fallow land and grassland.



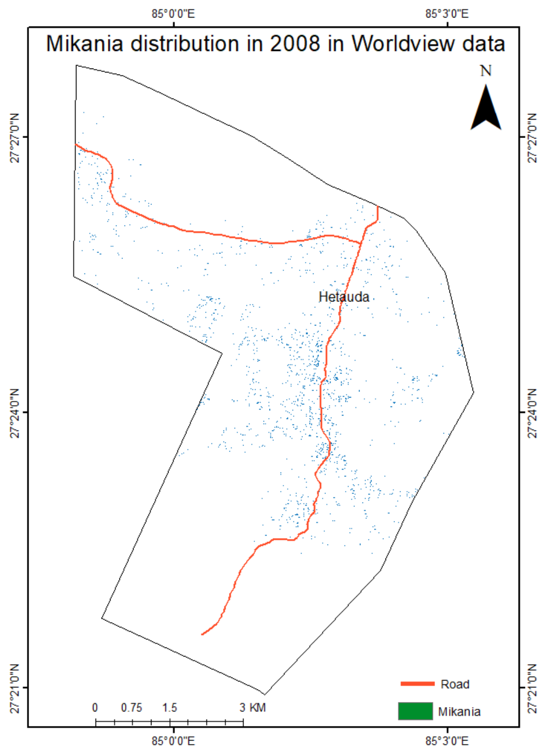
(a)



(b)



(c)



(d)

Figure 15: Distribution of *Mikania micrantha* in Chitwan-Makwanpur in (a) 2018 in Landsat data, (b) World view 2 data in 2018 and (c) Landsat data in 2008 and (d) World view 2 data

4.4 Comparison of area of distribution in Landsat and World view 2 data

The distribution of *Mikania micrantha* in different small patches of various localities were compared in between Landsat data and World view data for 2018 and 2008 (Table 5). All the small patches have higher distribution in Landsat data in both year 2018 and 2008. Highest distribution was found in Dumkibas area of Nawalparasi district in both Landsat (4.46%) and World view 2 (3.96%) data in 2018. Lowest distribution was found in Muglin area in both Landsat (1.03%) and World view 2 (0.9%) in 2018. Likewise, in 2008 Hetauda shows high distribution and Muglin shows low distribution of both data (Table 6).

Table 6: Comparison of area covered by *Mikania micrantha* in different AOI in World view 2 and Landsat satellite imageries in 2018 and 2008

District	Location (AOI)	Total area (sq km)	Area covered in 2018						Area covered in 2008					
			World view 2		Landsat		Difference		World view 2		Landsat		Difference	
			Sq km	%	Sq km	%	Sq km	%	Sq km	%	Sq km	%	Sq km	%
Chitwan	Rampur	42.764	0.89	2.10	1.43	3.34	0.54	60.67						
Nawalparasi	Dumkibas	30	1.1	3.66	1.34	4.46	0.24	21.82						
Nawalparasi	Rajahar	44.22	1.004	2.27	1.74	3.94	0.736	73.30	0.544	1.23	0.61	1.38	0.066	12.19
Chitwan, Tanahu	Muglin	39.85	0.36	0.9	0.41	1.03	0.05	13.89	0.23	0.57	0.41	1.02	0.18	78.26
Makwanpur	Manahari	107.2	1.35	1.26	2.48	2.31	1.13	83.7						
Makwanpur	Hetauda	54	1.78	2.79	2.61	3.31	0.83	0.47	0.93	1.73	1.10	2.04	0.17	18.27

4.5 Accuracy assessment

The accuracy of both Landsat and World view 2 satellite data, *M. micrantha* distributions was validated through field observations at different localities of classified map. Then the error matrix was created based on the ground truth points. The overall accuracy was varied between 68.75% to 82.5%. The kappa coefficient was ranged from 0.34 to 0.65.

4.5.1 Accuracy assessment of CHAL

Overall accuracy of distribution map of *Mikania micrantha* in CHAL is 69.5. Kappa coefficient is found to be 0.39 and the error matrix was shown in Table 7.

Table 7: Error matrix for CHAL

Classified data	Reference data			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	97	103	200	48.5
Absence	19	181	200	90.5
Column total	116	284		
Producer acccuracy (%)	83.62	63.73		
Overall accuracy (%)	69.5			
Kappa coefficient	0.39			

4.5.2 Accuracy assesment of small area of intrest of Landsat and World view 2

The overall accuracy of Landsat data varied between 68.75% and 76% and kappa indices between 0.34 and 0.52. The highest overall accuracy was achieved in Rampur of Chitwan district where as lowest was achieved in Manahari of Makwanpur district. The overall accuracy for the WV2 varied between 79 and 82.5% and kappa indices of 0.49 and 0.65. The highest overall accuracy was achieved in Hetauda of Makwanpur district where as lowest was achieved in Mugling district. If we compare the accuracy of the satellite data used, the accuracy is higher in the WV2 image than in the Landsat image. The higher accuracy was observed in image of high resolution since it is more precise for species level identification than low resolution imageries. Values of Producer Accuracy were higher compared to User Accuracy in most of the classified imageries in both landsat and World view 2 imageries (Annex 4).

