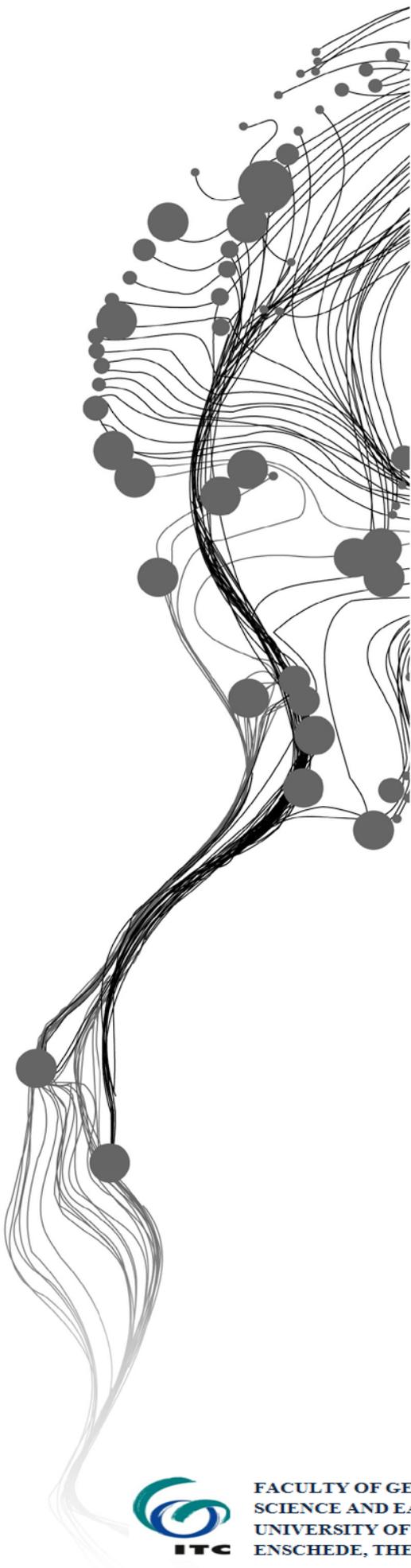


**IMPACT OF INFESTATION OF
SAL HEARTWOOD BORER
(*Hoplocerambyx spinicornis*)
ON THE CARBON STOCK OF
SAL (*Shorea robusta*)
FORESTS OF DOON VALLEY**

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March, 2014

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Enschede, The Netherlands [March, 2014]

Thesis submitted to the Faculty of Geo-information Science and Earth Observation (ITC) of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.

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Dedicated to my grandparents...

ABSTRACT

Forest carbon cycle greatly influences the global climate change. Forests are now considered to play crucial role in climate change mitigation. As forests sequester and store carbon it is important to assess the carbon stocked in the forest and the loss of carbon from forests due to various natural or anthropogenic reason. Difficulty is in estimating the accurate carbon stock present in the forest as forests are usually inaccessible and present in remote areas. To overcome this problem remote sensing can be used as a measure as it can cover large area. Accurate estimates of carbon stock can be made using high-resolution imagery like WorldView-2, Geo-Eye and IKONOS.

In the study WorldView-2 imagery was used to estimate the total above ground biomass which was then converted to carbon by the conversion factor of 0.47. For estimation of biomass volumetric equation was used. The volume calculated from this equation was converted to biomass by multiplying it with specific gravity of Sal and biomass expansion factor. The relationship between CPA and carbon was established and validated using 58 trees recognized in the field. CPA was obtained using object-based image analysis and was compared with the manually delineated reference polygons to assess the accuracy. A non-linear regression model was adopted to derive the relationship between CPA and carbon of the tree.

The regression model was then used for the prediction of carbon for the study area. In study area classification was done for four classes and carbon was predicted for *Shorea robusta*. The average carbon stock in the area was estimated to be 108 MgCha⁻¹. The non-linear model explained 78.4 percent of the predicted carbon. Shadow, image acquisition time, volumetric equation, biomass expansion factor and specific gravity of Sal were the sources of error in the estimation of carbon in the study.

Impact of infestation of Sal heartwood borer (*Hoplocerambyx spinicornis*) on the carbon stock was studied for the area. In past there has been huge loss of carbon from the study area due to infestation incidences. The pest is endemic to Sal forest therefore; these forests are at high risk of losing carbon due to infestation. The study modelled the infestation risk areas based on the parameters of distance to village, moisture in the area and diameter of the tree. As the value of infestation presence or absence was binary DBH was used for prediction as DBH had significant trend with infestation locations. The model predicted the values with an error of 0.05m.

Keywords: *Shorea robusta*, Sal heartwood borer, carbon stock, OBIA (Object based image analysis), Regression, Volumetric equation

ACKNOWLEDGEMENTS

I would like to take this opportunity to express my deep sense of gratitude to my IIRS supervisor Dr. Subrata Nandy and my ITC supervisor Ms. Ir. L.M. van Leeuwen for their constant support and valuable guidance.

My foremost thanks to Indian Institute of Remote Sensing (IIRS), ISRO and the Faculty of Geo-Information Science and Earth Observation, University of Twente, The Netherlands for giving me an opportunity to pursue this course. I would also like to thank Dr.P.K. Champati Ray , Course Director (NHDRM), IIRS for his support and guidance.

My sincere thanks to Dr. Y.V.N. Krishnamurthy, Director, IIRS for his support and providing all the necessary facilities.

I would also like to thank the whole staff of State Forest Department (Kalsi Division) for their support during the field work. I would like to take this opportunity to express my gratitude for Mr. Arjun and Mr. M.S. Thapa for their help and support during field visit.

I am grateful all my friends, room-mates and batch mates for their constant support. Special thanks to Haider Ali, student Forest Research Institute for providing the literature on Sal heartwood borer.

Last but not the least I would like to thank my parents for their continuous support and encouragement throughout the research period.

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1. INTRODUCTION

1.1. Background

Global warming and its consequences, being addressed as climate change, are the key issues which are pondered over, worldwide, for their impact and mitigation. Recent reports confirm that global atmospheric carbon dioxide concentrations have nearly reached alarming levels of 400 ppm (WMO 2013, IPCC 2006). The various agents which can be held responsible for increase in these concentrations are burning of fossil fuels, conversion of land, industrialization, urbanization, etc (IPCC 2007b). Forests are now accredited as natural 'brake' on climate change due to their capability to sequester and store carbon (Gibbs et al. 2007). Depending upon the health of a forest it can act as a sink or a source of carbon. Degradation of forests and deforestation release stored carbon in the form of carbon dioxide in atmosphere which is another reason for increased CO₂ concentrations. Some of the reasons for deforestation are direct conversion of forest land for purposes like agriculture, illegal logging, encroachment etc. (IPCC 2007a). Apart from human interventions another important reason for the loss of trees, from forests, is the pest attacks which damage forests, depending upon the spread and severity of the infestation (Nowak et al. 2001, Domec et al. 2013, Nuckolls et al. 2009). The forests, when affected by the disaster of pest outbreak, suffer huge losses in terms of wood, and consequently carbon, ecological and environmental values.

According to IPCC, carbon constitutes around 47 percent of the total above ground biomass (TAGB) which is defined as, "all biomass of living vegetation, both woody and herbaceous, above the soil; including stems, stumps, branches, barks, seeds and foliage" (IPCC 2006). Inaccessibility to forests, cumbersome enumeration and time consumption arouse the necessity to introduce remote sensing techniques and devise the statistical relationships between ground based sample data and satellite imageries, to map the carbon stock.

Use of high resolution images like WorldView-2, GeoEye, IKONOS, Quickbird, is becoming increasingly popular for the precise estimation of carbon stocks of forests (Baral 2011, Karna 2012, Maharjan 2012). With these images carbon can be mapped to a level of individual tree. They have also found their use in better classification of vegetation types and extraction of forest inventory information. For extraction of information from the high resolution imagery cannot be done with the conventional processes or methods, object – based image analysis (OBIA) is now used as an interpretation procedure (Blaschke 2010).

Importance of forests in combating climate change makes it vital to estimate forest biomass as accurate as possible (FAO 2008). With the help of OBIA better accuracy in biomass estimation can be achieved, as the biomass can be tracked down to individual trees in the forests (Baral 2011, Eckert 2012). Individual tree crown delineation from high resolution imageries has been an advantage of using OBIA over other analysis procedures. Segmentation technique has been found useful in differentiating various tree species in the forest, as OBIA creates the segmentation by combining the pixel information (Baral 2011). Classification of the segments based on their respective spatial, spectral and textural properties gives better classification accuracy and hence, better differentiation (Eckert 2012, Immitzer, Atzberger, and Koukal 2012, Jawak and Luis 2013) . OBIA software eCognition has proved to be a great aid in identifying and classifying the diseased

or infested trees in the forest; and also extracting various other forest inventory parameters like canopy cover percent (Chang et al. 2010).

The forests of Sal (*Shorea robusta*) of Doon valley possess a substantial carbon sequestration potential (Kaul, Mohren, and Dadhwal 2010). In the context of climate change, these forests play a crucial role by maintaining the ecological and environmental balance and by sequestering and storing carbon. But there is a threat of losing a large amount of carbon from Sal forests as they are prone to pest infestation. These forests have one associated endemic pest, popularly known as longicorn beetle or Sal Heartwood Borer (*Hoplocerambyx spinicornis*) (Thakur 2000). It usually attacks the stressed trees growing in the nutrient deficient soils; overmature stands, less dense stands, areas where the human disturbances are present, etc (Bhandari and Rawat 2001). The pest also prefers a girth class of 60 – 120 cm (Thakur 2000). The attack turns into epidemic when more than 1% of the forest area gets affected by the infestation (Thakur 2000). Infestation of Sal Heartwood Borer has been categorized into seven stages for individual tree, depending upon the severity of infestation; the seventh stage is the initial stage of infestation when resin oozes out of the bark and the first is the tree being completely dead (Thakur 2000). The management usually followed to curb the spread of infestation, is the removal of trees from categories fourth to first (Bhandari and Rawat 2001). This removal of trees causes loss of carbon from the forest. The removed infested trees are usually used for the burning purpose as they have lost their timber quality. The burning of the wood, releases carbon dioxide in the atmosphere thus, leading to an increase in its concentration. The past records indicate that the Doon valley Sal forests have encountered a number of epidemics since 1916 and due these epidemics around 0.1 million infested trees have been removed from the forest as a management practice (Thakur 2000, Bhandari and Rawat 2001).

Sal is important timber specie in India and it covers around 13.3 percent of the total forest area in India (Satya, Upreti, and Nayaka 2005). Its extent of distribution indicates the significance for the study of carbon storage and its economic importance makes it imperative to study the infestation. The study aims at assessment of loss of carbon from the forests due to pest infestation and predicting the infestation probable areas which could help the administration for effective management.

1.2. Doon (*dun*) valley sal forests

Shorea robusta Gaertn.f. belongs to family Dipterocarpaceae. The tree popularly known by its trade name, Sal, is a large deciduous (nearly semi-evergreen in very moist conditions) tree, attaining an average height of 18 – 32m. It's a gregarious tree and often forms pure crop over large areas. In India, Sal is distinctly distributed in two different regions, separated by Gangetic plains viz. the northern and Central Indian regions. Sal forests of Doon valley are part of the northern Indian region of Sal distribution.

The broad elevated valley within the outer ranges of the Himalayas and Siwalik hills is called the *Dun* valley. Sal forests present in this valley fall under two forest groups viz. Tropical Moist Deciduous forests and Tropical Dry Deciduous forests, according to Champion and Seth classification of Indian forests. These broadly classified groups can further be divided into sub-groups, type, sub-type and variety based on the topographic, edaphic and biotic factors.

Sal forests under Tropical Moist Deciduous forests occur on gentle slopes and light soils or boulders or high alluvium soils, where mean annual temperature varies from 21^o C to 26^o C. Those under Tropical Dry Deciduous forests occur on shallow, sandy, well-drained soil derived

from Siwalik sand rock and conglomerates. The mean annual temperature ranges from 24^o C to 27^o C.

1.3. Sal heartwood borer

1.3.1. Classification

Hoplocerambyx spinicornis Newn.

Sal heartwood borer has been classified in Class Insecta with Order Coleoptera. The pest belongs to family Cerambycidae (Thakur 2000). Life cycle of Sal heartwood borer is depicted in Figure 1.

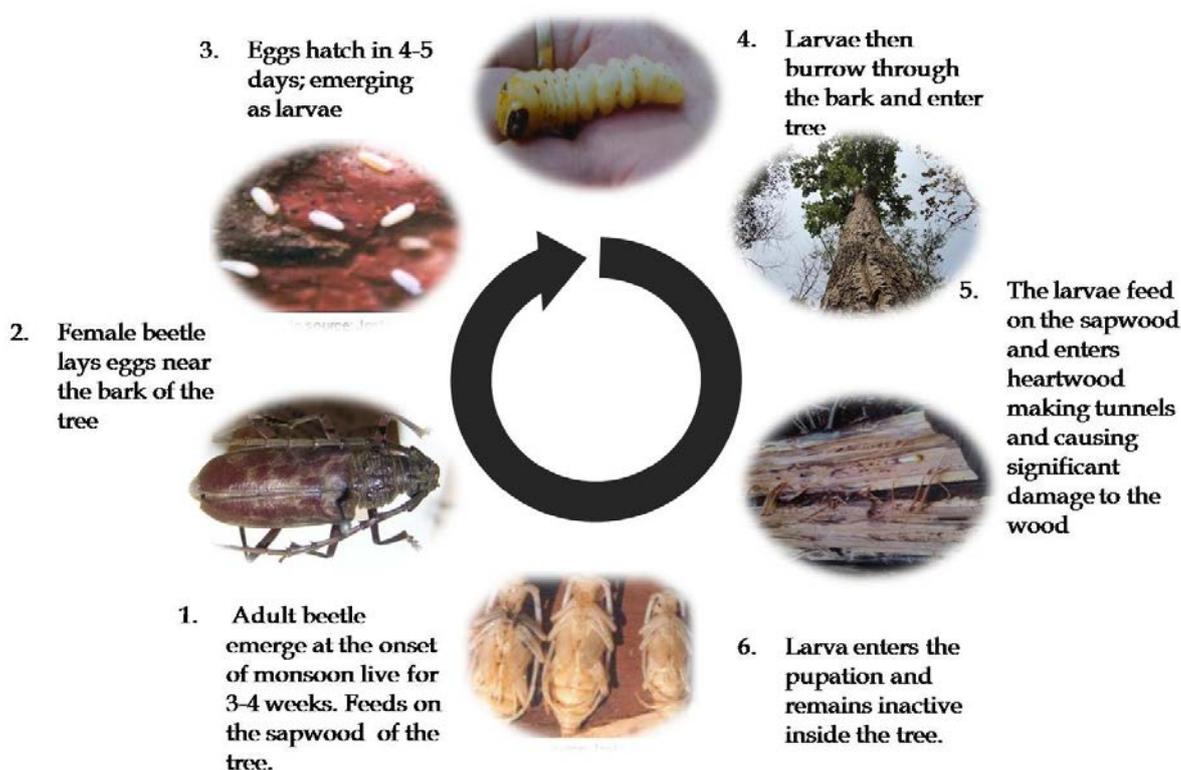


Figure 1: Life cycle of Sal heartwood borer

1.3.2. Management of Sal heartwood borer infestation

The infestation of Sal Heartwood borer has been divided into seven stages. According to those seven stages the management of infestation is carried out by the State Forest Department.

Following are the seven stages of infestation of Sal Heartwood Borer:

- TYPE I:** Crown foliage fallen, epicormic branches leafless, wood dust in heaps more than 7cm deep.
- TYPE II:** Crown foliage brown, epicormic branches dead or brown, wood dust more than 7cm deep.
- TYPE III:** Crown dead or brown, epicormic branches or bark dead in the upper part but alive in the lower part of trunk, wood dust in heaps more than 7 cm deep.
- TYPE IV:** Crown partly alive, green and partly dead or brown, epicormic branches green, wood dust scattered in less than 7cm deep.

- v. TYPE V: Crown alive, epicormic branches green, wood dust in heaps more than 7cm.
- vi. TYPE VI: Stumps with heap of wood dust.
- vii. TYPE VII: Crown alive, green epicormic branches, resin abundant and wood dust scanty. (Thakur 2000)

The remedial measures, in the past, have been adopted from recommendations of Forest Research Institute (FRI) Dehradun. The remedial measures to avoid the epidemic include:

- i. Catching and killing adult beetles under “trap – tree operation”.
- ii. Felling and removal of affected trees and stumps of stage I, II and IV from forest and their storage away from forest.
- iii. Burning of debris and left over material.

