Spatial and Temporal Distribution of *Pontederia crassipes* Mart. in Chitwan Annapurna Landscape (CHAL) Area, Nepal Using Satellite Imageries

A Dissertation Submitted for Partial Fulfillment of the Requirements for the Master's Degree in Botany

Submitted by

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Letter of Recommendation

This is to certify that the dissertation work entitled **"Spatial and Temporal Distribution of *Pontederia crassipes* Mart. in Chitwan Annapurna Landscape (CHAL) Area, Nepal using satellite imageries"** has been completed by **Mr. Himal Yonjan** under our supervision. This entire work was accomplished based on the candidate's original research work. To the best of my knowledge, the work has not been submitted to any other academic degree. It is hereby recommended for acceptance of this dissertation as part of the requirement of Master's Degree in Botany at the Institute of Science and Technology, Tribhuvan University, Kathmandu, Nepal.

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Declaration

I, Himal Yonjan, hereby declare that this dissertation entitled **"Spatial and Temporal Distribution of *Pontederia crassipes* Mart. in Chitwan Annapurna Landscape (CHAL) Area, Nepal using 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 parts to any other universities for any academic award.

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Letter of Approval

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Abstract

Invasive alien plant species (IAPS) are escalating in Nepal and harming species, communities, environment and human health. In recent years, remote sensing has become widely used method for mapping IAPS as remote sensing data provide broad aerial coverage of intermittently inaccessible area. *Pontederia crassipes* Mart. (formerly *Eichhornia crassipes*) is one of the invasive species established in wetlands of Nepal. It is a floating aquatic macrophyte, commonly known as water hyacinth. It is one of the members of family Pontederiaceae. The main objective of the research work was to study spatial and temporal distribution of *P. crassipes* from 1990 to 2020 A.D. at the gap of 10 years in Chitwan Annapurna Landscape (CHAL), Nepal. World View-2 and Landsat series imageries were used to map *P. crassipes*. The spatial resolution of Landsat image is 30 m × 30 m and of World View-2 image is 2 m × 2 m. Iso cluster unsupervised classification and maximum likelihood classification (supervised classification) by using training sample were done in Arc MAP 10.5. Knowledge-based classification and fusion of several terrain information including digital elevation model (DEM), water resources, human activities, and accessibilities like several ancillary data were integrated in ERDAS IMAGINE 2014. In 2018 A.D. it was found that 27.58 km^2 (0.086 %) of CHAL was infested by *P. crassipes.* Analyzing the map of 1990 A.D., it was found that *P. crassipes* was only in 9.6 km^2 (0.030%). In 2000 A.D., infestation area decreased to 2.93 km^2 (0.0092). In 2010 A.D. the area of infestation increased to 23.44 km^2 (0.073%). Again, that increased to 37 km^2 (0.116%) in 2020 A.D.

World View-2 imageries were also used in small area of interest (AOI). The same size of AOI was clipped in Landsat imageries. The overall accuracy varied from 81.25 to 86.96 % in World View-2 imageries. While overall accuracy in Landsat imageries was 62.96 to 68 %. The Kappa coefficient in World View-2 varied from 0.61 to 0.72, which is good accuracy. But kappa coefficient in Landsat is less and varied from 0.21 to 0.29. Not only World View-2 image (high resolution sensor) but also Landsat image (moderate resolution) can be used to map invasive species.

Keywords: *Pontederia crassipes*, World View-2, Landsat, Remote sensing, Iso cluster unsupervised classification, Maximum likelihood classification, Knowledge-based classification

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List of Acronyms and Abbreviations

A.D.	Anno Domini
AIAPS	Aquatic Invasive Alien Plant Species
AOI	Area of Interest
ASTER	Advanced Space borne Thermal Emission and Reflection
CBD	Convention on Biological Diversity
CHAL	Chitwan Annapurna Landscape
DEM	Digital Elevation Model
DN	Digital Number
ERDAS	Earth Resources Data Analysis System
et al.	and others
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographic Information System
GPS	Global Positioning System
IAPS	Invasive Alien Plant Species
ICIMOD	International Centre for Integrated Mountain Development
IUCN	International Union for Conservation of Nature
LiDAR	Light Detection and Ranging
LULC	Land Use and Land Cover
MFSC	Ministry of Forest and Soil Conservation
MLC	Maximum Likelihood Classification
MSI	Multispectral Instrument
NDVI	Normalized Difference Vegetation Index

NEGISS	The Nepal GIS Society
NIR	Near-infrared
OLI	Operational Land Imager
RS	Remote Sensing
SAR	Synthetic Aperture Radar
TM	Thematic Mapper
UAV	Unmanned Aerial Vehicle
USAID	United States Agency for International Development
USGS	United States Geological Survey

1. INTRODUCTION

1.1 Background

Invasive species are species of flora and fauna which do not occur naturally in a particular area but it’s introduction harm on other species, communities, environment and human health. Invasive species are a subset of naturalized species that are highly reproductive and can expand their range across a wide geographic range (Richardson *et al.,* 2000). Their ability to adjust to diverse ecological conditions and spread quickly gives them the potential to thrive in a wide range of environments (MEA, 2005). Human movement, global trade and transport are increasing biological invasions in the world (Hulme, 2015). Climate change and economic growth are likely to increase biological invasion in future mainly in Asia (Seebens *et al.,* 2015). The spread of invasive alien species, as identified by CBD (2009) is threatening biological diversity with serious disruption of ecological structure after habitat destruction (CBD, 2009).

Due to open border and ineffective quarantine, most of the naturalized alien plant species entered Nepal from India. 182 flowering plants are alien species naturalized in Nepal. Out of them 27 are invasive (Shrestha *et al*., 2021). *Pontederia crassipes* Mart. (formerly *Eichhornia crassipes*) is one of the invasive alien plant species that invade wetlands. It is commonly known as water hyacinth. *P. crassipes* is considered to be originated from the Amazon of South America but due to ornamental plant trade and aquarium trade, this species has rapidly spread to multiple tropical and subtropical countries across Africa, Southeast Asia, and the Pacific region (Wolverton & Mc Donald, 1979). It is established in all content except Antartica (Coetzee *et al., 2017).* Water hyacinth is known globally as an invasive weed of significant concern. (Chai *et al*., 2013). The primary challenge in managing *P. crassipes* within aquatic ecosystems arises from its ability to grow and propagate quickly. Furthermore, the IUCN has included this weed in its list of the 100 most harmful invasive species. (Tellez *et al*., 2008) and also been ranked among world’s top 10 worst weeds (Aboul-Enein *et al*., 2011).

The close geographic proximity between India and Nepal has led to the general belief that *P. crassipes* was introduced to Nepal from India. According to Maharjan and Ming's (2012) citation, the first report of *P. crassipes* in Nepal dates back to 1966.

The invasion of P. crassipes has affected several well-known wetlands in Nepal, including Phewa, Begnas, Rupa, and Bishazari. These lakes are significant tourist attractions for the country. However, the invasion of this weed had a severe negative impact on these natural resources, requiring significant financial investment for its removal.

1.2 Remote sensing technologies

Remote sensing (RS) has gained popularity in recent years as a method for mapping and monitoring invasive alien species. There is a wide range of sensors available for this purpose, including those with moderate to high spatial resolution, hyperspectral sensors, and advanced imaging technologies such as Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) (Huang and Asner 2009). Remote sensing data offer broad spatial coverage of affected areas that are often difficult to access, and this coverage is available at regular intervals over time. Therefore, remote sensing is an excellent tool for mapping and monitoring invasive alien species in various ecosystems worldwide.

Due to significant advancements in the spatial and spectral resolution of remote sensing, as well as improvements in its spatial and temporal coverage, it has become more practical to map and monitor the distribution of invasive alien species in a wide range of ecosystems, regions, and habitats. The use of remote sensing technology was introduced in Nepal during the late 1970s. In 1979, a Remote Sensing Data Analysis Laboratory was established in Kathmandu with the support of USAID (Paudel 2007).

1.3 Rationale

Aquatic Invasive Alien Plant Species (AIAPS) pose a significant threat to the aquatic biodiversity of Nepal. Among them, *Pontederia crassipes* has been problematic in major lakes, ponds, roadside ditches, paddy fields etc. In the past, conventional techniques involving field surveys were commonly used to monitor aquatic weeds. However, it is not possible in large area due to time consuming and labor intensive. Distribution pattern *P. crassipes* has not been studied in Nepal. Satellite sensor's imageries provide spatial and temporal distribution pattern of aquatic invasive species including *P. crassipes*. Remote sensing can quickly and synotypically monitor large areas. Hence, it can be essential tool for studying distribution pattern and mitigating *P. crassipes*.

1.4 Hypothesis

The southern lowland and middle part of the Chitwan Annapurna Landscape (CHAL) area is extensively dominated by the aquatic invasive species *Pontederia crassipes*. Thus, there is possibility of *P. crassipes* gradually increasing towards the northern part.

1.5 Objectives

The overall objective of the research work is use of satellite imageries to map the distribution of aquatic invasive species *P. crassipes* in the Chitwan Annapurna Landscape (CHAL) region, Nepal.

The specific objectives include:

- Study of spatial and temporal distribution of *P. crassipes* from 1990 to 2020 A. D. at the gap of 10 years.
- Study the pattern of distribution of the *P. crassipes* in the CHAL region.

1.6 Limitations

Limitations of this research work are as follows

- Lack of cloud free imageries.
- Small water bodies are not detected in Landsat imageries.
- Moderate spatial resolution sensors like Landsat are unable to detect IAPS within a heterogeneous vegetation.
- High resolution sensors like World View-2 are temporarily restricted. It was launched in 2009.

2. REVIEW OF LITERATURE

2.1 Invasive alien plant species in Nepal

The tropical and subtropical climate conditions found in the Terai and Siwalik regions of Nepal have a higher distribution and abundance of invasive alien plant species compared to other areas. (Tiwari *et al*., 2005). The eastern and central regions of Nepal have more species of Invasive Alien Plant Species (IAPS) compared to the western parts of the country (Bhattarai *et al*., 2014). The four plant species - *Chromolaena odorata, Pontederia crassipes, Lantana camera,* and *Mikania micrantha* - have been identified as among the most harmful invasive alien plant species (IAPS) in the world, appearing on a list of 100 such species (Low *et al*., 2000). Mainly, *Pontederia crassipes, Pistia stratiotes* and *Myriophyllum aquaticum* are invading wetlands rapidly; *Chromolaena odorata, Lantana camera,* and *Ageratina adenophora* in shrubs and forests; *Bidens pilosa,* and *Parthenium hysterophorus* in grasslands and residential areas; and *Oxalis latifolia, Ageratum houstonianum, Ageratum conyzoides* and *Gallinsoga quadriradiata* in agroecosystems (Shrestha *et al.,* 2017). The growth of native plants is being inhibited and the regeneration of other species is being prevented by the presence of *Mikania micrantha* in Chitwan National Park and Koshi Tappu Wildlife Reserve (Siwakoti, 2007). Habitat of one horned Rhino in Chitwan National Park is being degraded by *Mikania micrantha* (Murphy *et al.*, 2013). *Ageratina Adenophora* is rapidly invading Annapurna Conservation Area and replacing native grasses (Thapa and Maharjan, 2014).

2.2 Remote sensing of *Pontederia crassipes*

A literature review related to the spatiotemporal distribution of aquatic invasive plants, especially using the remote sensing and GIS techniques is presented below:

Everitt *et al*. (1999) conducted a study in southern Texas that examined the light reflection properties of two aquatic plant species, water hyacinth and hydrilla, as well as their associated species. They discovered that water hyacinth typically had a higher level of near-infrared reflection compared to other plant species and water. On the other hand, hydrilla had a lower level of near-infrared reflection compared to other plant species but higher compared to water. The spectral characteristics of submerged hydrilla plants were similar to that of water. An evaluation of the classified image showed an overall accuracy of 87.7%.

Verma *et al*. (2003) examined satellite images captured by the Indian Remote Sensing Satellite (IRS) LISS-II and III from different years and seasons between 1988 and 2001. Their aim was to compare the extent of water hyacinth-covered areas in six distinct bodies of water situated in and around the northern area of Bangalore, India. The result showed that the coverage of water hyacinth has increased in recent times as compared to previous years. They suggested that observing the changes in water hyacinth over time would facilitate the comprehension of the weed's ecology and dynamics, as it is recognized as the "most successful colonizer."

Albright *et al*. (2004) conducted a study on the growth and decline of water hyacinth in Lake Victoria and the Kagera River Basin between 1989 and 2001.The researchers utilized a technique that combined unsupervised image classification with manual adjustments to generate maps and measure the extent of coverage. The findings validated the seriousness of the water hyacinth invasion, particularly in the northern regions of the lake, where the coverage was at its maximum, reaching 17,374 hectares in 1998. In the late 1990s, several lakes in the Kagera basin, including Lake Mihindi in Rwanda, experienced significant infestations. However, by the early 2000s, the extent of water hyacinth infestation had significantly declined in most of these lakes.

Gidley (2009) utilized high-resolution satellite imagery to create maps of aquatic macrophytes on various lakes in Northern Indiana, USA. The study aimed to assess different techniques for mapping aquatic plants by analyzing high-resolution Quickbird satellite imagery obtained during 2007 and 2008. She employed an unsupervised classification approach to generate two levels of classification. The Level I differentiated the vegetation into specific categories of emergent and submerged vegetation based on plant structure. The Level II classification merged these categories into broader groupings. The accuracy of the Level I classification was 68% for the 2007 imagery and 58% for the 2008 imagery, while the overall accuracy of the Level II classification was higher for both years, with 75% and 74% accuracy for 2007 and 2008, respectively. Among the classes, those that included bulrushes had the lowest accuracy in the Level I classification. In the Level II classification, the class with the least accuracy was submerged vegetation. On the other hand, water and man-made surfaces were accurately mapped with the highest degree of precision in both classification methods.

Zhao et al. (2013) employed Landsat remote sensing images, including MSS, TM, and ETM+, to assess the spatio-temporal dynamics of aquatic vegetation in Taihu lake, China. They used these images to map the composition and distribution of aquatic vegetation approximately every five years over the past 30 years, with the aim of quantifying the spatio-temporal dynamics of the vegetation. They found an overall increase in the area of aquatic vegetation from 187.5 km2 in 1981 to 485.0 km2 in 2005, followed by a sudden decline to 341.3 km2 in 2010. They also noted that the area of submerged vegetation rose from 127.0 km2 in 1981 to 366.5 km2 in 2005, but then decreased to 163.3 km2. In contrast, the area and percentage of floating-leaf vegetation continued to increase throughout the study period, expanding from 12.9 km2 and 6.88% in 1981 to 146.2 km2 and 42.8% in 2010. In terms of spatial distribution, the aquatic vegetation in Taihu lake gradually spread from the East Bay to the surrounding regions, with the proportion of vegetation in the East Bay relative to that of the entire lake decreasing continuously from 62.3% in 1981 to 31.1% in 2005 and then to 21.8% in 2010. Overall, the study suggested that significant changes have occurred in both the relative composition and amount of area occupied by the aquatic vegetation, as well as its spatial pattern over the last three decades.

Shekede et al. (2013) conducted a study on six different types of aquatic weeds, namely *Hydrocotyle ranunculoides, Pontederia crassipes, Pistia stratiotes, Typha camensis, Phragmites australis*, and *Persicaria senegalensis* in lake Chivero, Zimbabwe. Their main aim was to distinguish and differentiate between these weeds using their spectral properties. The study showed each of the six aquatic weeds examined has distinct spectral features that enable significant spectral differentiation (with $p<0.05$) of these plants. The research also indicates that the long wavelength part of the electromagnetic spectrum is more effective in achieving greater spectral separability among the aquatic weeds, compared to the short wavelength region. Additionally, the study underscores the importance of conducting more research on the spectral differentiation of aquatic weeds, not only in lake Chivero but in all water bodies that are vulnerable to invasion by these weeds, particularly through the use of airborne hyperspectral techniques to cover larger and more representative areas.