Table 8: Comparison of accuracy between Landsat and World view 2 imageries of 2018

District	Location	World view 2 imageries		Landsat images	
		Overall accuracy (%)	**Kappa**	**Overall accuracy (%)**	**Kappa**
Chitwan	Rampur	81	0.53	76	0.34
	Muglin	75	0.5	71.67	0.43
Makwanpur	Manahari	79	0.58	68.75	0.37
	Hetauda	82.5	0.65	69	0.38
Nawalparasi	Pragatinagar	81.25	0.62	73.75	0.52
	Dhumkibas	79	0.49	73	0.46

5. DISCUSSION

In CHAL, *Mikania micrantha* was found distributed in tropical part of Chitwan, Makwanpur, Nawalparasi, Dhading and Gorkha. *M. micrantha* is native to tropical region of world (Wang, 2008) and until now, it is confined to this region however, northward movement of the species was expected by Shrestha (2016) cannot be ruled out. In present study its invasive pathway was noted from South west to north eastern side. *M. micrantha* has spread extensively in the last few decades Apart from the invasive characteristics of the invasive plant itself, this has been due to (i) a lack of natural enemies, (ii) a wide range of habitats, and (iii) increased human disturbance associated with recent economic growth.

Landsat satellite imageries were used for mapping the distribution of *M. micrantha* in temporal time series.Distribution of *M. micrantha* was increasing since 1990. Results show 31.29 sq km (0.1%) of total area of CHAL was covered by *M. micrantha* in 1990. Similarly, 59.07 sq km (0.19%) and 208.65 (0.65)% of total area of CHAL was covered by *M. micrantha* in 2000 and 2008 respectively. Currently, in 2018 invasion increased up to 1.39%, i.e., 435.86 sq km in total area of CHAL.

Since, it was introduced from eastern tropical part of Nepal, it was highly confined to the tropical part of CHAL. Roads are the major pathways of invasion, roads not only provide suitable conditions for the establishment and growth of exotic species, but also act as effective corridors for the spread of alien plant species. The significantly greater occurrence of invasive species along road edges than in the forest interior may result from various forms of human disturbance. *Mikania micrantha* shows a strong invasiveness and can rapidly form dense seedling populations and aggressive colonies. Once established, this species smothers and displaces the native vegetation.

Invasive Alien Plant species often competitively exclude native plant species due to high rates of vegetative and sexual reproduction, high seed viability and longevity, and tolerance of extreme edaphic and micro environmental conditions (Barrilleaux and Grace, 2000). Invasive species may also affect ecosystem structure by altering soil properties (e.g., allelopathy, nutrient dynamics) or rapidly sequestering limited resources (Lundgren *et al.,* 2004). For example, soils of some grassland ecosystems dominated by invasive species have been found to have lower organic matter and available nitrogen than areas of predominantly native plant species (Olson, 1999). All these facts result in increasing trend of distribution of *M. micrantha* in the study area.

The timing of data acquisition is crucial for Remote Sensing analysis (Everitt *et al*., 2001), since the data may only be useful if the targeted alien plant is distinct from its background and neighboring areas. Distinct flowering colors of *Mikania micrantha* afforded an even wider window of opportunity for plant detection, and increased the possibility of monitoring the invasion through time using multiple photographs. Studies have demonstrated that it may be possible to monitor vegetation dynamics by using vegetation index time-series data (Justice *et al.*, 1985). A vegetation index, such as the commonly used the Normalized Difference Vegetation Index (NDVI), enhances the signal of photosynthetically active vegetation with a combination of visible and near-infrared spectral bands (Tucker and Sellers, 1986).