Chemical measures for control are not adopted as they are not effective because beetle’s larva remains deep inside the heartwood. Also, chemicals may have serious effects on environment. (Thakur 2000)

1.3.2.1. Trap-tree operation

“Trap-tree operation” method is devised in order to take advantage of the fact that borer is attracted towards the sap of Sal wood and after consuming the sap of tree, it becomes intoxicated. In this condition, borers are unable to cover a long distance. Trap tree operation is aimed at collecting and killing beetles at this stage before they attack other trees. According to the guidelines, trap tree operation is carried out immediately after first shower of monsoon and continued till the day the insect catches are nil for 3 days. For this operation trees with girth of 60-90 cm are preferred. One or two trees per hectare, of mentioned girth, are felled and cut into 2-3 m long logs. Figure 2 presents the log selected for trap tree operation. These logs are then beaten, up to 30 cm, at the ends to exude sap and provide shelter to beetle under the bark. These logs are then checked daily, morning and evening, for beetles under the bark of log. After severing head thorax of borer, counting for catch is done. After 10 days, when the exposed ends get dried, next 30 cm bark is beaten. When the trap-tree operation is over, the logs are debarked and burnt or converted. (Thakur 2000, Bhandari and Rawat 2001)

1.4. Estimation of carbon stock using OBIA

Advances in earth observation and geo-information studies have led to increase in earth observation satellites and availability of high resolution imageries like WorldView-2, OrbView, Geo-Eye, and IKONOS. Conventional pixel based classification use only pixels’ spectral information for feature extraction, and may not explore the potential spectral and spatial information from high resolution image. With the innovations and progress in researches and usefulness of high resolution images, novel image analysis technique, OBIA is considered ideal for high resolution image processing, as it includes both spectral and spatial information for classification.

For estimating carbon or biomass of a tree, DBH (diameter at breast height) and height of tree are the key parameters. Inaccessibility of forests and cumbersome field measurements make it impossible to enumerate each and every tree for precise estimates of forest carbon stock. This can be overcome by using remote sensing techniques as with the help of optical images it is possible to cover large areas. The problem lies in the fact, that optical remote sensing satellites are incapable of determining height or DBH of a tree from space and can only record the canopy reflectance values.

With ground based sampling and optical images a meaningful statistical relationship can be built between forest carbon and canopy reflectance values. As high resolution images make it possible to delineate individual trees in the forest (Jing, Hu, and Noland 2012), another important tree parameter which can be used for building a statistical relationship is the canopy projection area (CPA). It has also been proved, in various studies, that there exists a relationship between CPA and diameter of the tree (Shimano 1997). Therefore, by devising a relationship between ground based sampling data of diameter, carbon and CPA; carbon of the forest can be estimated.

Delineation of individual trees or crowns in the forest can be achieved by image segmentation. Image segmentation works by partitioning an image into a set of disjoint regions based on uniformity and homogeneity of attributes such as layer value, shape, texture etc. (Patil and Junnarkar 2013). Automated feature extraction software like eCognition, deserve an appreciation as they provide various parameters and their combination for accurate segmentation and classification of the objects. For segmentation the scale parameter can be defined according to the features in the image. Various other parameters like shape, texture, roundness, compactness etc. can be defined by user according to its requirement. Different image segmentation techniques like multi-resolution segmentation; chessboard segmentation etc. can be used for segmentation of the given scene depending upon the properties of the features. Thus, OBIA makes a fair judgment with the spatial and spectral information present in the high resolution images.

1.5. Modelling of infestation risk

Pest infestation depends upon a number of environmental or biotic variables e.g. moisture, canopy density, human interventions, presence or absence of predator, undergrowth etc. These parameters make the conditions favourable or unfavourable for a pest to infest. Modelling of infestation probability aims at predicting the areas which are prone to future infestation, depending upon the status of current infestation. Various modelling approaches can be adopted to predict the infestation prone areas. In this study universal kriging was used as constant mean could not be assumed for the prediction of infestation. Infestation in the study area was dependent upon moisture, diameter of the tree, stress condition of the tree and distance of tree from village.

1.6. Research identification

This study aims at assessing the impact of sal heartwood borer infestation on the carbon stock of sal forest of Doon valley. The study area is the part of Timli range where, in past, incidences of pest infestation have been recorded.

1.6.1. Research objectives

- i. To assess the total above ground carbon stock in the study area using OBIA.
- ii. To develop a remote sensing based method for identification of the stressed trees.
- iii. To assess loss of carbon from the forest due to pest infestation in the period of 2011 – 2013.
- iv. To predict the probable areas of future infestation.

1.6.2. Research questions

- i. Which stage of infestation can be detected using RS?
- ii. What is the relationship between the CPA and the carbon of the non-stressed trees and the carbon of stressed trees?

- iii. How much carbon stock is present in the non – stressed trees in the span 2011 - 2013?
- iv. What are the environmental factors that lead to the infestation?
- v. How much carbon will be lost due to the recent infestation?
- vi. Which are the probable areas where infestation can take place?
- vii. What is the accuracy of the infestation probability model?

1.7. Concepts and definitions

1.7.1. Biomass and carbon

According to (IPCC 2006) biomass is the “Organic material both aboveground and belowground, and both living and dead, e.g., trees, crops, grasses, tree litter, roots etc. Biomass includes the pool definition for above - and below - ground biomass”.

Tree is divided into two components viz. above ground and below ground. These two parts are separated by the surface of the ground, as illustrated in Figure. 2.

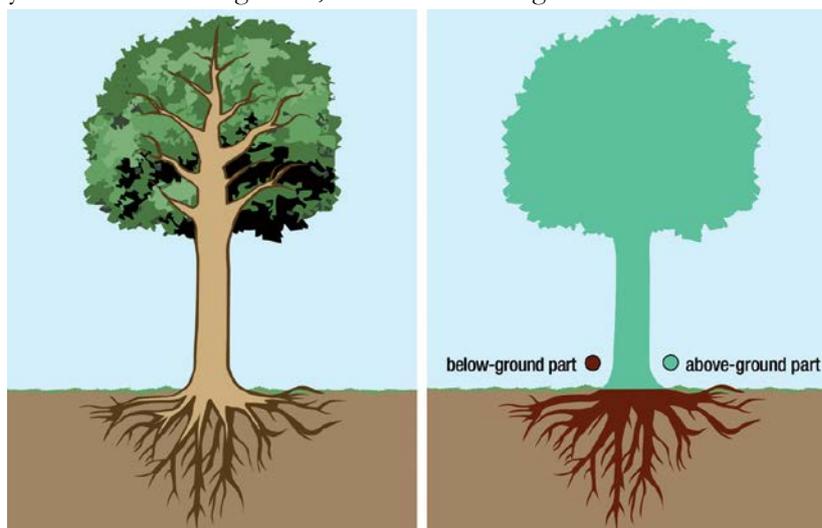


Figure 2: Above and below ground parts of tree. Source: Gschwantner et al (2009)

“All living biomass above the soil including stem, stump, branches, bark, seeds, and foliage”, is the total above ground biomass.

According to IPCC guidelines, carbon in a tree is the 0.47 fraction of the total above ground biomass

To calculate the total above ground biomass another term biomass expansion factor is used, which is defined as, “a multiplication factor that expands growing stock, or commercial roundwood harvest volume, or growing stock volume increment data, to account for non-merchantable biomass components such as branches, foliage, and non-commercial trees”.

1.7.2. Crown projection area (CPA)

According to (Gschwantner et al. 2009), “the crown consists of the living branches and their foliage”. “The crown projection area (CPA) of a tree, is the area of the vertical projection of the outermost perimeter of the crown on the horizontal plane”, (Gschwantner et al. 2009) as illustrated in Figure 3.

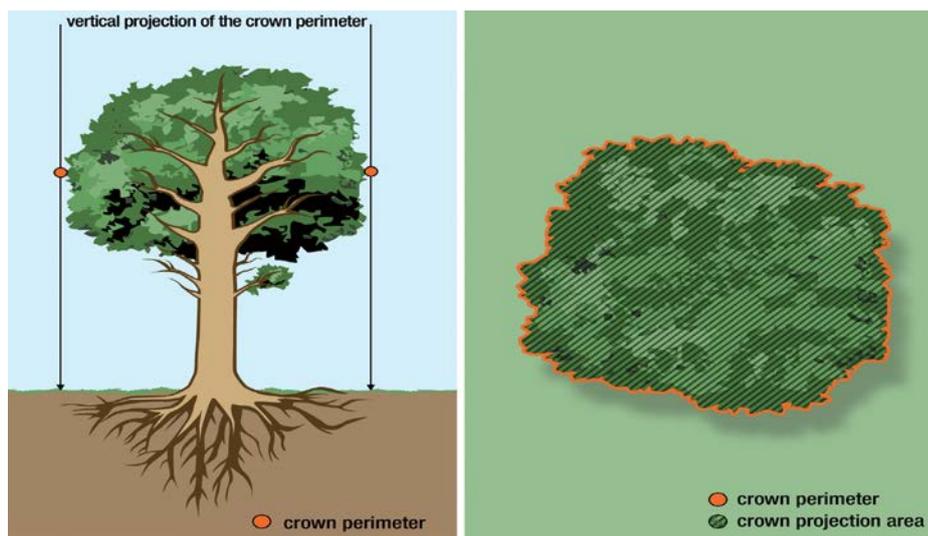


Figure 3: Crown projection area. Source: Gschwantner et al (2009)

2. Literature review

2.1. Forests, carbon and role in climate change mitigation

Tropical, temperate and boreal forests cover around 42 million km sq, making it around 30 percent of the total land surface. Forests have been looked upon for climate change mitigation as they influence the climate through various physical, chemical and biological processes. Today, these forests bear the tremendous pressure under climate change scenario. To explore the potential of the world's forest in combating climate change study has been done by Bonan(2008). The study gives an insight into the biogeophysical, biogeochemical processes taking place in tropical, temperate and boreal forests. It also explains the biogeographical processes in different forests with alteration of forest atmosphere (Bonan 2008). Malhi and Grace (2000), illustrates the role of tropical forests in estimating the atmospheric concentration of CO₂. Conclusions of the study state that CO₂ emissions due to deforestation and degradation of tropical forests might approach the rate of 3.0 Pg C per year and the sink rate at 1 – 3 Pg C per year. Thus, depicting the imbalance in the flux of CO₂ in the atmosphere (Malhi and Grace 2000) . In an attempt to manage forests for mitigating climate change McKinley *et al* (2011) suggested three strategies viz. land use change to bring more area under forests and restricting deforestation, managing carbon of forests and replacing wood with other building material in order to store carbon. The strategies were evaluated on the basis of carbon benefits, environmental and monetary costs, risk and trade-offs. Results suggest that as forest carbon loss increases the risk of climate change, avoiding deforestation and disturbances with encouragement to afforestation and reforestation is the best strategy (McKinley *et al.* 2011). Increasing concerns over climate change and importance of forests in mitigating it have led to the indulgence of remote sensing studies for assessing and monitoring of forest carbon. As studied by Gonzalez Alonso *et al* (2006), carbon sinks of forest can be monitored by devising satellite based ratios like NDVI and field measurements. Using remote sensing is advantageous as it covers large areas and reduces the time requirement (González Alonso *et al.* 2006). Importance of retaining and managing the forests can be concluded from the fact that after a productivity increase, intact rainforests can accumulate carbon for more than a century, as stated by Chambers *et al* (2001) (Chambers *et al.* 2001).

2.2. Infestation and its impact on tree carbon

Forests, with their environmental, ecological, scientific and recreational values, have an important hold in the climate change mitigation programmes. Besides anthropogenic factors, natural factors like forest fire and pest outbreak are the potential threat to forest carbon. Nuckolls *et al.* (2008) studied the short term change, due to hemlock woolly adelgid, to the carbon cycle of Southern APP. Forests. The study indicates that Hemlock basal area increment declined significantly with 20 – 40 % decline in root biomass. Impact on soil CO₂ efflux was also recorded (Nuckolls *et al.* 2008). Another study by Nowak *et al* (2001) in New York City and Chicago illustrated the potential effects of *Anoplophora glabripennis* on urban trees. Study states that thousands of infested trees were removed from the urban areas in order to eradicate the beetle infestation. The estimates reflect that the infestation caused loss of 34.9 percent of the total canopy cover and affected 1.2 billion trees with the value loss of \$669 billion (Nowak *et al.* 2001). Analysis of pest risk study by MacLeod *et al* (2001) assessed the risk of wood boring pest on the hardwood tree species in European

community. Results of the analysis compelled the authority to add pest to quarantine list of European community (MacLeod, Evans, and Baker 2002). Study on Hemlock woolly adelgid by Domec *et al* (2013) assessed the water relations, anatomy and gas exchange measurements of healthy and infested trees of eastern and Carolina hemlock trees. Results indicate that physiological properties of the infested trees were adversely affected. There was reduction of water usage by the infested trees and gross primary productivity was reduced by 25 percent. The study concluded that infestation had a direct effect on plant water relations and carbon assimilation. There by decreasing the potential of carbon assimilation of trees (Domec et al. 2013). Modelling of infestation risk is another field of infestation studies. Overbeck and Schmidt (2012) modelled infestation risk of Norway spruce by *Ips typographus*. According to the study, risks at silvicultural level planning units must be identified and quantified for effective forest management. The statistical model used for the study was GAMM (Generalized mixed additive regression model), which uses the age and proportion of spruce, available water capacity, thermal sum and Topex-to-distance index as the input parameters. The study reflected that development of such models is suitable for identifying the susceptible stands to infestation (Overbeck and Schmidt 2012). Modelling the infestation probability can be linked to species distribution modelling, as both model the probability of presence of specie or infestation based on the stand and environmental variables. A study done by Latimer *et al.* (2006) on the geographic distribution of *Protea mundii* and *P. punctata* in Cape Floristic region of South Africa described four species distribution models out of which one is the non-spatial model. All the models are based on Bayesian statistics. The non-spatial model was a simple generalized linear model, the three spatial models were, simple spatially explicit model, a point-level spatial model and hierarchical spatially explicit model. Results illustrate that the spatial models outperformed the non-spatial model. Among the three spatial models the hierarchical spatially explicit model gave the best results for the distribution of the species. The comparison of these three models was done on the basis of AUC (Area under curve) and MPA (Minimum predicted area) (Latimer et al. 2006).

2.3. Object based image analysis (OBIA)

T. Blaschke (2010) emphasized the need of conversion of tangible information from imagery which can be integrated with other data sets. Study also discusses the progression of image processing techniques from pixel based to sub-pixel and then to object based. These advances in image processing techniques can be accredited to improvement in the spatial resolution of the sensors. OBIA methods are an improvement over pixel based methods, for OBIA methods can extract spatially explicit information, required for planning in many sectors and monitoring various events (T. Blaschke 2010). In order to exploit image information more “intelligently”, Blaschke and Lang (2006) investigated the technical and methodological status of OBIA in regard to scientific progress in algorithms and methodologies, software situation and commercial exploitation and automated feature extraction. Study gives an insight into the concepts and methods of OBIA and its applications. Image segmentation has been a crucial part of OBIA (Thomas Blaschke and Lang 2006). Dezso *et al* (2012) describes segments as homogeneous areas of images, consisting of neighbouring pixels and explains several merge – based and cut – based segmentation methods. The study discusses five different applications of segmentation technique viz. delimiting individual trees, identification of ineligible land on pastures, observation of red mud spill, rag weed monitoring and recognition of built infrastructure in rural areas (Dezso et al. 2012). Wenxia *et al* (2005) accentuate the use of OBIA for high resolution images as pixel based image classification cannot satisfy classification precision of high resolution imagery. OBIA extracts the information,

from the image, not only on the spectrum basis but also geometry and structure information of objects. The study was done using Quickbird image for Beijing, where five cultures were used for assessing classification accuracy (Wenxia, Chen, and Ma 2005).

