

# Multi-Source Forest inventory - MS-NAFORMA

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Regional Course on REDD+ MRV, NFI and Monitoring  
11 - July 2011, Sokoine University of Agriculture, Morogoro,  
Tanzania

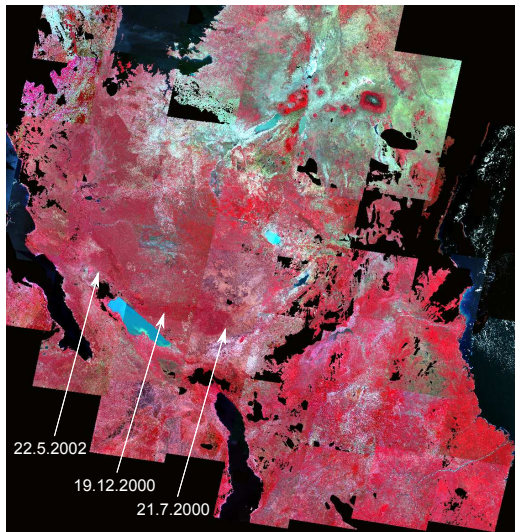
# The role of remote sensing in NAFORMA

- ▶ Statistics for smaller area units than what is possible using field data only
  - ▶ District and Village level statistics for forestry and environment planning
  - ▶ Information for REDD+ MRV
- ▶ Accurately localized information, maps
  - ▶ timber procurement
  - ▶ REDD+ MRV
  - ▶ ecological and other studies

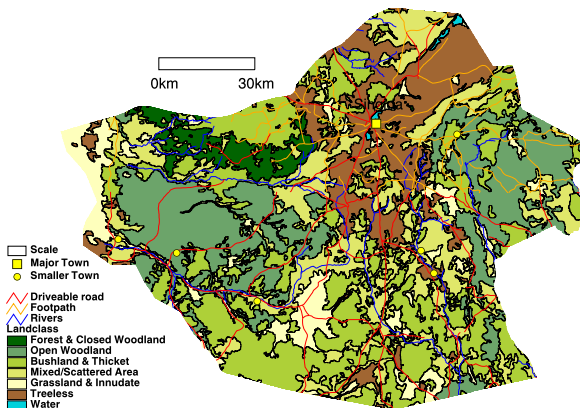
## The data sets needed

1. Field data
2. Vegetation maps, LULC under process
  - ▶ Hunting technical maps (IRA), will be replaced with the newer products
3. Roads
4. Built-up land (a sub-category on Hunting map?)
5. DEM, resolution to be decided
6. Satellite images, (1990 ??) -2010 Landsat TM and ETM+ plus additional material
7. District and Village boundaries

# Mosaic of Atmospherically Corrected Landsat Images

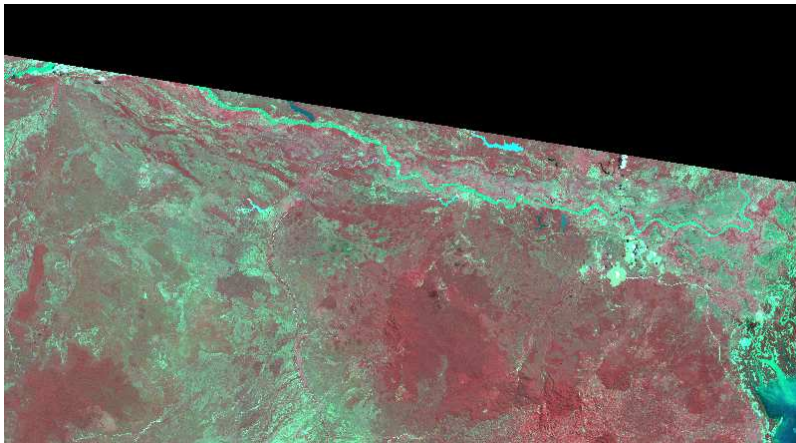


# Re-classified vegetation types based on Hunting map, Singida District, newer LULC products in the future

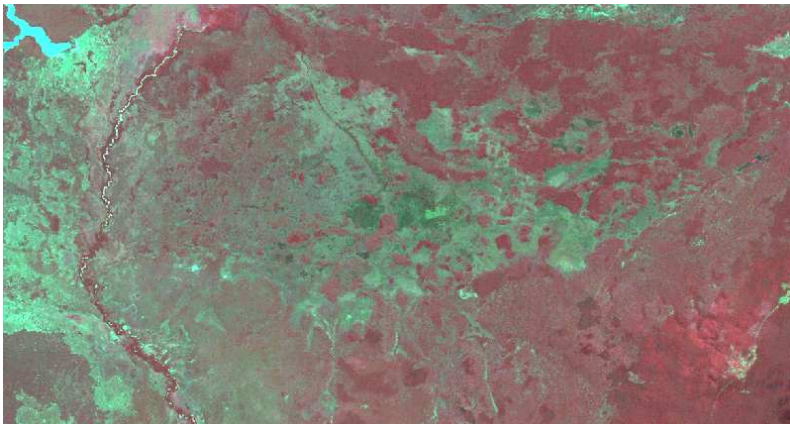


Metla MS-NFI team 23.11.2009

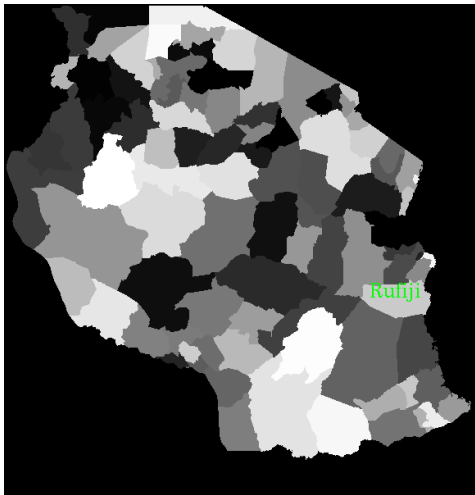
Input data, Landsat 7 ETM+ 2010, covers a part of Rufiji District, bands 4, 3, 2, red, green, blue



Input data, Landsat 7 ETM+ 2010, a sub-area, about 20 km  $\times$  30 km in Rufiji District, bands 4, 3, 2, red, green, blue