The distribution map resulted from two different satellite imageries, i.e., Landsat and World view 2 images of different locations shows differnt distribution. All Landat imageries had higher distribution than World view 2 and the results were more precise in World view images. Like the results of this study, Laba *et al*. (2008) applied a maximum-likelihood classification on QuickBird, another multi-spectral satellite system (DigitalGlobe, Longmont, Colorado, USA) with even finer spatial resolution (2.4 m), to estimate the presence of multiple alien plants (*Lythrum salicaria*, *Phragmites australis* and *Trapa natans*) in diverse tidal wetlands of the Hudson River National Estuarine Research Reserve, USA. They demonstrated that QuickBird was a relatively reliable data source for wetland non-native plant mapping. Similarly, successful remote detection of invasive species has been the use of Landsat imagery to identify presence of cheatgrass (*Bromus tectorum*) in the Great Basin, USA (Peterson, 2005; Bradley and Mustard, 2005). Underwood *et al.* (2003) were able to use airborne visible/infrared imaging spectrometer (AVIRIS) imagery with 4 m resolution to detect iceplant (*Carpobrotus edulis*) and jubata grass (*Cortaderia jubata*) in Mediterranean-type ecosystems of California because such invasive species showed higher leaf water content than native co-occurring species. Specific remote sensors and analytical methods used in tracking invasive species vary widely, depending on the geographical scale of interest. As with spatial resolution, enhanced spectral and radiometric resolutions may also be an advantage in the detection and mapping of invasive plants (Underwood, 2003). The availability of new, fine-spatial resolution satellite imagery from can greatly advance detecting and mapping of invasive plant populations since, unlike Landsat Enhanced Thematic Mapper +

(ETM+) imagery, they allow detection of individual tree crowns (Asner and Warner, 2003)

Accuracy Assessment was done for both Landsat data and World view 2 data by creating error matrix table. Overall accuracy, producer accuracy, user accuracy and kappa coefficient reflect the accuracy of classified map as compared to the field observation and data. The overall accuracy of Landsat data varied between 68.75% and 76% and kappa indices between0.37 and 0.66. For World view 2 data, overall classification accuracy ranged from 79%-82.5%. Accuracy of World view 2 imageries of 2 m × 2 m shows higher accuracy and have high Kappa coefficient than Landsat imageries. On the basis of Kappa value the image classification was fair for most of landsat images (value ranging from 0.2-0.4), for digital globe the image classification was moderate (0.4-0.6) and substantial (0.6-0.8). Data with high spatial resolution were more effective for the delineation of *M. micrantha.*

Like in this study, Domacx and Suzen (2006) in the Amanos Mountains region of southern-central Turkey used knowledge-based classifications in which they combined Landsat TM images with environmental variables and forest management maps to produce regional scale vegetation maps. They were able to produce an overall high accuracy when compared with the traditional maximum likelihood classification method. Another example for improving classification accuracy by incorporating vegetation-related environmental variables using GIS with remotely sensed data was the work of that of Yang (2007) at Hunter Region in Australia. He used digital aerial photographs, SPOT-4, and Landsat-7 ETM+ images for riparian vegetation delineation and mapping. The overall vegetation classification accuracy was 81% for digital aerial photography, 63% for SPOT-4, and 53% for Landsat-7 ETM+.

High-spatial-resolution imageries resulted substantial improvement in Kappa coefficient, similar to the results of earlier studies which relied on airborne hyperspectral data (Anderson, 2005). In the use of Hyperion, TM5 and QB data for tamarisk mapping, 88%, 80% and 91% of reference pixels, respectively, were classified correctly Multispectral data at high spatial resolution (QB, 2.5 m Ground Spatial Distance or GSD) proved more effective in tamarisk delineation than either multispectral (TM5) or hyperspectral (Hyperion) data at moderate spatial resolution (30 m GSD) (Carter *et al.*, 2009). The combination of high spectral and spatial resolutions previously enabled high-accuracy mapping of tamarisk in the Southern California (Hamada *et al.*, 2007) with high overall agreement (70 to 95%) with the reference data generally had more false detections (15 to 30%).

Values of Producer Accuracy were usually higher compared to User Accuracy. Although the UA (expressing the commission error) seems important for natural protection applications, the PA (omission error) is important for efficient control measures because it reflects the error of omitting of some plants that can later serve as a source of diaspores (Mullerova *et al.*, 2013). An acceptable level of accuracy depends on the map purpose; it should be maximized if the goal is to locate infestation hotspots, but can be lower if all possible locations of the invasive species are to be addressed (Hamada *et al*., 2007).

6. CONCLUSION AND RECOMMENDATION

6.1 Conclusion

The study used multispectral satellite imageries of high spatial resolution of World view 2 and low spatial resolution of Landsat Data. Results show that invasion of *Mikania micrantha* increased in the last 20 years from past to present date. *M. micrantha* becomes a threat to native biodiversity and it has been highly invaded in tropical part of CHAL especially in Makwanpur, Chitwan and Nawalparasi. Large area of CHAL was invaded in a short period of time and the unique phenological, spectral, and structural characteristics of *M. micrantha* were analysed to distinguish from non-target species. Forest edge, riparian vegetation, afforested land and grassland with sparse trees and shrubs are being degraded due to high invasion of the weed. The weed was found invading towards northern and western side in CHAL. Remote sensing is an important tool for mapping of invasive species, that helps in early detection of invasive weed that provide a great opportunity to develop predictive models for invasion risk analysis. World view 2 imageries produced much better and accurate distribution maps than Landsat. Landsat imageries showed 20 to 50% more coverage of Mikania micrantha than World view 2, nevertheless, Landsat imageries can also be used to note the distribution pattern of weed as it is freely available in archive and World view 2 images are very expensive.