John and Kavya (2014) conducted research on the combination of multispectral satellite and hyperspectral field data to classify aquatic macrophyte species through unsupervised classification using different spectral subsets. The results showed that the unsupervised classification achieved an overall accuracy of 100% using the Red-Edge, Green, Coastal blue & Red-edge, Yellow, Blue band combinations. The NIR-1, Green, Coastal blue & NIR-1, Yellow, Blue band combinations resulted in an accuracy of 82.35%. Based on these findings, the study concluded that high-resolution images with both spectral and spatial information are valuable tools for natural resource managers, particularly for identifying the location and mapping distribution of macrophyte species.

Thamaga and Dube (2018) conducted a review of the application and challenges of remote sensing in detecting invasive *P. crassipes*. They observed an increase in the number of studies utilizing remote sensing techniques to estimate water hyacinth invasions. However, they suggested that while most of these studies focus on mapping water hyacinth in larger water bodies, it is also important to extend this focus to smaller water bodies.

Ghoussein et al. (2019) utilized Sentinel-2 images to investigate P. crassipes in a Mediterranean river. They proposed a new approach for image analysis that involved utilizing a time series of a biophysical variable obtained from the Sentinel-2 images. The approach involved defining a reference period between two growing cycles and using the fractional vegetation cover (FVC) to estimate the extent of water hyacinth in the river.

Mukarugwiro *et al*. (2019) mapped *P. crassipes* in Rwanda using Landsat 8 OLI multispectral imagery. They examined the effectiveness of multispectral imagery in detecting and mapping water hyacinth in water bodies in Rwanda, using Random Forest and Support Vector Machine algorithms. They discovered that Random Forest had a considerably higher overall accuracy rate of 85%, compared to Support Vector Machine, which had an accuracy rate of 65%.

Asmare *et al.* (2020) studied spatiotemporal trend of water hyacinth in lake Tana, Ethiopia during 2013, 2015 and 2017 using Landsat 8 imageries. The study was done using decision tree and maximum likelihood classification. The overall accuracy was 99.5% and kappa coefficient 0.98.

Damtie *et al.* (2021) studied spatial seasonal coverage of water hyacinth on lake Tana, Ethiopia. In 2019, the water hyacinth area was observed to be 15.35 km2 in winter, 4.14 km2 in autumn, 11.82 km2 in summer, and 13.59 km2 in spring. The study showed high overall accuracy rates of 95.11%, 99.41%, 99.07%, and 99.77% and overall kappa coefficients of 0.93, 0.99, 0.98, and 0.97 for the winter, autumn, summer, and spring, respectively.

Simpson *et al.* (2022) studied *P. crassipes* infestation in Kuttand, India by using Sentinel-1 SAR (Synthetic aperture system) data. The result proved water hyacinth can be detected by using Sentinel-1 data with 90-95% accuracy.

Padua *et al.* (2022) monitored *P. crassipes* in lower Mondego region, Portugal by using remote sensing data. They used Sentinel-2 MSI and UAV multispectral imagery and obtained greater than 97% accuracy.

2.3 Research gap

The invasive aquatic plant species *Pontederia crassipes*, has encroached upon the natural wetlands in Nepal. To control the invasion of an invasive species, it is crucial to first understand the phenomenon and quantify the location and extent. Remote sensing techniques and methods can be highly beneficial in this regard. The main aim of this research work is to know the distribution pattern of Pontederia crassipes through the utilization of Landsat series images and worldview-2 images.

Remote sensing methodology is a relatively new approach in invasion research, having been developed only in recent years. The majority of the literature available on aquatic invasions is based on large lakes. This research work utilizes a knowledge-based approach to map out the spread of *Pontederia crassipes* in smaller water bodies. And until now, no remote sensing research has been conducted in Nepal regarding the detection of invasive species *Pontederia crassipes*.

3. MATERIALS AND METHODS

3.1 Description of the study species

Pontederia crassipes Mart. is a floating aquatic invasive species under family Pontederiaceae. The aquatic monocot macrophyte is often referred to as water hyacinth because of its aquatic habitat and its flower's resemblance to that of garden hyacinths in color (Parson *et al.*, 2001). It reproduces by stolons asexually and by seeds sexually (Havel *et al.*, 2015). It consists of 6-10 green glabrous leaves on elongate or bulbous petiole (Center *et al.*, 1981). Two types of leaves are found: erect, narrow up to 60 cm length; and rounded, curved upwards up to 30 cm diameter (Parson *et al.*, 2001). The feathery fibrous roots and rhizomes are submerged under water (Xie *et al.*, 2003). Flowers are attractive with six lobes of perianth and borned in spike. Fruit possesses 3-celled capsule with up to 300 seeds. Seeds are about 1 to 1.5 mm in length (Malik, 2007). The seeds are viable up to 20 years (Gopal, 1987).

Pontederia crassipes Mart.

3.2 Description of the study area

3.2.1 Geographic location

This research project was conducted in the Chitwan Annapurna Landscape (CHAL), situated in central Nepal, covering a total area of 32,090 sq km. The elevation within the landscape varies between 200 m and 8,091 m above sea level (asl) (WWF, 2013). It covers either the entire or portions of 19 administrative districts, namely Mustang, Manang, Gorkha, Rasuwa, Nuwakot, Dhading, Lamjung, Tanahun, Chitwan, Nawalparasi, Syanja, Kaski, Parbat, Baglung, Myagdi, Gulmi, Arghakhachi, Makwanpur, and Palpa (Figure 1). The CHAL includes six protected areas (Chitwan National Park, a portion of Parsa Wildlife Reserve, Shivapuri Nagarjung National Park, Annapurna Conservation Area, Manaslu Conservation Area and a portion of Langtang National Park. According to the Department of Hydrology and Meteorology's (DHM) 2017 report, the landscape in Nepal is representative of four of the country's five physiographic regions, including the Siwalik region (200-1500 m), middle mountain region (1000-2500 m), high mountain region (2200-4000 m), and high Himalayan region (> 4000 m) (DHM, 2017).

3.2.2 Climate

The Chitwan Annapurna Landscape (CHAL) exhibits a varied climatic pattern due to its diverse topography. The southern lowlands, known as Siwalik, experience a tropical to subtropical climate. The hilly region, referred to as middle mountain, has a subtropical to temperate climate. The northern part of the country, which comprises the high mountain and high Himalaya regions, is characterized by cold and dry climatic conditions due to its rugged topography, deep gorges, glaciers, and snow-capped peaks.

The annual rainfall in CHAL varies at the district level, with Mustang receiving the lowest amount of rainfall (< 200 mm annual rainfall) and Kaski, Parbat, Tanahun, Lamjung, and Nuwakot receiving more than 2000 mm of annual rainfall (DHM, 2017). The average temperature in Siwalik exceeds 25°C, while mid-hills experience temperatures around 20°C, and high mountains have temperatures ranging from 10-20°C (MoE, 2011). A notable rise in temperature between 0.022 to 0.051°C was observed by Luitel *et al*. (2020) in the different bioclimatic zones at higher elevations in CHAL.

Table 1: Average temperature and rainfall along different bioclimatic zones in CHAL (1970-2019)

Bioclimatic zones	Average annual temperature (^{0}C)	Average annual rainfall (mm)
Lower tropical bioclimatic zone (< 500 m)	24.1	2002.1
Upper tropical bioclimatic zone (500-1000 m)	21.8	2613.1
Lower subtropical bioclimatic zone (1000-1500 m)	19.7	2223.9
Upper subtropical bioclimatic zone (1500-2000 m)	17.5	3146.4
Temperate bioclimatic zone (2000-3000 m)	13.3	1447.2
Lower subalpine bioclimatic zone (3000-3500 m)		952.1
Alpine bioclimatic zone (> 3500 m)		361.7

(Source: Luitel *et al.*, 2020)

3.2.3 Biodiversity and vegetation

CHAL is rich in biological diversity with numerous species of flora and fauna. This landscape includes three global ecoregions (Terai-duar savanna and grasslands, Himalayan subtropical broadleaf forests, and Himalayan subtropical pine forests)

(Dinerstein *et al.*, 2017). More than 3034 plant species were recorded from CHAL (Biodiversity Profile Project, 1995). The tropical forests are mainly dominated by *Shorea robusta*, *Acacia catechu*, *Dalbergia sissoo*, *Terminalia* species, *Adina cordifolia*, *Bombax ceiba*, *Lagerstroemia parviflora*, *Albizia* spp., etc. Similarly, the subtropical forests are dominated by *Schima wallichii*, *Castanopsis indica*, *Alnus nepalensis*, *Cedrella toona* and *Pinus roxburghii*. Temperate forests consist of lower temperate mixed broad-leaved forests of *Castanopsis tribuloides*, *Quercus lamellosa*, etc. and upper temperate broadleaved forests of *Quercus semecarpifolia*, *Acer* spp., *Rhododendron* spp., etc. Likewise, temperate conifer forests are dominated by *Pinus wallichiana*, *Abies spectabilis*, *Tsuga dumosa*, *Larix himalaica*, etc. Subalpine forests are dominated by *Abies spectabilis*, *Rhododendron* spp., *Betula utilis*, etc. The alpine region is only with scrub of *Juniperous* spp. and *Rhododendron* spp., and grasslands.

Chitwan National Park harbors a total of 540 bird species (Baral and Upadhyay, 2006), 47 species of reptiles, nine species of amphibians and 56 species of mammals (DNPWC, 2001). Animals like *Elephas maximus, Panthera tigris, Rhinoceros unicornis, Bos gaurus, Gavialis gangeticus, Python molurus* etc. are found in siwalik region. *Panthera pardus, Macacca mulata, Canis aureus, Vulpes vulpes, Muntiacus muntjak, Ursus thibetanus* etc. are found in mid-hilly regions. *Uncia uncia, Hemitragus jemlahicus, Felis lynx, Canis lupus, Nemorhaedus goral* etc. are found in mountain region (MFSC, 2015).

3.2.4 Land use pattern

Land use pattern is diverse in CHAL region. Largest portion of CHAL is covered by forest followed by agriculture, sand/bare soil, snow/ice, grasslands, alpine meadow/scrub and water (WWF, 2013).

Table 2: Areas of different land use in CHAL

Land use	**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

(Source: WWF, 2013)

3.2.5 Wetland

A total of 626 lakes are documented in Nepal (NLCDC, 2021), out of which 52 are located in CHAL region. The drainage system of CHAL comprises eight significant rivers, namely Kali Gandaki, Seti, Madi, Marsyangdi, Daraundi, Budi Gandaki, Trishuli, and Rapti, along with their respective tributaries (WWF, 2013). Within the landscape of CHAL, two sites have been recognized as Ramsar sites - the Beeshazari and associated lakes of Chitwan, and the lake clusters of Pokhara valley.