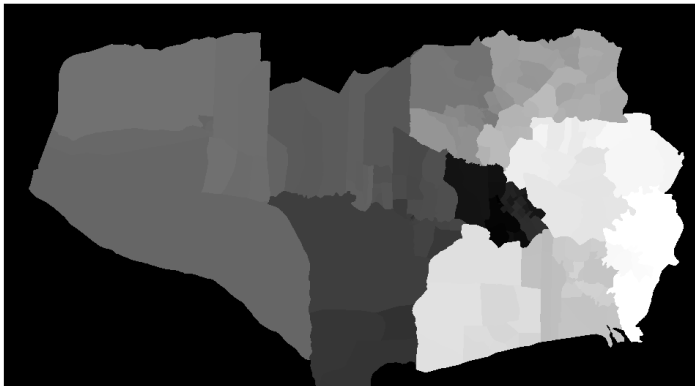


# Tanzania and the Districts

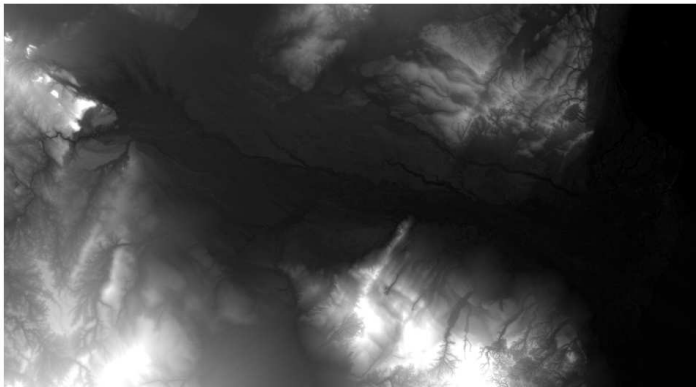




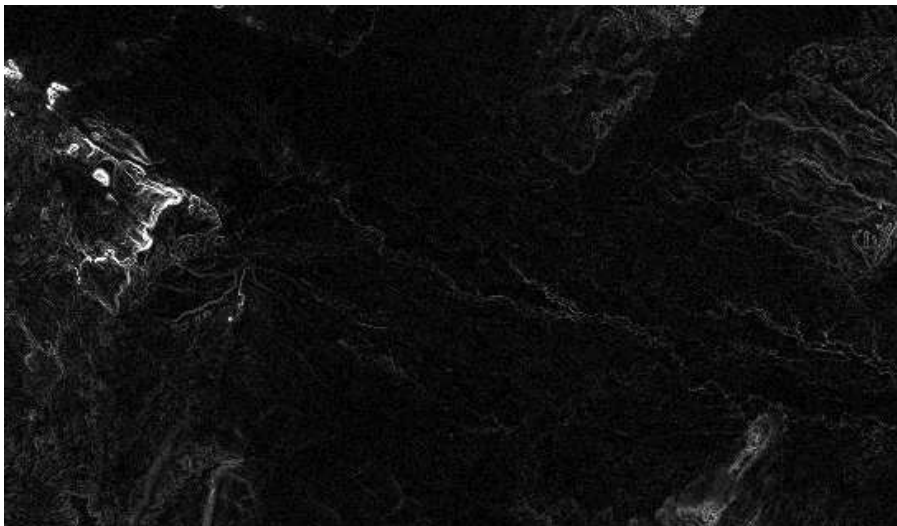
## Input data, Village boundaries, Rufiji District



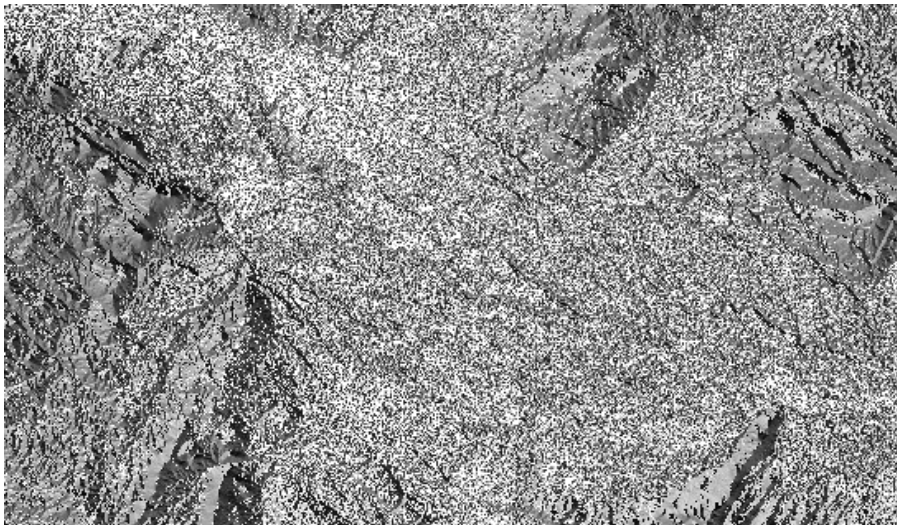
# Input data, DEM, Rufiji District



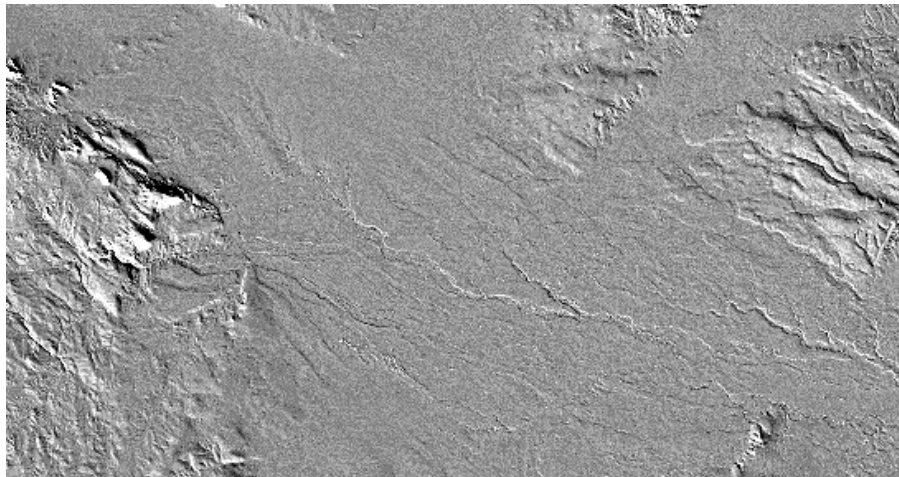
# Slope steepnes, Rufiji District



## Slope aspect, Rufiji District



## Input data, angle between sun illumination angle and terrain normal, Rufiji District



## Correction of the effect of the slopes on the variation of the spectral values

The angle  $\alpha$  between the normal to the land surface and the sun illumination angle at the time of the satellite overpass is used in correcting the observed spectral values. The dependence of the normalized spectral value  $I_n$  on the angle  $\alpha$  and the original spectral value  $I$  is assumed to be of the form

$$I_n = I / \cos^n(\alpha)$$

where  $0 < n \leq 1$ . The value of  $n$  can be found by a system of trial and error.

For the calculation of the unit vector towards the sun and the surface normal unit vector, see, e.g., Tomppo et al. 2008a.