6.2 Recommendations

Based on the results and past studies I would recommend the following points:

- Landsat imageries can also be used to determine the distribution of invasive alien plant species.
- The invasive weed is moving towards north-west direction, hence the government should make plan and programme to check its invasion in new area.
- The satellite population of *M. micrantha* has been found in northern and western part of CHAL. There satellite populations, if eradicated at its earlier stage will minimize the spread of this weed in new areas.

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ANNEXES

Annex 1: Data sheet

Checklist **Remarks**

Locality:

Management- 1 = Chemical, 2 = Physical, 3 = Biological, 4 = No management, 5 = Other

Magnitude - 1 = Low, 2 = Moderate, 3 = Dense, 4 = Just invaded, 5 = Absent

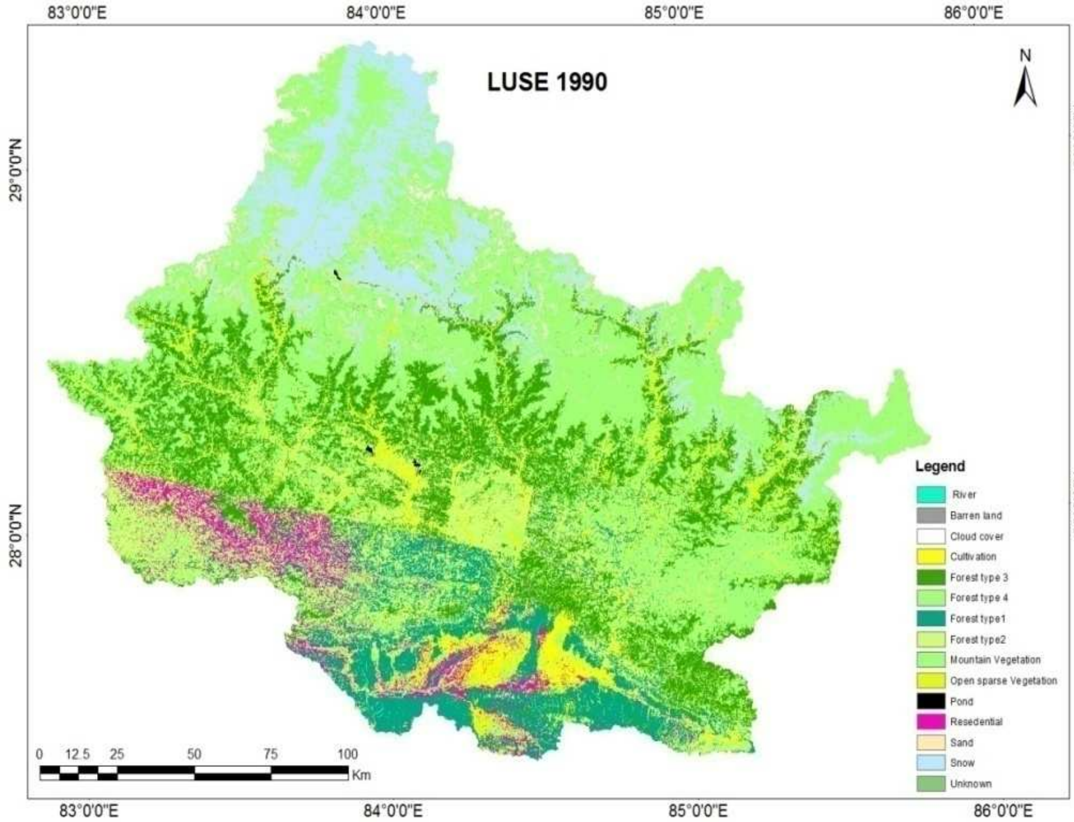
SN	Latitude	Longitude	Elevation	Aspect	Slope	Species	Associated species	Landuse	Magnitude	Management
						Mikania micrantha				