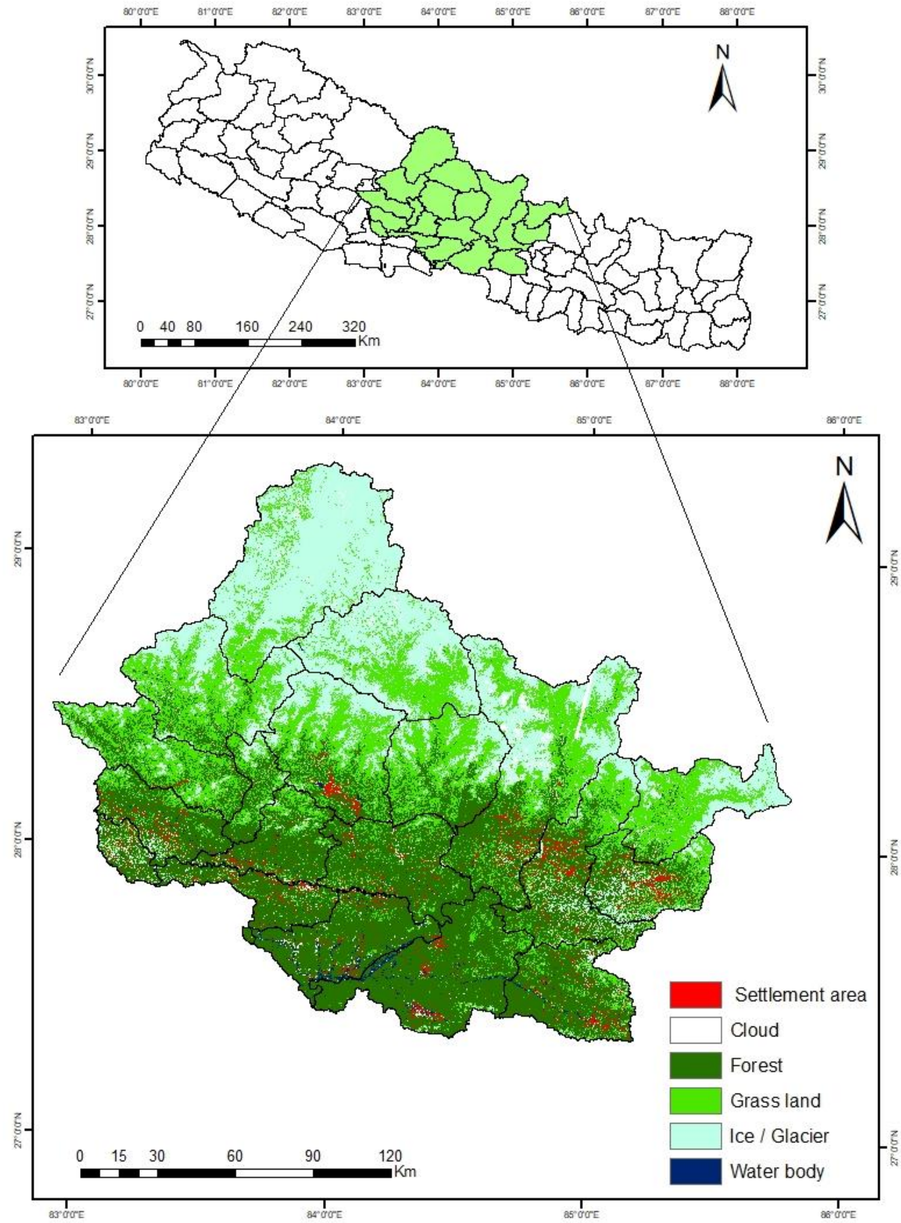

Figure 1: Map of CHAL area in Nepal

3.3 Research design

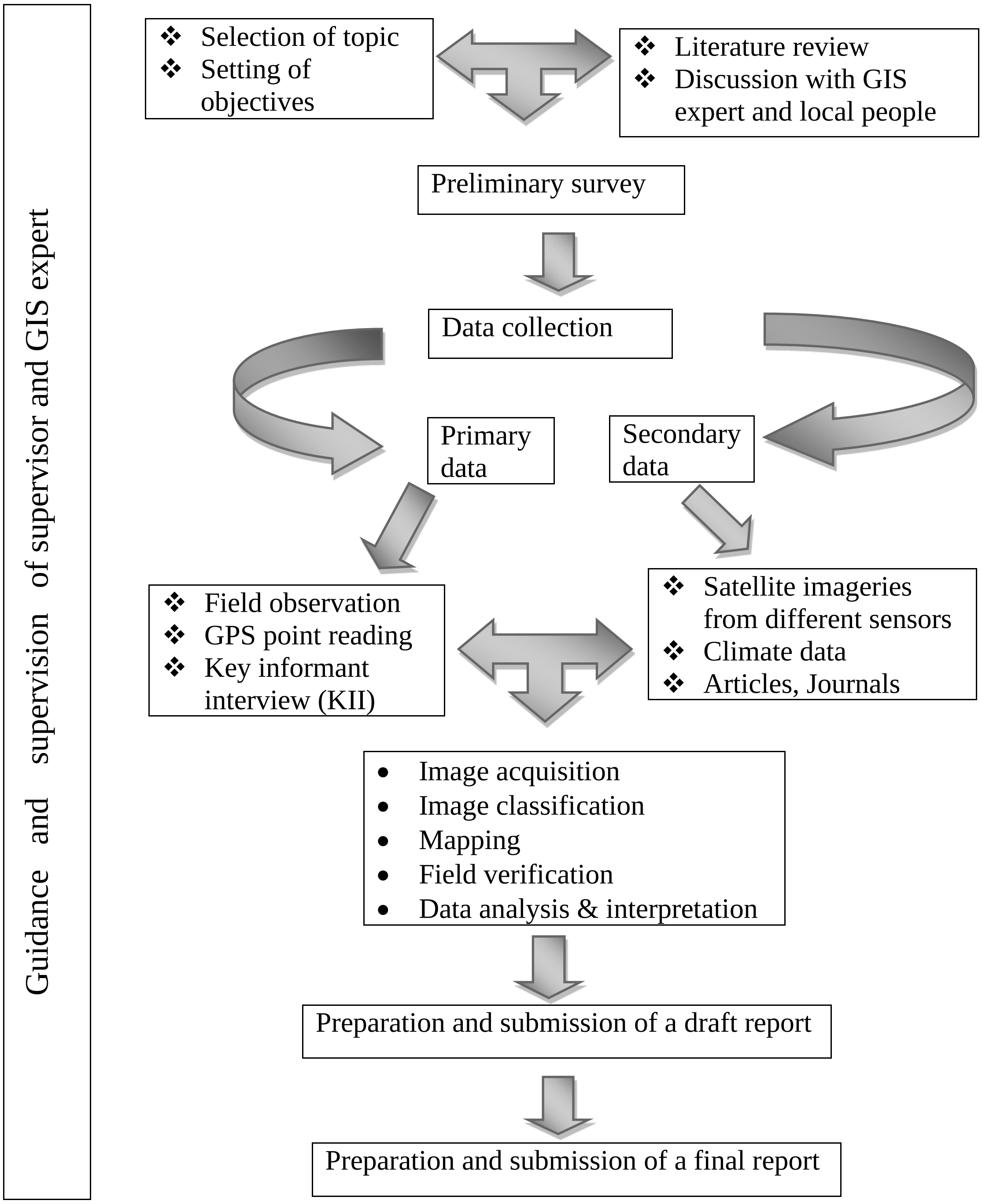

Figure 2: Research design

3.4 Tools used

Following tools were used in this research work:

- Global Positioning System (GPS)
- Toposheet maps
- Satellite imageries (Landsat imageries and World View-2)
- Arc Map 10.5 (Arc GIS 10.5 software package)
- ERDAS IMAGINE 2014 (software)

3.5 Methods

3.5.1 Imageries acquisition

Currently, there exists a variety of satellite data types, each with distinct spatial, temporal, and spectral resolutions. But in this research work, satellite imageries of four different sensors (World View-2, Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI) were used to study distribution of *P. crassipes* (Table 3). World View-2 is a high spatial resolution, commercial satellite that was launched by Digital Globe company in 2009. World View-2 of 2 m × 2 m resolution was provided by the USAID project (purchased from the vendor). Other three sensors (Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI) of Landsat series of 30 m × 30 m resolution are freely available and downloaded from the archives of the U. S. Geological Surveys (USGS) by using the web engine Earth Explorer (http://earthexplorer.usgs.gov) as per the terms and condition of the copyright.

Table 3: Sensors used in the research work

Sensor	Spectral bands	Resolution (m)	Swath width(km)	Frequency (days)
Landsat 5 TM	7	30 (Band 1-5 and 7) 120 (Band 6)	185	26
Landsat 7 ETM+	8	30 (Band 1-7) 15 (Band 8)	185	18
Landsat 8 OLI	9	30 (Band 1-7 and 9) 15 (Band 8)	185	16
World View-2	8	2 (All multispectral bands) 0.48 (Panchromatic band)	16.4	1.1

Landsat 5 TM imageries were used for the year 1990 A.D., Landsat 7 ETM+ imageries were used for the year 2000 and 2010 A.D., and Landsat 8 OLI imageries were used for the year 2018 and 2020 A.D. The reason behind using Landsat series imageries is due to availability and launched date of the satellites (Table 4).

Table 4: Landsat series satellite launched and terminated date

Satellite	Launched	Terminated
Landsat 1	July 23, 1972	January 6, 1978
Landsat 2	January 22, 1975	February 25, 1982
Landsat 3	March 5, 1978	March 31, 1983
Landsat 4	July 16, 1982	December 14, 1993
Landsat 5	March 1, 1984	June 5, 2013
Landsat 6	October 5, 1993	October 5, 1993 (*Failed to reach orbit)
Landsat 7	April 15, 1999	Still active
Landsat 8	February 11, 2013	Still active

According to Shingare and Kale (2013), a Digital Elevation Model (DEM) is a continuous model that represents the surface of a terrain and contains XYZ coordinates. It provides information of elevation along with other topographic information like land cover, slopes and aspects. In most of the research studies in remote sensing, DEM is taken as indispensable quantitative environmental variable (San and Suzen, 2005). DEM in this study was downloaded from the USGS and other topo sheets from the site Pahar.com.

3.5.2 Imageries preprocessing

The Landsat imageries were mosaic (merged) and masked by CHAL outline shape file. Radiometric and atmospheric correction were done. Spectral bands of imageries in 8-bit unsigned integer format were also converted into 16-bit unsigned integer. The raw pixel value or digital number (D.N.) was converted to TOA reflectance using product metadata file (Landsat user's guide and World View-2 manual).

3.5.3 Imageries classification

After the acquisition and mosaic of satellite imageries from the archives, Iso Cluster Unsupervised Classification and Maximum Likelihood Classification (supervised classification) were done in Arc MAP 10.5. GPS points recorded during field visits were also used in the classification. Knowledge-based classification and use of several variables like terrain information including DEM, water resources, human activities, and accessibilities like several ancillary data were integrated in ERDAS IMAGINE 2014.

Table 5: Variables used during Knowledge-based Classification in ERDAS IMAGINE

Rules For Knowledge based classification	Methods	Suitable Criterion
Elevation	Reclassifying DEM File	75-1500 m
Slope	Reclassifying DEM File	1.71-15.60°
Aspect	Reclassifying DEM File	All aspect except North
Temperature(max)	From DHM data	20-40°C
Temperature(min)	From DHM data	16-20°C
Precipitation	From DHM data	1600mm– 3600mm
NDWI	(NIR - SWIR) / (NIR + SWIR)	0.5-0.7
Land uses	Supervised classification	Water bodies (wet lands)
Spectral value	Band blue, green, red, red edge	0.4-0.7 µm

Finally, from these processes, aquatic invasive species *P. crassipes* domination in 2018 and 2020 was mapped. The same process was also used in back date series.

3.5.4 Accuracy assessment

Accuracy assessment and triangulation test of the images was done in Arc GIS 10.5 by making error matrix. Ground truth point and local knowledge were incorporated about the alien species from the social survey conducted among the local knowledgeable people.

An error matrix (also known as confusion matrix) is a table that compares information from a reference source with information on a map that has been classified. It shows how many sample areas have been assigned to a particular category in one classification compared to the number of sample areas that have been assigned to the same category in another classification. The matrix is arranged in rows and columns, with each number indicating the number of sample units that fall into a particular category. The columns typically represent the reference data, while the rows represent the classification that has been created from remotely sensed data i.e., map. The reference data has often been referred as the ground truth data. An error matrix is a highly useful method for presenting map accuracy because it clearly shows the accuracy of each category, as well as the commission errors (errors of inclusion) and omission errors (errors of exclusion) present in the classification. Commission errors occur when an area is included in a category to which it does not belong, while omission errors occur when an area is excluded from the category to which it actually belongs.

This research involves a classification that has two distinct categories, namely 'Present' and 'Absent'. Binary map was prepared. Error matrix was calculated from classified map data and reference data (ground truth point) (Congalton and Green 2008). Fifty presence and fifty absence ground truth points were noted from AOI. The formulas used to calculate User's Accuracy, Producer's Accuracy, Overall Accuracy, and Kappa Coefficient were as follows:

Producer's accuracy (%) = $\frac{\text{No.of correctly classified in each category}}{\text{Total no.actually in that category (the column total)}} \times 100$

User's accuracy (%)= $\frac{\text{No. of correctly classified in reference data}}{\text{Total number of pixels that were classified in that category (the row total)}} \times 100$

Overall accuracy (%) = $\frac{\text{Total no. of correctly classified pixels (diagonal)}}{\text{Total number of reference pixel}} \times 100$

Kappa coefficient = $\frac{(\text{TS} \times \text{TCS}) - \Sigma\,(\text{column total} \times \text{row total})}{\text{TS2} - \Sigma\,(\text{column total} \times \text{row total})\text{l}} \times 100$

where, TS = Total no. of sample and

TCS = Total no. of corrected sample

The Kappa Coefficient is a statistical measure used to assess the accuracy of a classification (Bishop *et al.,* 1975). Essentially, Kappa evaluates how well the classification performed compared to a random assignment of values. The Kappa Coefficient has a range of -1 to 1. If the value of Kappa is 0, it means that the classification is no better than a random assignment. A negative value of Kappa indicates that the classification is significantly worse than random. A value close to 1 suggests that the classification is significantly better than random.

The work flow chart is shown (Figure 3).

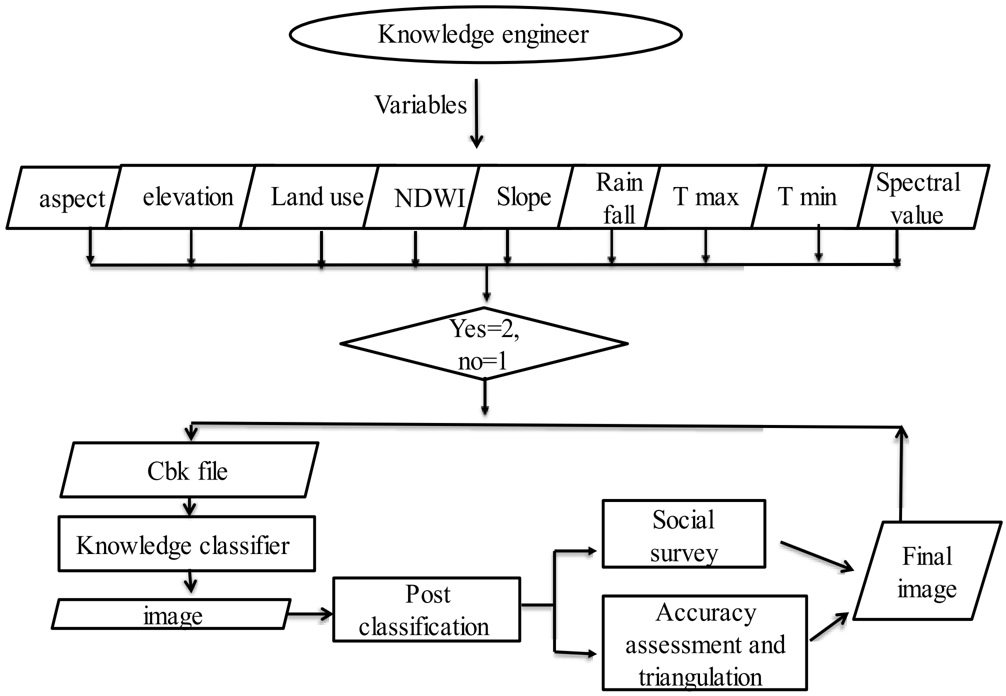

Figure 3: Work flow chart

4. RESULTS

World View-2 imageries for Chitwan (Ghaila Ghari lake), Nawalparasi (Shashwat Dham), Makwanpur (Manhari), and Kaski (Fewa lake) were taken of 2018 A.D. The imageries were classified and final *Pontederia* distribution maps were prepared. The same place's maps of Landsat 8 OLI of 2018 A.D. were also clipped and analyzed. Finally, whole CHAL area map of Landsat 8 OLI of 2018 was classified and analyzed. The same process was done for imageries of 1990, 2000, 2010 and 2020 A.D.

4.1 Distribution of *P. crassipes* in small AOI of World View-2 and Landsat 8

4.1.1 Worldview-2 and Landsat 8 OLI of Chitwan

The first field visit was done in the month of September 2018 in Chitwan district. The area of interest (AOI) was Ghaila Ghari lake near Ghaila Ghari Buffer Zone Community Forest, Chitwan. During the field visit, geographical coordinates were recorded by GPS and key interviews were taken with local people.

The total area of World View-2 (Digital globe) of small AOI of Chitwan district was 42.829 km^2 (42829000 m^2). At first, Land Use Land Cover (LULC) map was prepared. The classified LULC map is presented in Figure 4.

The LULC map was further analyzed and *Pontederia* map was prepared. From final map, *Pontederia* coverage in the World View-2 was found to be 507 m^2 (0.00051 km^2) i.e., 0.0012 % of total AOI (Figure 5). In Landsat 8 OLI map. *Pontederia* covers 415 m^2 (0.000415 km^2). Out of total area, only 0.00097 % was infested by *Pontederia* (water hyacinth) (Figure 6).

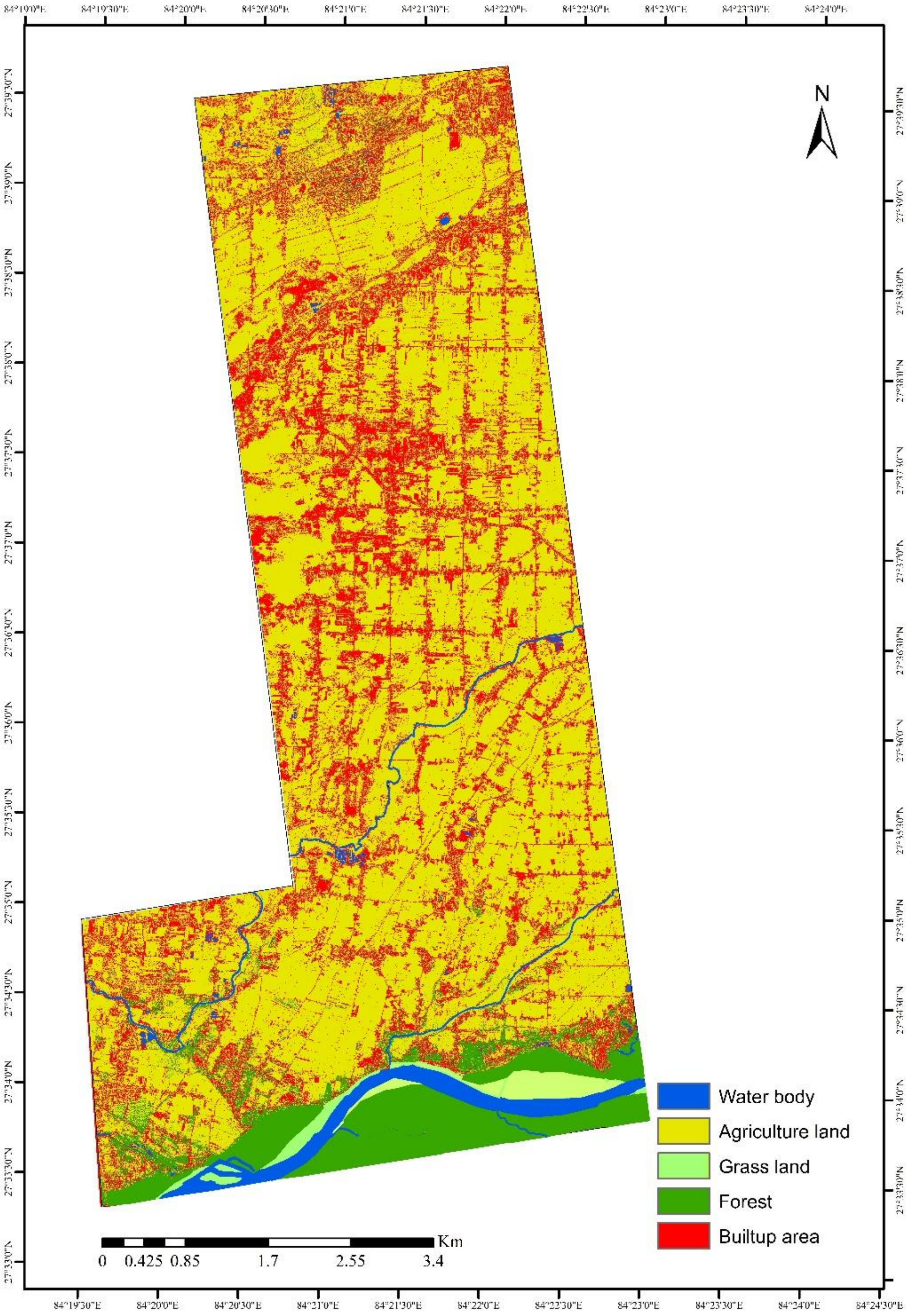

Figure 4: LULC map of Ghaila Ghari AOI in Chitwan (World View-2)

