Remote Sensing based Estimation of Forest Biophysical Variables using Machine Learning Algorithm

Ritika Srinet, Subrata Nandy and NR Patel

Forestry and Ecology Department
Indian Institute of Remote Sensing
Indian Space Research Organisation
Dehradun, India
ritikasrinet@gmail.com

Introduction

- Leaf Area Index (LAI), Fraction of Intercepted Photosynthetically Active Radiation (fIPAR) and forest Aboveground Biomass (AGB) are the regulatory parameters for several canopy functions.

- LAI is the interface for gaseous exchange and light absorption for photosynthesis, fIPAR gives the amount of light intercepted by the forest canopy while AGB is relates to the amount of carbon sequestered and stocked.

- An accurate information about spatial variability of these biophysical variables is vital to capture the variability in estimates of gross primary productivity, carbon exchange and microclimate in terrestrial ecosystems.

Objectives

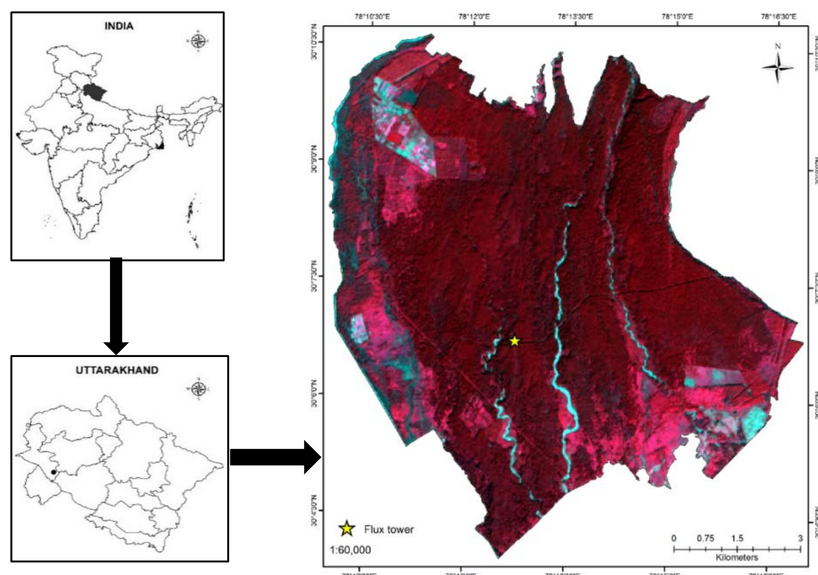
- To optimize spectral and texture variables for estimation of LAI, fIPAR and AGB using random forest (RF) algorithm.
- To map the spatial distribution of LAI, fIPAR and AGB.