# MS-NFI

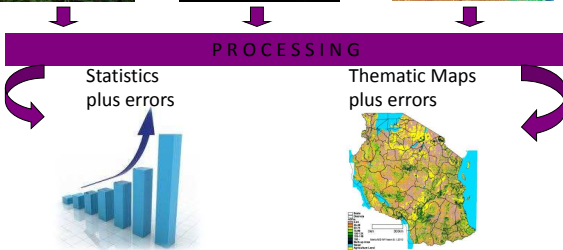
Field Data



Remote Sensing



Map Data



## A non-parametric k-NN estimation with covariates

- ⇒ Distance metric  $d$  in the *covariate space*, i.e. in the space of image features  $\times$  coarse scale forest variables
- ⇒ For the pixel  $p$  to be analysed, compute  $d_{p_i,p} = \|p_i - p\|$  to each pixel  $p_i$  whose ground truth is known (to pixel with field plot  $i$ )
- ⇒ for  $k \approx 5-10$ , let  $p_{(1)}, p_{(2)}, \dots, p_{(k)}$  be the  $k$  nearest field plot pixels with respect to  $d$
- ⇒ The weight of field plot  $i$  to pixel  $p$  is defined as

$$w_{i,p} = \frac{1}{d_{p_i,p}^t} / \sum_{j=1}^k \frac{1}{d_{p_{(j)},p}^t}$$

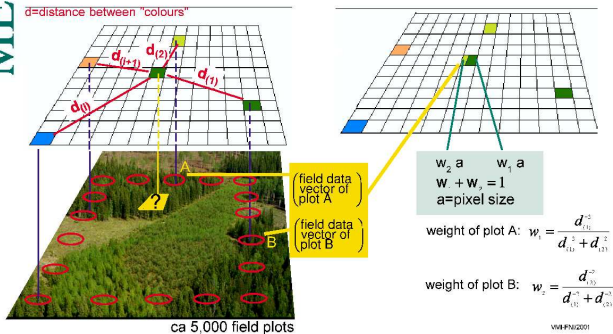
if pixel  $p_i$  is among the  $k$  nearest to  $p$ , otherwise  $w_{i,p} = 0$



## The k-NN method with k=2

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## K-nn method with k=2



## k-NN estimation, cont

In the image analysis process, weights  $w_{i,p}$  are summed over pixels  $p$  by computation units.

The weight of the field plot  $i$  to computation unit  $u$ , '**plot expansion factor**', is defined as

$$c_{i,u} = \sum_{p \in u} w_{i,p}$$

The estimation returns to the estimation with pure field data, e.g. mean timber volumes estimates by forestry land strata are

$$v = \frac{\sum_{i \in I_s} c_{i,u} v_{i,t}}{\sum_{i \in I_s} c_{i,u}},$$

where  $v_{i,t}$  is the volume per hectares of the timber assortment  $t$  in sample plot  $i$ .

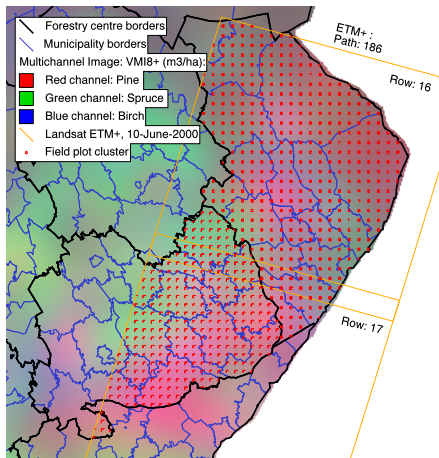
## Reasons to select k-NN

- ▶ **COST-EFFICIENCY:** much more detailed information with very low additional costs compared to FIELD MEASUREMENT based method
- ▶ **PRACTICAL:**
  - ▶ all inventory parameters for each computation unit
  - ▶ small area statistics and thematic maps
- ▶ **NON-PARAMETRIC:** no need for modelling of the dependence between ground and image data
- ▶ **STATISTICALLY ORIENTED:** preserves natural dependence structure between forest variables
- ▶ **SYNTHETIC ESTIMATOR:** information outside the area is utilised
- ▶ **VERSATILE:** same method can be applied to different environments and different remote sensing material

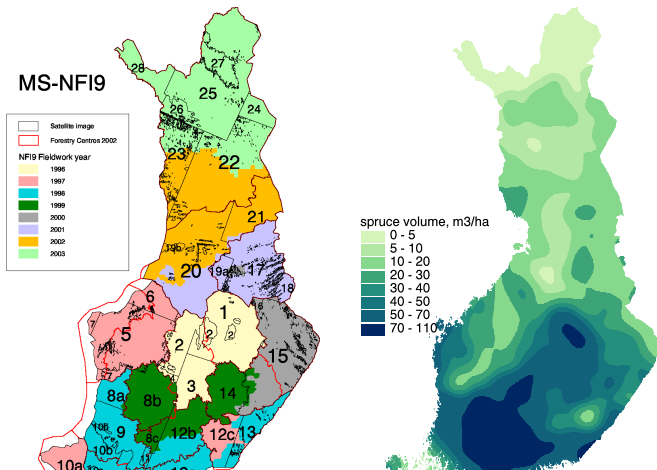
# Practical problems

1. How to select the geographical area from which the nearest neighbours are sought in k-NN method
  - ▶ Old method: moving window for avoiding neighbours from different vegetation zone
  - ▶ Current method: coarse scale forest variables
  - ▶ Demonstration in the three following slides with examples from Finland

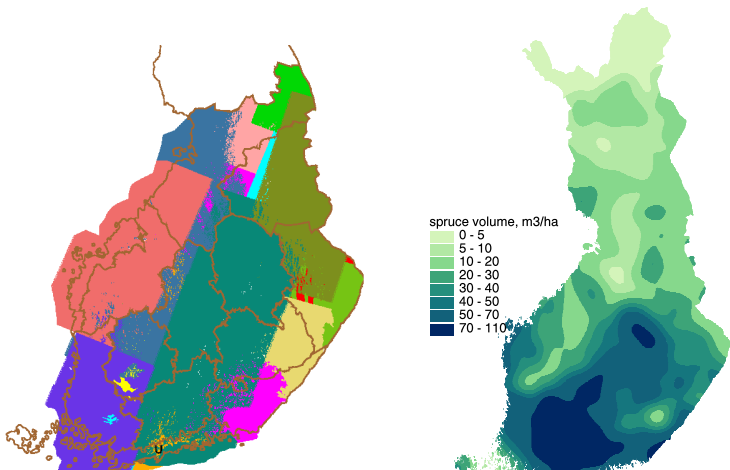
## Practical problems, cont. A typical set-up from East Finland with LS 7 ETM+ scenes, field plot clusters and coarse scale forest variables



# Practical problems, cont. The satellite images in the Finnish MS-NFI9 (1996-2003) and the mean volume of spruce



## Practical problems, cont. The satellite images in MS-NFI10 (2004-2005) and the mean volume of spruce



## Practical problems, cont

- 2 What kind of features (image variables) should be used in the estimation, original bands, transformations
- 3 What is the distance metric

### Solution

- ▶ Euclidean distance, in the product space of image variables and large scale forest variables
- ▶ The weights of elements by means of a genetic algorithm

### Examples of other possible distance metrics

- ▶ Mahalanobis distance  $d_{p_j,p} = (\mathbf{X}_{p_j} - \mathbf{X}_p)' \mathbf{M} (\mathbf{X}_{p_j} - \mathbf{X}_p)$



## Distance metric

- ▶ A non-parametric k-NN estimation with covariates, e.g., satellite images and large scale forest variables

- ▶ Distance metric

$$d_{p_j,p}^2 = \sum_{l=1}^{n_f} \omega_{l,f} (f_{l,p_j} - f_{l,p})^2 + \sum_{l=1}^{n_g} \omega_{l,g} (g_{l,p_j} - g_{l,p})^2 \quad \text{where}$$

*$f_{l,p}$  are the image variables,*

*$g_{l,p}$  are the coarse scale forest variables and*

*$n_f$  and  $n_g$  are the numbers of the spectral and large area forest variables*

*$\omega_{l,f}$  and  $\omega_{l,g}$  are the variable weights*

- ▶ Genetic algorithm based optimisation in weighting the features
- ▶ See, Tomppo & Halme. 2004. Remote Sensing of Environment 92:1-20

## GENETIC ALGORITHMS

- ▶ metaheuristic strategies that direct and modify search heuristics to overcome local optima
- ▶ often efficient when no exact methods easily available
- ▶ often produce good solutions
- ▶ always a great deal of fine tuning needed

Genetic algorithm imitates the evolution.