2.4. Forests and OBIA

Johnson *et al* (2013) described a multiscale object-based classification method for detecting the diseased trees in Japan, viz. Japanese oak wilt and Japanese pine wilt. The method described three techniques which could improve the classification accuracy of the diseased trees. The first technique was the hybrid pansharpening technique, where the authors compare the application of only IHS (Intensity hue and saturation) and application of a hybrid IHS-SMIF (Intensity hue saturation smoothing filter – based intensity modulation) technique. The second was performing SMOTE (Synthetic minority oversampling technique) before classification, which was used to minimize the imbalance in the training datasets arising due to less training data for minority class. The third technique was the comparison of single scale and multiscale classification. The study concluded that the hybrid pansharpening approach increases the overall classification accuracy. Performing SMOTE before classification and multiscale classification technique improved the classification accuracy. The studies were carried out using high resolution multispectral images (Johnson, Tateishi, and Hoan 2013). A study conducted for Great lake-St. Lawrence forest, Ontario, Canada by Jing *et al.* (2012) described a new method of individual crown delineation for avoiding the over segmentation of the crowns. The method suggested the multiscale filtering and the image segmentation. Gaussian filters were used for the smoothening of the images before applying the watershed segmentation. The resultant multiscale segmented maps were then integrated to generate the individual crown map (Jing et al. 2012). The study done by Shah (2011) depicts the modelling of the relationship between tree crown projection area and the above ground carbon stock. The study was done on Chitwan forests of Nepal with GeoEye image. The work discusses the delineation methods and deals with the intermingling tree crowns. It compares the various regression models for the relationship between CPA, basal area, biomass and carbon. It compares at the levels of standalone and dominant species of *Schima wallichii*, *Shorea robusta* and *Terminalia alata* (Shah 2011). Another study done by Baral (2011) on the Chitwan forests of Nepal explores the comparison between the segmentation of the GeoEye and Worldview 2 imagery. The study explores the relationship between crown projection area (CPA) and carbon and gives an estimation of the carbon stock present in the study area (Baral 2011). The study will be helpful in applying image segmentation on Worldview 2 image and also deriving the relationship between CPA and carbon.

2.5. Sal forests and carbon stock

Sal tree, because of its gregarious nature usually forms pure crop over large areas, thus, significantly influencing the climate of the area. Commercially, Sal is one of the most important timber species in India. Therefore, considering the ecological and commercial values, many carbon sequestration studies have been conducted on sal. Kaul *et al* (200) studied the carbon storage and sequestration potential of four tree species viz. eucalyptus and poplar for rotation and teak and sal for long rotation studies. The study concluded that net annual carbon sequestration rate for sal was 1 Mg C per ha per yr. The study also analyzed the sequestration rates after increasing the prescribed rotation age of the species (Kaul, Mohren, and Dadhwal 2010). Carbon sequestration rate of

selected tree species of India has been studied by [raizada et al.] where the annual carbon flux rate calculated for Sal was 5.07 Mt C per yr. study done by Negi *et al* (2003) estimated the carbon allocation in different parts of the tree viz. bark, leaf and wood. Various Indian tree species were taken into account for the study. The estimated carbon content percent in *Shorea robusta* bark, leaf and wood were around 41.72, 42.58 and 45.66 respectively (Negi, Manhas, and Chauhan 2003). Temporal assessment of Indian forests for their growing stock, biomass and carbon stock was studied by Manhas *et al* (2006). The study made the comparisons of forest area, growing stock, biomass and carbon of forest between the year 1984 and 1994 for different forest types of India. It was revealed that for forests of *Shorea robusta*, the forest area reduced from 7.58 to 7.54 (Mha), growing stock reduction was from 550.29 to 514.12 (Mm³), biomass from 396.57 to 371.48 (Mt), carbon in terms of Mt reduced from 182.42 to 170.88 and carbon in terms of t per ha declined from 24.07 to 22.66 (Manhas et al. 2006).

2.6. Sal heartwood borer

The study done on Sal Heartwood Borer by Bhandari and Rawat (2001), described the ecology of the insect. It gives an insight into the life cycle of the borer and explains the causes of the epidemics. It also described the nature of damage and the categorization of the infested trees. The paper suggested the control and remedial measures for the management of the infestation in the forests (Bhandari and Rawat 2001). The study is significant in the context of determining the factors which influence the distribution of infestation of the pest and understanding the ecology of the pest. FAO, 2007 described the wide distribution of Sal Heartwood borer over Asian countries. The report gives a brief history of sal heartwood borer epidemics in India, with the major one in year 1998 when about 1 million trees were affected and killed due to infestation. FAO (2007) explains the plausible cause of some of these outbreaks. Most pest outbreaks in natural forest occur in tree species that grow gregariously, like in a monoculture, and indications are that at least in some species, outbreaks begin in epicentres where the trees are under stress due to ageing, drought or other causes (FAO 2007). The theory may be applied in Sal trees, as they are gregarious, often forming pure crop. It has also been studied that stressed Sal trees are more susceptible to pest attack (Thakur 2000).

3. STUDY AREA

3.1. Criteria for study area selection

Timli range of Kalsi forest division was selected for this study as the area has been recently affected by cerambycid beetle; also it has the past history of attacks where a number of trees have been cut down as a management practice. The area is rich in Sal crop and sequesters a huge amount of carbon. Therefore, it is important to assess present carbon in the forest and its loss due to infestation. Availability of WorldView-2 image for the area was another reason for its selection. Figure 4 represents the area selected for the study.

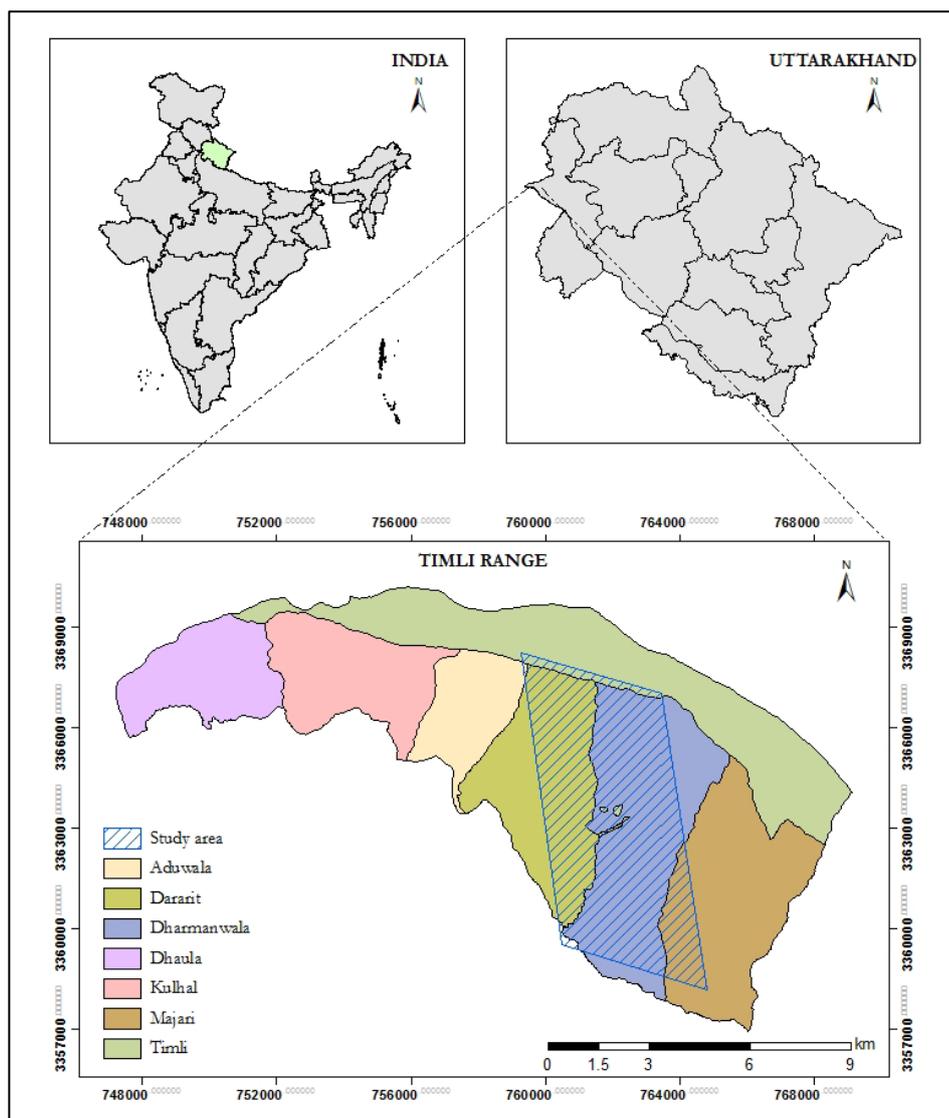


Figure 4: Study area

3.2. Overview of Timli range

Timli range falls under Kalsi forest division of Uttarakhand State Forest Department. Out of the total 16385.363 ha area of Sal working circle of Kalsi, Timli constitutes 42.78 percent i.e. 7009.170 ha. The regeneration is usually natural supported by artificial regeneration. Sal forests in the range are managed under of Indian irregular shelterwood system. In this silvicultural system the forest area is divided into periodic blocks for the management of forest. Periodic block is part or parts of forest set aside to be regenerated in a particular period.

Area and percent area covered by different periodic blocks in Timli range is summarized in Table 1 and illustrated in Figure 5, respectively.

Table 1: Area of periodic blocks

PERIODIC BLOCK	AREA (ha)
PB IA	397.55
PB IB	545.00
II (Middle)	2580.99
III (Regeneration)	3156.10

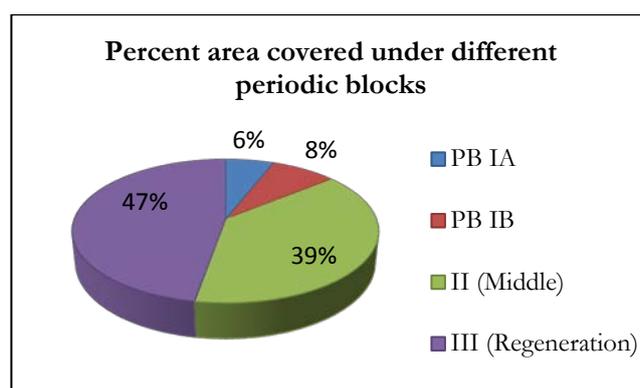


Figure 5: Percent area covered by periodic blocks

The classification of the periodic blocks in Timli area is as follows:

- i. PB IA is the area with sufficient recruits and considerable pole crop but regeneration in whippy and sub – whippy stages.
- ii. PB IB is the area, fully or partially, treated under artificial and natural regeneration during the last plan period after carrying out regeneration felling. Regeneration in the area is significant.
- iii. II (Middle) is the area comprising of middle aged crop and some mature trees.
- iv. III (Regeneration) is the area constituting young to middle aged crop and have been registered satisfactorily in past.

3.2.1. Sal quality classes

Sal quality class has been defined according to the average height of dominant trees. The quality class represents the quality of the site in which Sal is growing. Table 2 summarizes the criterion of Sal quality class.

Table 2: Sal quality classes

Quality class	I	I / II	II	II / III	III	III / IV	IV

Average height of the dominant trees	> 30.5	27.5 – 30.5	24.4 – 27.5	21.4 – 24.4	18.3 – 21.4	15.3 – 18.3	15.3 & below
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3.2.2. Forest types found in study area

According to the classification of Champion and Seth of Indian forests, forests of two major groups were found in the study area. Further classification of the groups is given in Table 3.

Table 3: Forest types in study area

GROUP	SUB-GROUP	TYPE	SUB-TYPE	VARIETY
3 – Tropical Moist Deciduous Forests	3C – North Indian Moist Deciduous Forests	3C/C ₂ - Moist Sal - bearing forests	3C/C _{2b} – Moist <i>bhabar</i> Sal	3C/C _{2b(i)} – Moist <i>bhabar-dun</i> Sal
5- Tropical Dry Deciduous Forests	5B – Northern Tropical Dry Deciduous Forests	5B/C ₁ – Dry Sal-bearing forest	5B/C _{1a} – Dry Siwalik Sal forest	-

3.2.3. Territorial Classification of Forest Organization

Territorially, forest area is divided into block and compartment. They are usually bounded by natural features. Block and compartment can be defined as follows

- i. Block: It is the main territorial division of forest. It is usually bounded by natural features.
- ii. Compartment: A block is divided into several compartments whose size depends upon the intensity of management. Compartments are defined permanently and carefully chosen on ground, for purposes of administration and record. Compartments are preferably designated as Arabic numerals.

3.3. History of Sal heartwood borer infestation in Timli range

Earliest records indicate infestation of borer in the year 1934 when the infestation was reported in 13b compartment of Dharmanwala block of Timli range. Again in 1958 infestation was reported in the same block. In the attack, reported in 1966, Majri and Dararit blocks were affected. In the decade 1999-2009 around 1700 trees were affected from borer infestation.

In the recent infestation, from December 2012, around 700 trees have been affected.

4. MATERIALS AND METHODS

4.1. Data used

4.1.1. Satellite data

The satellite data used for the study was acquired from WorldView-2 platform which was launched in October, 2009. The image set comprised of pan image with resolution of 0.46m resampled to 0.5m and eight multispectral bands with resolution of 1.84m resampled to 2.0 m. The eight multispectral bands included coastal band (400-450 nm), blue band (450-510 nm), green band (510-580 nm), yellow band (585-625 nm), red band (630-690 nm), red-edge band (705-745 nm), NIR₁ band (770-895 nm) and NIR₂ band (860-1040 nm). The MSS bands cover the range of 400 nm – 1050nm, while the pan band covers 450 nm – 800 nm of electromagnetic spectrum. The image was acquired on 23rd October, 2011 and was procured from DigitalGlobe, Inc. Data received was geometrically corrected and registered to WGS 84 and Universal Transverse Mercator (UTM) Zone 43 projection.

4.1.2. Software

The software used for the study are listed in Table 4. Various software were used for data analysis, image processing, statistical analysis, modelling etc.

Table 4: Software used in the study

S.no.	SOFTWARE	PURPOSE
1.	ERDAS Imagine 13	Image processing
2.	ArcGIS 10	GIS analysis
3.	eCognition Developer 8	OBIA
4.	R 3.0	Statistical analysis and geospatial modelling
5.	Microsoft Excel	Statistical analysis
6.	Microsoft PowerPoint	Presentations
7.	Microsoft Word	Thesis writing

4.1.3. Field equipment

Field equipments were used for navigation purposes, registering infested trees' locations, recording the plot location etc. The various equipments which were used in the study are listed in Table 5, with their purpose of use.

Table 5: Equipment used during fieldwork

S.no.	EQUIPMENT	USE
1.	Trimble GPS (Juno-SD)	Navigation and recording locations
2.	Tape (25m)	Crown measurement and plot measurement
3.	Tape (5m)	Diameter measurement
4.	Field work dataset	Data collection

4.2. Image pre-processing

Image pre-processing is required for removal of noise and rectification of the data prior to any analysis and information extraction. Raw data may contain noise or errors in terms of geometric or radiometric errors which may be atmospheric or sensor induced. These distortions must be removed in order to extract accurate information. Image used in the study was ortho-rectified; hence ortho rectification was not done.

4.2.1. Image fusion / Pan-sharpening and its evaluation

Pan sharpening process involves the fusion of high resolution panchromatic image (PI) and comparatively low resolution multispectral (MSS) bands, on pixel basis, which enhances the spatial quality of the resulting image besides preserving the spectral properties of MSS bands. PI is acquired, usually from the same platform and at the same time as the acquisition of MSS data. If it is not acquired at the same time minimal time lag is accepted in order to avoid any differences.

The WorldView2 platform acquires the PI and MSS bands at the same time. The image set comprised of PI with resolution of 0.5m and eight MSS bands with resolution of 2.0 m. In this study seven different techniques viz. High Pass Filter (HPF) resolution merge, Modified- Intensity-Hue-Saturation (M-IHS), Ehler's fusion, Wavelet Resolution merge, Hyperspherical Colour Space (HCS) , Principal Component (PC) and Brovey transform, were used for pan sharpening of the image. These seven techniques were tried with some modifications in interpolation like nearest neighbor and cubic convolution. In some of the techniques the pan image was filtered by 7×7 edge enhancement filter before pan sharpening.

4.2.1.1. HPF Resolution merge

First described by Schowengerdt (1980), the High Pass Filter (HPF) resolution merge technique extrapolates the edge information from high resolution PAN band to the MSS bands. The method can be expressed as follows:

$$F_{i,j} = M_{i,j} + [P_{i,j} - \bar{P}_{i,j(w,h)}] \dots\dots\dots \text{Equation1: HPF}$$

where $F_{i,j}$ is the pixel of the resulting fused image at coordinate (i,j) , $M_{i,j}$ and $P_{i,j}$ are the pixel values of low resolution MSS image and high resolution PI respectively, and $\bar{P}_{i,j(w,h)}$ stands for the local mean of high resolution channel, under a window with width w and height h , pixels located centrally at (i,j) .

In the present study HPF resolution merge was performed twice. First, after filtering the PI with 7×7 edge enhancement filter and second without edge enhancement filtering. (Yuhendra et al. 2012)

4.2.1.2. Modified I H S

IHS fusion involves the replacement of the intensity component by the high resolution PAN band and the hue and saturation bands are resampled to the high resolution. Modified IHS proposed by Siddiqui (2003), is an improvement over traditional IHS pan-sharpening method. It approximates the spectral characteristics from the MSS bands while preserving the spatial characteristics coming from the PAN band.