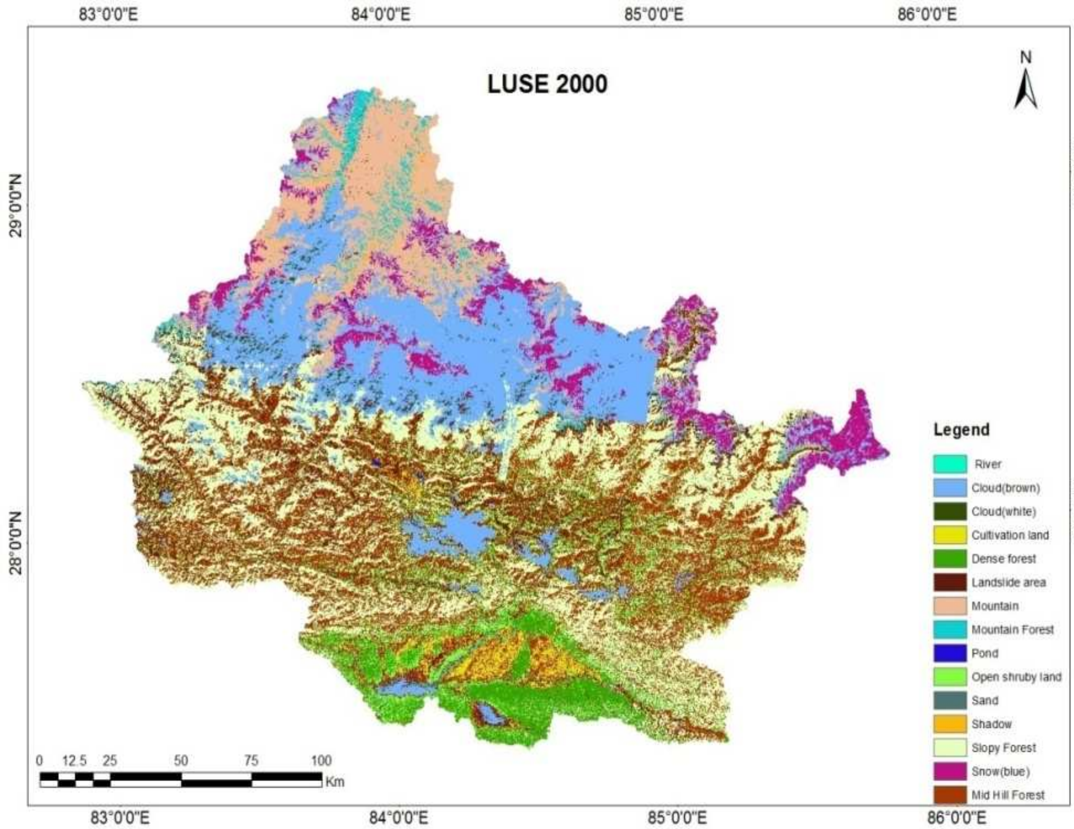
Annex 2: Annual rainfall and temperature data