The fitness function to be minimised

$$f(\omega, \gamma, \hat{\delta}, \hat{e}) = \sum_{j=1}^{n_e} \gamma_j \hat{\delta}_j(\omega) + \sum_{j=1}^{n_e} \gamma_{j+n_e} \hat{e}_j(\omega)$$

where

$\hat{\delta}_j(\omega)$  is the standard error of the estimate of the forest variable  $i$

$\hat{e}_j(\omega)$  is the bias of the estimate of the forest variable  $i$

$n_e$  the number of the forest variables used in the algorithm

$\gamma_j$  fixed constants

See, Tomppo & Halme. 2004. Remote Sensing of Environment 92:1-20

## ALGORITHM IN NUTSHELL

- ⇒ random initial population
- ⇒ selection (tournament)
- ⇒ population (set of parents)
- ⇒ crossover producing children - elitism - mutation  
(guaranteeing diversity)
- ⇒ result: new population (= next generation)
- ⇒ go to selection

## Genetic algorithm, cont

### Key parameters

- ▶  $n_{pop}$  - number of weights vectors in one population  $\sim 50$
- ▶  $n_{gen}$  - number of generations  $\sim 30 - 80$
- ▶  $cross$  - probability for elements to be switched in two weights vectors  $\sim 0.75$
- ▶  $muta$  - mutation probability  $\sim 0.05$
- ▶  $p_{rm}$  - radical mutation probability  $\sim 0.35$
- ▶  $calm$  - probability of accepting an inferior solution created by mutation  $\sim 0.5$
- ▶  $p_{t1}$  - tournament probability 1  $\sim 0.95$
- ▶  $p_{t2}$  - tournament probability 2  $\sim 0.03$

## Examples of pixel level estimates, Rufiji District, Tanzania, volume of growing stock

**Table:** Bias of the k-NN and ik-NN with Genetic algorithm (GA) estimates at pixel level (field plot level) using leave-one-out cross-validation and field data based volume estimates  $\hat{V}_F$  in comparison, 739 field plots, Rufiji and surrounding area. Trees with dbh  $\geq 10$  cm.

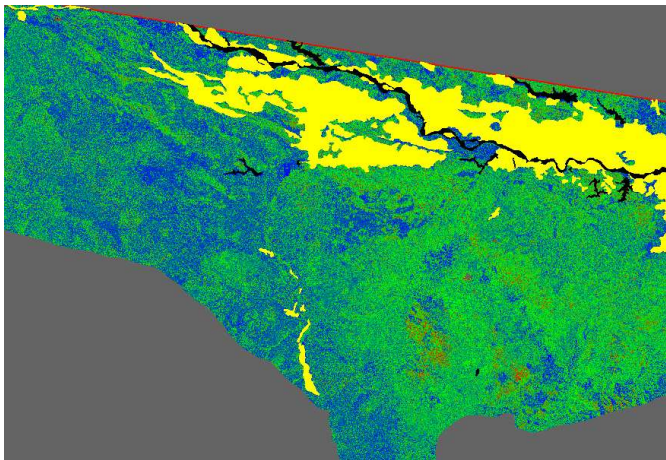
Variable	Estimate	Bias k-NN	Bias ik-NN	Reduction % k-NN/ik-NN
Volume $m^3/ha$	49.5	2.771	1.736	37.3
Basal area $m^2/ha$	7.8	0.350	0.238	32.1
Number of stems / ha	174.1	1.283	0.830	35.3

## Examples of pixel level estimates, Rufiji District, Tanzania

**Table:** Root mean square error (RMSE) of the k-NN and ik-NN with Genetic algorithm (GA) estimates at pixel level (field plot level) using leave-one-out cross-validation and field data based volume estimates  $\hat{V}_F$  in comparison, 739 field plots, Rufiji and surrounding area. Trees with dbh  $\geq 10$  cm.

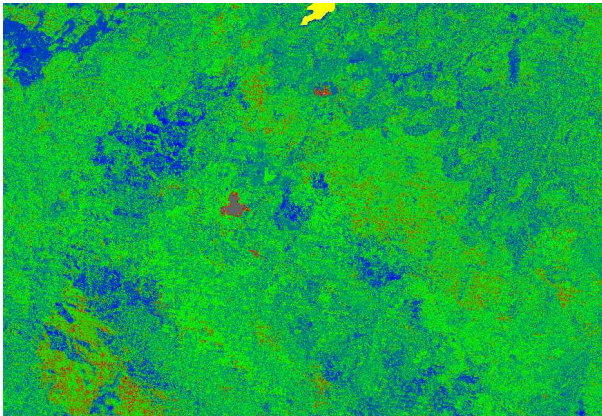
Variable	Estimate	RMSE k-NN	RMSE ik-NN	Reduction % k-NN/ik-NN
Volume $m^3/ha$	49.5	27.480	25.805	6.1
Basal area $m^2/ha$	7.8	3.391	3.176	6.3
Number of stems / ha	174.1	70.221	67.165	4.4

Estimated volume, a part of Rufiji District Vol 0-200  
 $\text{m}^3/\text{ha}$  (blue-red), arable, built-up (yellow) water (black)

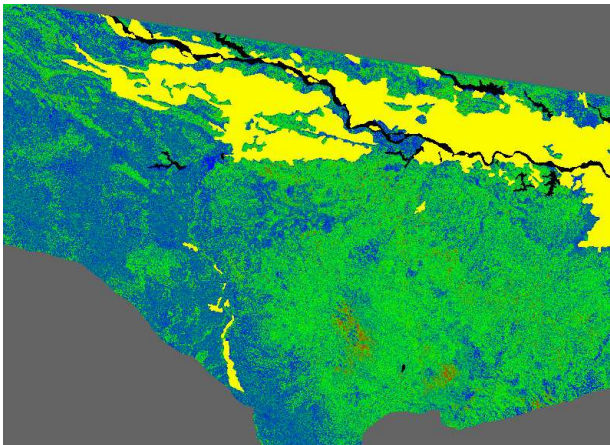




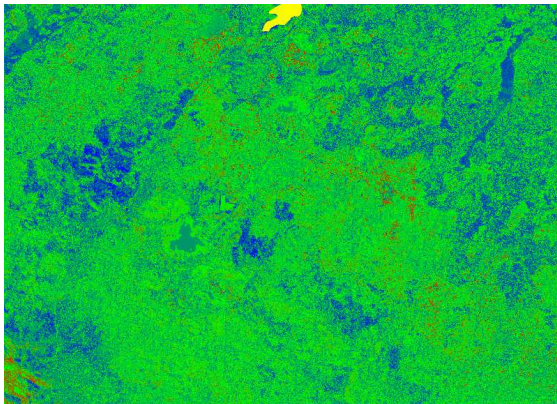
Estimated volume, Rufiji District,  $\sim 20$  km x 30 km Vol  
0-200 m<sup>3</sup>/ha (blue-red), arable, built-up (yellow) water  
(black)