4.2.1.3. Ehler fusion

Ehler fusion particularly preserves the spectral information contained in the MSS bands of the imagery. The method is also known as FFT (Fast Fourier Transform) enhanced intensity, hue,

saturation transform. FFT decomposes image into intensity components and a fused intensity component is developed which contains low frequency details from MSS bands and high frequency details from high resolution PI.

The study evaluates the Ehler fusion method with two interpolations, one nearest neighbor and other, cubic convolution.

4.2.1.4. Wavelet – PC

The wavelet resolution merge method is executed in three steps. In the first step the high resolution PAN band is decomposed into a set of low resolution PAN images with wavelet coefficient for each component. Next follows the replacement of low resolution PAN components by MSS bands, here the spatial resolution is low. Lastly, a reverse transform converts the decomposed and replaced PAN and bring to the original PAN resolution.

4.2.1.5. HCS

HCS is the transformation between native colour space to hyperspherical colour space. For an input of N bands, one forms the single intensity component and N-1 angles on the hypersphere. Transformation of HCS includes definition of colour or hue by the variables and intensity of the colour by radial component. In HCS pan-sharpening method once the colours are defined, intensity scale can be changed without changing the colour.

In the present study HCS was performed four times with two different combinations of interpolation and edge enhancement.

4.2.1.6. Principal component

Principal Component Analysis (PCA) includes the transformation of correlated bands, in the image, to uncorrelated components, called the principal components. In PC pan-sharpening the high resolution and low resolution images are arranged in two vector columns after which their empirical means are subtracted. The result of this transformation is the vector of $(n \times 2)$ where n is the length of each image vector. For this eigenvector is computed followed by computation of eigenvalues. From the resulting eigenvector the normalized components are computed.

4.2.1.7. Brovey transformation

Brovey transformation follows the procedure of multiplication of each MSS band with the high resolution PAN band and division of each product with the sum of the MSS bands.

For all performed pan sharpening methods, seven evaluation techniques were adopted to assess the quality of the resulting images. Table 6 gives the details of the evaluation methods used in the study.

Table 6: Evaluation methods for pan sharpening techniques

Sno.	METHOD	EQUATION	DESCRIPTION
1	Mean Square Error	$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I_F(i,j) - I_R(i,j))^2$	MSE and RMSE are the measure of spectral distortion in the image. $I_F(i,j)$ Represents the pixels of PI and $I_R(i,j)$ the pixels of fused image. M×N is the size of the image.
2	Root Mean Square Error	$RMSE = \sqrt{MSE}$	

3	Peak Signal to signal Noise Ratio	$PSNR = 10 \log_{10} \left(\frac{L^2}{MSE} \right)$	PSNR is the measure of radiometric distortion in the resulting image. L is the radiometric resolution of the sensor.
4	Spatial Correlation Coefficient	$CC_{\text{spatial}}(P(k), M(k))$	Correlation coefficient is the measure of correlation or similarity between the two images. Pearson correlation coefficient was calculated between the original MSS and fused images for assessing spectral correlation. For calculating spatial correlation reference image, i.e., PI was first filtered with Laplacian filter.
5	Spectral Correlation Coefficient	$CC_{\text{spectral}}(P(k), M(k))$	
6	Universal Image Quality Index	$UIQI = \left(\frac{\sigma_{xy}}{\sigma_x \sigma_y} \right) \left(\frac{2\mu_x \mu_y}{\mu_x^2 + \mu_y^2} \right) \left(\frac{2\sigma_x \sigma_y}{\sigma_x^2 + \sigma_y^2} \right)$	UIQI assesses the overall similarity between the reference and fused image. σ_{xy} is the covariance of two images, σ_x and σ_y are the standard deviations of the images. μ_x and μ_y are the mean of the images.
7	Relative dimensional-ess global error in synthesis	$ERGAS = 100 \frac{h}{l} \sqrt{\frac{1}{N} \sum_{N=1}^N \left(\frac{RMSE(n)}{\mu(n)} \right)^2}$	ERGAS assesses the global quality and measures the trade-off between spectral and spatial quality, respectively. h and l are the spatial resolutions of the high resolution and low resolution images, respectively. N is the number of bands and $\mu(n)$ is the mean of nth band.

4.3. Research method

As the study aims at estimating the loss of forest carbon due to pest infestation and predicting the probable areas of infestation; methodology was divided into two parts. First part deals with estimation of forest carbon and second modelling of infestation probability. The work flow of the study is depicted in Figure 6 and Figure 7.

The steps of the method may be distinguished into remote sensing, field work, statistical analysis and spatial modelling. Remote sensing, in the study, is involved in pan sharpening of the image and segmentation into individual crowns while field work was carried out to locate the infested trees and estimate the carbon. Statistical analysis was required to establish the relationship between CPA and DBH or carbon. Infestation modelling was done with spatial model.

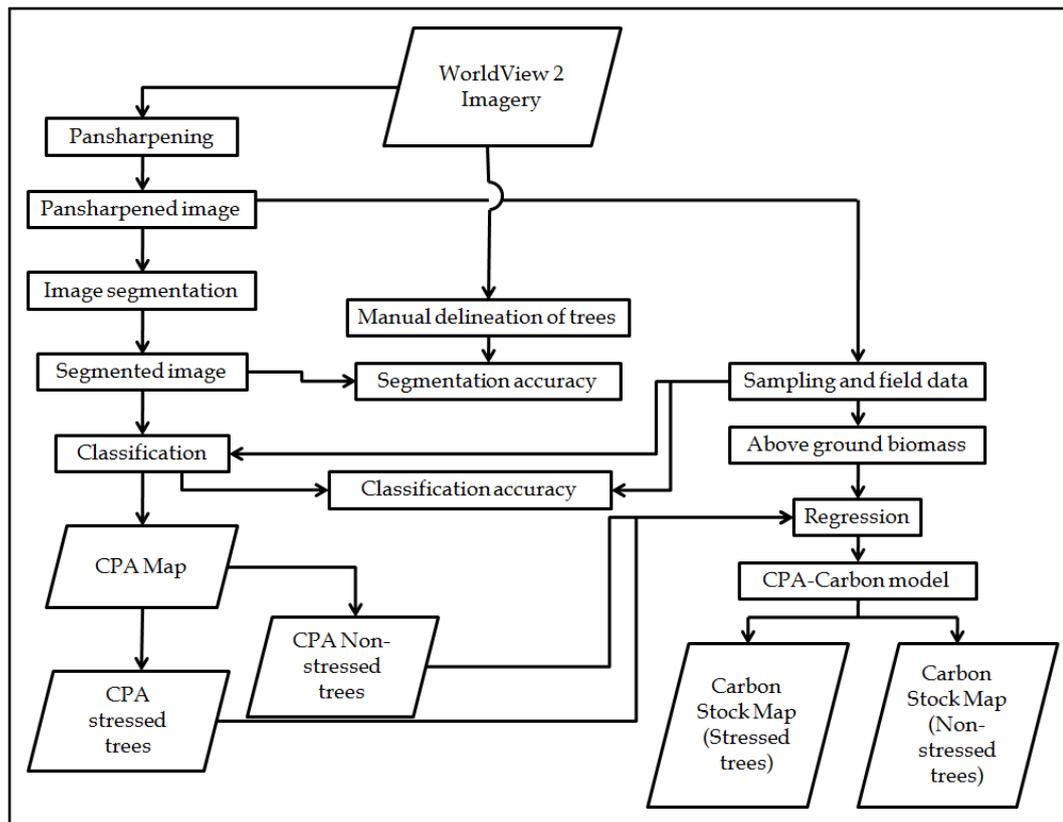


Figure 6: Methodology for carbon estimation

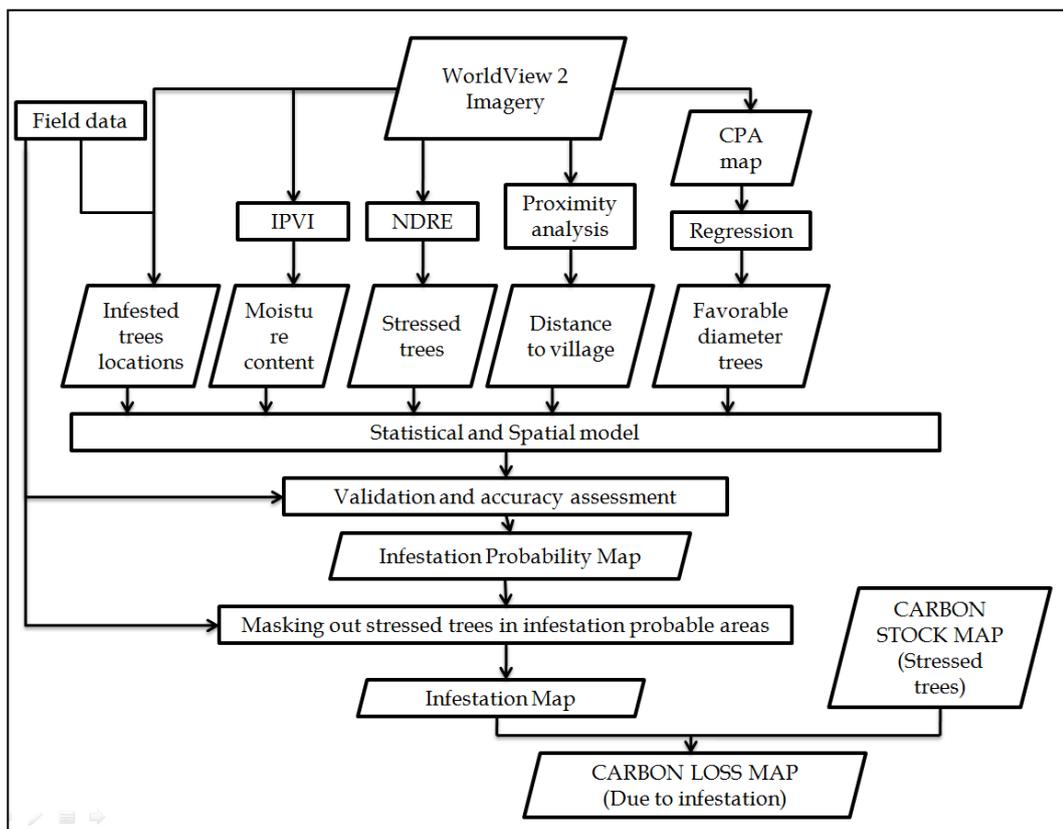


Figure 7: Methodology for infestation modelling and estimation of loss of carbon

4.4. Field work

4.4.1. Sampling design

Before the fieldwork a sampling design was prepared in order to collect the samples over the study area. Stratified random sampling was done for the area. Forest density was considered as a stratum for sampling. Four density classes viz. Less than 10 percent, 10-40 percent, 40-70 percent and were prepared on the basis of visual interpretation.

4.4.2. Field data collection

Field data per plot and locations of infestation were collected from the field.

4.4.3. Sampling plots

Total of 19 plots were selected and plotted on the field.

4.5. Field data analysis

All the data collected from the field was entered into appropriate formats. Point shapefile for the infested trees location was created. These tree locations were used as input to infestation model and validation. Manual delineation of the crowns was done in ArcGIS, which were further used for regression model, assessing segmentation accuracy and validation.

4.5.1. Manual delineation of crowns

The trees which were recorded during the field work were identified on the image and delineated for the purpose of assessing segmentation accuracy, devising relationship between CPA and carbon and its validation. Considering the following points, crowns were delineated:

- i. All the crowns were delimited at the same scale (1:250)
- ii. Crown width, recorded in the field, was used as reference.

A total of 115 crowns were delineated in the WorldView-2 image.

4.6. Image segmentation

Image segmentation may be defined as the process of spatial clustering, which divided the image into non-overlapping sub-divisions called segments (Moller, Lymburner, and Volk 2007). There are different types of segmentation techniques. (Patil and Junnarkar 2013) divided the segmentation techniques into three types viz. edge based, region based and cooperative segmentation methods. In the study region based segmentation was used.

According to (Patil and Junnarkar 2013) region based segmentation methods can be further divided into following:

Region growing in which the implementation of the algorithm starts from starting point called seed pixel. The region then expands by adding similar neighbouring pixels according to homogeneity criterion. The homogeneity criterion is the function which decides upon whether the pixel belongs to certain region or not.

Region splitting is the method where the whole image is the seed region initially. The seed region is divided into quadrant if the region is not homogeneous. These quadrants or sub regions now become individual seed region. The process iterates until all sub regions are homogeneous.

Split and merge technique follows two basic steps. In the first step, the whole image is considered as seed region and then split according to heterogeneity. In the second step the split sub regions are checked for homogeneity and merged accordingly

4.6.1. Multi-resolution segmentation

Multi-resolution segmentation (MS) is a bottom-up region-merging technique, and is regarded as a region-based algorithm. In this each pixel is considered as a separate object. Subsequently, pairs of image objects are merged into bigger segments. Local homogeneity criterion, decides the merging by describing the similarity between adjacent image objects. The pair of image objects is merged if the smallest increase is within the defined criterion. The process ceases when the smallest increase of homogeneity exceeds a user defined threshold, the scale parameter. (Definiens 2012b)

In the study eCognition Developer 8 was used to carry out MS.

4.6.2. Scale parameter

Scale decides the size of the object or segments to be created and could be adjusted according to the features to be extracted and the objective of the study. Scale parameter determines the maximum allowed heterogeneity for the resulting objects or segments. Resulting objects from a certain scale parameter would be smaller for heterogeneous data than the homogeneous data. Minimized heterogeneity is homogeneity. The homogeneity criterion is a combination of colour and shape properties. Shape further splits up in smoothness and compactness (Definiens 2012b). Shape value alters the relationship between colour and shape criteria (shape = 1- colour). Therefore, decrease in shape value leads to increase in colour criteria. Compactness criterion optimizes the resulting objects in terms of compactness. However, this should be used if the objects are compact and are differentiated from non-compact objects by weak spectral differences. Figure 8 presents the conceptual flow of multi-resolution segmentation.

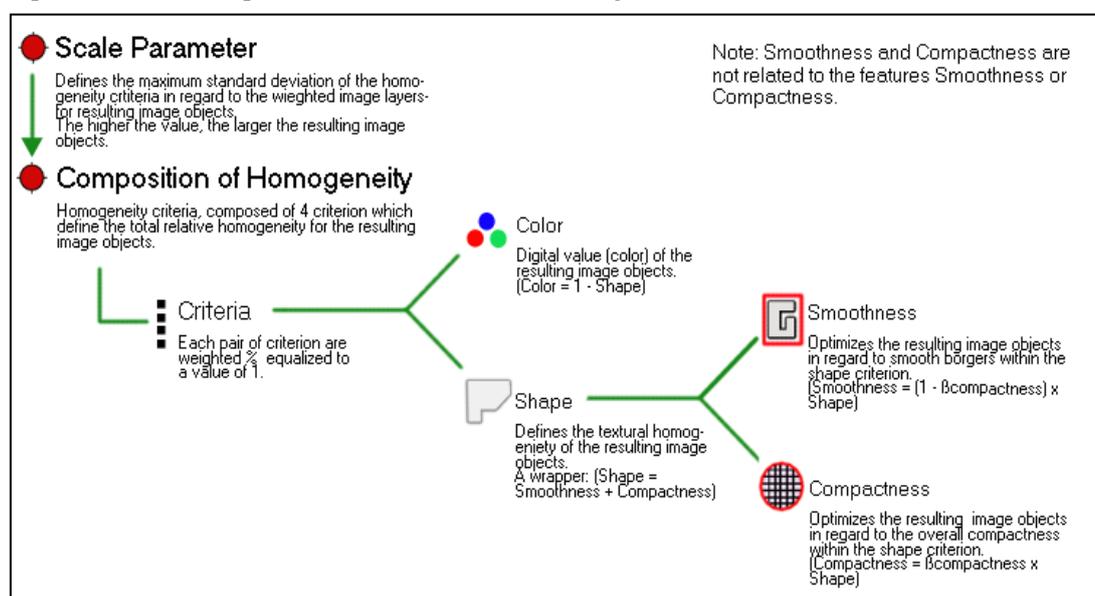


Figure 8: Multi-resolution segmentation conceptual flow

4.7. Segmentation procedure

A series of processes was carried out for segmentation. Preprocessing, segmentation, watershed transformation, morphology etc. were the major steps.

Figure 9 illustrates the flow of the steps being followed for delineation of individual trees.