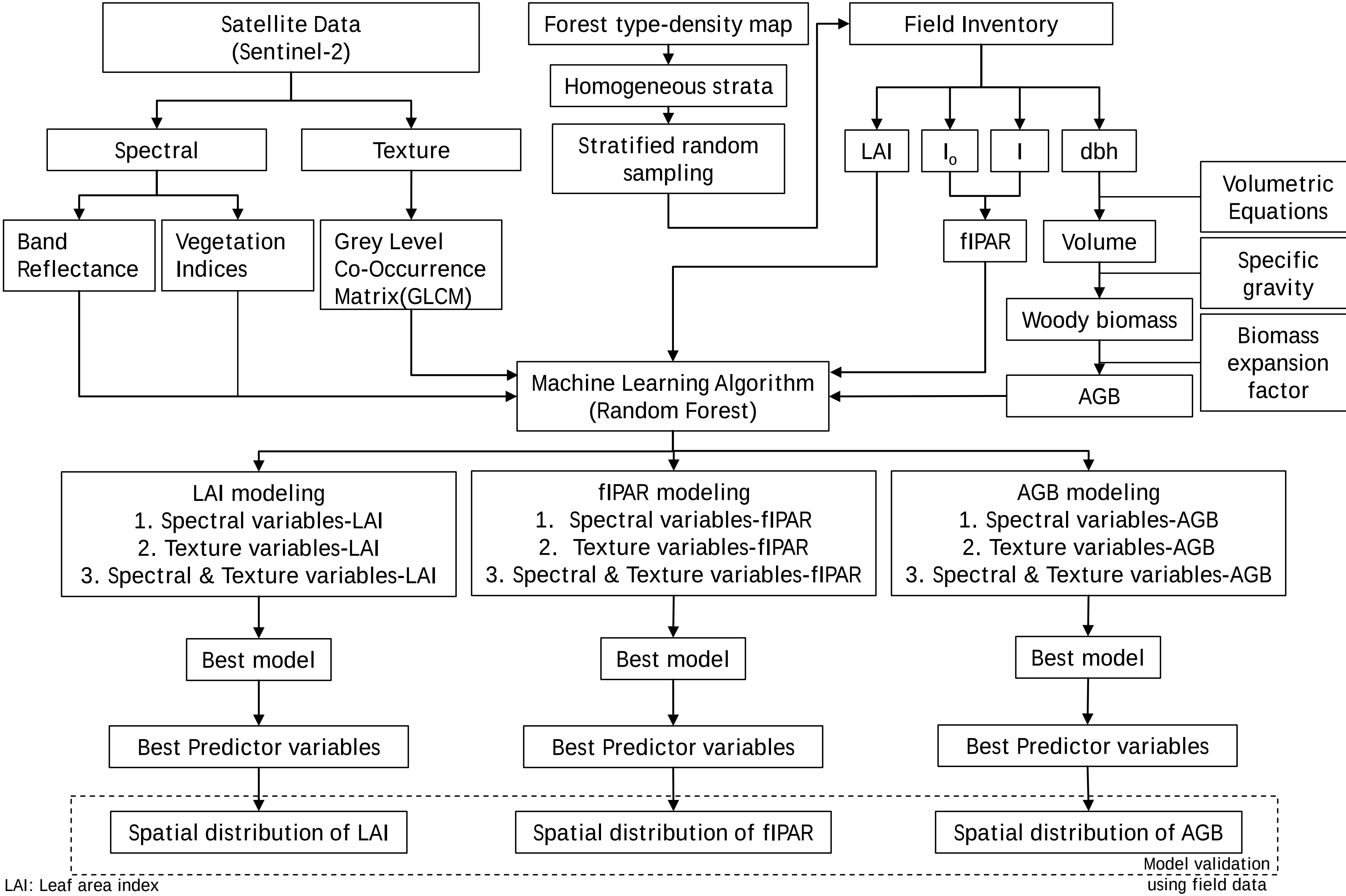
Objectives

- To optimize spectral and texture variables for estimation of LAI, fIPAR and AGB using random forest (RF) regression algorithm.
- To map the spatial distribution of LAI, fIPAR and AGB.

Study site

- Barkot Reserve Forest (30°03′52″-30°10′43″N and 78°09′49″-78°17′09″E)
- Forest type: Sal dominated Tropical Moist Deciduous Forest





LAI: Leaf area index
I_o: Light intensity incident above canopy
I: Light intensity below canopy
dbh: Diameter at breast height
fIPAR: Fraction of intercepted photosynthetically active radiation
AGB: Aboveground biomass

Field Sampling

- A pilot study was carried out by laying sample plots in different strata.
- No. of plots, n, is given by (Chacko, 1965):

$$n = \frac{CV^2 \times t^2}{SE^2}$$

- Optimum number of plots were calculated for LAI, fIPAR and AGB.
- It was distributed to each stratum using probability proportional to size (pps)

$$n_H = \frac{N_H}{N} \times n$$

Field Sampling: LAI and PAR

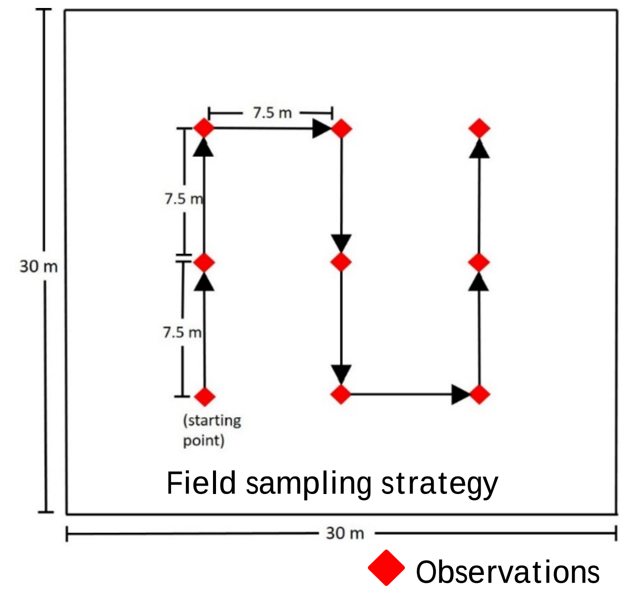
- Field observations of LAI and I_o and I were recorded using CI-110 Plant Canopy Imager.
- The recorded LAI ranged from 0.28 to 1.72.
- fIPAR was calculated as:

$$fIPAR = \frac{I_o - I}{I_o}$$

where, I= Light intensity below canopy

I_o=Light intensity incident above canopy

- fIPAR ranged from 0.25 to 0.9.