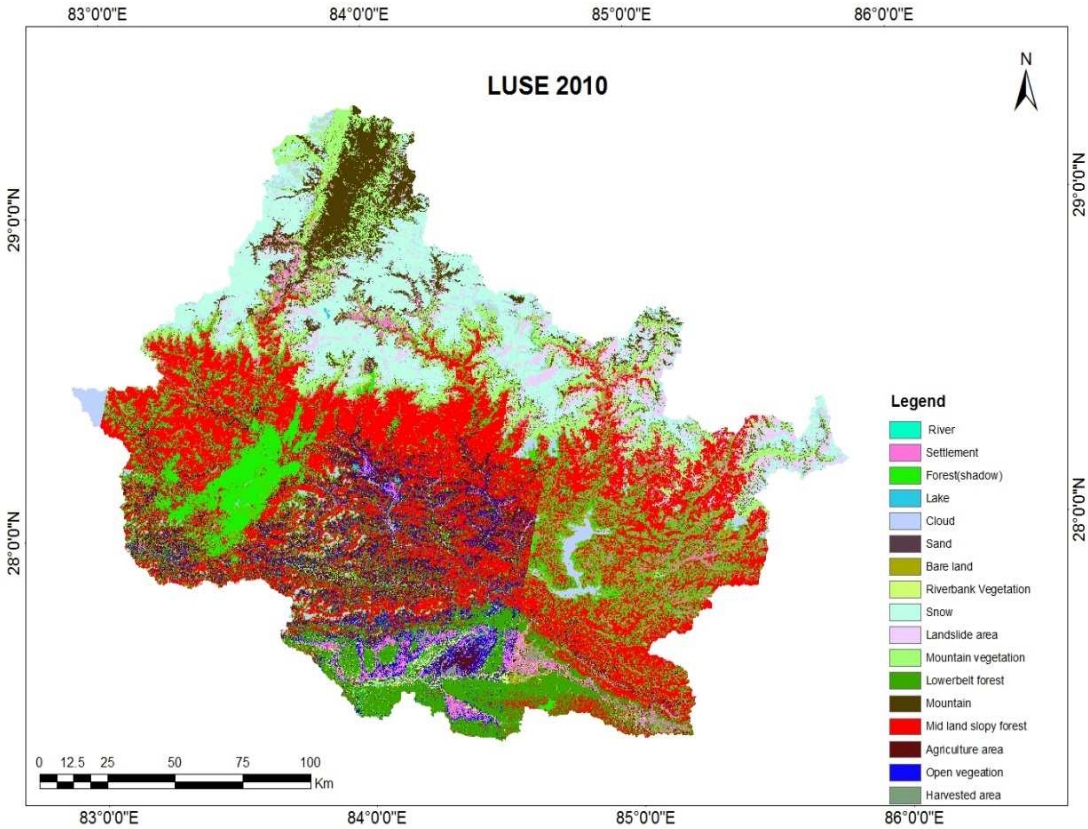
Station ID	Station name	District	Latitude	Longitude	Annual Rainfall (mm) (1970-2016)	Tmax (ºC) (1970-2016)	Tmin (ºC) (1970-2016)
715	Khanchikot	Arghakhachi	27.93333	83.15	1595.88	22.32	15.20
605	Baglung	Baglung	28.26667	83.6	1705.26	29.89	18.57
927	Bharatpur	Chitawan	27.66667	84.43333	1896.56	33.16	22.49
902	Rampur	Chitawan	27.61667	84.41667	1868.95	32.74	21.85
809	Gorkha	Gorkha	28	84.61667	1514.29	28.40	18.82
806	Larke Samdo	Gorkha	28.66667	84.61667	600.43	28.56	18.57
725	Tamghas	Gulmi	28.06667	83.25	1719.81	24.85	15.73
814	Lumle	Kaski	28.3	83.8	5122.36	22.17	14.90
811	Malepatan (Pokhara)	Kaski	28.11667	84.11667	3474.70	29.00	18.30
804	Pokhara Airport	Kaski	28.21667	84	3606.14	28.67	18.80
866	Pokhara Reg. Off.	Kaski	28.21667	83.98333	2651.04	29.47	19.79
802	Khudi Bazar	Lamjung	28.28333	84.36667	3000.31	28.89	18.24
905	Daman	Makwanpur	27.6	85.08333	1518.94	20.65	11.35
906	Hetaunda N.F.I.	Makwanpur	27.41667	85.05	2216.22	31.05	20.48
816	Chame	Manang	28.55	84.23333	677.52	19.32	7.72
633	Chhoser	Mustang	29.18333	83.98333	160.77	18.27	4.67
623	Dhiee	Mustang	29.1	84	76.72	20.64	7.84
601	Jomsom	Mustang	28.78333	83.71667	186.78	20.46	9.30
607	Lete	Mustang	28.63333	83.6	986.58	19.07	9.87
612	Mustang (Lomangthang)	Mustang	29.18333	83.96667	111.23	16.59	4.01
604	Thakmarpha	Mustang	28.75	83.7	296.81	19.52	8.87
609	Beni Bazar	Myagdi	28.35	83.56667	1390.91	30.48	18.71
616	Gurja Khani	Myagdi	28.6	83.21667	1583.39	20.00	8.52
706	Dumkauli	Nawalparasi	27.68333	84.21667	2214.45	32.82	22.86