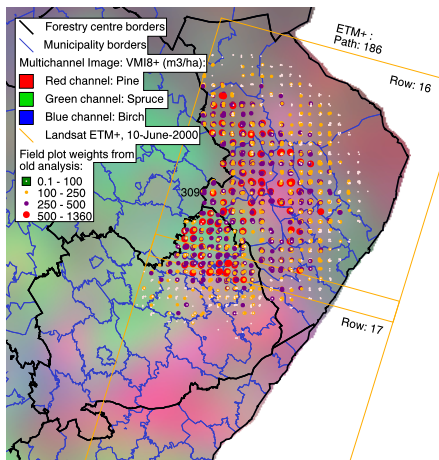
Estimated number of trees, a part of Rufiji District No of trees 0-5000 m<sup>3</sup>/ha (blue-red), arable, built-up (yellow) water (black)



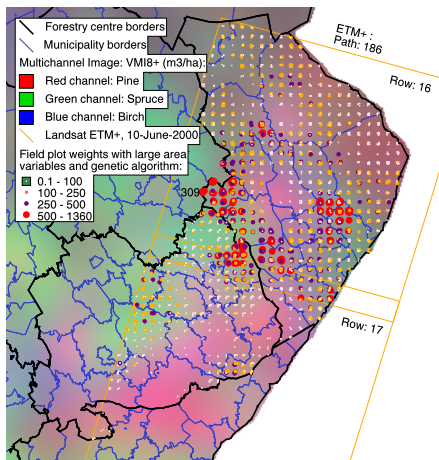
Estimated number of trees,  $\sim 20 \text{ km} \times 30 \text{ km}$  No of trees  $0\text{-}5000 \text{ m}^3/\text{ha}$  (blue-red), arable, built-up (yellow) water (black)



## Examples from East Finland. Field plot weights for one municipality with the basic k-NN method



## Examples from East Finland. Field plot weights for one municipality with ik-NN method



## Examples from East Finland, cont

**Table:** Bias of the k-NN and ik-NN estimates at pixel level (field plot level) using leave-one-out cross-validation and field data based volume estimates  $\hat{V}_F$  in comparison, 1953 field plots on mineral soil stratum.

	$\hat{V}_F$	Bias k-NN	Bias ik-NN	k-NN/ik-NN	Reduction GA
Volume	$m^3/ha$	$m^3/ha$	$m^3/ha$	%	%
Pine	63.75	2.430	-0.002	99.9	99.9
Spruce	38.88	-3.167	-0.005	99.8	99.9
Birch	15.90	-0.961	-0.199	79.3	87.3
Other broad leaved	3.87	-0.382	-0.133	65.2	69.1
Total	122.40	-2.021	-0.259	87.2	94.1

## Examples from East Finland, cont

**Table:** Bias of the k-NN and ik-NN estimates at pixel level (field plot level) using leave-one-out cross-validation and field data based volume estimates  $\hat{V}_F$  in comparison, 638 field plots on peatland soil stratum.

	$\hat{V}_F$	Bias k-NN	Bias ik-NN	Reduction k-NN/ik-NN	GA
Volume	$m^3/ha$	$m^3/ha$	$m^3/ha$	%	%
Pine	50.10	1.735	0.012	99.3	99.2
Spruce	10.50	-1.482	-0.019	98.7	99.4
Birch	7.63	-0.454	-0.303	33.3	72.2
Other broad leaved	0.30	-0.029	-0.062	-113.8	10.1
Total	68.53	-0.231	-0.367	-58.9	83.6





**Table:** Difference between multi-source volume estimates  $\hat{M}$  and field data based estimates  $\hat{F}$  with k-NN and ik-NN methods for municipality group b1, forest area 167 000 ha

	$\hat{V}_F$	k-NN	
	$m^3/ha$	$\hat{V}_M - \hat{V}_F$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
		$m^3/ha$	
Pine	54.7	-5.6	-1.3
Spruce	29.7	0.4	0.1
Birch	17.0	-0.8	-0.5
Other broad leaved	4.4	-0.9	-0.9
Total	105.8	-6.9	-1.8
Weighted average	of % bias	<b>6.6</b>	

	$\hat{V}_F$	ik-NN	
	$m^3/ha$	$\hat{V}_M - \hat{V}_F$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
		$m^3/ha$	
Pine	62.3	2.0	0.5
Spruce	28.9	-0.4	-0.1
Birch	18.4	0.6	0.4
Other broad leaved	5.3	0.0	0.0
Total	114.9	2.2	0.6
Weighted average	of % bias	<b>2.7</b>	

**Table:** Difference between multi-source volume estimates  $\hat{M}$  and field data based estimates  $\hat{F}$  with k-NN and ik-NN methods for municipality group 3, forest area 240 000 ha

	$\hat{V}_M$ $m^3/ha$	k-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	53.8	5.2	1.8
Spruce	35.6	-2.9	-1.2
Birch	15.7	-0.0	-0.0
Other broad leaved	3.7	-0.6	-1.0
Total	108.8	1.6	0.5
Weighted average	of % bias	<b>4.7</b>	

	$\hat{V}_M$ $m^3/ha$	ik-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	49.7	1.1	0.4
Spruce	40.3	1.8	0.7
Birch	15.9	0.2	0.2
Other broad leaved	3.1	-1.2	2.0
Total	108.9	1.7	0.5
Weighted average	of % bias	<b>2.8</b>	

**Table:** Difference between multi-source volume estimates  $\hat{M}$  and field data based estimates  $\hat{F}$  with k-NN and ik-NN methods for municipality group IV, forest area 270 000 ha

	$\hat{V}_M$ $m^3/ha$	k-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	48.4	3.4	1.4
Spruce	25.3	-9.9	-3.4
Birch	14.0	-1.7	-1.5
Other broad leaved	3.1	-0.6	-1.0
Total	90.8	-8.8	-2.2
Weighted average	of % bias	<b>14.1</b>	

	$\hat{V}_M$ $m^3/ha$	ik-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	46.5	1.5	0.6
Spruce	31.1	-4.1	-1.4
Birch	14.2	-1.5	-1.4
Other broad leaved	3.7	0.0	0.0
Total	95.6	-4.0	-1.0
Weighted average	of % bias	<b>6.8</b>	

**Table:** Difference between multi-source volume estimates  $\hat{V}_M$  and field data based estimates  $\hat{V}_F$  with old and new methods for North Karelia and part of Etelä-Savo, forest area 1,93 mill. ha.