Field Sampling: AGB

- Field inventory for trees was carried in plots of 0.1 ha (31.5m × 31.5m)
- cbh were recorded, dbh was calculated from cbh
- By applying volume equations for the tree species the tree volumes were calculated
- $woody\ biomass = tree\ volume \times specific\ gravity$
- $AGB = woody\ biomass \times biomass\ expansion\ factor$ (Haripriya, 2000)
- Biomass ranged from 118.70 Mg/ha in open mixed plantation to 580.98 Mg/ha in very dense sal forest

Spectral and Texture Variables

- 62 spectral variables were extracted:
  - Band reflectance (blue, green, red, red edge 1, red edge 2, red edge 3, NIR, NIR_{narrow}, SWIR 1, SWIR 2)
  - 52 spectral indices

ARVI	CI	CI_RE1	DVI	EVI
EVI_NIR_N1	EVI_NIR_N2	EVI_RE1	EVI_RE2	GARI
GDVI	GNDVI	GRVI1	IPVI	IRECI
MSAVI	MSI	MSR	MSR_NIR_N1	MSR_NIR_N2
MSR_RE1	MSR_RE2	NDII	NDMI	NDVI
NDVI705	NG	NLI	NLI_NIR_N1	NLI_NIR_N2
NLI_RE1	NLI_RE2	NR	OSAVI	PSRI
PSRI_NIR	PSSR	RDVI	RE_NDWI	RSR
RSR_NIR_N1	RSR_NIR_N2	RSR_RE1	RSR_RE2	RVI
S2REP	SARVI	SAVI	STVI	TNDVI
TSAVI	VARI_G			

- Grey level co-occurance matrices :
  - Mean
  - Variance
  - Homogeneity
  - Contrast
  - Dissimilarity
  - Entropy
  - Second moment
  - Correlation
- 80 texture variables were extracted.

Random Forest based modeling

- To optimize the number of independent variables, Random Forest (RF) algorithm was used.
- Three models were tested for estimation of LAI, fIPAR and AGB.
  - Model 1: Spectral Variables (No. of independent variables= 62)
  - Model 2: Texture Variables (No. of independent variables= 80)
  - Model 3: Spectral and Texture Variables (No. of independent variables= 142)
- The resulting models were compared to select the best predictor model.
- Using random forest cross validation, the optimum number of variables were selected.
- Final models, with optimum number of independent variables were used to map the spatial distribution of the said biophysical variables.

Random Forest based modelling for LAI, fIPAR and AGB

LAI	Model 1	Model 2	Model 3
R^2	0.92	0.92	0.93
RMSE	0.117	0.121	0.114
%RMSE	11.45%	11.60%	10.85%

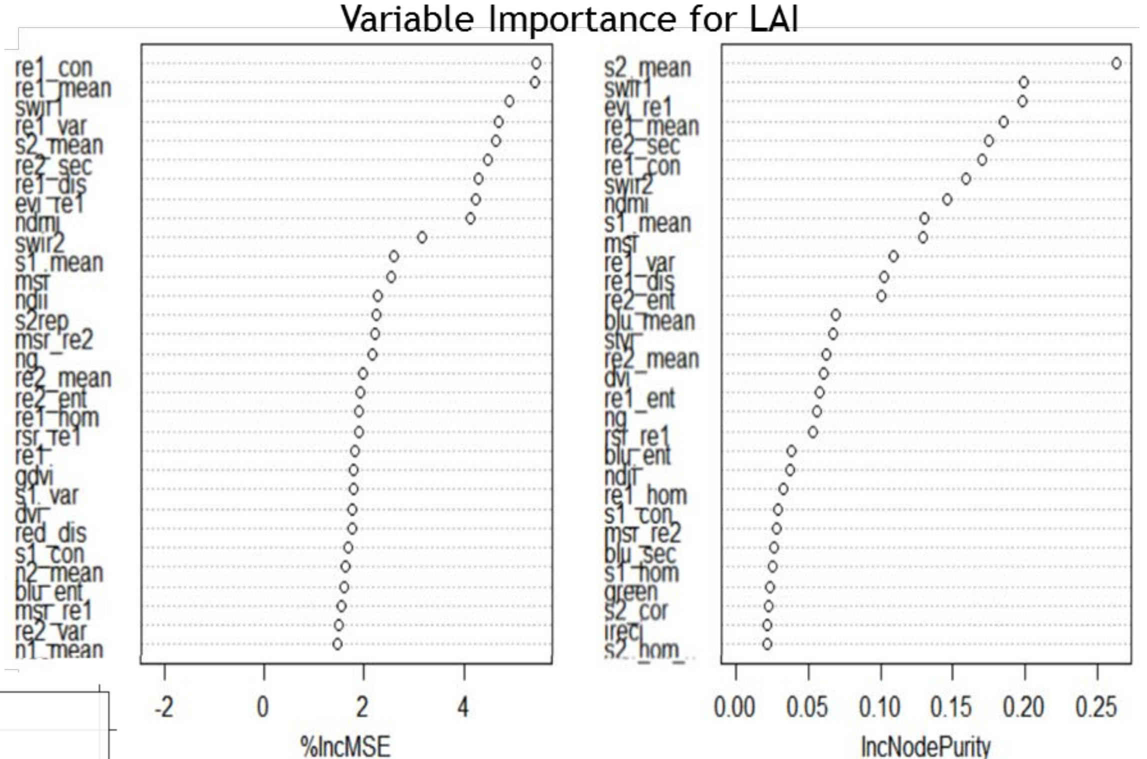
fIPAR	Model 1	Model 2	Model 3
R^2	0.91	0.92	0.94
RMSE (mol m^{-2} s^{-1})	0.073	0.067	0.065
%RMSE	11.19%	10.27%	10.01%