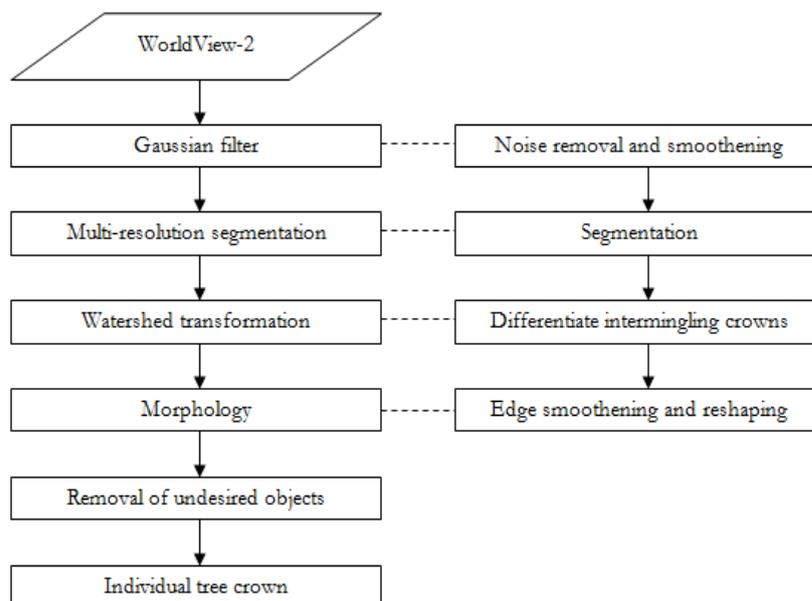


Figure 9: Steps in Segmentation

4.7.1. Preprocessing (Gaussian filter)

Prior to segmentation, image was filtered by running Gaussian filter over the image. The filter removes the noise in the image present due to various reasons like the internal structure of vegetation. The kernel can be user defined. For the study 7×7 kernel was used. Kernel is a square matrix of a value that is applied to the image pixels which is used by convolution filter. Value of each pixel is replaced by the average of the square area of the matrix centered on the pixel (Definiens 2012a).

4.7.2. Masking out shadow

The viewing angle of the sensor introduced many prominent shadow areas in the image. For appropriate delineation of trees shadow areas were masked out from the image. Pixels with value less than 350 were masked out as shadow.

4.7.3. Watershed transformation

The watershed transformation algorithm separates image objects from others. In the study it was used to address the intermingling situation of crowns. In order to delineate the individual trees accurately it is vital to separate the trees whose crowns are intermingled.

The algorithm first calculates an inverted distance map. The inverted distance is calculated from each pixel in the object to the border. This distance is then increased i.e. the level is increased by flooding the minima. Individual objects are split at the level when the two catchment basins touch

each other. Thus, in the overlapping crown condition, trees are considered as catchment. The threshold for the transformation is based on the properties of the objects and expert knowledge in the domain

4.7.4. Morphology

After watershed transformation, morphology was carried out to smooth the borders of the objects. There are two basic operations in morphology, provided by eCognition viz. open image objects and close image objects. Open Image Object separates pixels from an image object that cannot contain the mask completely. Close Image Object adds surrounding pixels to an image object i.e. the area near an image object that cannot contain completely the mask, is filled. In the study close image objects was applied so that the left out areas due to shadow or other spectral properties are added to the image objects.

4.7.5. Removal of undesired objects

After segmentation tiny objects with object area of less than 20 pixels were removed as they had the crown diameter around 2.5 m. Detecting reflectance from such crowns would be difficult in the dense forest.

4.7.6. Segmentation accuracy and validation

To check the “goodness of fit” of the segmentation (Clinton et al. 2008) suggested the method of calculating D-value. The D-value measures the “closeness” between the pre-defined polygons, the reference polygons, and the extracted polygons, segments. He suggested calculation of over-segmentation and under-segmentation to assess the overall segmentation results. The values for over-segmentation and under-segmentation lie between 0 to 1. D -value of zero means perfect segmentation. Over-segmentation and under-segmentation are calculated as follows:

$$\text{Over - segmentation}_{ij} = 1 - \frac{\text{area}(x_i \cap y_j)}{\text{area}(x_i)} \dots\dots\dots \text{Equation 2}$$

$$\text{Under - segmentation}_{ij} = 1 - \frac{\text{area}(x_i \cap y_j)}{\text{area}(y_j)} \dots\dots\dots \text{Equation 3}$$

Where x_i is the reference polygon and y_j is the corresponding segment.

The D-value is calculated as follows

$$D = \frac{\sqrt{(\text{over-segmnetation}^2 + \text{under-segmnetation}^2)}}{2} \dots\dots\dots \text{Equation 4}$$

Image segmentation algorithms are becoming increasingly (Moller, Lymburner, and Volk 2007) . To check the reliability of segmentation results there is need to validate them. Quality of the segmentation results is related to data quality in terms of noise, spatial, spectral resolution; and also the optimal customization of parameter settings. Quality assessments can be done by assessing object differences in terms of topological and geometric relationships. ‘Containment’ and ‘overlap’ are interests of topological relationship while comparison of object positions determines the geometric differences in objects.

Manual digitization of reference polygons to test the automatic segmentation is one of the methods to validate segmentation. Best scores are given when the reference polygon is covered by automatically produced segments.

In the study validation of the segmentation was done by matching the manually digitized reference polygons and those generated by automatic in terms of topological and geometric relationships. For topological relationships area of overlap was considered while for topological relationships positions of the segments were considered. (Zhan and Molenaar 2005) in their study considered the reference polygon and extracted objects to be matching, if the area of overlap, between the two, was greater than 50 percent. One to one matching assesses the quality of extracted objects from perspective of position, size, and shape and as well as overall quality, correctness, and completeness. Figure 10 depicts the various matching conditions of reference polygon and automatically generated segments. Red part is the matched region while green is the undefined region. Case a) depicts more than 50 percent overlap between reference polygon and extracted object, b) shows that shape and size of objects are same but the centroid do not match hence, geometrically different. Case c) and d) shows the difference in spatial extent whilst the objects match geometrically.

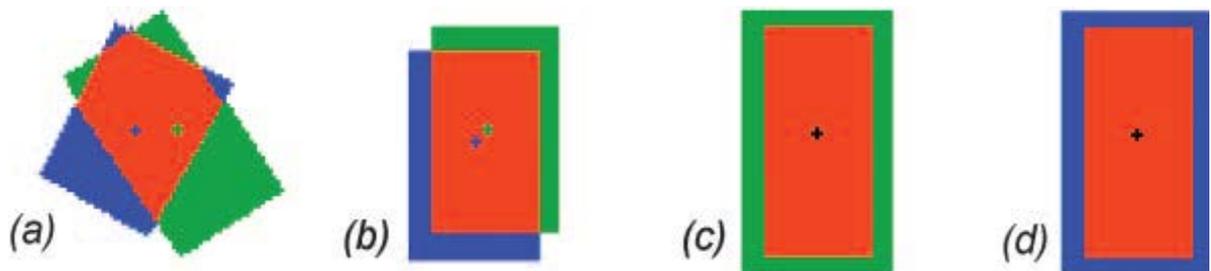


Figure 10:After (Zhan et al, 2005), different conditions of one to one match

4.8. Object based classification and accuracy

4.8.1. Object based classification

For the study rule based image classification was performed. According to defined criteria, classification algorithms evaluate image objects and assign them to a class that best meets the criterion. Classification in eCognition assigns all objects of the image to the class specified by the user. The membership value for the assigned class is set to 1 for all objects independent of the class description. Evaluation of the membership value of an image object against a list of selected classes is done and classification results are updated accordingly.

For the study area four classes were made viz. shadow, tree, non-forest and lantana. Tree class included all the vegetation except lantana; non-forest included the settlements in the area, roads and river bed. Lantana (*Lantana camara*) shrubs present in the power line were separated from other vegetation. Study area had gregarious and pure crop of Sal so specie level classification was not done as the top canopy was covered by Sal.

4.8.2. Classification accuracy

Classification accuracy, in the study, was assessed in eCognition after collecting samples from all the classes. Samples for accuracy assessment were collected on the basis of field survey and visual

interpretation. Accuracy was assessed by generating the confusion matrix which computed producer's accuracy, user's accuracy, commission and omission error, and overall accuracy.

4.9. Above ground biomass calculation and carbon stock calculation

Use of allometric equation for estimating biomass is one the most common methods of biomass estimation. Allometric equations are region and specie specific. The constraint for estimating biomass of the study area was the unavailability of allometric equation for the region. To overcome this limitation a new method was formulated to calculate the above ground biomass of trees. Instead of allometric equation volumetric equation was available for the area. Using volumetric equation volume of trees was calculated; this volume was then multiplied to the specific gravity and biomass expansion factor which are species specific. This gives the biomass of the tree which can further be used to estimate carbon by using the conversion factor of 0.47 given by(IPCC 2006).

Figure 11 depicts the procedure to estimate the biomass of trees using volumetric equation

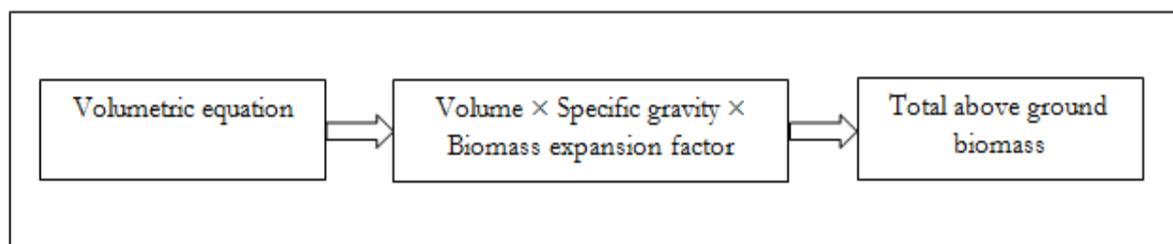


Figure 11: Calculation of TAGB from volumetric equation

Volumetric equations for Sal were created using destructive analysis. To check the reliability of these equations regression model was developed and values of correlation coefficient were evaluated.

The volumetric equation for the study area has been adopted from FSI (Forest Survey of India) Volume equations for India, Nepal and Bhutan. The volumetric equation used for the Sal trees in the study area is

$$i. \text{ Volume} = (0.03805 - 0.77794D + 8.42051D^2 + 5.91067D^3) \dots \dots \text{Equation 5: Volumetric equation for } Shorea \text{ robusta}$$

Where D, stands for DBH of a tree.

To calculate the total above ground biomass (TAGB) of a tree following equation was followed

$$ii. \text{ TAGB} = \text{Volume} \times \text{Specie specific gravity} \times \text{Biomass expansion factor} \dots \dots \text{Equation 6: Estimation of biomass}$$

TAGB obtained from these equations can be converted into carbon stock by following steps

$$C = \text{TAGB} \times \text{CF}$$

Where C, is the carbon stock in Mg C

TAGB is total above ground biomass

CF is the Carbon fraction of biomass (0.47)

In this study specific gravity, for calculation of biomass, was taken as 728 and biomass expansion factor as 1.74.

4.10. Regression analysis and validation of the model

Regression analysis is done to develop a relationship between independent and dependent variable. Changes in the independent variable induce changes in the value of dependent variable. In the study the regression analysis was done between CPA and carbon where CPA was the independent variable and carbon, dependent. A non-linear regression model was developed between CPA and carbon using the data collected from the field.

After developing the model it is required to validate the model for its reliability check. It was done from the test data set, also collected from the field. Validation of the model was done by establishing a linear regression model between the predicted carbon and field calculated amount. To check the error in prediction of carbon, root mean square error (RMSE) was calculated. The equation for calculating RMSE is as follows

$$RMSE = \sqrt{\sum \frac{(C_p - C_o)^2}{N}} \dots\dots\dots \text{Equation 6: RMSE}$$

Where, RMSE is the root mean square error

C_p is the carbon predicted by model

C_o is the carbon calculated from field data

N is the number of observations

4.11. CPA and carbon relationship for stressed and non-stressed trees

To differentiate between the stressed and non-stressed trees NDRE values were used. The normalized differential rededge index has been used previously in the studies to detect the stressed trees. One of the question in the research deals with assessment of CPA – carbon relationship in the stressed and non-stressed trees. In order to devise this relationship, CPA-NDRE relationship was first assessed. In the regression model between CPA and NDRE, the values of NDRE were taken for the trees which were infested.

4.12. Infestation modelling

Sal heartwood borer infestation is influenced by a number of environmental or biotic variables e.g. moisture, human interventions, presence or absence of predator, undergrowth etc. These parameters make the conditions favourable or unfavourable for a pest to infest on Sal trees. The parameters which were considered in the study for infestation modelling are locations of infested trees, Infrared Percent Vegetation Index (IPVI), Normalized Differential Red-edge Index (NDRE), diameter map and distance to village.

Universal kriging was used for predicting the high risk areas for infestation. Universal kriging is often known as regression kriging. Universal kriging was adopted for the prediction of infestation as the infestation locations were spatially correlated with the distance to village. Also constant mean cannot be assumed for the prediction as infestation varied with the values of NDRE, IPVI and diameter of the trees. Therefore, an empirical model approach was required for prediction. As the values of observation were either 1 or 0 it was difficult to estimate the variogram and its parameters. To resolve this trend of infestation was evaluated for all the four parameters included in the model. After analysis, DBH gave the best trend with infestation.

As DBH gave the best trend result, instead of predicting infestation, DBH was predicted using values of IPVI, NDRE and distance to village. The range of the DBH values, prone to infestation

was decided and trees having predicted DBH values within this range were considered risk prone to infestation.

The method was applied in ArcGIS geostatistical analysis tool. For prediction first order trend was given to DBH, IPVI and NDRE; second order trend was given to distance to village. The distribution for all the trends was transformed. DBH trend was transformed to Gaussian, IPVI to quadratic, NDRE to polynomial order 5 and distance to exponential. The semivariogram obtained from the trend was than experimented for range and fitted to the best model based on their SSErr value. R software was used for calculation of SSErr. After fitting the model and prediction, predicted values were cross validated for accuracy assessment of the results.

The basic equation for regression kriging is as follows

$$Y(u) = \beta_0 + \sum \beta_i X_i + S(u) + \epsilon \dots \text{Equation 7}$$

Where, Y(u) is the predicted value at location u

β are the coefficients of regression

X_i is the independent variable

S is the uncertainty associated with prediction, and

ϵ is the error in prediction

4.12.1. Locations of infested trees

GPS locations of the infested trees were recorded in the field. The recording was done compartment wise with the information provided by the forest department of Timli range. The infested trees locations included the currently infested trees and the trees which were cut as a measure of management. 93 infested trees were located and recorded in the field.

4.12.2. IPVI

In the field it was noticed that the moisture content in the area had a strong influence on the presence or absence of infestation. To assess the moisture content IPVI was used which basically estimates the return in the infra red band. As NIR is absorbed by water, its reflectance would be less from the areas where water is present. Therefore, areas with high moisture content would have less value of the ratio.

The formula for computing IPVI is

$$IPVI = \frac{NIR_1}{RED+NIR_1} \dots \dots \dots \text{Equation 8: IPVI}$$

4.12.3. NDRE

The red-edge band in the WorldView-2 image has been used in early detection of stressed trees (Eckert 2012). As discussed by (FAO 2007), the stressed trees may act as an epicenter for the infestation and after affecting the epicenter the infestation may spread to healthy trees as well. Therefore, stressed trees in the forest are vulnerable to pest infestation. To include stressed trees in the modelling, NDRE was used as an input which can be calculated as follows

$$NDRE = \frac{NIR_1 - Rededge}{NIR_1 + Rededge} \dots \dots \dots \text{Equation 9: NDRE}$$

4.12.4. Diameter

It has been found in the studies that Sal heartwood borer has a preference for particular diameter or girth class. Therefore in order to include diameter as an input parameter in the model diameter for each tree was estimated after generating a regression model between CPA and DBH. Data used in the regression model was collected in the field.

4.12.5. Distance to village

Studies and literature suggest that nearness to settlements or disturbances induces infestation of Sal heartwood borer. In the study area there were two villages and according to literature trees near to them are more vulnerable to pest attack. Therefore, buffers at different distances were created from the villages in order to include nearness to the village as a parameter in modelling.

4.13. Estimation of carbon loss due to infestation (2011-2014)

As a management practice infested trees in type I to III are removed from forest to control the spread of infestation. In the infestation, reported in the year 2011 around 400 trees were enumerated and marked by forest department in August 2012 in Timli range. In January- February 2014, the department again enumerated and marked the infested trees. In this enumeration 383 trees were marked under different stages of infestation.

The enumeration data of both years was provided by the State forest department. In the data, marked infested trees were given compartment and infestation category wise. From this data trees falling under type I to III were added, compartment wise.

After estimating the carbon for whole study area, average carbon in kg per tree was calculated. To calculate the loss of carbon due to current infestation the average carbon stock was multiplied to the total number of trees, cut or to be cut due to infestation, in the compartment. The result of loss of carbon due to infestation was produced compartment wise. As some of the compartments had very less area in the study area those were not considered in the estimation of loss of carbon.