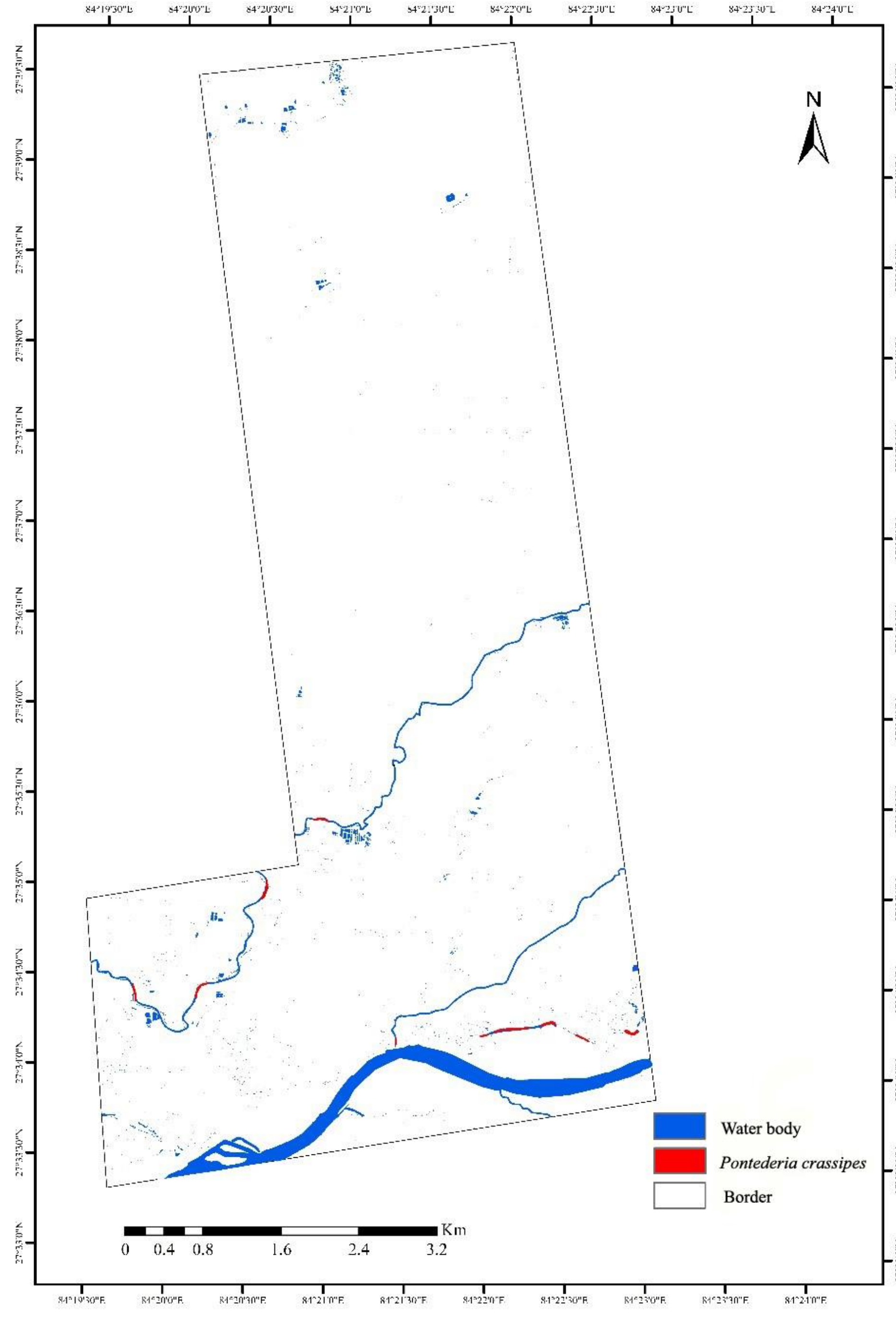

Figure 5: Distribution of *P. crassipes* in Ghaila Ghari AOI in Chitwan (World View-2)

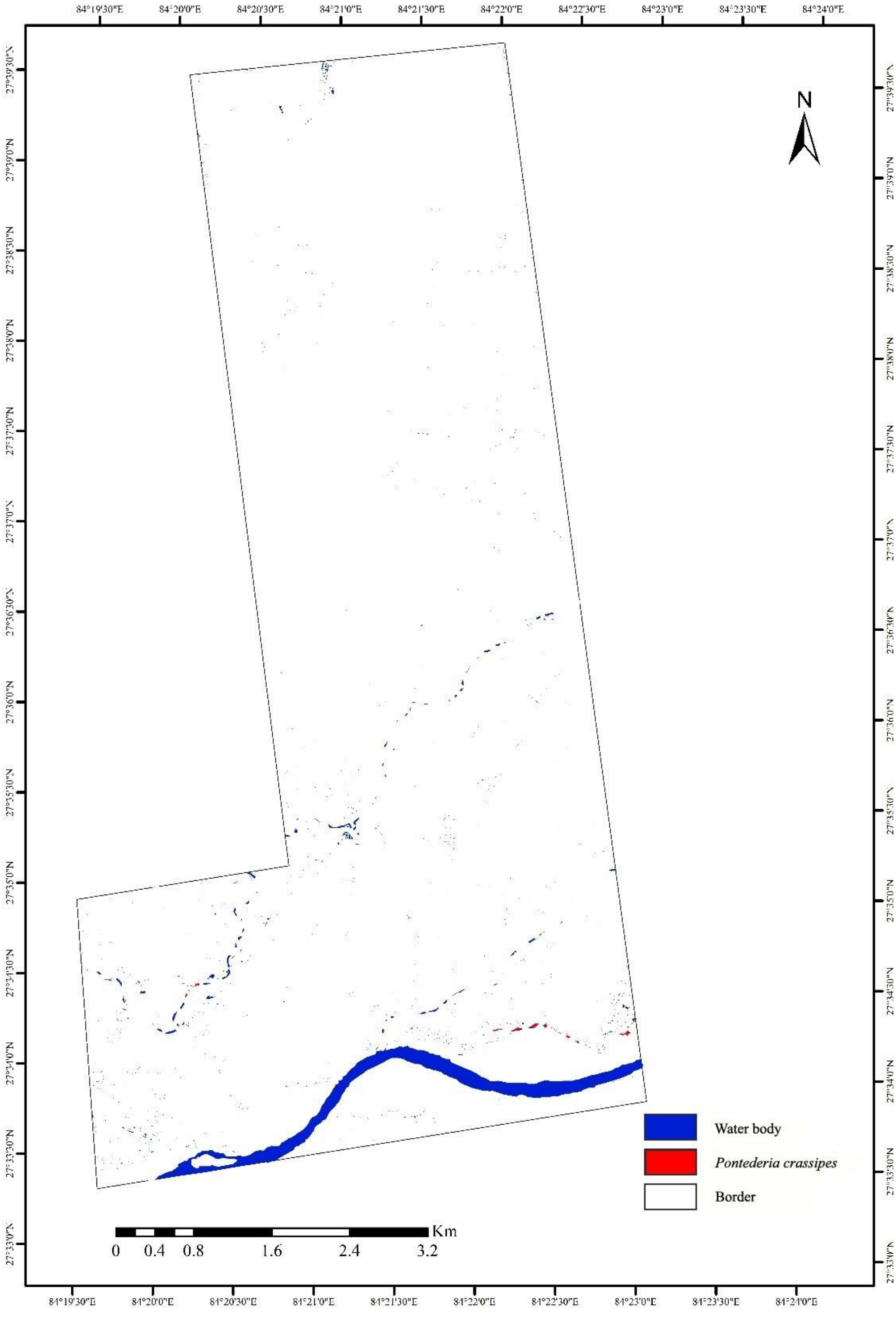

Figure 6: Distribution of *P. crassipes* in Ghaila Ghari AOI in Chitwan (Landsat 8 OLI)

4.1.2 World View-2 and Landsat 8 OLI of Nawalparasi

The total area of small AOI of Nawalparasi is 44 km^2 (44000000 m^2). This AOI map is of Shaswat Dham, Dumkali area. Narayani river is at the edge of the map. Other small ponds and ditches are also present. At first, LULC map was prepared of World Wiew-2 in Arc GIS 10.5. The same area map was also clipped in Landsat 8 OLI and LULC classification was done. Only LULC map of World-View-2 is shown in Figure 7.

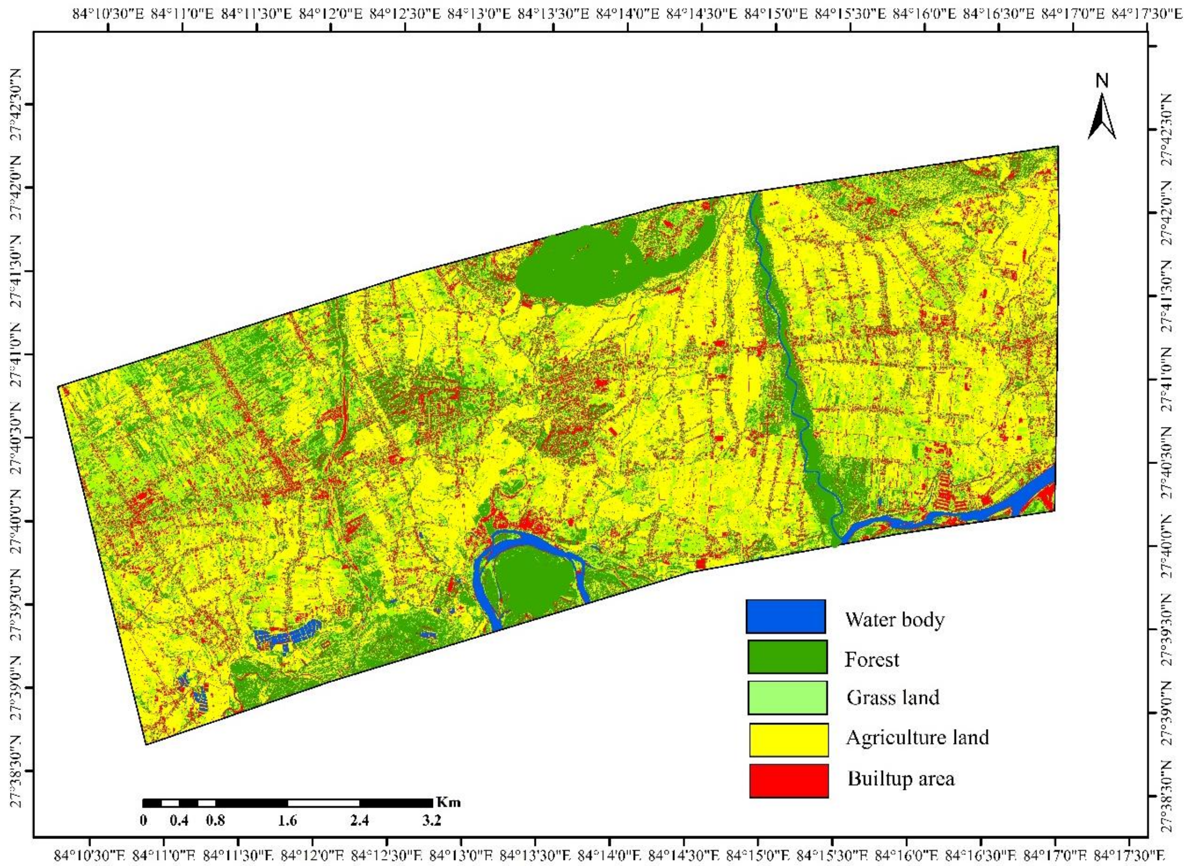

Figure 7: LULC map of Shaswatdham AOI in Nawalparasi (World View-2)

The LULC maps of both sensors were further analyzed in ERDAS IMAGINE 2014 by using primary and secondary data. The area of distribution of *P. crassipes* in World View-2 map was found to be 170 m^2 (0.00017 km^2). Out of total area in AOI, only 0.00039% was infested by *Pontederia* (Figure 8).

In Landsat 8 OLI map, *Pontederia* covered 125 m^2 (0.000125 km^2). Out of total area, only 0.00028 % was infested by *Pontederia* (Figure 9).

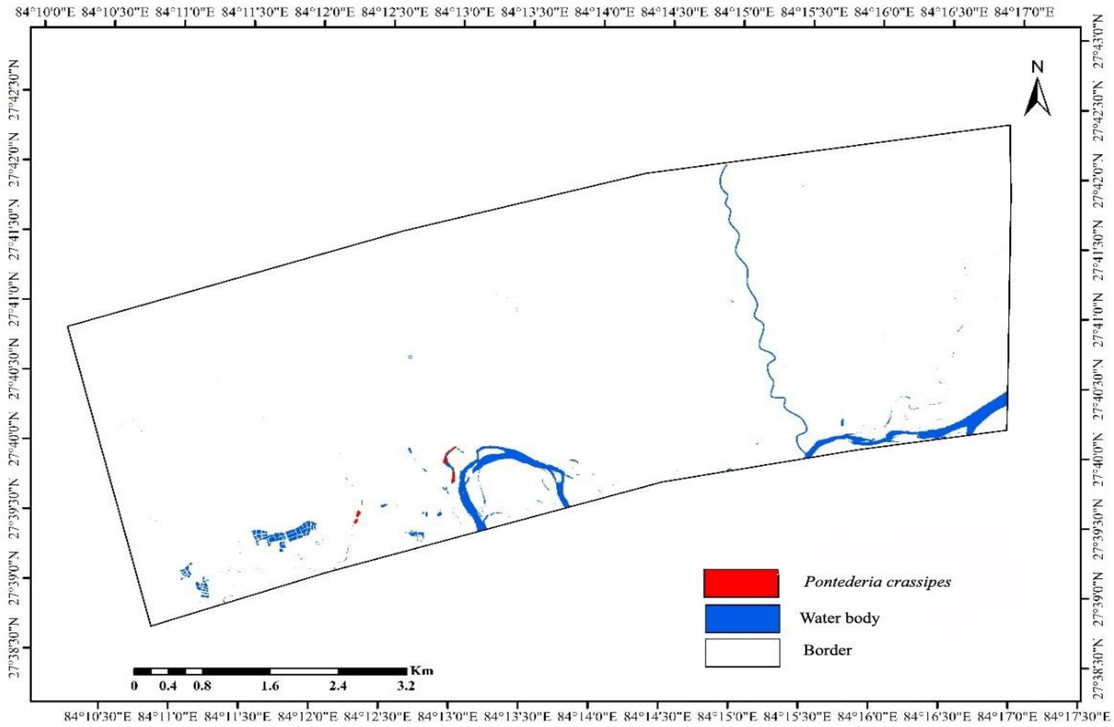

Figure 8: Distribution of *P. crassipes* Shaswatdham AOI in Nawalparasi (World View-2)