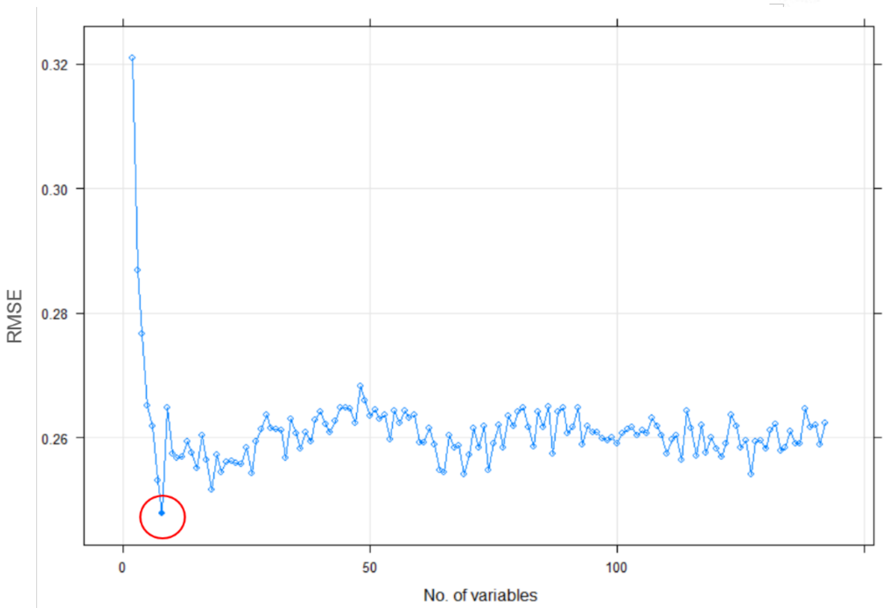
AGB	Model 1	Model 2	Model 3
R^2	0.91	0.92	0.94
RMSE (Mg ha^{-1})	49.83	47.23	46.49
%RMSE	11.77%	11.15%	10.98%

Random Forest based modelling for LAI

- For *LAI*, model 3 with spectral and texture variables gave better results.

- Using cross validation, the minimum RMSE was found for 8 (4 spectral + 4 texture) variables.