5. RESULTS AND DISCUSSION

5.1. Pan-sharpening

Results of various applied pan sharpening techniques were evaluated statistically and also on the basis of visual interpretation. Out of the 12 applied techniques HPF resolution merge gave the best results of statistical evaluation. HPF resolution merge satisfied four methods out of seven evaluation methods. HCS gave the next best results for pan sharpening. Table 7 summarizes the results of statistical evaluation of pan sharpening methods. Figure 12 presents the fused images of various pan-sharpening methods.

Table 7: Results of pansharpening evaluation

Pan-sharpening Methods	MSE	RMSE	PSNR	CC _{spatial}	CC _{spectral}	UIQI	ERGAS
HPF resolution merge (with edge enhancement)	104.56	9.99	46.43	0.93	0.71	0.64	1.15
HPF resolution merge (without edge enhancement)	103.78	9.96	46.46	0.97	0.73	0.71	1.15
Modified I H S (7,5,4)	148.8	12.10	44.64	-0.19	0.94	0.59	1.62
Ehler's fusion (NN)	114.63	10.54	45.91	0.72	0.84	0.59	1.31
Ehler's fusion (CC)	111.82	10.40	46.03	0.85	0.79	0.59	1.31
Wavelet resolution merge	109.70	10.27	46.17	0.56	0.76	0.64	1.17
HCS (with edge enhancement) (NN)	111.72	10.33	46.14	0.89	0.63	0.74	1.14
HCS (with edge enhancement) (CC)	110.51	10.26	46.22	0.96	0.66	0.75	1.14
HCS (without edge enhancement) (NN)	109.04	10.19	46.27	0.86	0.71	0.75	1.14
HCS (without edge enhancement) (CC)	106.02	10.04	46.31	0.95	0.75	0.77	1.13
Principal component	135.54	11.56	45.03	0.57	0.74	0.54	2.01
Brovey transform	266.60	16.32	41.97	0.77	0.78	0.07	13.37

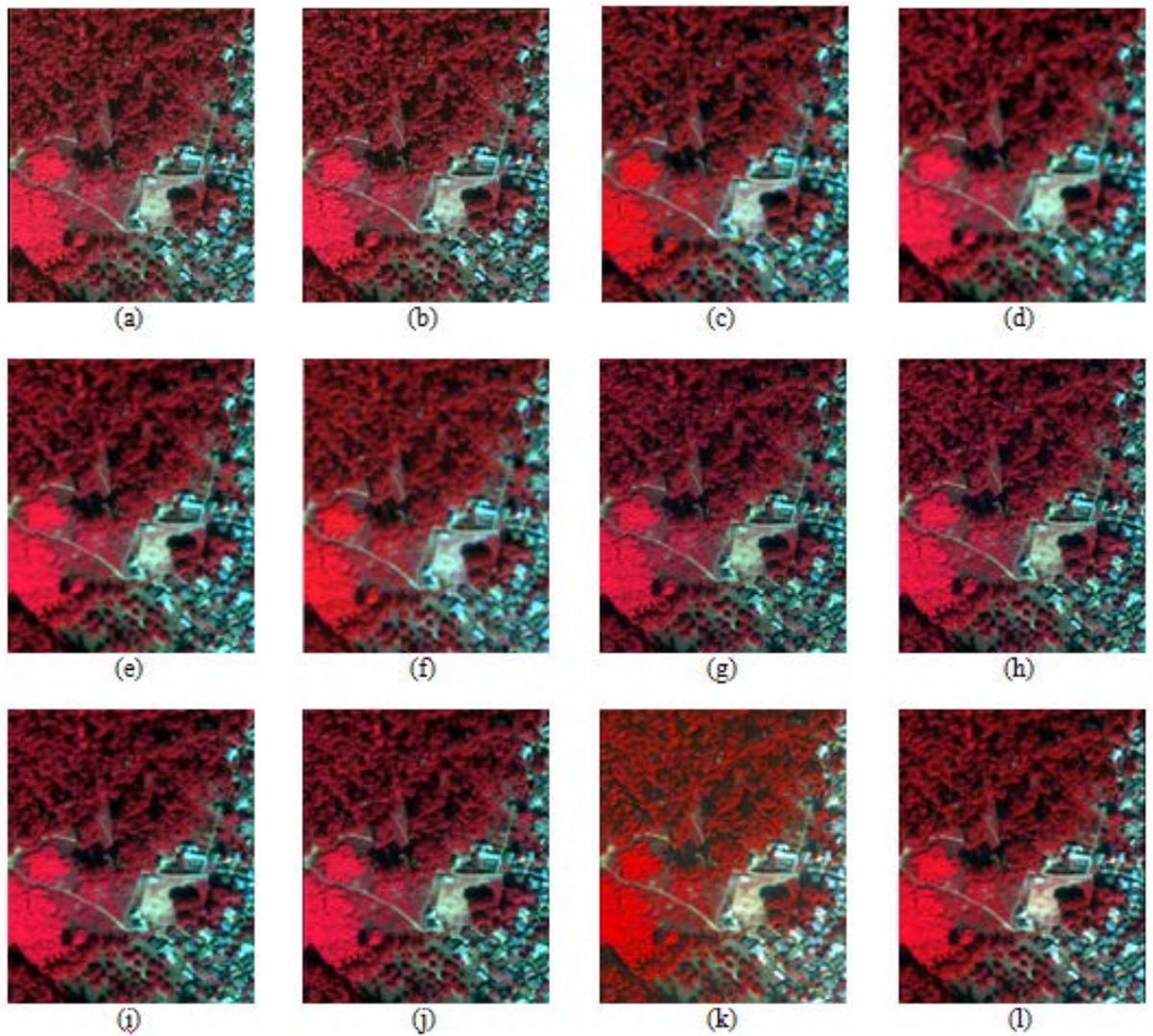


Figure 12: Results of pan-sharpening

Visually HCS gave the best results. In Figure 12 results of pansharpeing are compared (a) HPF (with edge enhancement), (b) HPF (without edge enhancement), (c) M-IHS, (d) Ehler fusion (NN), (e) Ehler fusion (CC), (f) Wavelet-PCA, (g) HCS (With edge enhancement –NN), (h) HCS (With edge enhancement –CC), (i) HCS (Without edge enhancement –NN), (j) HCS (Without edge enhancement –CC), (k) Principal Component, (l) Brovey transform. CC represents the cubic convolution interpolation method while NN is nearest neighbor.

5.2. Image segmentation

Image segmentation was done on HPF resolution merge image of WorldView-2. Multi-resolution segmentation was carried out in order to group pixels into the homogeneous areas forming objects or segments. Since Estimation of Scale Parameter (ESP) tool was unavailable, scale parameter from

19 to 21 was tried to find the appropriate scale parameter. Scale parameter of 20 was selected for multi-resolution segmentation on the basis of visual interpretation and D-value.

5.2.1. Multi-resolution segmentation

To measure the “goodness of fit” of the multi-resolution segmentation can be assessed by calculating D -value. D –value gives ratio of over-segmentation and under-segmentation. Value of D is interpreted as “closeness” between the reference polygons and extracted polygons. The distance index is defined for each segment and averaged over all the reference polygons. The ideal value for the distance index is zero, which means there is neither over-segmentation nor under-segmentation.

The D-value for scale factor 20 was 0.32. D-value for different scale factors has been given in table 8

Table 8: Comparison of D- values

Scale factor	D-value
19	0.41
20	0.32
21	0.34

Figure 13 presents the result of multi-resolution segmentation for the scale factor 20.

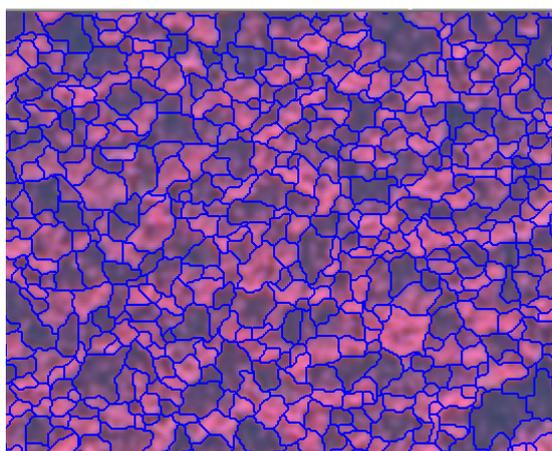


Figure 13: Multi-resolution segmentation

The D- value achieved in the study is good as the D-value must be near to zero for perfect segmentation results. The value is comparable with the results of Karna, 2012 and Baral, 2011 who conducted similar study on forests of Nepal. Both the studies did multi-resolution segmentation of the high resolution imagery. (Karna, 2012) got D- value of 0.33 while (Baral, 2011), 0.47.

5.2.2. Segmentation accuracy

To assess the accuracy of segmentation comparison between manually delineated reference polygon and segmented polygons was done on one to one basis. Out of 115 reference polygons 83 extracted polygons matched on one to one basis. Thus, 72.17 percent segmentation accuracy was achieved in the study. Figure 14 illustrates few results of one to one basis.

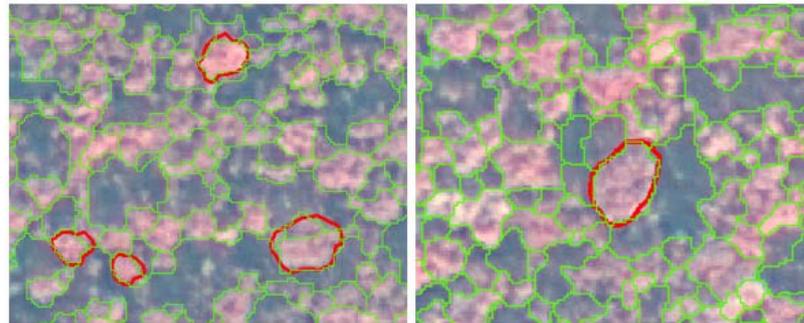


Figure 14: Reference polygons (red) versus automatic segmentation (green)

5.2.3. Object based classification

Objects obtained from multi-resolution segmentation were classified using the spectral properties of the pan sharpened HPF resolution image. Parameters used for classifying the objects were Normalized differential vegetation index (NDVI) and mean of layer 7 i.e. NIR₁. The objects were classified into four classes viz. shadow, non-forest, lantana and tree. As the Sal growth in the area was gregarious and top canopy was occupied by Sal, specie level classification was not done. Figure 15 represents the classification results for the part of study area.

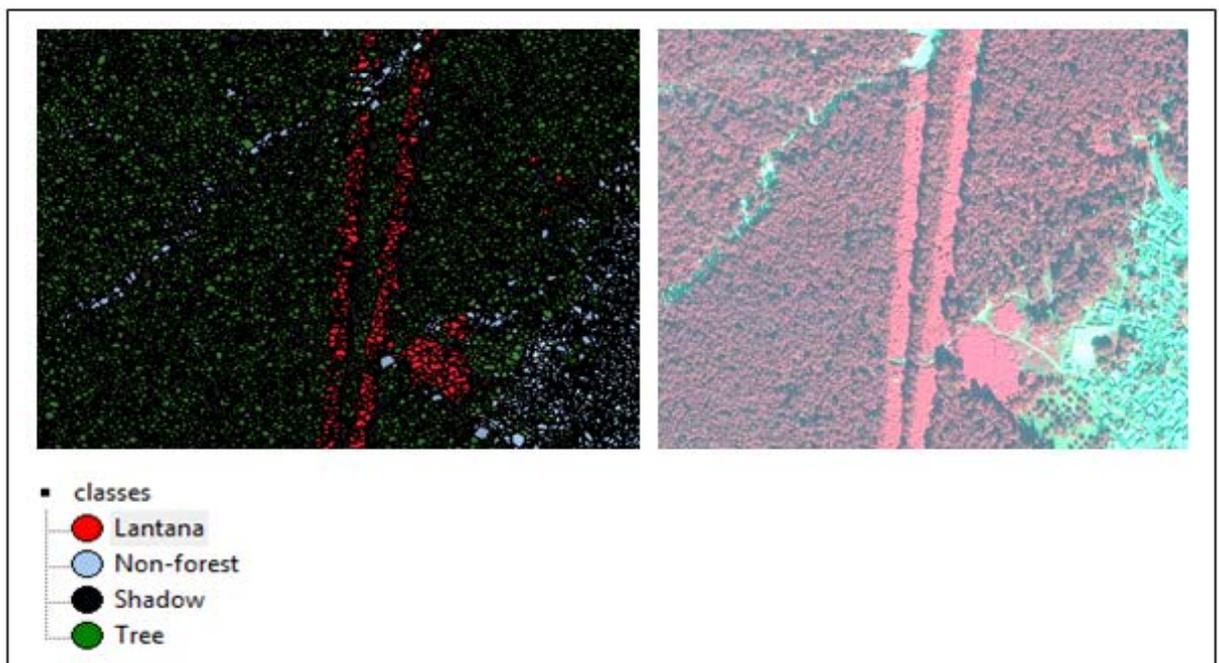


Figure 15: Object based classification result comparison with the original image

5.2.4. Classification accuracy

Classification accuracy was assessed in eCognition after collecting the samples for all the defined classes. Overall accuracy of 84.82 percent was achieved. Table 9 presents confusion matrix for the classification.

Table 9: Confusion matrix for classification accuracy

Class	Tree	Shadow	Non-forest	Lantana	Sum
Tree	126	0	0	28	154
Shadow	0	64	0	0	64
Non-forest	0	40	107	0	147
Lantana	0	0	0	83	83
Sum	126	104	107	111	-
Producer's accuracy	1	0.61	1	0.74	-
User's accuracy	0.82	1	0.73	1	-
Overall accuracy	0.85				
KIA	0.79				

The reason for high accuracy is due to the fact that only four classes were made, which were well separable from each other. Specie based classification was not done in the study as the study area had Sal as dominant specie and composed top canopy of the forest.

5.3. Regression model and validation

Non-linear regression model was devised for assessing the relationship between CPA and carbon of Sal. Non-linear regression was preferred over simple linear regression model on the basis of values of R². Regression was done using 37 field observations. The correlation coefficient of model obtained for CPA-carbon relationship was 0.78. Figure16 presents the non-linear regression graph between CPA and carbon. The regression equation for CPA and carbon of Sal, obtained from model is

$$\text{Carbon stock} = 0.032(\text{CPA})^2 + 0.550 (\text{CPA}) + 251.2 \dots \dots \dots \text{Equation10}$$

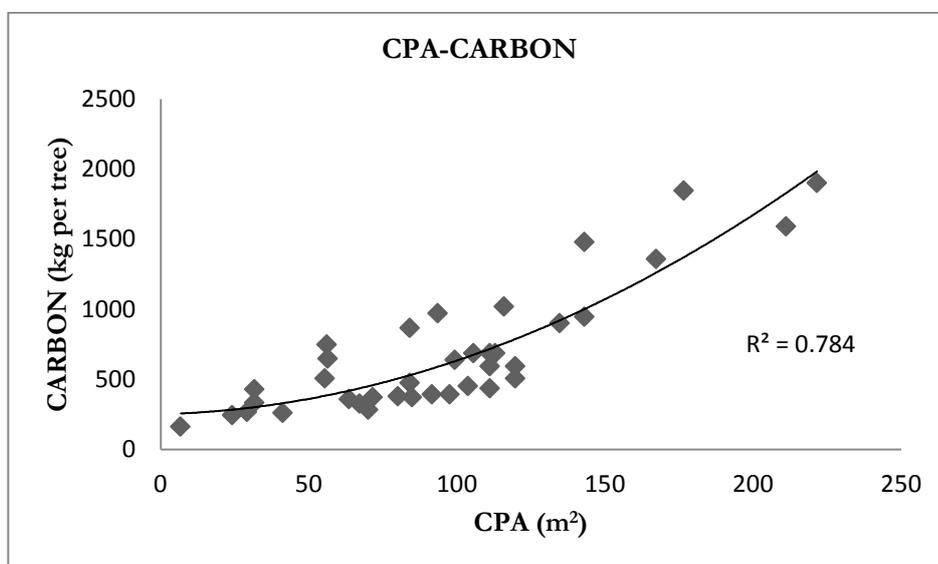


Figure 16: Regression between CPA-Carbon

Model validation was done using 21 observations by plotting predicted carbon to the calculated carbon. The R^2 of the model was 0.87 which means the predicted carbon explained 87 percent of the calculated carbon in field. Figure17 shows the predicted to calculated carbon plot

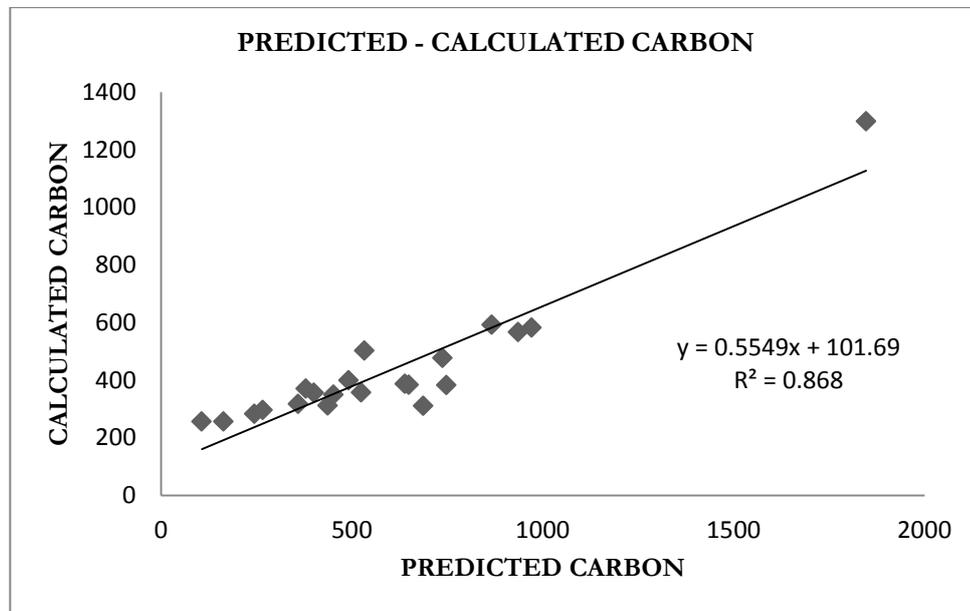


Figure 17: Predicted versus calculated carbon

5.4. Carbon stock mapping

The validated non-linear regression model was used to estimate the amount of carbon present in the study area. Total of 3807876.85 Mg of carbon was estimated in the area. Study area covered around 3569.43 ha area. Therefore the study area had approximately 108 Mg C ha⁻¹. The carbon stock map of the area is presented in figure18. Most of the trees had less than 500 kg carbon per tree while very few trees had carbon greater than 2000 kg.