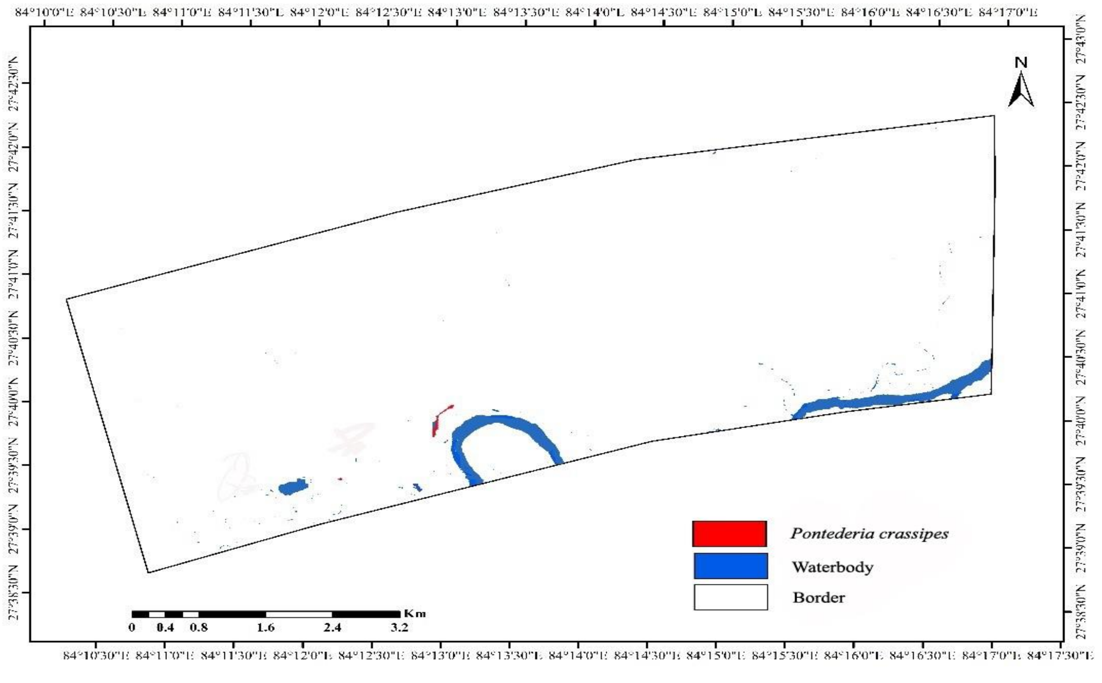

Figure 9: Distribution of *P. crassipes* in Shaswatdham AOI in Nawalparasi (Landsat 8 OLI)

4.1.3 World View-2 and Landsat 8 OLI of Makwanpur

Total area of Manhari AOI of Makwanpur is 107.18 km^2 (107180000 m^2). This map covers area from Hetauda to Manhari. Narayani river is at the edge of the map. Other small ponds and ditches are also present. At first, LULC map was prepared of World Wiew-2 in Arc GIS 10.5. The same area map was also clipped in Landsat 8 OLI and LULC classification was done. Only LULC map of World-View-2 is shown in Figure 10.

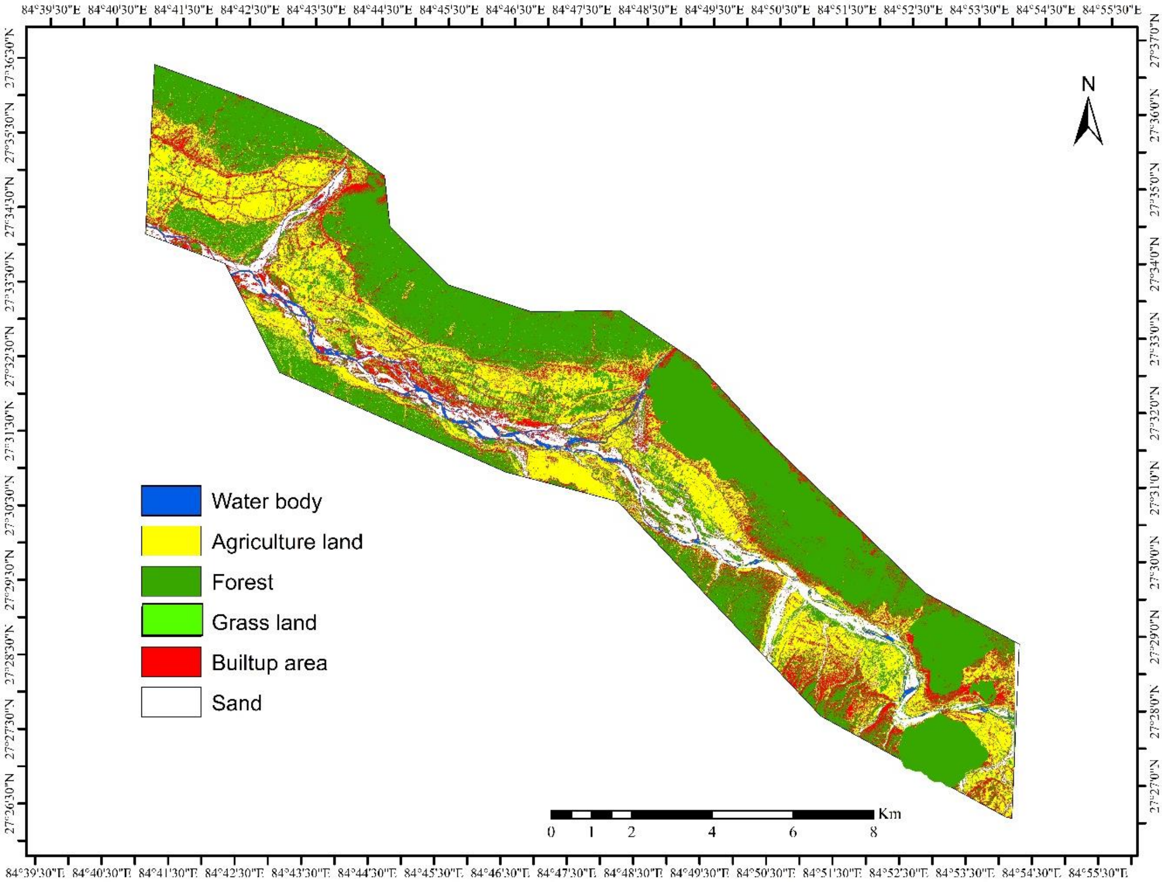

Figure 10: LULC map of Manhari AOI in Makwanpur (World View-2)

The LULC map of both sensors were also further analyzed in ERDAS IMAGINE 2014 by using primary and secondary data. The area of distribution of *P. crassipes* in World View-2 map was found to be 447.6 m^2 (0.00045 km^2). Out of total area, only 0.00042% was infested by *Pontederia* (Figure 11).

The same process was done in Landsat 8 OLI map. *Pontederia* infested area was 375 m^2 (0.00038 km^2). Out of total area, only 0.00035 % was infested by *Pontederia* (Figure 12).

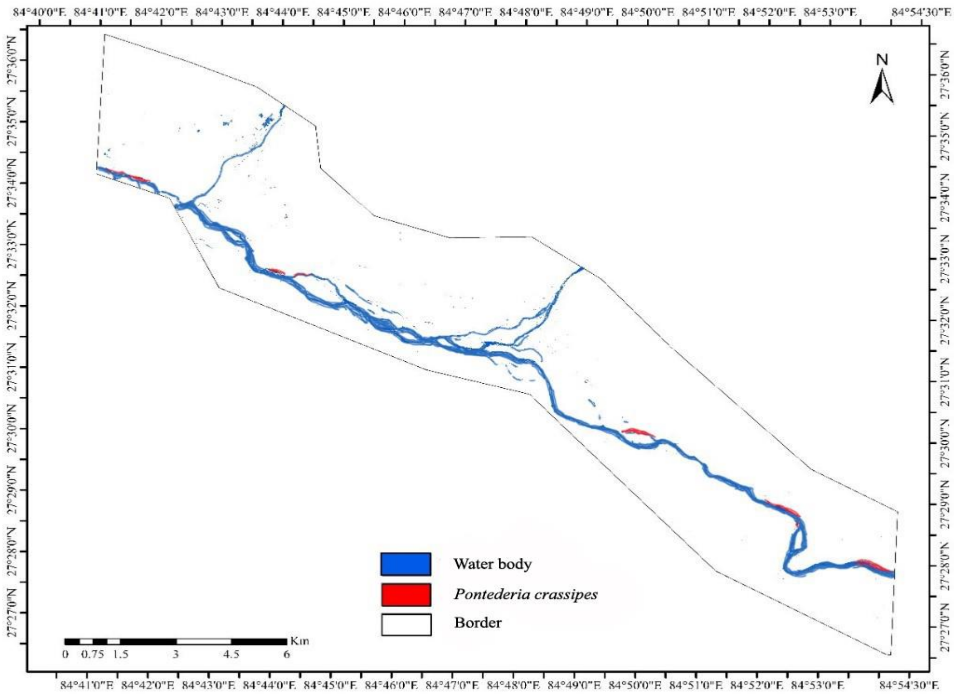

Figure 11: Distribution of *P. crassipes* in Manhari AOI in Makwanpur (World View-2)

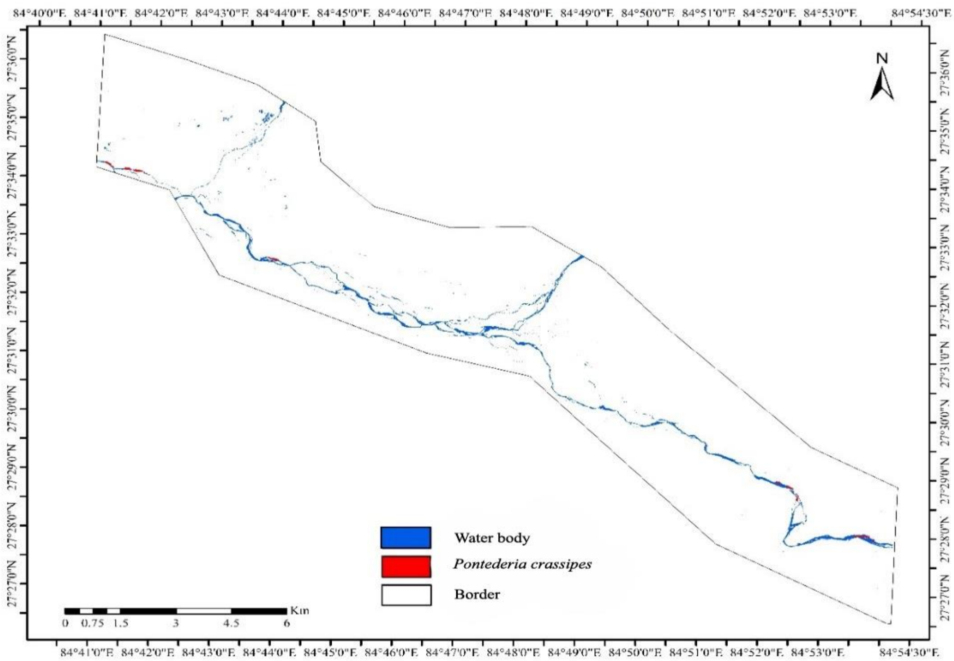

Figure 12: Distribution of *P. crassipes* in Manhari AOI in Makwanpur (Landsat 8 OLI)

4.1.4 World View-2 and Landsat 8 of Kaski

The small AOI in Pokhara in Kaski district is 96.05 km^2 (96050000 m^2). This map covers area of Pokhara with a small portion of Fewa lake and Begnas lake. At first, LULC map was prepared of World Wiew-2 in Arc GIS 10.5. The same area map was also clipped in Landsat 8 OLI and LULC classification was done. Only LULC map of World-View-2 is shown in Figure 13.

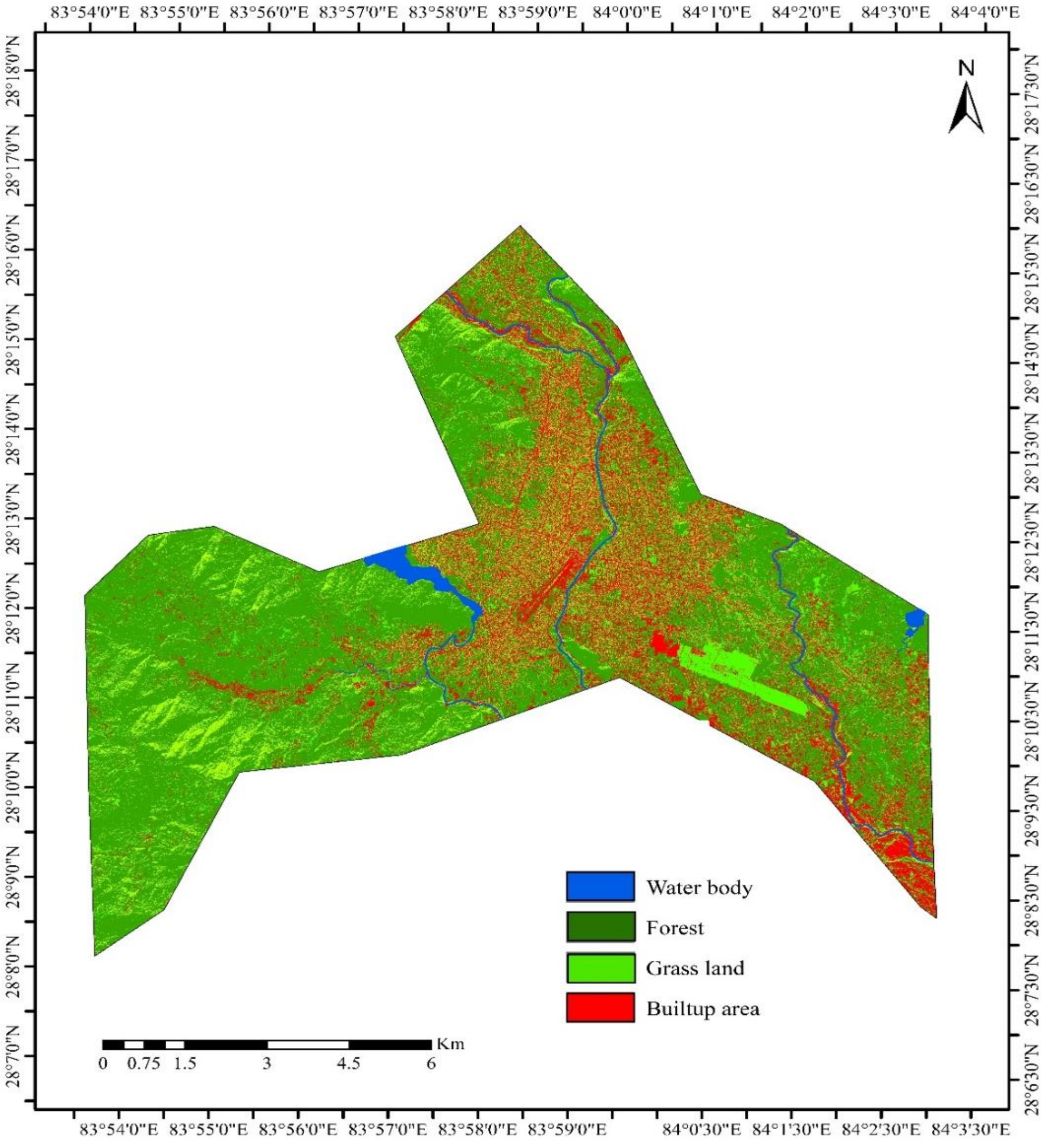

Figure 13: LULC map of Kaski (World View-2)

The LULC maps of both sensors were further analyzed in ERDAS IMAGINE 2014 by following same process. The area of distribution of *P. crassipes* in World View-2 map was found to be 347.5 m^2 (0.00035 km^2). Out of total area, only 0.00036 % was infested by *P. crassipes* (Figure 11).