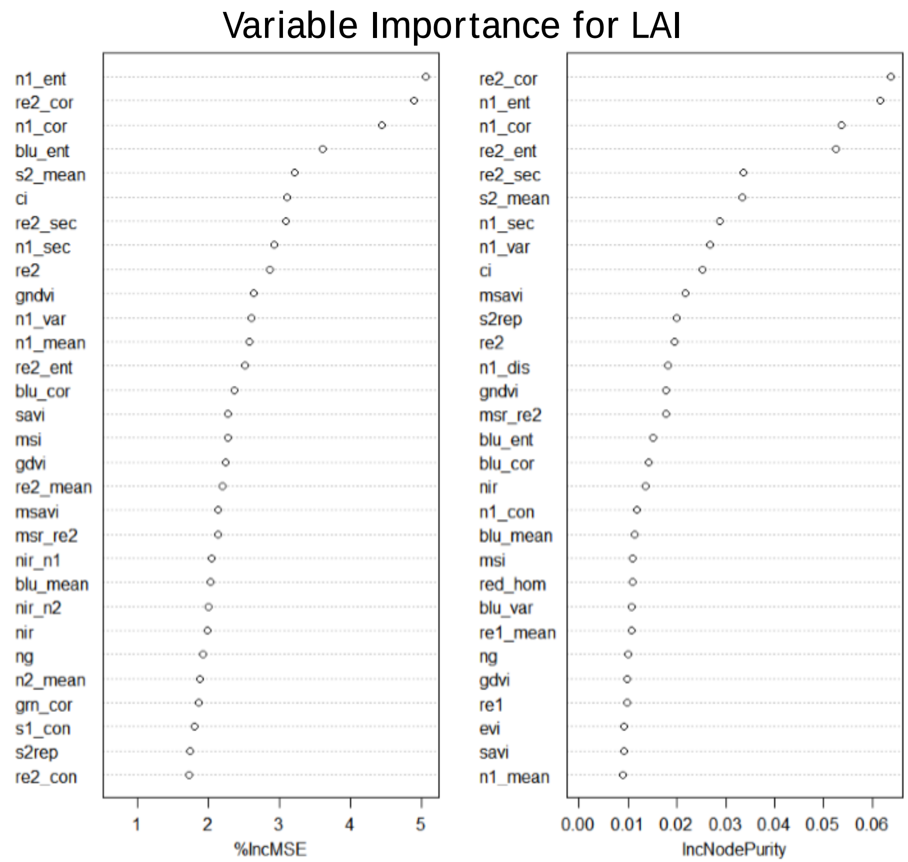


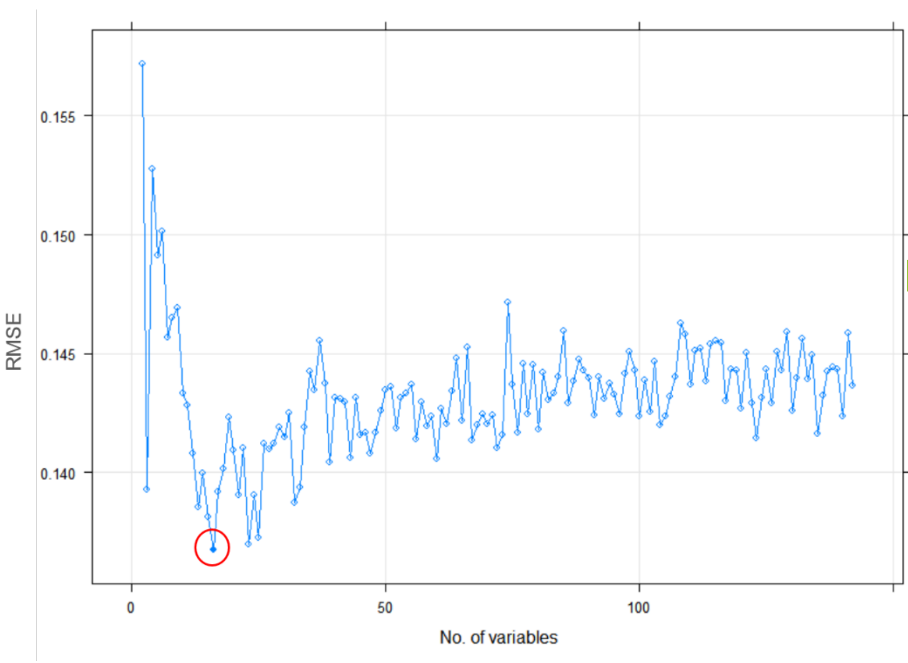


- swir1, swir2, re2_sec, s2_mean, evi_re1, re1_mean, re1_con, and ndmi were the top variables.

Random Forest based modelling for fIPAR

- For *fIPAR*, model 3 with spectral and texture variables gave better results.
- Using cross validation, the minimum RMSE was found for 15 (6 spectral + 9 texture) variables.