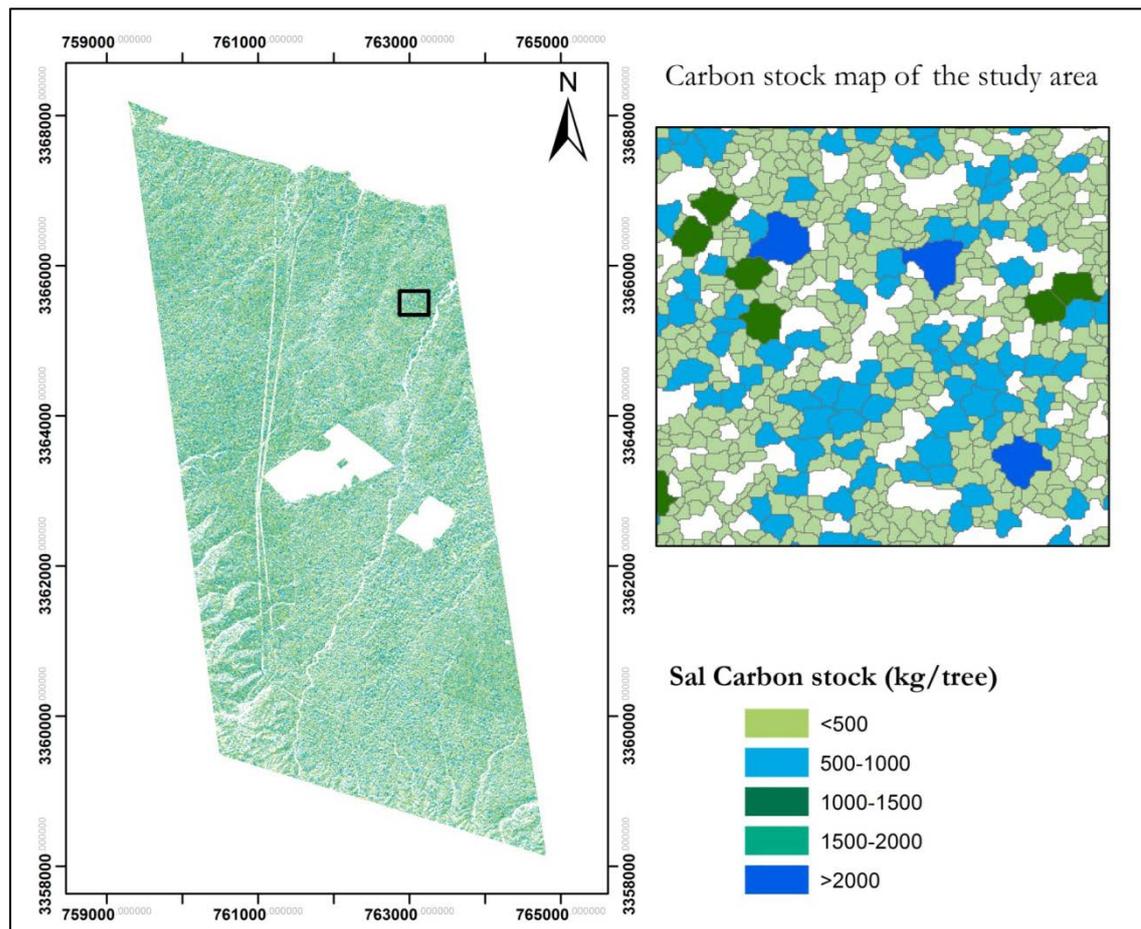


Figure 18: Carbon stock map

5.4.1. Uncertainties and errors in carbon stock estimation

In estimation of carbon stock the errors which would have introduced uncertainties in the result are trees masked out due to shadow, image segmentation and volumetric equation.

While masking out shadow, trees present in the shadow regions of the image were left and could not be segmented. Therefore, this error led to underestimation of carbon. As the image was acquired in Oct, 2011 at around 0600 hrs many areas were not illuminated by sun and therefore were misclassified as shadow.

Another error was introduced while image segmentation. As the segmentation accuracy is only around 72 percent it is possible that many of the trees were not segmented correctly either due to over-segmentation or under-segmentation.

Volumetric equation was another factor which could have added error in estimation of carbon stock. As the data used in derivation of volumetric equation was unavailable, it was difficult to assess the uncertainty associated with volumetric equation. Besides volumetric equation the biomass expansion factor and specific gravity may have added uncertainty in the carbon stock estimation.

5.5. Relationship of carbon and CPA of stressed and non-stressed trees

NDRE values were used to determine the stressed trees in the study area. Trees with low NDRE value were considered to be stressed. So, in order to derive the relationship between CPA and

carbon of stressed and non-stressed trees it was first required to test the relationship between CPA and NDRE. 37 observations of infested trees were used to assess the relationship between CPA and NDRE (Figure 19). As there was no significant relationship between CPA-NDRE it was not derived separately for stressed and non-stressed tree class.

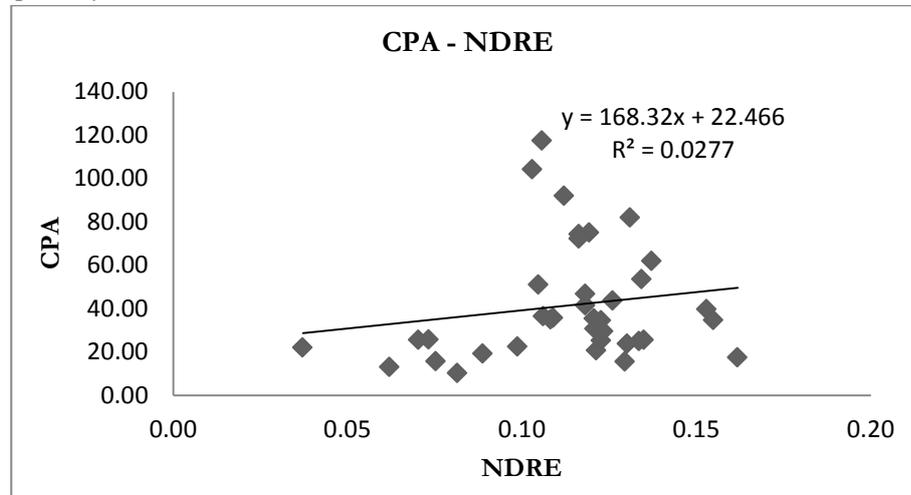


Figure 19: NDRE versus CPA

5.6. Infestation modelling

For infestation modelling universal kriging was used. As DBH presented best trend with infested trees, DBH was predicted using NDRE, IPVI and distance values. The trend of the variables is depicted in figure 20.

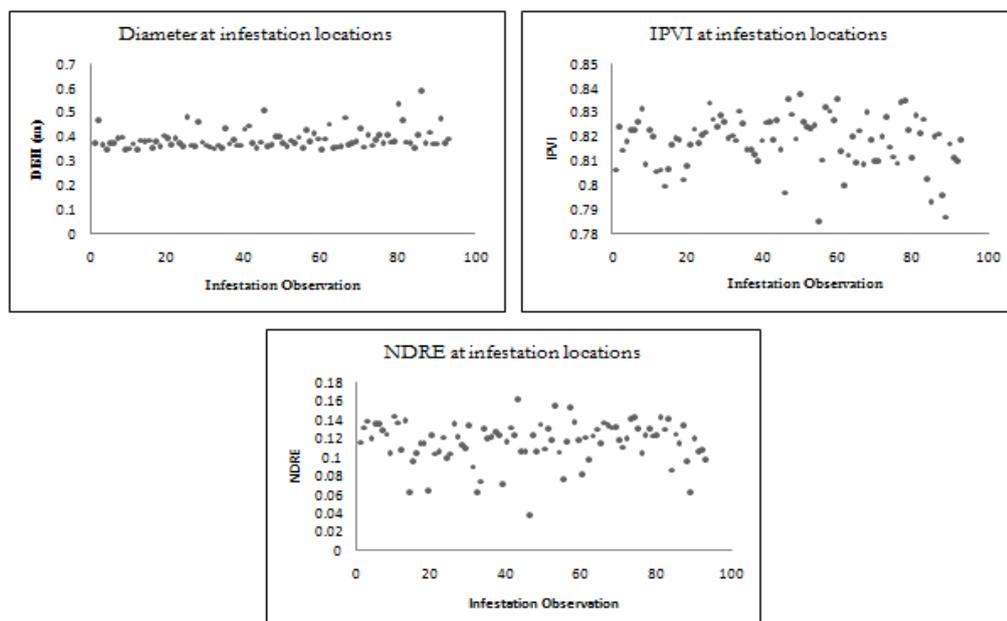


Figure 20: Trend analysis

Based on the trend DBH values of range 0.35 to 0.45 were found to be vulnerable to infestation. In the prediction, trees with DBH value falling under this range were classified as trees at high risk of infestation.

Figure 21 represents the fitted semivariogram with adjusted range. Initial range of 512 was increased to 2512 in order to get the predictions over larger area. Semivariogram was fitted with circular model as it gave least SSErr (Sum of square error). Table 10 compares the SSErr values for various fitted models.

Table 10: SSErr values

S.no.	Model	SSErr
1	Exponential	3.3e-05
2	Spherical	2.4e-05
3	Gaussian	4.53e-05
4	Circular	2.34e-05
5	Linear	2.45e-05

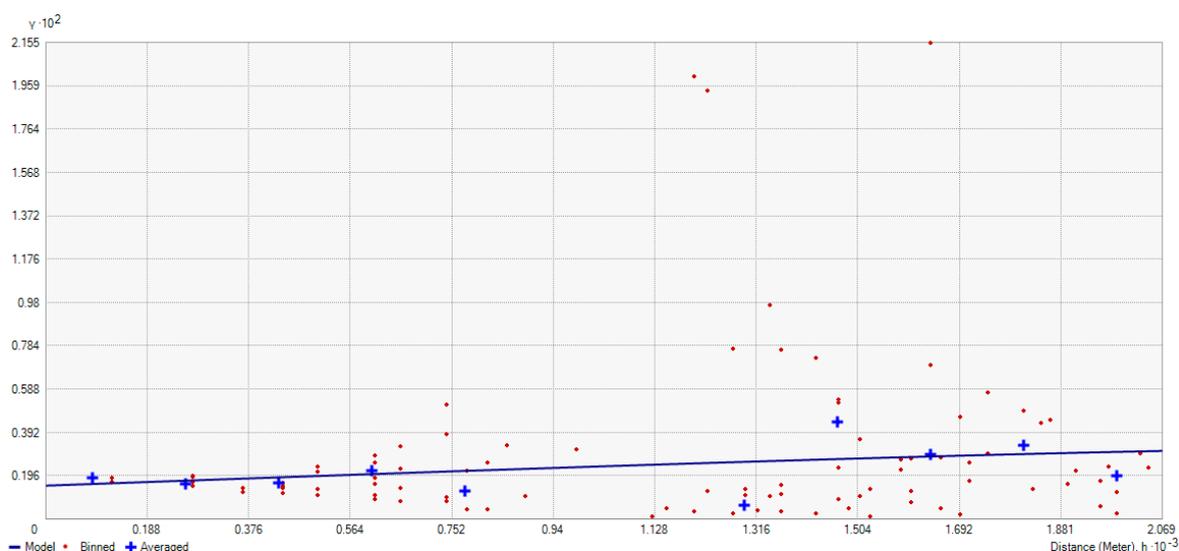


Figure 21: Semivariogram

5.6.1. Accuracy assessment

To assess the accuracy of the model cross validation between the predicted and measured values were done. RMSE of the model was 0.05 m. Figure 22 and 23 present measured versus predicted and measured versus error plot, respectively.