The same process was also done in Landsat 8 OLI map. *P. crassipes* covered 305 m^2 (0.00031 km^2). Out of total area, only 0.00032 % was infested by *P. crassipes* (water hyacinth) (Figure 12).

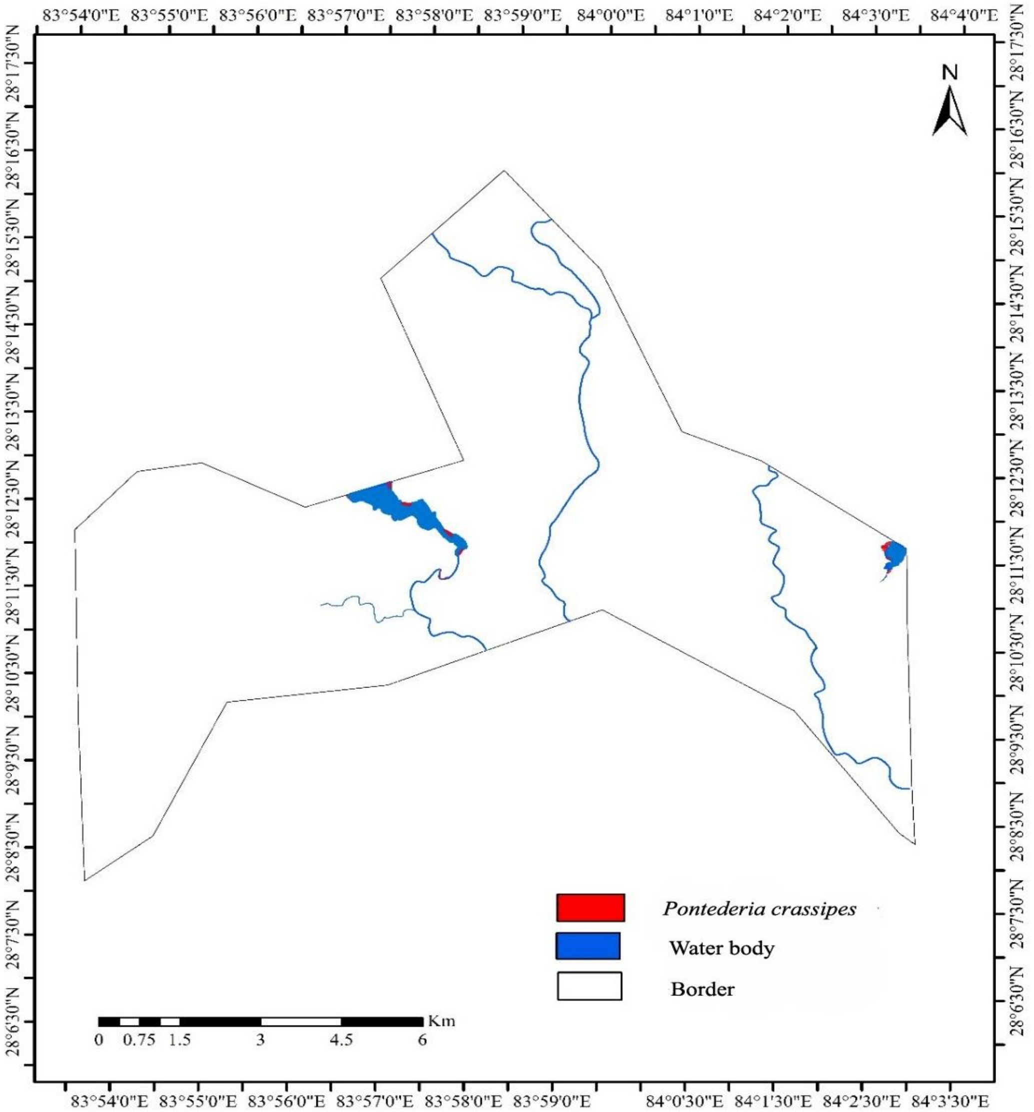

Figure 14: Distribution of *P. crassipes* in Phewa and Begnas lakes in Kaski (World View-2)

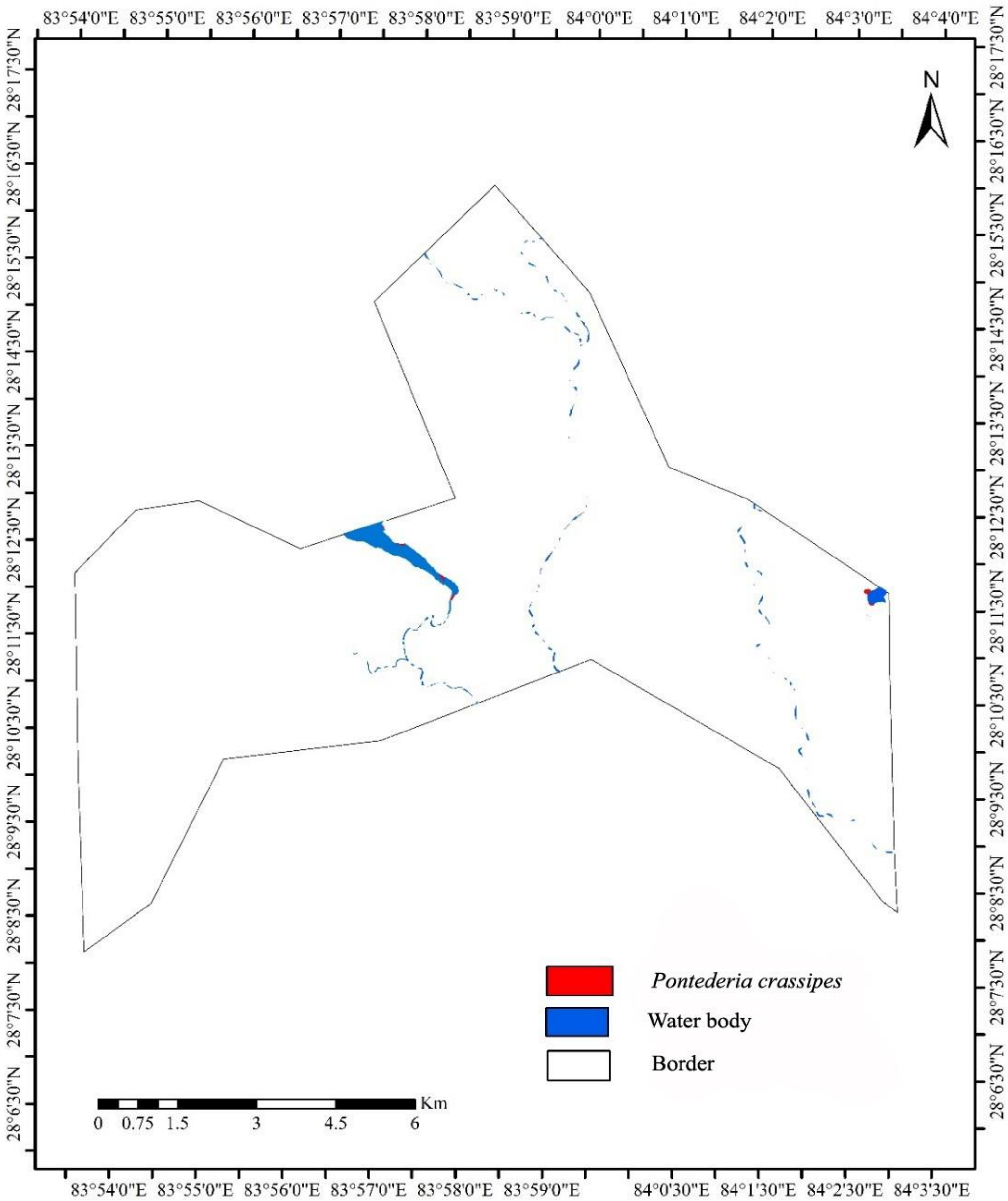

Figure 15: Distribution of *P. crassipes* in Phewa and Begnas lakes in Kaski (Landsat 8 OLI)

4.2 Distribution of *P. crassipes* in CHAL region in Landsat image

The same method was applied in the Landsat imageries too. Landsat imageries have low resolution than World View-2. Landsat imageries of CHAL area was classified and analyzed from 1990 to 2020 at the gap of 10 years.

4.2.1 Landsat 8 OLI – 2018 A.D.

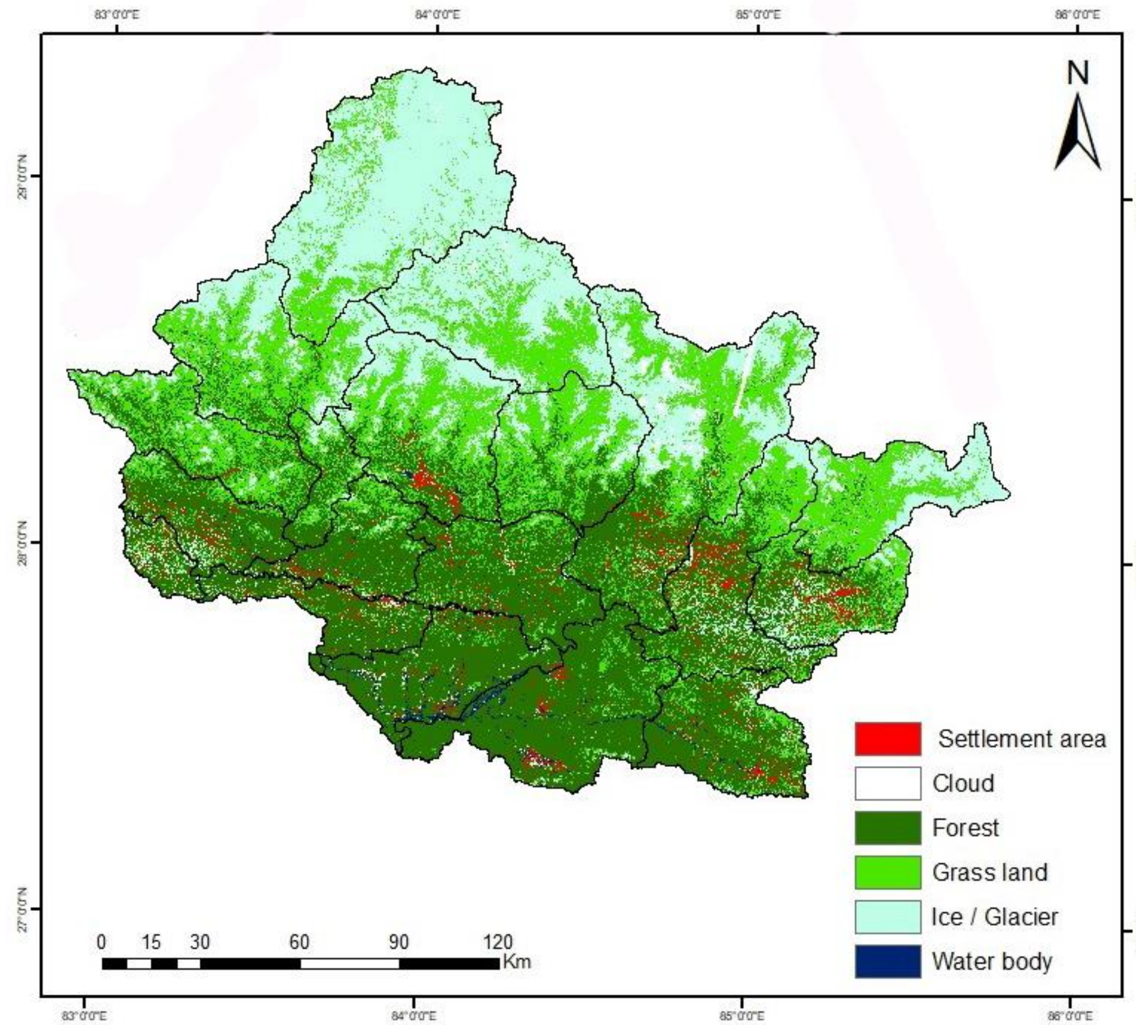

Figure 16: LULC map of CHAL (Landsat 8)

P. crassipes coverage in the CHAL area was found to be 27.58 km^2 in 2018 A.D. i.e., 0.086% of the total CHAL area. The coverage was seen in Phewa lake, Kaski district, Chitwan, Nawalparasi and Makwanpur districts (Figure 17).

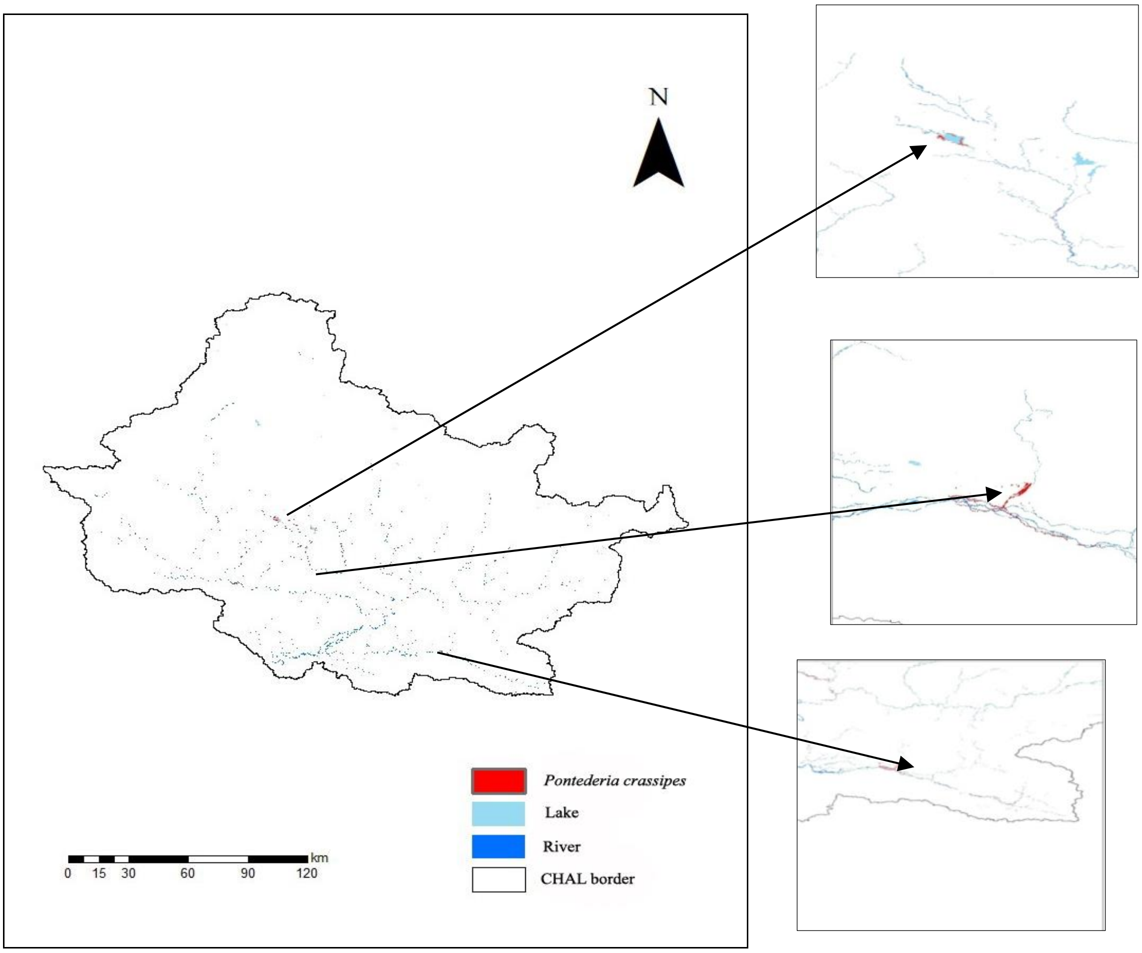

Figure 17: Map of CHAL 2018 showing *P. crassipes* (Landsat 8)

4.2.2 Landsat 5 TM – 1990 A.D.

The *P. crassipes* coverage in the CHAL area was found 9.6 km^2 in 1990 A.D. i.e., 0.030% of the total CHAL area (Figure 18).