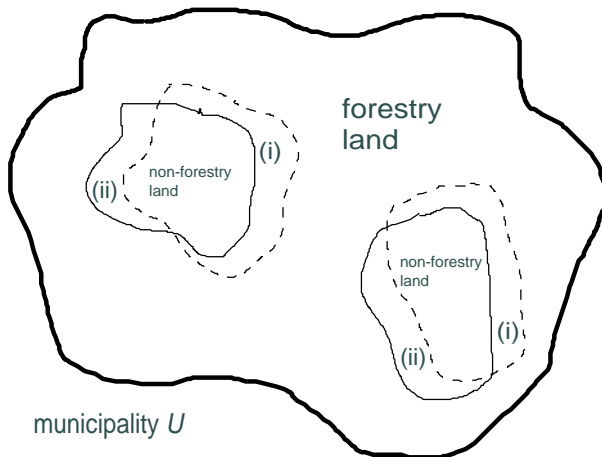
	$\hat{V}_M$ $m^3/ha$	k-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	56.5	1.6	1.5
Spruce	33.5	-1.1	-1.0
Birch	15.9	-1.1	-2.8
Other broad leaved	3.7	-0.9	-4.5
Total	109.6	-1.6	-1.1
Weighted average	of % bias	<b>1.5</b>	

	$\hat{V}_M$ $m^3/ha$	ik-NN $\hat{V}_M - \hat{V}_F$ $m^3/ha$	$(\hat{V}_M - \hat{V}_F)/\hat{\sigma}_F$
Pine	57.2	2.3	2.1
Spruce	33.9	-0.7	-0.7
Birch	16.4	-0.7	-2.5
Other broad leaved	3.9	-0.7	-3.5
Total	111.3	0.1	0.1
Weighted average	of % bias	<b>0.8</b>	

## Utilization of land use maps

- ▶ Earlier: k-NN within forestry land
- ▶ Problems
  - ▶ not inventory criteria in map classification
  - ▶ maps out-dated
- ▶ Methods to deal with map errors
  - ▶ calibration method using confusion matrix
    - ▶ Katila, Heikkinen & Tomppo, Can. J. For. Res. 2000. 30:1329-1339.
  - ▶ stratification on the basis of ancillary data
    - ▶ Katila & Tomppo, Can. J. For. Res. 2002. 32:1548-1561.

## Two types of map errors in small area estimation



## Calibrated area estimators

Katila M., Heikkinen J., and Tomppo E. 2000. Calibration of small-area estimates for map errors in multisource forest inventory. *Can. J. For. Res.* 30:1329–1339.

A statistical calibration method has been introduced aimed at reducing the effect of map errors on multi-source forest resource estimates.

If map strata are reasonably homogeneous with respect to the ‘map errors’, we may estimate the proportions of LU classes for small areas  $U$  using the proportions  $\hat{P}_{R_h,l}$  estimated from a larger area  $R$  (synthetic estimation).

$$A_{U,l}^* = \sum_h \hat{P}_{R_h,l} A_{U_h}$$

## Error estimation

### Two levels

- ▶ An error estimator for a pixel level prediction
- ▶ An error estimator for a parameter for an area of interest

### Difficulties arise because:

- ▶ errors depend on the actual value of the variable to be predicted and so pixel-level errors are spatially dependent
- ▶ the variables measured or observed on the field plots are also spatially dependent
- ▶ the spectral values of adjacent pixels of a satellite image are dependent due to the atmospheric properties (scattering) and imaging technique

Furthermore, several error sources make the error estimation complex, e.g., Tomppo et al. 2008a (Springer).



## Model based error estimation

The direct statistical squared error estimate for an estimate  $\hat{M}$  of the parameter  $M$  is the mean square error (MSE)

$$E(\hat{M} - M)^2$$

and similarly for the prediction  $\tilde{y}(x_i)$  of the variable  $y(x_i)$  the MSE is

$$E(\tilde{y}(\mathbf{x}_i) - y(\mathbf{x}_i))^2$$

## Model based error estimation, cont

When  $\hat{M}$  and  $\tilde{y}(x_i)$  are unbiased estimators for  $M$  and  $y(x_i)$  respectively, MSE's are identical to the error variances:

$$\sqrt{\text{Var}(\hat{M} - M)}$$

and

$$\sqrt{\text{Var}[\tilde{y}(x_i) - y(x_i)]}$$

but are rarely know in practice.

## Model based error estimation, cont

Accommodation spatial dependencies need a model-based approach.

Assume that observed value  $y_i$  of pixel  $i$  is considered to be a realisation of a random variable, e.g., a realisation of the distribution of all possible realisations associated with the same covariate data vector,  $\mathbf{x}_i$ , e.g., satellite image data vector.

$$y_i = \mu_i + \epsilon_i$$

where

$$E(\epsilon_i) = 0$$

$$Var(\epsilon_i) = \sigma_i^2$$

$$Cov(\epsilon_i \epsilon_j) = \rho_{ij} \sigma_i^2 \sigma_j^2$$

McRoberts, Tomppo, Finley, Heikkinen. 2007. Rem. Sens. Env. 111:466-480.

## Model based error estimation, cont

The estimator of the variance of the prediction of a realization,  $y_i$  was expressed as a function of  $\sigma_i^2$  and  
 The estimator for  $\sigma_i^2$  when using equal weights:

$$\hat{\sigma}_i^2 = \frac{\sum_{j=1}^k (y_j^i - \tilde{y}_i)^2}{k - \frac{1}{k} \sum_{j_1=1}^k \sum_{j_2=1}^k \rho_{j_1 j_2}}$$

An iterative approach using the connection between variogram  $\gamma_{ij}$  and spatial correlation  $\rho_{ij}$  to estimate  $\hat{\sigma}$ ,  $\hat{\gamma}_{ij}$  and  $\hat{\rho}_{ij}$ .  
 It can be shown that

$$Var(\hat{y}_i) = \frac{\sigma_i^2}{k^2} \left( \sum_{j_1=1}^k \sum_{j_2=1}^k \rho_{j_1 j_2} - 2k \sum_{j=1}^k \rho_{ji} + k^2 \right)$$

## Model based error estimation, cont

The variance estimators for superpopulation means

$$\bar{Y}_{M1} = \frac{1}{N} \sum_{i=1}^N \hat{\mu}_i$$

and the mean over the predictions from the superpopulation

$$\bar{Y}_{M2} = \frac{1}{N} \sum_{i=1}^N \hat{y}_i$$

can be estimated in a straightforward way from the previous formulas.