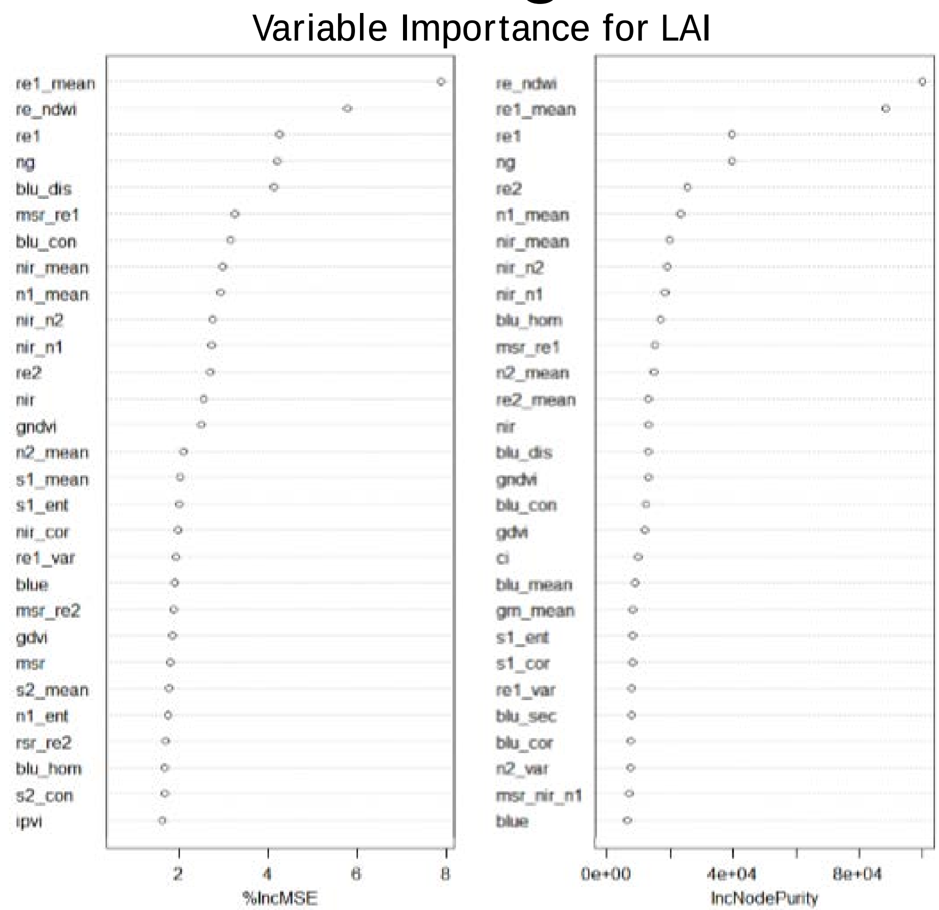


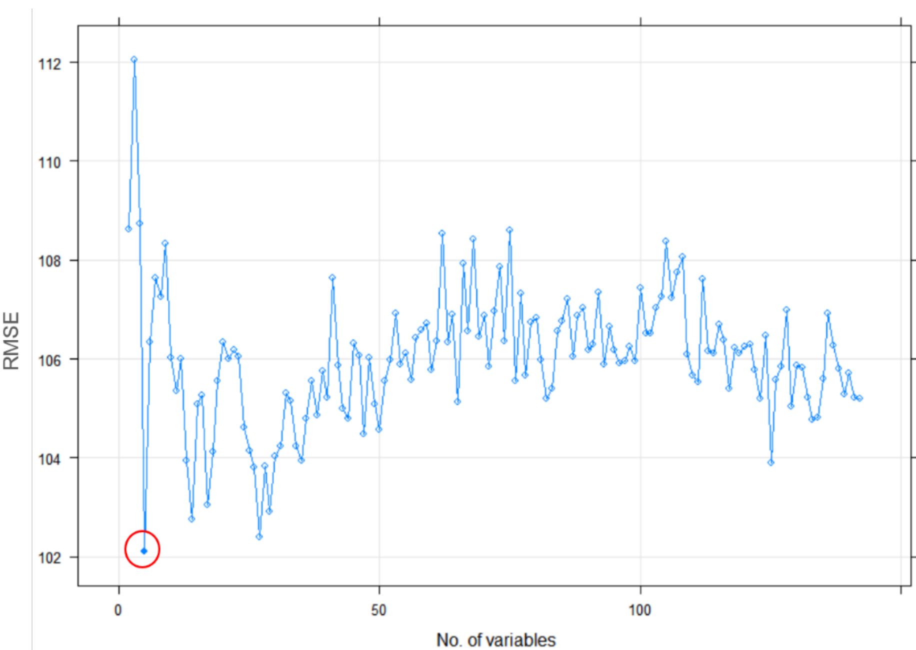


- re2_cor, n1_ent, n1_cor, re2_ent, re2_sec, s2_mean, n1_sec, n1_var, ci, msavi, s2rep, re2, n1_dis, gndvi, and msr_re2 were the top variables.

Random Forest based modelling for AGB

- For *AGB*, model 3 with spectral and texture variables gave better results.
- Using cross validation, the minimum RMSE was found for 8 (5 spectral + 3 texture) variables.





- re_ndwi, re1_mean, re1, ng, re2, n1_mean, nir_mean, and nir_n2 were the top variables.