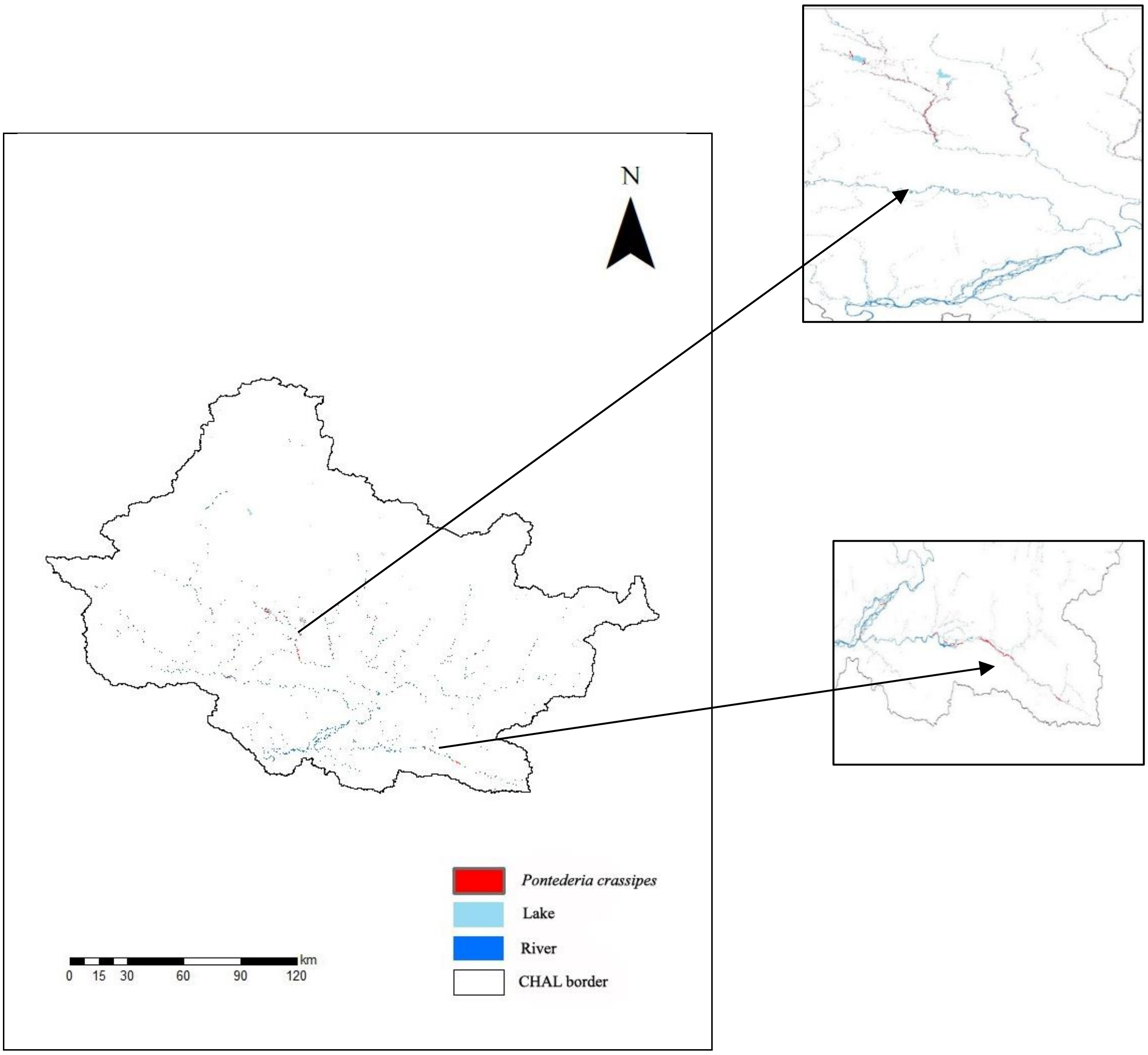

Figure 18: Map of CHAL 1990 showing *P. crassipes* (Landsat 5)

4.2.3 Landsat 7 ETM+ - 2000 A.D

The *P. crassipes* coverage in the CHAL area was found 2.93 km^2 in 2000 A.D. i.e., 0.0092% of the total CHAL area (Figure 19).

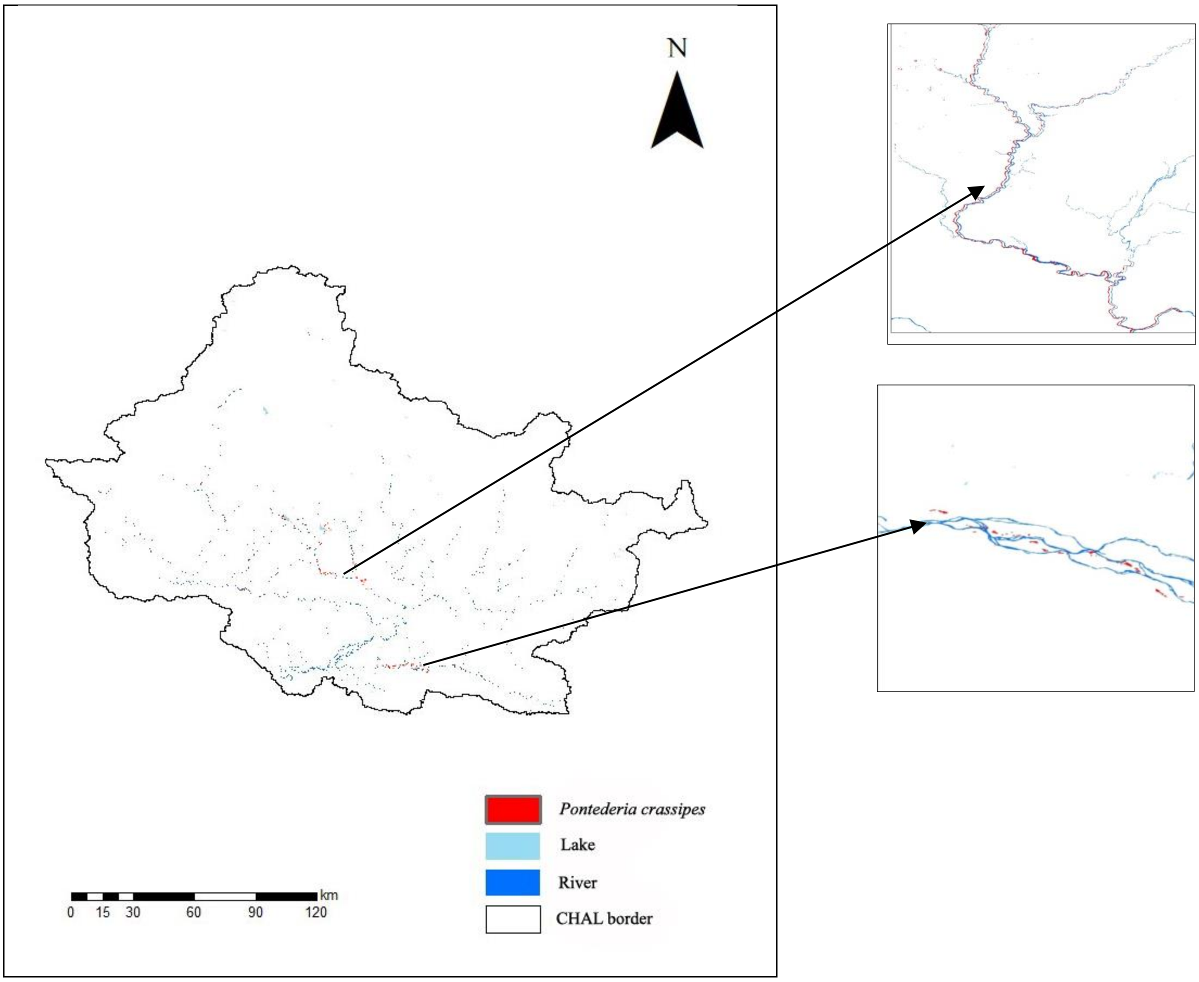

Figure 19: Map of CHAL 2000 showing *P. crassipes* (Landsat 7)

4.2.4 Landsat 7 ETM+ – 2010 A.D.

The *P. crassipes* coverage in the CHAL area was found 23.44 km^2 in 2010 A.D. i.e., 0.073% of the total CHAL area (Figure 20).

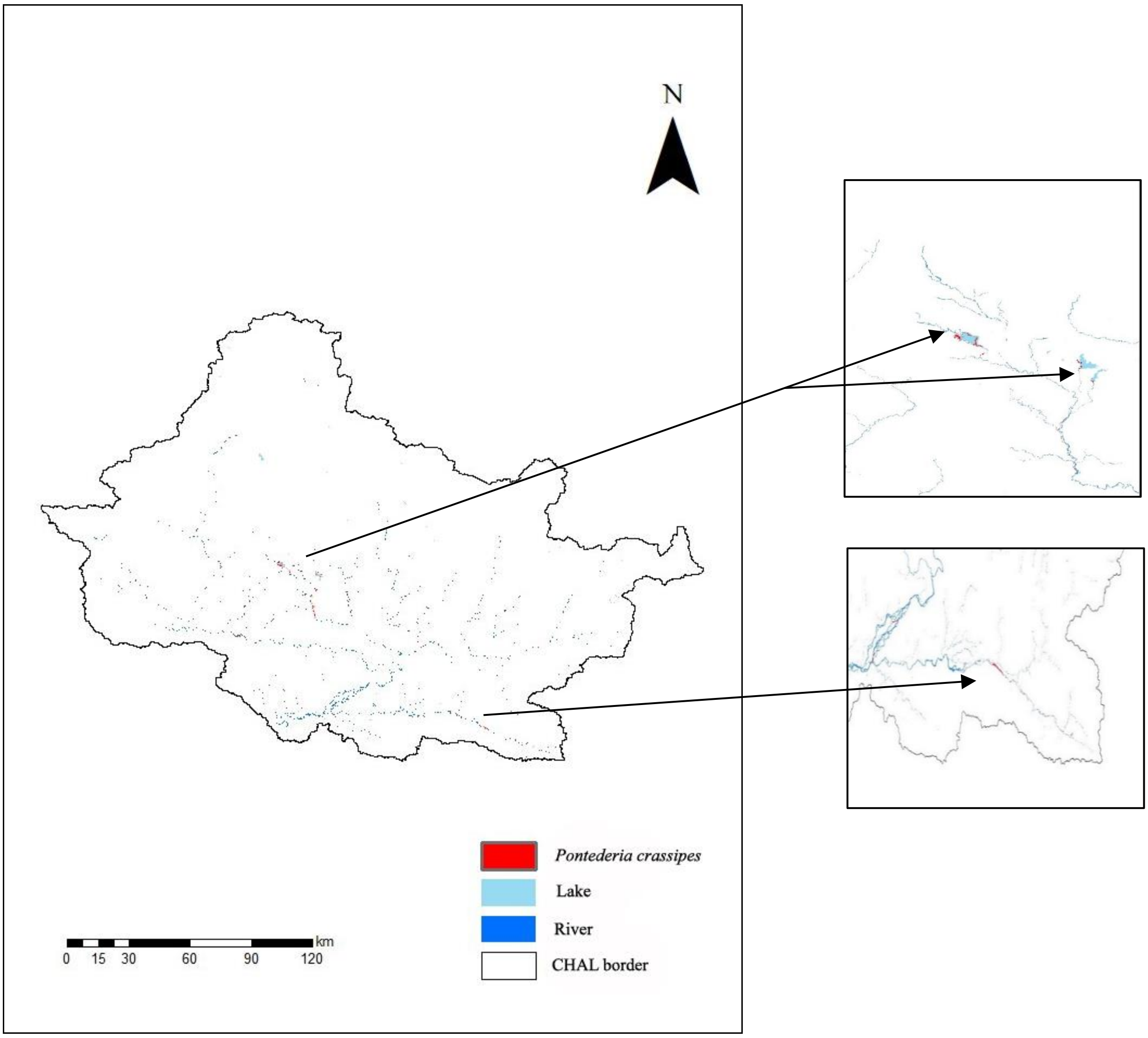

Figure 20: Map of CHAL 2010 showing *P. crassipes* (Landsat 7)

4.2.5 Landsat 8 OLI – 2020 A.D.

The *P. crassipes* coverage in the CHAL area was found to be 37 km^2 in 2020 A.D. i.e., 0.116 % of the total CHAL area (Figure 21).

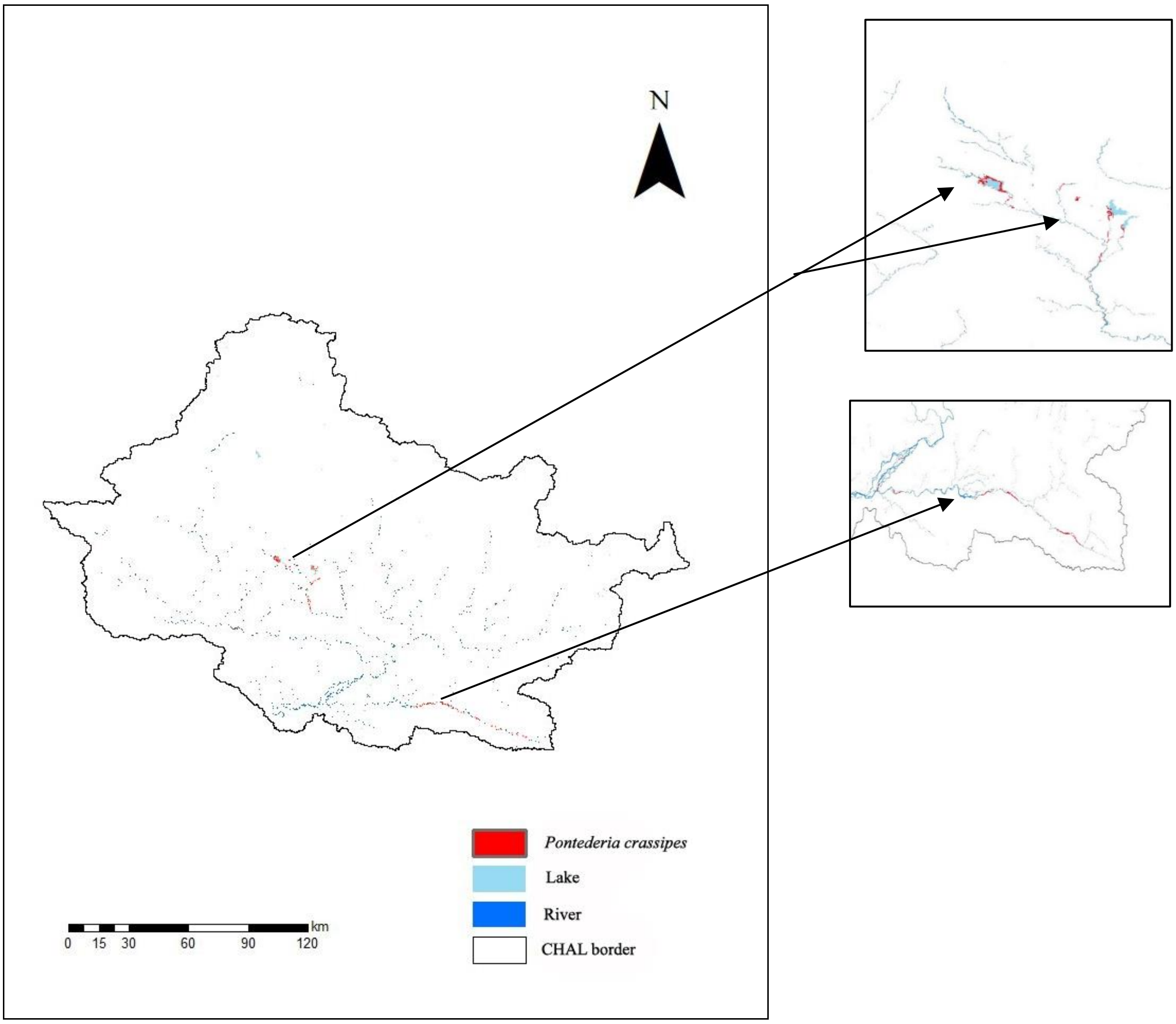

Figure 21: Map of CHAL 2020 showing *P. crassipes* (Landsat 8)

4.3 Comparison of *P. crassipes* in World View-2 and Landsat 8 data

The area of spatial distribution of *P. crassipes* was compared in AOI of four districts in World View- 2 and Landsat 8 data. As World View –2 image has higher resolution in compare to Landsat 8, higher distribution of *P. crassipes* was seen in World View-2 data. In World View-2 data, higher percentage of area infestation was seen in Chitwan district (Ghaila ghari lake) i.e., 0.0012 % and less in Kaski district (Pokhara) i.e., 0.00036%. In Landsat 8 data also, more area was infested with Water hyacinth in Chitwan district (Ghailaghari lake) i.e., 0.00097 % and less in Nawalparasi district (Dumkauli) i.e., 0.00028 %. The detail of area infestation in different AOI is shown in table 6.