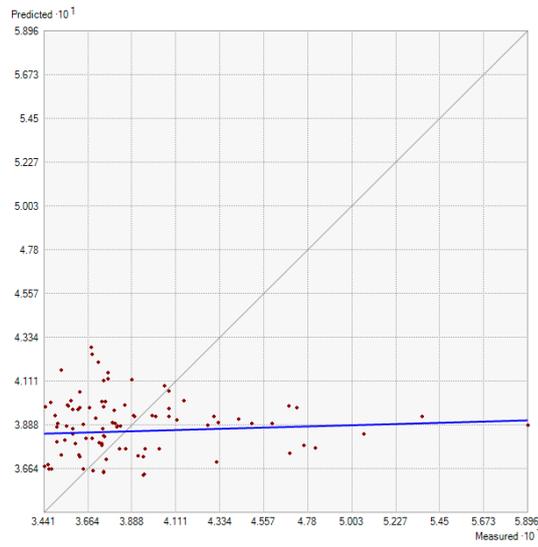


Figure 22: Measured versus predicted values

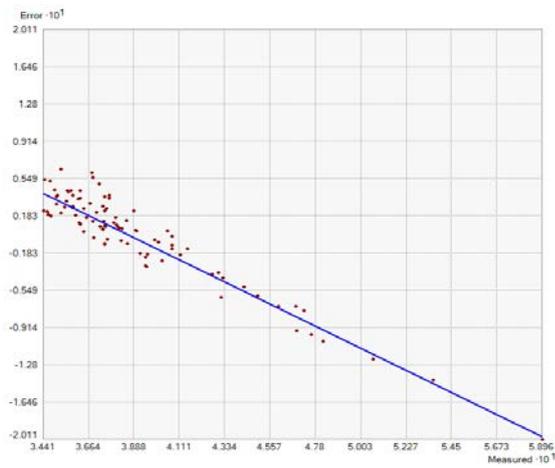


Figure 23: Standard error plot

Figure 24 presents the results of infestation modelling

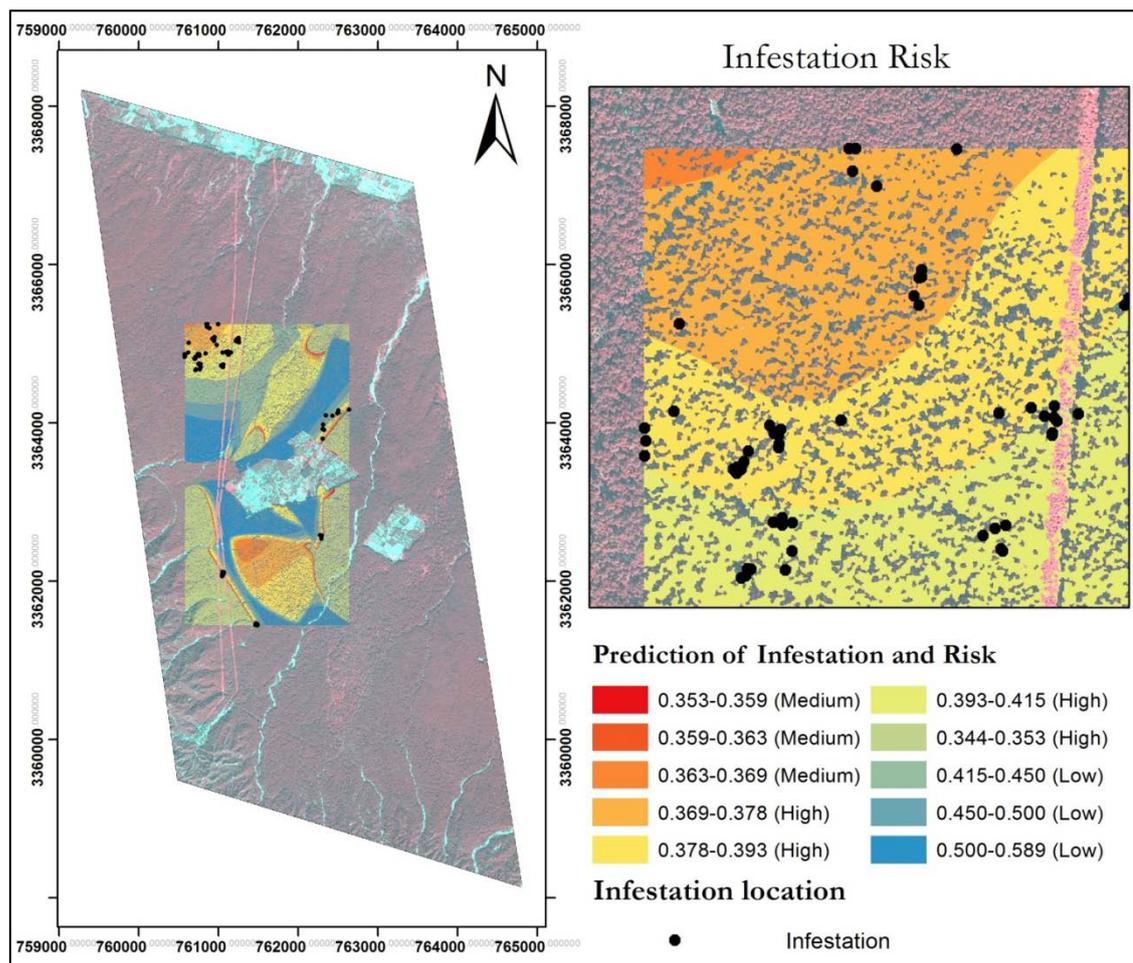


Figure 24: Infestation risk

A general trend can be inferred from the prediction that areas near to villages and areas with high moisture (e.g. near to water channels or rivers) are at high and medium risk of infestation. The results are in agreement with the theory that areas with more human interventions are prone to infestation. The inclusion of moisture in the modelling was based on fieldwork. However, the major constraint is that the trend of NDRE could not be interpreted from the predictions.

5.7. Estimation of loss of carbon from the study area

Loss of carbon from the study area was estimated compartment wise by multiplying the number of trees enumerated in type I to III, to the average carbon per tree. The average carbon per tree in the study area was calculated around 453.71 kg per tree. Figure 25 presents the carbon loss in the study area due to the infestation from 2011 to 2014.

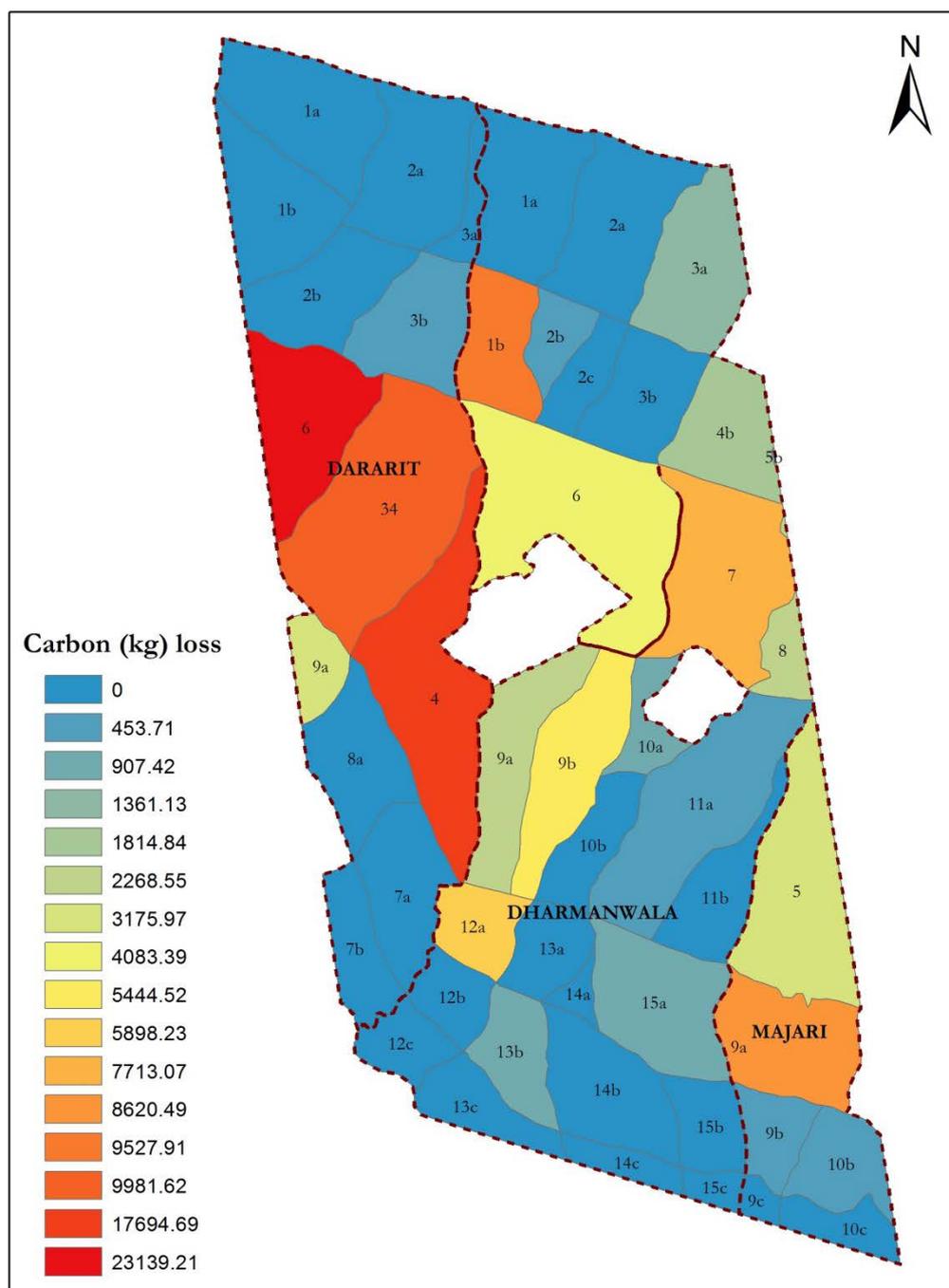


Figure 25: Loss of carbon due to infestation (2011-2014)

The loss of carbon from the forest was highest from block Dararit followed by Dharmanwala and Majari. In Dararit the infestation was severe in compartment 6, 5 and 4. In Dharmanwala highest loss of carbon occurred from compartment 1b followed by 12a, 9b and 6. In Majari block compartment 9a lost the highest carbon.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

Use of high resolution imagery has been useful in carrying out segmentation and classification. In the study significant relationship between CPA and carbon was also achieved. The infestation risk modelling presented a general trend with moisture, DBH and nearness to village.

6.1.1. Which stage of infestation can be detected using RS?

In the field it was found that changes in the canopy can only be detected from stage III. Therefore, it might be possible to detect this stage by remote sensing satellites. Due to the lack of availability of data, for the study area, after 2011, validation of this answer could not be done.

6.1.2. What is the relationship between the CPA and the carbon of the non-stressed trees and the carbon of stressed trees?

As discussed in results, there was no significant relationship between NDRE and CPA, therefore CPA and carbon relationship between stressed and non-stressed trees could not be derived separately. However, significant relationship between CPA and carbon for was derived for the area with R^2 of 0.78.

6.1.3. How much carbon stock is present in the non – stressed trees in the span 2011 - 2013?

As the carbon was not predicted separately for stressed and non-stressed trees, total carbon present in the area was estimated. The total carbon in the area was 108 Mg Cha⁻¹.

6.1.4. What are the environmental factors that lead to the infestation?

From theory, fieldwork, data analysis and interaction with the forest officials it could be interpreted that the trees near to village, are more vulnerable to infestation, moisture also affected the infestation, locations were also found correlated to DBH of the trees, but significant relation with NDRE could not be found.

6.1.5. How much carbon will be lost due to the recent infestation?

Total of around 112 Mg carbon was lost due to current infestation with highest of around 23139 kg carbon was lost from the forest.

6.1.6. Which are the probable areas where infestation can take place?

The probable areas for the selected part of the study area are block Dararit and Dharmanwala. Where compartment 4 and 6 of block Dararit are at high risk. In Dharmanawala block compartment 1b is at high risk.

6.1.7. What is the accuracy of the infestation probability model?

After the cross-validation the estimated error in the prediction of DBH was 0.05m.

Related to objective 1: total above ground biomass of the area

The total above ground biomass of the area was estimated to be 823567.78 Mg.

Related to objective 2: identification of stressed trees

The identification of stressed trees was done on the basis of NDRE.

Related to objective 3: assess loss of carbon from forest due to current infestation

The carbon loss was assessed by multiplying the average carbon per tree to the number of trees to be cut in the compartment.

Related to objective 4: prediction of infestation probability areas

The risk prone areas were predicted using universal kriging.

6.2. Recommendation

The methodology could not differentiate completely, the carbon and CPA relation of stressed and non-stressed trees.

Due to lack of allometric equation for the area, volumetric equation was used for prediction. The allometric equation for the area can be derived and uncertainty related with volumetric equation.

The prediction of the infestation probability can be done with Bayesian statistics and for larger area.

7. References

- Baral, S. 2011. *Mapping Carbon Stock using High Resolution Satellite Images in Sub-tropical Forest of Nepal*, ITC, University of Twente, Enschede, The Netherlands.
- Bhandari, R.S., and J.K. Rawat. 2001. "Sal heartwood borer *Hoplocerambyx spinicornis* (Coleoptera: Cerambycidae) and its management." *Indian Forester* no. 127.
- Blaschke, T. 2010. "Object based image analysis for remote sensing." *ISPRS Journal of Photogrammetry and Remote Sensing* no. 65:2-16.
- Chang, A., E.O. Yangdam, S. Kim, and Y. Kim. 2010. "Canopy-cover thematic-map generation for Military Ma products using remote sensing data in inaccessible areas." *International Consortium of Landscape and Ecological Engineering*.
- Clinton, N., A. Holt, L. Yan, and P. Gong. 2008. "An accuracy assessment measur for object based image segmentation." *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences* no. XXXVIII.
- Definiens. 2012a. Definiens : Developer XD 2.0.4, Reference Book. Definiens Documentation.
- Definiens. 2012b. "Reference book."
- Domec, Jean-Christophe, Laura N. Rivera, John S. King, Ilona Peszlen, Fred Hain, Benjamin Smith, and John Frampton. 2013. "Hemlock woolly adelgid (*Adelges tsugae*) infestation affects water and carbon relations of eastern hemlock (*Tsuga canadensis*) and Carolina hemlock (*Tsuga caroliniana*)." *New Phytologist* no. 199:452-463.
- Eckert, S. 2012. "Improved Forest Biomass and Carbon Estimations Using Texture Measures from WorldView-2 Satellite Data." *Remote Sensing* no. 4:810-829. doi: 10.3390/rs4040810.
- FAO. 2007. Forest Health & Biosecurity Working Papers : OVERVIEW OF FOREST PESTS, INDIA. Food and Agriculture Organization of the United Nations.
- FAO. 2008. Managing forests for climate change: Strategic framework for forests and climate change. Food and Agriculture Organisation.
- Gibbs, Holly K , Sandra Brown, John O Niles, and Jonathan A Foley. 2007. "Monitoring and estimating tropical forest carbon stocks: making REDD a reality." *Environmental Research Letters* no. 2:13.
- Gschwanter, T., K. Schadauer, C. Vidal, E. Tomppo, L. di Cosmo, N. Robert, D. E. Duursma, and M. Lawrence. 2009. "Common tree definitions for national forest inventories in Europe." *Silva Fennica* no. 43:303-321.
- Immitzer, M., C. Atzberger, and T. Koukal. 2012. "Tree Species Classification with Random Forest Using Very High Spatial Resolution 8-Band WorldView-2 Satellite Data." *Remote Sensing*. doi: 10.3390/rs4092661.
- IPCC. 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Kanagawa, Japan: Intergovernmental Panel on Climate Change.
- IPCC. 2007a. Forestry. In *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. United Kingdom and New York: Intergovernmental Panel on Climate Change.

- IPCC. 2007b. Synthesis Report. In: Climate Change 2007: Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change.
- Jawak, S.D., and A.J. Luis. 2013. "Improved land cover mapping using high resolution multiangle 8-band WorldView-2 satellite remote sensing data." *Journal of Applied Remote Sensing*.
- Jing, L., B. Hu, and T. Noland. 2012. "An individual tree crown delineation method based on multi-scale segmentation of imagery." *ISPRS Journal of Photogrammetry and Remote Sensing*:88-98.
- Karna, Y.K. 2012. *Mapping above ground carbon using world view satellite image and lidar data in relationship with tree diversity of forests*, ITC, University of Twente, Enschede, The Netherlands.
- Kaul, M., G.M.J. Mohren, and V.K. Dadhwal. 2010. "Carbon storage and sequestration potential of selected tree species in India." *Mitigation and Adaptation Strategies for Global Change* no. 15:489-510.
- Maharjan, S. 2012. *Estimation and mapping above ground woody carbon stocks using lidar data and digital camera imagery in the hilly forests of gorkha, Nepal*, ITC, University of Twente, Enschede, The Netherlands.
- Moller, M., L. Lymburner, and M. Volk. 2007. "The comparison index: A tool for assessing the accuracy of image segmentation." *International Journal of Applied Earth Observation and Geoinformation* no. 9:311–321.
- Nowak, David J. , Judith E. Pasek, Ronaldo A. Sequeira, Daniel E. Crane, and Victor C. Mastro. 2001. "Potential Effect of *Anoplophora glabripennis* (Coleoptera: Cerambycidae) on Urban Trees in the United States." *Journal of economic Entomology* no. 94 (1):116-122.
- Nuckolls, April E. , Nina Wurzburger, Chelcy R. Ford, Ronald L. Hendrick, James M. Vose, and Brian D. Kloeppel. 2009. "Hemlock declines rapidly with Hemlock Woolly Adelgid infestation: Impacts on the carbon cycle of Southern Appalachian forests." *Ecosystems* no. 12:179-190.
- Patil, S., and A.A. Junnarkar. 2013. "Overview of Colour Image Segmentation Techniques." *International Journal of Advanced Research in Computer Science and Software Engineering* no. 3.
- Satya, D. K. Upreti, and Sanjeeva Nayaka. 2005. "*Shorea robusta* – an excellent host tree for lichen growth in India." *Current Science* no. 89 (4).
- Shimano, K. 1997. "Analysis of the Relationship between DBH and Crown Projection Area Using a New Model." *J. For. Res.* no. 2:237-242.
- Thakur, M.L. 2000. *Forest Entomology (Ecology and management)*: International Book Distributors.
- WMO. 2013. The global climate 2001 – 2010 :A decade of climate extremes. Geneva, Switzerland: World Meteorological Organization.
- Yuhendra, I. Alimuddin, J. Tetuko, and H. Kuzw. 2012. "Assessment of panshrpening methods applied to image fusion of remotely sensed multi-data band." *International Journal of Applied Earth Observation and Geoinformation* no. 18.
- Zhan, K., and M. Molenaar. 2005. "Quality assessment for geo-spatial objects derived from remotely sensed data." *International Journal of Remote Sensing* no. 26:2953–2974. doi: 10.1080/01431160500057764.

ACRONYMS

CO₂: Carbon dioxide
CPA: Crown projection area
DBH: Diameter at breast height
HCS: Hyperspherical Colour Space
HPF: High Pass Filter
IHS: Intensity Hue Saturation
IPCC: Intergovernmental Panel on Climate Change
IPVI: Infrared Percent Vegetation Index
NDRE: Normalised Difference Red-edge Index
OBIA: Object based image analysis
WHO: World Health Organisation