Spatial distribution of LAI

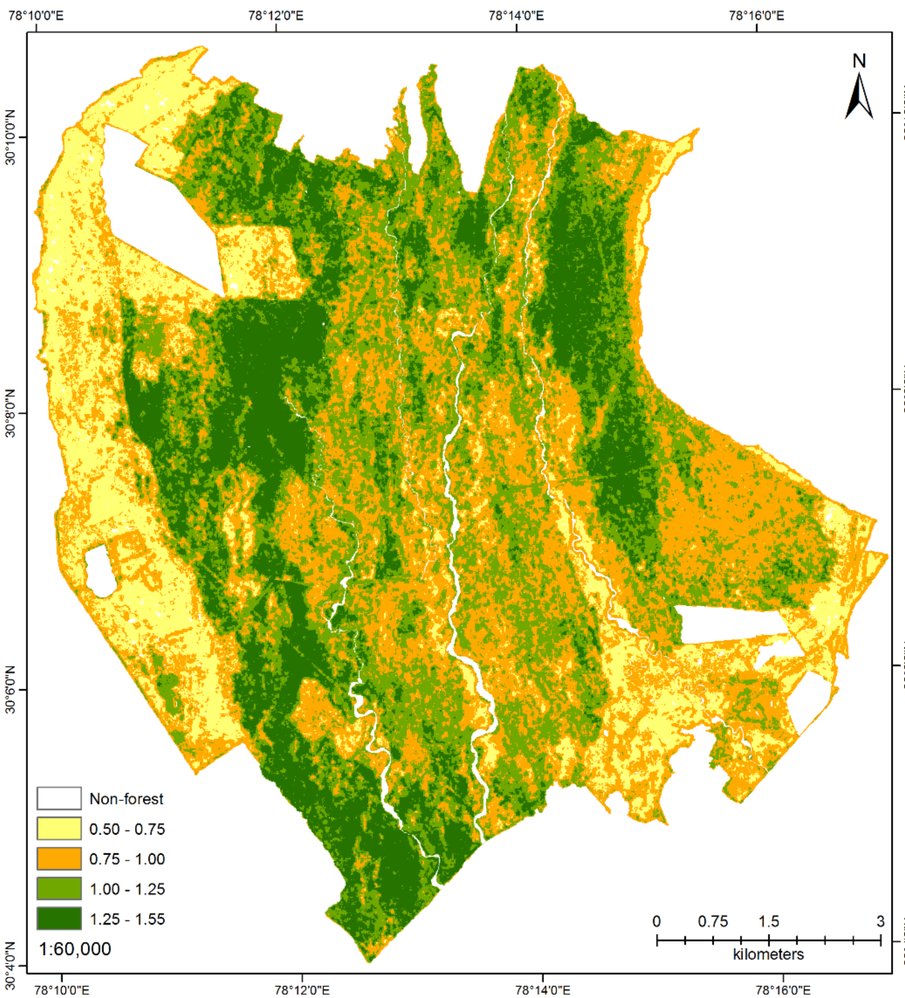
- The spatial distribution was mapped using the best predictor variables in Random Forest (RF) algorithm.

- Model validation (LAI):