Table 6: Comparison of distribution of *P. crassipes* in different AOI in World View-2 and Landsat 8

District	AOI (location)	Area of AOI (sq. m)	World View-2		Landsat 8		Difference
			sq. m	%	sq. m	%	sq. m
Chitwan	Ghailaghari lake	42829000	507	0.0012	415	0.00097	92
Nawalparasi	Dumkauli	44000000	170	0.00039	125	0.00028	45
Makwanpur	Hetauda-Manhari	107180000	447.6	0.00042	375	0.00035	72.6
Kaski	Pokhara	96050000	347.5	0.00036	305	0.00032	42.5

4.4 Accuracy assessment of AOI of World View-2 and Landsat

Accuracy assessment of the classified maps was done by making error matrix. Producer's accuracy, user's accuracy, overall accuracy and kappa coefficient were calculated based on classified and reference data (ground truth points). Among World View-2 imageries, different AOI have different value of overall accuracy and kappa coefficient. Higher overall accuracy and higher kappa coefficient was in classified map of Makwanpur district (Hetauda-Manhari) i.e., 86.96%. and 0.72 respectively. Overall accuracy varied from 81.25 to 86.96 % in World View-2 imageries.

In Landsat imageries, different AOI have different value of overall accuracy and kappa coefficient. Higher overall accuracy was in Makwanpur district (Hetauda-Manhari) i.e., 68% and low overall accuracy in Chitwan district (Ghailaghari lake). Overall accuracy varied from 62.96 to 68 %. Higher kappa coefficient was in Kaski district (Pokhara) i.e., 0.29 and less in Chitwan district (Ghaila ghari lake). Comparison of overall accuracy and kappa coefficient is shown in Table 7. The detail of error matrix is in Annex 4-11.

Table 7: Comparison of overall accuracy and kappa coefficient between World View-2 and Landsat 8 imageries

District	AOI (location)	World View-2 image		Landsat 8 image	
		Overall accuracy (%)	Kappa coefficient	Overall accuracy (%)	Kappa coefficient
Chitwan	Ghailaghari lake	85.00	0.69	62.96	0.21
Nawalparasi	Dumkauli	81.25	0.59	64.29	0.26
Makwanpur	Hetauda-Manhari	86.96	0.72	68.00	0.27
Kaski	Pokhara	81.25	0.61	64.29	0.29

4.5 Accuracy assessment of CHAL

Accuracy assessment and triangulation of whole CHAL region was done by making error matrix from classified data and reference data. The overall accuracy of Landsat 8 OLI is 69.45 % and kappa coefficient is 0.34.

Table 8: Error matrix of CHAL region Landsat 8 OLI image

Classified data	Reference data			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	15	9	24	62.50
Absence	13	35	48	52.08
Column total	28	44		
Producer accuracy (%)	53.57	79.55		
Overall accuracy (%)	69.45			
Kappa coefficient	0.34			

5. DISCUSSION

5.1 Distribution of *Pontederia crassipes*

Among 19 districts of CHAL, *Pontederia crassipes* is found in wetlands of Makwanpur, Chitwan, Nawalparasi and Kaski. The paddy fields also consist of this invasive plant. From group discussion and interview it was found that the farmers eradicate it physically. And some farmers also have wrong differentiation between Pistia and Water hyacinth. They consider Pistia as young stage of water hyacinth. Water hyacinth was introduced in the districts for ornamental purpose and mostly in the name of waste water treatment which later on invade natural wetlands.

From the result of classified maps, in 2018 A.D. it was found that 27.58 km^2 (0.086 %) of CHAL was infested by *P. crassipes.* Analyzing the map of 1990 A.D., it was found that *P. crassipes* was only in 9.6 km^2 (0.030%). In 2000 A.D., infestation area decreased to 2.93 km^2 (0.0092). During the field visit, it was confirmed through a group discussion that the decrease in infestation might have been a result of flooding in numerous rivers that were not detected by sensors. Additionally, while the government initially attempted to manage the problem, the invasion eventually escalated out of control. So, in 2010 A.D. the area of infestation increased to 23.44 km^2 (0.073%). Again, that increased to 37 km^2 (0.116%) in 2020 A.D.

According to Thuiller *et al*. (2007), Climate change is likely to enhance the capacity of alien species to invade new areas. From the observation during field visit and classified maps, northward movement of *P. crassipes* is not seen. It was noted that *P. crassipes* movement is along with the flow of water. Climate change could make habitat suitable but introduction of the plant in new area by human is not seen.

5.2 Accuracy assessment

Maximum likelihood classification (MLC) is most extensively used supervised classification algorithm for satellite multispectral imageries (Dewidar, 2004; Xie *et al*., 2008; Ahmad 2012). This is attributed to its simplicity in execution and widespread availability in commonly used software applications (Carle *et al.*, 2014). The method of classification used in this research work is similar as used by Xu and Ji (2014), knowledge-based classification was performed for the maps obtained from unsupervised (Iso cluster unsupervised) and supervised (Maximum likelihood) classification. Piyasinghe *et al.* (2018) did unsupervised, supervised and knowledge-based classification separately for invasive species *Austroeupatorium inulifolium.* Carle *et al.* (2014) also performed maximum likelihood classification and support vector machine and found more overall classification accuracy in MLC in mapping fresh water marsh species.

Findings of this research work show the better capability of Landsat 8 OLI than its predecessors for mapping. Landsat imageries has 30 m spatial resolution. Pahlevan and Schott (2013) also reported better accuracy of the Landsat 8 sensor than its predecessors in the process of monitoring the water resources of coastal areas.

Between Landsat 8 OLI and World View-2 imageries, World View-2 has relevant classification of land use land cover categories (built up area, forest, grassland, agriculture land, water body etc.). World View-2 imageries has 2 m spatial resolution That's why World View-2 has better ability to discriminate *Pontederia crassipes* with more accuracy. Landsat imageries were incapable of detecting and mapping *Pontederia crassipes* in narrow water bodies. The variation in performance of different sensor's imageries may be due to difference in sensor design. The same type of result was obtained when Stych *et al*. (2019) compared the application of World View-2 and Landsat 8 OLI to identify the forest damaged by bark beetle. Rasel *et al.* (2016) also did comparative analysis of World View-2 and Landsat 8 OLI for mapping coastal saltmarsh species. They performed maximum likelihood classification (MLC), support vector machine (SVM) and artificial neutral network (ANN). Overall classification accuracy was higher in World View-2 than Landsat 8 OLI.

Like in this research work, Thamaga and Dube (2018) mapped *P. crassipes* in the Greater Letaba river system, Tzaneen, South Africa by using Landsat 8 OLI and Sentinel-2 multispectral images. Sentinel-2 is with 10 m spatial resolution. The overall accuracy of *P. crassipes* in Landsat 8 OLI was 68.44 % and in Sentinel-2 was 77.56%. They also found blue, red, red edge, SWIR-1 and SWIR-2 bands outstanding for mapping *P. crassipes.*

The same type of research was done by Dube *et al.* (2017). They also evaluated the performance of Landsat 8 OLI in mapping the spatial configuration of *P. crassipes* in lake Chivero, Zimbabwe. They compared the performance of Landsat 8 OLI and

Landsat 7 ETM+. They found overall accuracy of 72% in Landsat 8 OLI and 57% in Landsat 7 ETM+.

Landsat imageries are suitable for large scale research work/regions (Griffiths *et al.,* 2014). But, World View-2 imageries is high cost and have high spatial resolution. It is useful in small scale research work/regions (Immitzer and Atzberger, 2014). The possible error source in remote sensed map of *P. crassipes* is mixed pixel. Coarse resolution sensor can overestimate *P. crassipes* by mapping fully occupied pixel for partially occupied. Small patch of *P. crassipes* is not detected if it does not exceed width threshold that is resolvable by sensor. According to Albright *et al.* (2004), three types of error can be considered in mapping *P. crassipes*: confusion, resolution related and definitional error. These possible types of errors were tried to solve during the methodology by the help of ancillary data.

6. CONCLUSION & RECOMMENDATIONS

6.1 Conclusion

A study in spatio-temporal distribution of aquatic invasive plant *Pontederia crassipes* in Chitwan Annapurna Landscape (CHAL) area was done using Landsat multispectral imageries and World View-2 imageries to assess distribution trend between 1990-2020 A.D. In 2020 A.D. it was found that 37 km^2 (0.116%) of CHAL was infested by *P. crassipes* whereas it was 9.6 km^2 (0.030%) in1990 A.D. Its invasion has increased as climatic change might also accelerated the rate of invasion.

Overall accuracy in Landsat imageries was less in compare to World View-2. It varied from 62.96 to 68 % in Landsat imageries. The Kappa coefficient in World View-2 varied from 0.61 to 0.72, which is good. But kappa coefficient in Landsat is less and varied from 0.21 to 0.29. The spatial resolution of Landsat image is 30 m × 30 m and of World View-2 image is 2 m ×2 m. While comparing the performance between them, more accuracy was in World View-2.

6.2 Recommendations

Based on the results obtained, following are the recommendations:

- It is recommended to use high spatial resolution imageries like World View-2 and hyperspectral imageries in smaller water bodies.
- Analysis of remote sensed data in machine learning algorithm for better accuracy.
- *P. crassipes* has shown increasing trend. Hence, plans and rules should be made by communities and government to check increase in invasion.

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ANNEXES

Annex 1: Landsat imageries used for mapping *Pontederia crassipes* in CHAL

Data sensor	Year	Path/row	Acquisition date
Landsat 5 TM	1990	142/040	1992/11/15
		142/041	1992/11/15
		143/040	1992/11/06
		141/041	1992/11/08
		142/040	1991/11/29
Landsat 7 ETM+	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
		142/041	2009/10/29
Landsat 7 ETM+	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
		141/041	2018/06/25
Landsat 8 OLI	2018	141/040	2018/06/25
		142/040	2017/06/13
		142/041	2016/06/10
		143/040	2017/06/04
Landsat 8 OLI	2020	141/041	2020/06/2
		142/040	2020/06/15
		143/040	2020/06/15
		143/040	2020/06/20
		141/040	2020/06/27

Annex 2: World View-2 imageries used for mapping *Pontederia crassipes*

Data sensor	AOI (Location)	Date
World View-2	- Ghailaghari lake (Chitwan)	2018-01-22
	- Dumkauli (Nawalparasi)	2018-01-25
	- Hetauda-Manhari (Makwanpur)	2018-01-22
	- Pokhara (Kaski)	2018-03-09

Annex 3: Questionnaire

Name of the respondent: ....

Address: ....

1. Is this plant available near water bodies of your locality (Showing photographs of *Pontederia crassipes*)?

   ....

2. What is local name of this plant?

   ....

3. When was this plant introduced in this area / How long have you seen this in this area?

   ....

4. Does is plant have positive or negative impact on water bodies / rice field?

   ....

5. Is it given as fodder to animal?

   ....

6. How is growth of this plant in the area?

   ....

7. Do local community use this plant for any purposes?

   ....

8. Are all people aware of this plant?

   ....

9. How local community are controlling spatial growth of this plant?

   ....

10. Are there any aids from organizations and government to control growth of this plant?

    ....

Annex 4: Error matrix of Chitwan (Ghailaghari lake) World View-2 image

Classified data	Reference data			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	15	4	19	78.95
Absence	3	27	30	90
Column total	18	31		
Producer accuracy (%)	83.33	87.09		
Overall accuracy (%)	85			
Kappa coefficient	0.69			

Annex 5: Error matrix of Nawalparasi (Dumkauli) World View-2 image

Classified data	Reference data			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	4	2	6	66.67
Absence	1	9	10	90
Column total	5	11		
Producer accuracy (%)	80	81.82		
Overall accuracy (%)	81.25			
Kappa coefficient	0.59			

Annex 6: Error matrix of Makwanpur (Hetauda-Manhari) World View-2 image

Classified data	Reference data			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	7	1	8	87.50
Absence	2	13	15	86.67
Column total	9	14		
Producer accuracy (%)	77.78	86.67		
Overall accuracy (%)	86.96			
Kappa coefficient	0.72			

Annex 7: Error matrix of Kaski (Pokhara) World View-2 image

Classified data	**Reference data**			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	5	1	6	83.33
Absence	2	8	10	80
Column total	7	9		
Producer accuracy (%)	71.43	88.89		
Overall accuracy (%)	81.25			
Kappa coefficient	0.61			

Annex 8: Error matrix of Chitwan (Ghailaghari lake) Landsat 8 OLI image

Classified data	**Reference data**			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	5	4	9	55.56
Absence	6	12	18	66.67
Column total	11	16		
Producer accuracy (%)	45.45	75		
Overall accuracy (%)	62.96			
Kappa coefficient	0.21			

Annex 9: Error matrix of Nawalparasi (Dumkauli) Landsat 8 OLI image

Classified data	**Reference data**			
	Presence	**Absence**	**Row total**	**User accuracy (%)**
Presence	3	2	5	60
Absence	3	6	9	66.67
Column total	6	8		
Producer accuracy (%)	50	75		
Overall accuracy (%)	64.29			
Kappa coefficient	0.26			

Annex 10: Error matrix of Makwanpur (Hetauda-Manhari) Landsat 8 OLI image

Classified data	Reference data			
	Presence	Absence	Row total	User accuracy (%)
Presence	4	3	7	57.14
Absence	5	13	18	72.22
Column total	9	16		
Producer accuracy (%)	44.44	81.25		
Overall accuracy (%)	68			
Kappa coefficient	0.27			

Annex 11: Error matrix of Kaski (Pokhara) Landsat 8 OLI image

Classified data	Reference data			
	Presence	Absence	Row total	User accuracy (%)
Presence	4	2	6	66.67
Absence	3	5	8	62.50
Column total	7	7		
Producer accuracy (%)	57.14	71.43		
Overall accuracy (%)	64.29			
Kappa coefficient	0.29			

Annex 12: Photo plates

1. *Pontederia crassipes* with flower

2. *P. crassipes* at the edge of flowing river

3. *P. crassipe*s covered fully in stagnant pond

4. Interview with local people, Chitwan

5. Focal group discussion

6. Observing morphological charaters of *P. crassipes*

7. Plant collection in Bishazari lake, Chitwan lake

8. *P. crassipes* in the shore of Bishazari

9. *P. crassipes* in Manahari canal

10. *P. crassipes* fully covering water

11. Participation at International Youth Conference on Science, Technology and Innovation

12. Participation at National Conference on Integrating Biological Resources for prosperity