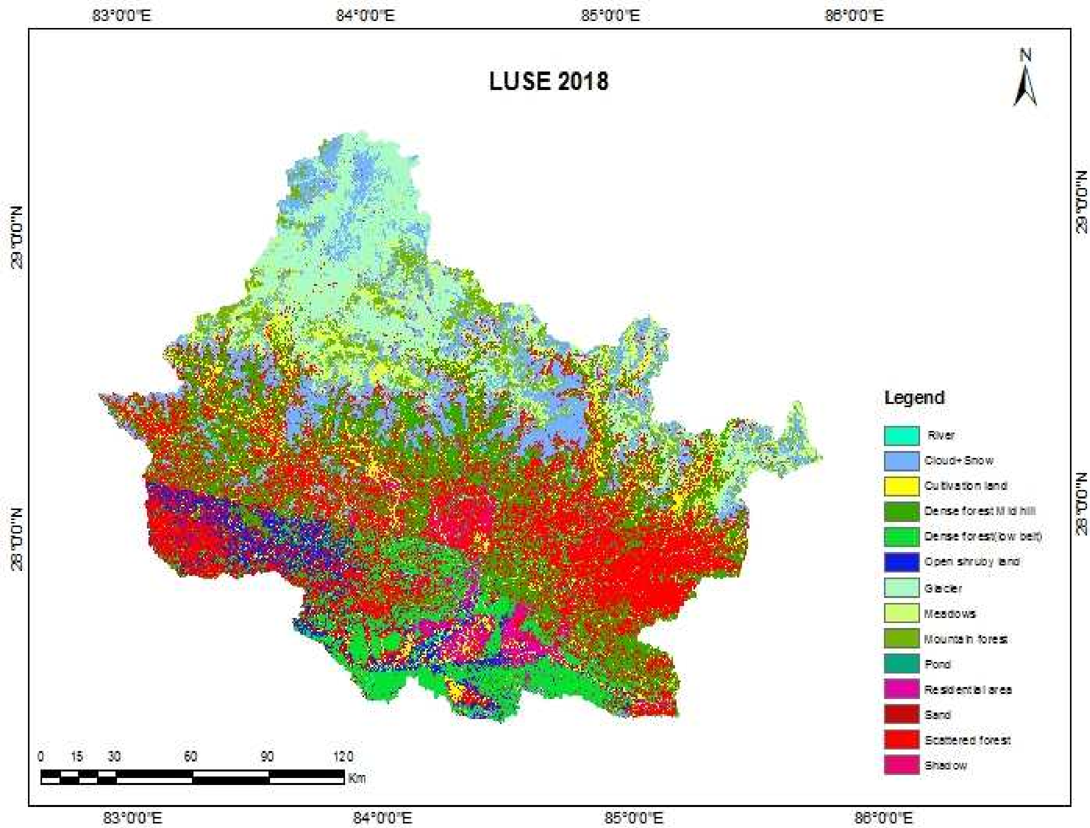
708	Parasi	Nawalparasi	27.53333	83.66667	1649.10	35.31	22.60
728	Semari	Nawalparasi	27.53333	83.75	1758.03	34.36	22.26
1007	Kakani	Nuwakot	27.8	85.25	2565.50	21.70	13.56
1004	Nuwakot	Nuwakot	27.91667	85.16667	1683.71	29.45	19.22
1057	Pansayakhola	Nuwakot	28.01667	85.11667	2755.97	21.10	12.39
702	Tansen	Palpa	27.86667	83.53333	1241.37	27.33	17.77
614	Kushma	Parbat	28.21667	83.7	2284.75	30.66	18.78
1055	Dhunche	Rasuwa	28.1	85.3	1642.30	22.59	13.40
1001	Timure	Rasuwa	28.28333	85.38333	752.91	24.91	14.31
805	Syangja	Syangia	28.1	83.88333	2670.25	29.52	18.63
810	Chapkot	Syangja	27.88333	83.81667	1673.41	31.18	20.51
832	Dandaswara	Syangja	28.08333	83.91667	2845.36	26.49	16.16
808	Bandipur	Tanahun	27.93333	84.41667	1633.39	27.68	18.78
817	Damauli	Tanahun	27.96667	84.28333	1520.04	32.59	21.07
815	Khairini Tar	Tanahun	28.03333	84.1	2025.16	31.04	20.73
303	Jumla	Jumla	27.28333	82.16667	617.0706897	23.38	9.23
310	Dipal Gaun	Jumla	26.26667	83.21667	710.7225	24.66	9.27
409	Khajura (Nepalganj)	Banke	26.1	81.78333	1264.286957	33.27	22.48
416	Nepalgunj (Reg.Off.)	Banke	28.06667	81.61667	1227.825581	33.32	23.68
420	Nepalgunj Airport	Banke	28.1	81.66667	1416.975	33.49	22.56
716	Taulihawa	Kapilbastu	27.55	83.06667	1366.064444	33.4	22.22
918	Birganj	Parsa	27	84.86667	312.94	36.24	22
1009	Chautara	Sindhupalchok	27.78333	85.71667	417.2174603	26.88	16.58
1016	Sarmathang	Sindhupalchok	27.95	85.6	709.805	18.69	10.46
1027	Bahrabise	Sindhupalchok	27.78333	85.9	588.6857143	29.94	15.92
1030	Kathmandu Airport	Kathmandu	27.7	85.36667	311.5291667	27.27	16.39
1039	Panipokhari (Kathmandu)	Kathmandu	27.73333	85.33333	322.0651163	27.24	16.99

Annex 3: Landuse classified map






LUSE 2010
N
83°0'0"E
84°0'0"E
85°0'0"E
86°0'0"E
29°0'0"N
28°0'0"N
Legend
River
Settlement
Forest(shadow)
Lake
Cloud
Sand
Bare land
Riverbank Vegetation
Snow
Landslide area
Mountain vegetation
Lowerbelt forest
Mountain
Mid land slopy forest
Agriculture area
Open vegeation
Harvested area
0 12.5 25 50 75 100
Km