  R^2= 0.83

  RMSE= 0.139

  %RMSE= 13.25 %



Spatial distribution of LAI

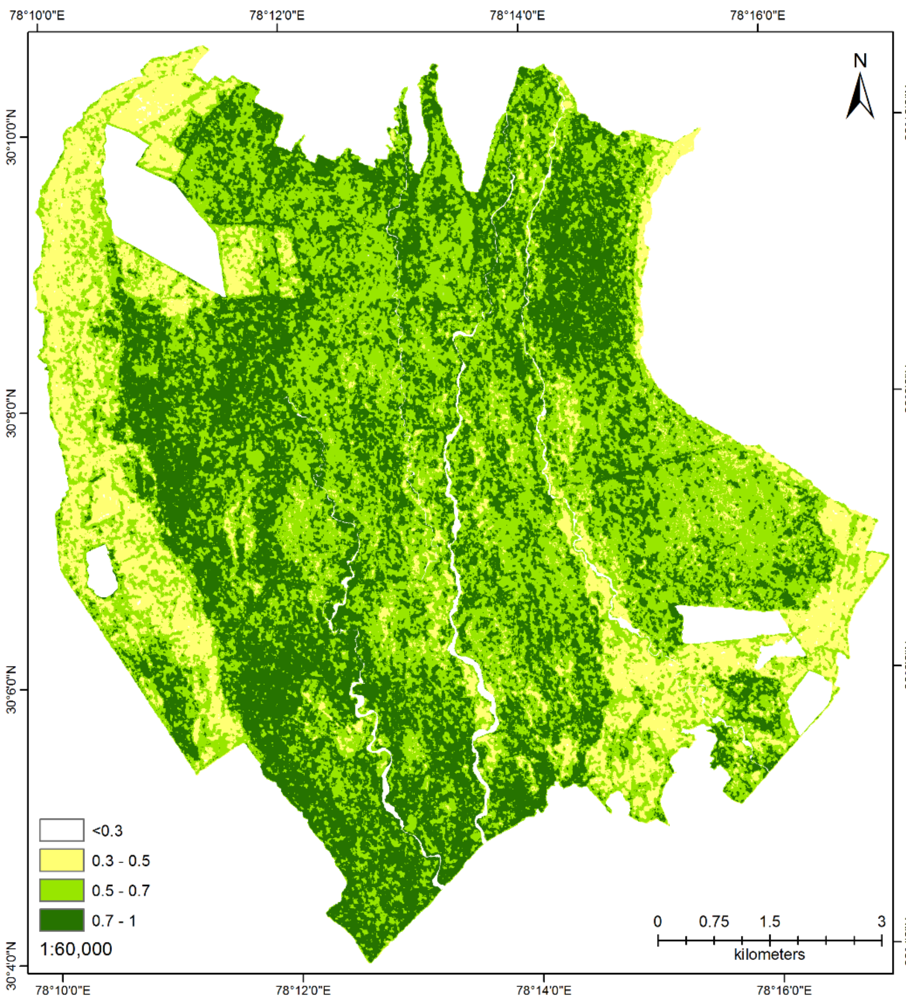
Spatial distribution fIPAR

- Model validation (fIPAR):

  R^2= 0.87

  RMSE= 0.086 $molm^{-2}s^{-1}$

  %RMSE= 13.24 %



Spatial distribution of fIPAR

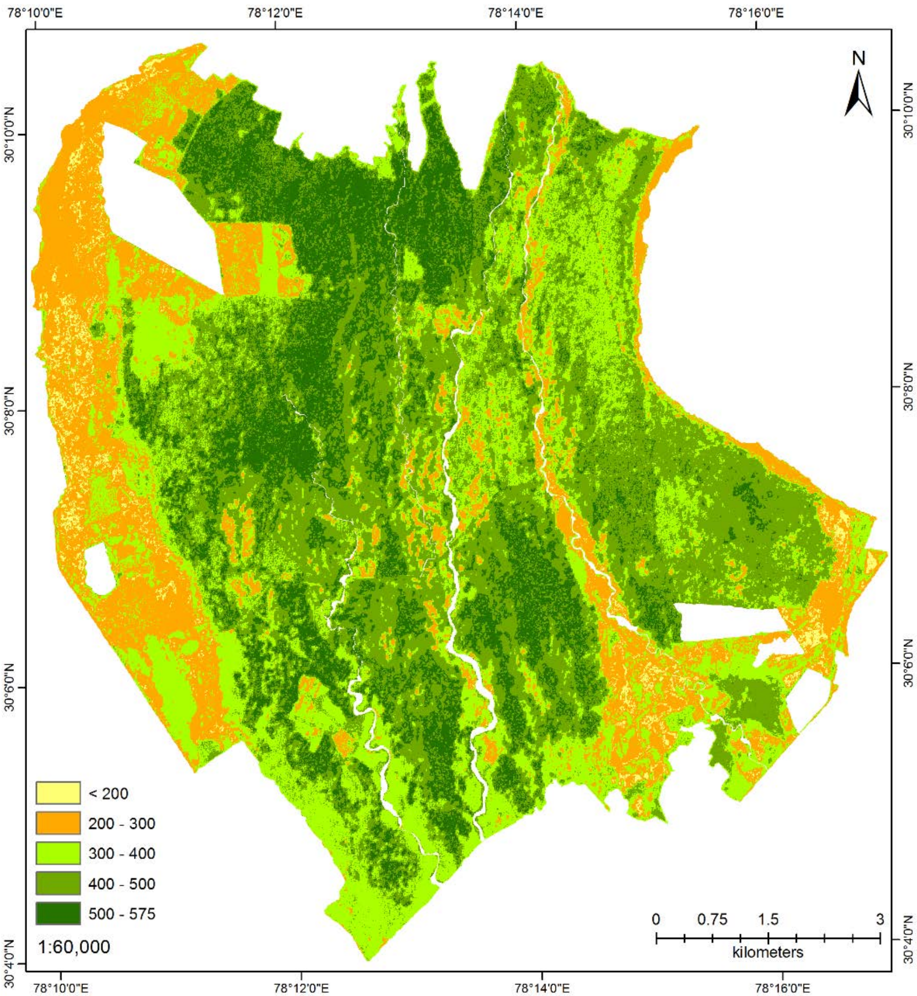
Spatial distribution of AGB

- Model validation (AGB):

  R^2= 0.85

  RMSE= 51.54 Mg ha^{-1}

  %RMSE= 12.17 %



Spatial distribution of AGB

Conclusion and future directions

- The developed models demonstrated that RF can be effectively applied to predict the spatial distribution of forest biophysical variables like LAI, fIPAR and AGB with adequate accuracy.
- It also stressed the importance of SWIR, Red-edge and texture variables in the estimation of forest biophysical variables.
- Study will be replicated in different seasons to capture the temporal variation of these biophysical parameters.
- The estimates of uncertainty in the predictive models needs to be carried out.

Thank you