## Model based error estimation, cont

An approach by Kim & Tomppo. 2006. Rem. Sens. Env. 104:257-263

- ▶ A model-based estimator for the error variance of the pixel-level predictions
- ▶ The weight  $w$  is the inverse of the squared Euclidean distance
- ▶ The error variance as a function of the distances and **variogram in the satellite image feature space**

$d_{oi}$  = the distance in the feature space from the target pixel  $o$  to pixel  $i$

$\gamma$  = variogram in the satellite image space

$\mathbf{x}_i$  = spectral vector of pixel  $i$

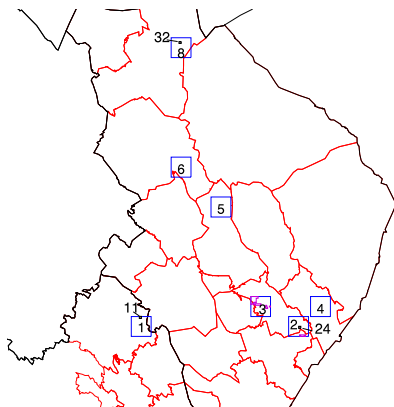
$$\text{Var}(\tilde{y}(\mathbf{x}_i) - y(\mathbf{x}_i)) = - \sum_i \sum_j \left( \frac{d_{oi}^{-2}}{\sum_i d_{oi}^{-2}} \right) \left( \frac{d_{oj}^{-2}}{\sum_i d_{oi}^{-2}} \right) \gamma(\mathbf{x}_i - \mathbf{x}_j) + 2 \sum_i \left( \frac{d_{oi}^{-2}}{\sum_i d_{oi}^{-2}} \right) \gamma(\mathbf{x}_i - \mathbf{x}_0)$$

Models fitted to the residuals can be employed to estimate  $\gamma$ .

## Empirical error estimation

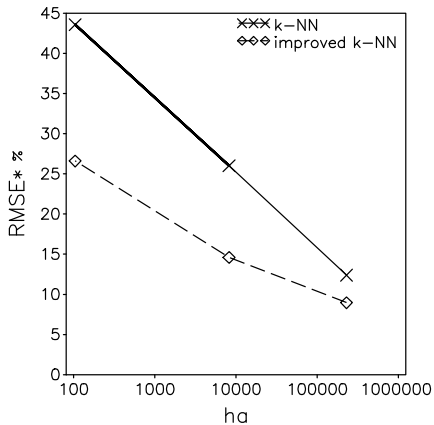
- ▶ Comparisons to NFI -data estimates at the level of 200 000 ha, 8 units
- ▶ Comparisons to estimates derived from special measurements
  - ▶ 7 test units  $\sim$  10 000 ha, in total 5775 plots
  - ▶ 3 test units  $\sim$  100 ha, in total 462 plots
  - ▶ see, Katila & Tomppo. 2005. Sampling simulation on multi-source wall-to-wall forest maps - an application for small areas. Manuscript. Metla

# The sites for empirical error estimation and method development

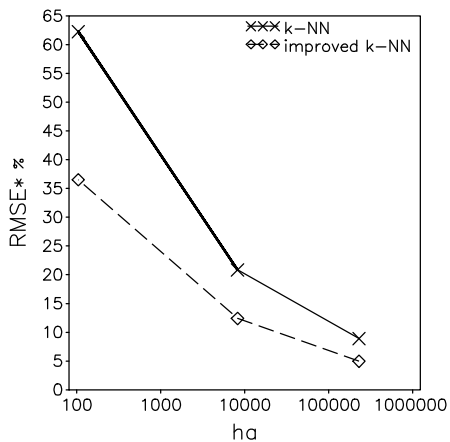




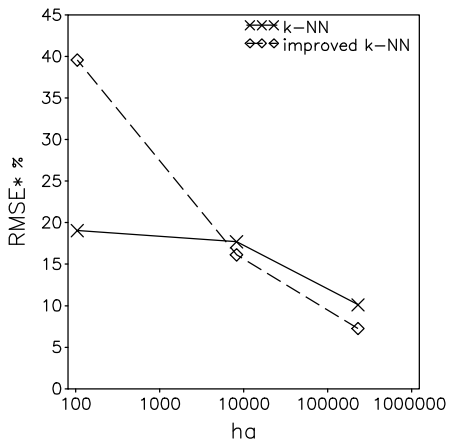
# Root mean square error of mean volume of spruce



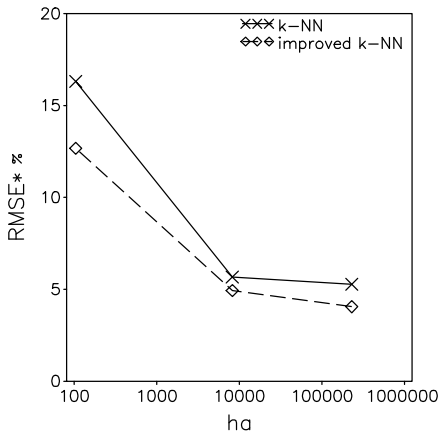
# Root mean square error of mean volume of pine



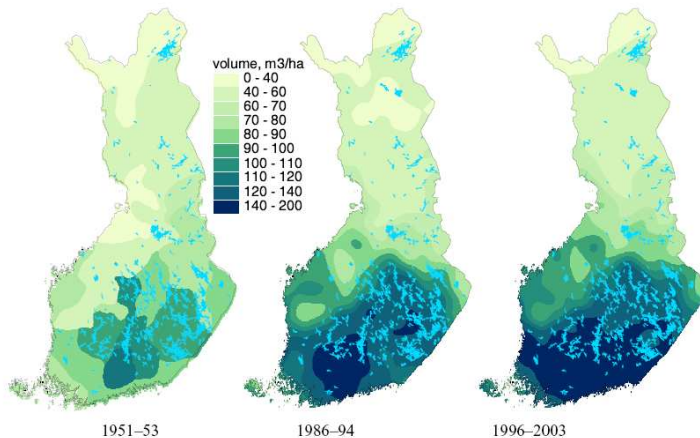
# Root mean square error of mean volume of birch



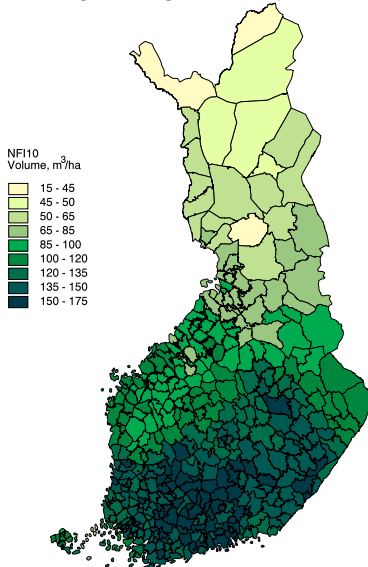
# Root mean square error of mean volume, all species



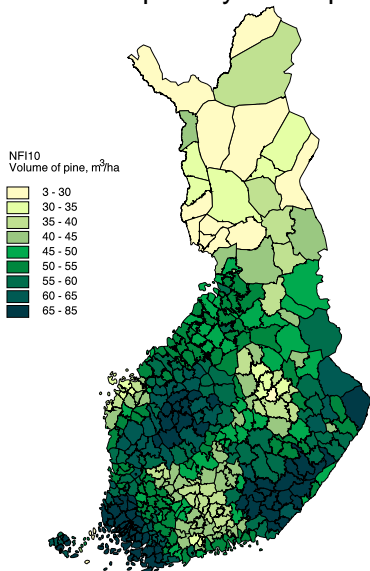
## The volume of growing stock in 1951-53, 1986-94 and 1996-2003