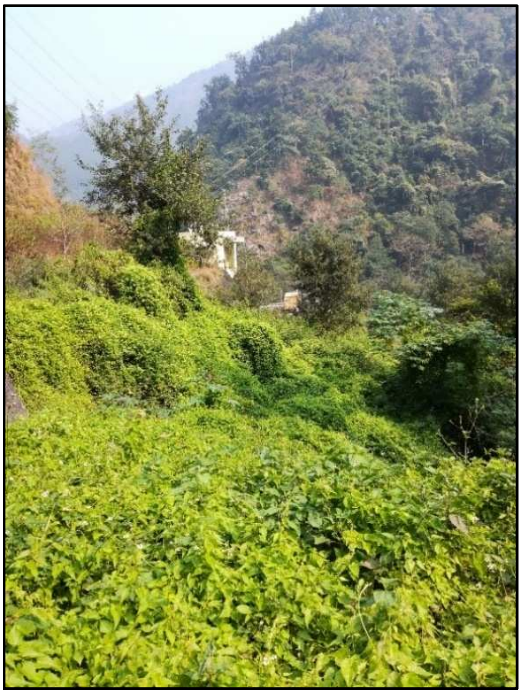

LUSE 2018
N
83°0'0"E
84°0'0"E
85°0'0"E
86°0'0"E
29°0'0"N
28°0'0"N
Legend
River
Cloud+Snow
Cultivation land
Dense forest Mid hill
Dense forest(low belt)
Open shruby land
Glacier
Meadows
Mountain forest
Pond
Residential area
Sand
Scattered forest
Shadow
0 15 30 60 90 120
Km

Annex 4: Error matrix

District	Location	Class	World View 2 Imageries				Landsat Images			
			Producer's	User	Commission error	Omission error	Producer's	User	Commission error	Omission error
Dhading	Mahadevbesi	Presence	77.4	87.2	0.12	0.22	85	54	0.45	0.15
		Absence	87.9	78.4	0.21	0.12	65	89.6	0.35	0.1
	Majimtar	Presence	72	83	0.28	0.16	75	48	0.52	0.25
		Absence	86	75	0.24	0.16	61	84	0.38	0.16
Tanahun	Dhulegauda	Presence	91	84.6	0.15	0.08	84.2	69.2	0.3	0.15
		Absence	83.3	90.9	0.09	0.16	66.6	82.3	0.17	0.33
Chitwan	Rampur	Presence	77.4	87.2	0.12	0.22	68	75	0.24	0.28
		Absence	87	78.4	0.12	0.21	78	71.2	0.31	0.21
Makwanpur	Hetauda	Presence	91.1	82	0.18	0.08	77.08	74	0.26	0.22
		Absence	83	92	0.08	0.16	75	78	0.25	0.22
Nawalparasi	Devchuli	Presence	92	82.2	0.26	0.08	70.8	80.9	0.19	0.2
		Absence	74	83	0.23	0.08	84.6	75.8	0.24	0.15
	Dhumkibas	Presence	88.6	78	0.22	0.11	87.1	68	0.32	0.12
		Absence	80.3	90	0.1	0.19	73.7	90	0.1	0.26

Annex 5: Photo Plates

Flowering stage of *Mikania*



Moderate patch of *M. micrantha* at *micrantha* Marsyangdi hydropower

Moderate patch of *M. micrantha*

Low patch of *M. micrantha* at at Manahari Makwanpur Rajahar, Nawalparasi

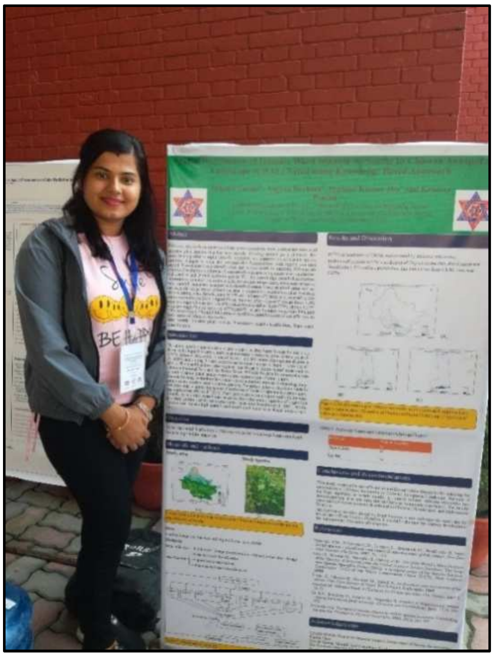
Dense patch at road side in Pokhara

Dense patch at damp side Rampur, Chitwan

Field data collection

Plant sample collection

Group discussion



Poster presentation at International Youth Conference on Science, Technology and Innovation organized by NAST

Oral presentation at National Conference on Integrating Biological Resources for Prosperity