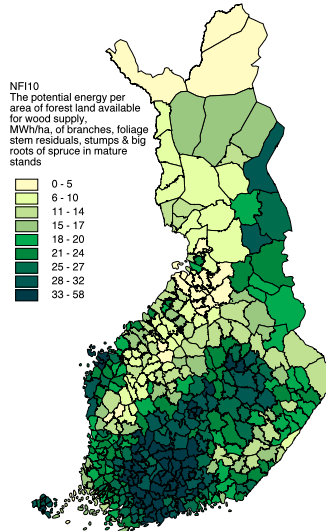
## The mean volume of growing stock by municipalities in 2005



## The mean volume of pine by municipalities 2005

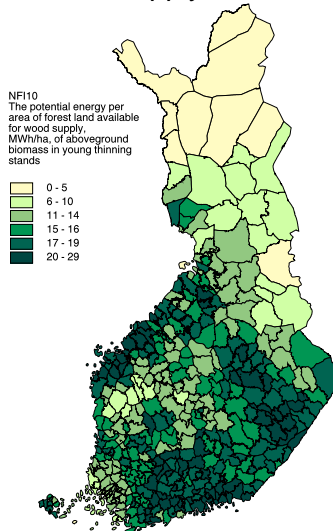


# The energy of spruce cutting residues, stumps and roots, MWh/ha, in mature forests available for wood supply in 2005





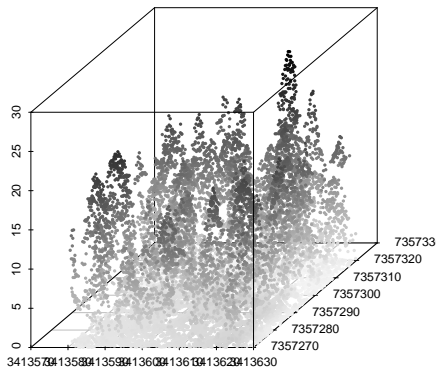
## The potential energy, MWh/ha, in young forests available for wood supply in 2005



## Conclusions about Multi-Source NAFORMA

- ▶ Input data
  - ▶ NAFORMA plots
  - ▶ Remote sensing data, optical area satellite images
  - ▶ Digital map data
  - ▶ District / Village boundaries
- ▶ Output
  - ▶ Estimates and error estimates for Districts / Villages
  - ▶ Maps
    - ▶ Biomass, volumes, number of trees
    - ▶ Vegetation types, land use categories,
    - ▶ Change maps, e.g., for REDD+ MRV, Operational level
- ▶ The methods should be selected thoroughly, error estimates are always needed
- ▶ Important to recognise the strengths and weaknesses of remote sensing (still some variables from field data, such as dead wood, undergrowth, etc)
- ▶ Remote sensing makes forest inventories more efficient

## An example of laser scanner data, 50 m $\times$ 50 m

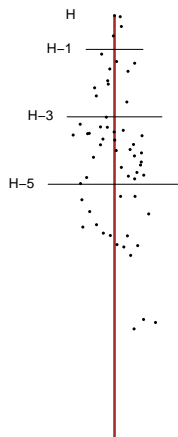


## LiDAR data

Four lines over the NFI9 and NFI10 field plots were scanned

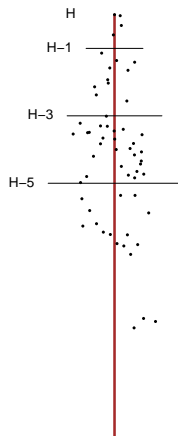
- ▶ Flight altitude 600 metres
- ▶ Pulse repetition frequency 100 kHz
- ▶ Scanning frequency 70 Hz
- ▶ Maximum half scan angle  $10^{\circ}$
- ▶ Flight speed 75 metres/second
- ▶ The average point spacing, 0.29 metres by 0.54 metres
- ▶ The average point density  $6.37 \text{ pulses/m}^2$ 
  - ▶ instrument capable to separate three returns
    - ▶ 0=single
    - ▶ 1=the first one of many returns
    - ▶ 2=an intermediate of many returns
    - ▶ 3=the last one of many returns

## The laser features employed



1. H, maximum height
2. H - height of the lowest echo of all echos above 1 metre
3. H - height of the lowest echo of echos of type 2 or 3 above 1 metre
- 4.-7.  $no_i$ , The number of the echos of type  $i$ ,  $i = 0, 1, 2, 3$
- 8.-10. The sum of the echos of type 0 or 1 above  $H - \Delta h$ ,  $\Delta h = 1, 3, 5$
11. The sum of the echos of type 2 above  $H - 5m$
12. The sum of the echos of type 3 above  $H - 5 m$

## The laser features employed, cont



13.-15. The maximum distance of all lidar points above  $H - \Delta h$ ,  $\Delta h = 1, 3, 5$  projected on the  $(x,y)$  plane

16.-18. The mean of the four maximum radius of the points in the three previous features, maxima calculated in four angle sectors of 90 degrees

## Examples of publications

McRoberts, R.E., Cohen, W.B., Naesset, E., Stehman, S.V. & Tomppo, E.O. 2010. Using remotely sensed data to construct and assess forest attribute maps and related special products. *Scandinavian Journal of Forest Research* 25: 340-367.

McRoberts, R.E., Tomppo, E.O. & Naesset, E. 2010. Advances and emerging issues in national forest inventories. *Scandinavian Journal of Forest Research* 25: 368-381.

Tomppo, E. 2006. The Finnish multi-source National Forest Inventory - small area estimation and map production. In: Kangas, A. & Maltamo, M. (eds.). *Forest inventory. Methodology and applications. Managing Forest Ecosystems. Vol 10.* Springer, Dordrecht. p. 195-224.

Tomppo, E. & Halme, M. 2004. Using coarse scale forest variables as ancillary information and weighting of variables in k-NN estimation: a genetic algorithm approach. *Remote Sensing of Environment* 92: 1-20.

Tomppo, E., Haakana, M., Katila, M., Peräsaari, J. 2008a. *Multi-Source National Forest Inventory Methods and Applications* Springer, Series: *Managing Forest Ecosystems*, Vol. 18 374 p. Hardcover. ISBN: 978-1-4020-8712-7.

## Examples of publications, cont

Tomppo, E., Olsson, H., Ståhl, G., Nilsson, M., Hagner, O. & Katila, M. 2008b. Combining national forest inventory field plots and remote sensing data for forest databases. *Remote Sensing of Environment* 112: 1982-1999.

Katila, M. & Tomppo, E. 2002. Stratification by ancillary data in multisource forest inventories employing k-nearest-neighbour estimation. *Canadian Journal of Forest Research* 32(9): 1548-1561.

Katila, M., Heikkinen, J. & Tomppo, E. 2000. Calibration of small-area estimates for map errors in multisource forest inventory. *Canadian Journal of Forest Research* 30: 1329-1339.

Kim, H.-J. & Tomppo, E. 2006. Model-based prediction error uncertainty estimation for k-nn method. *Remote Sensing of Environment* 104: 257-263.

McRoberts, R., Tomppo, E.O., Finley, A.O. & Heikkinen, J. 2007. Estimating areal means and variances of forest attributes using the k-Nearest Neighbors technique and satellite imagery. *Remote Sensing of Environment* 111: 466-480.

McRoberts, R.E. & Tomppo, E.O. 2007. Remote sensing support for national forest inventories. *Remote Sensing of Environment* 110: 412-419.