Deforestation trend and future outlook of forest carbon stocks in tropical forests using ALOS-PALSAR mosaic data

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Contents

1. Introduction (challenges)

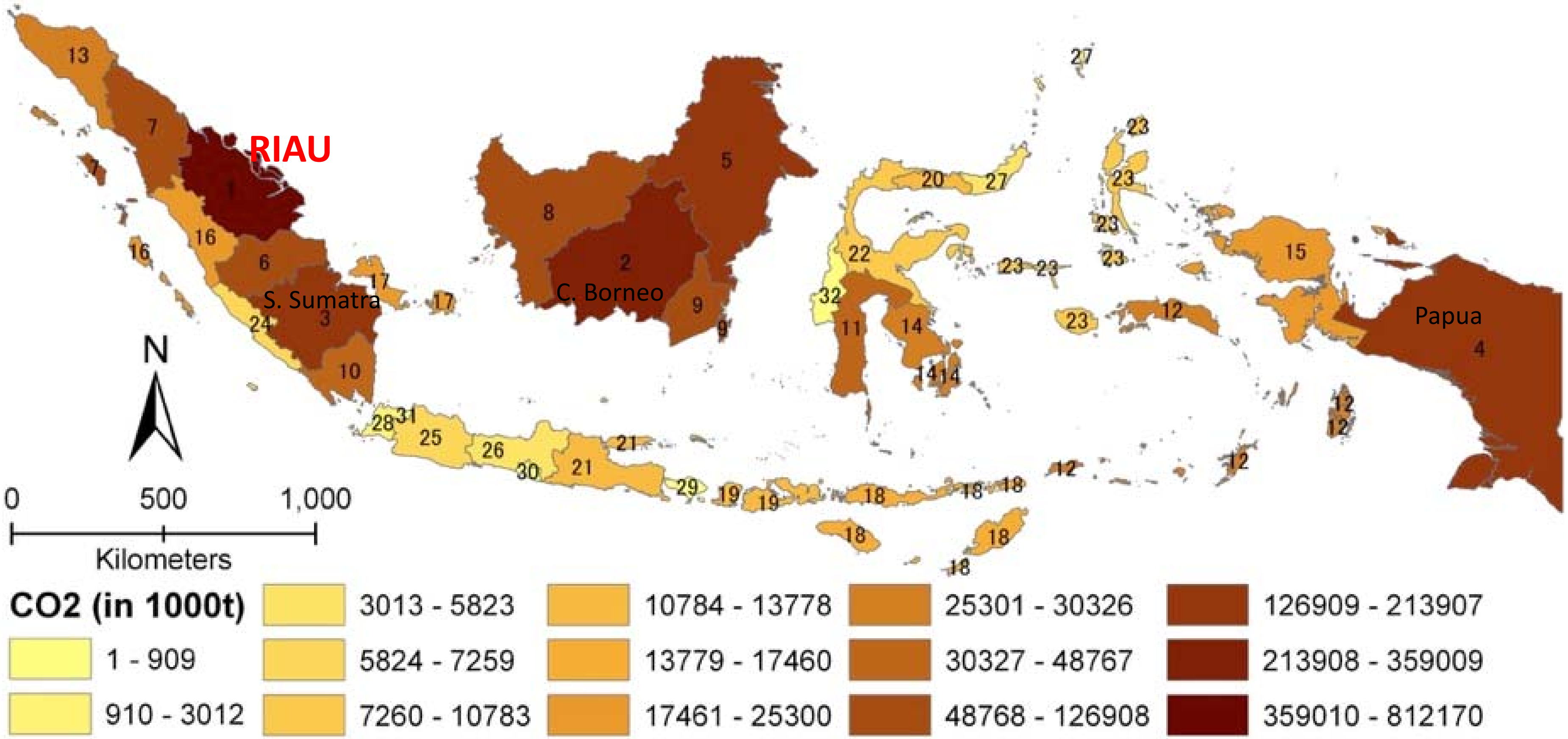
- Currently, tropical deforestation is considered as the second largest source of GHG emissions and likely continue for the next several years.
- In order to cope with the impact of GHG emissions on global climate change and reduce deforestation and forest degradation in tropical countries, REDD+ projects are recently being progressed in many developing countries.
- Regularly updated spatial information on natural forest cover changes and the development of baseline scenario for projecting the deforestation and associated emissions are prerequisite of the REDD+ projects.
- Therefore, quantification of accurate deforestation and associated carbon emission are in urgent need in the tropical region, where integration of PALSAR data and spatial modeling techniques provide ultimate tool to derive geographic solutions even in atmospherically prone areas.

1. Introduction (objective)

- In this research, we aim to monitor deforestation and aboveground forest carbon stocks (AFCS) using PALSAR mosaic data and estimate the future likelihood of AFCS patterns under different forest policies in Riau Province, Indonesia.

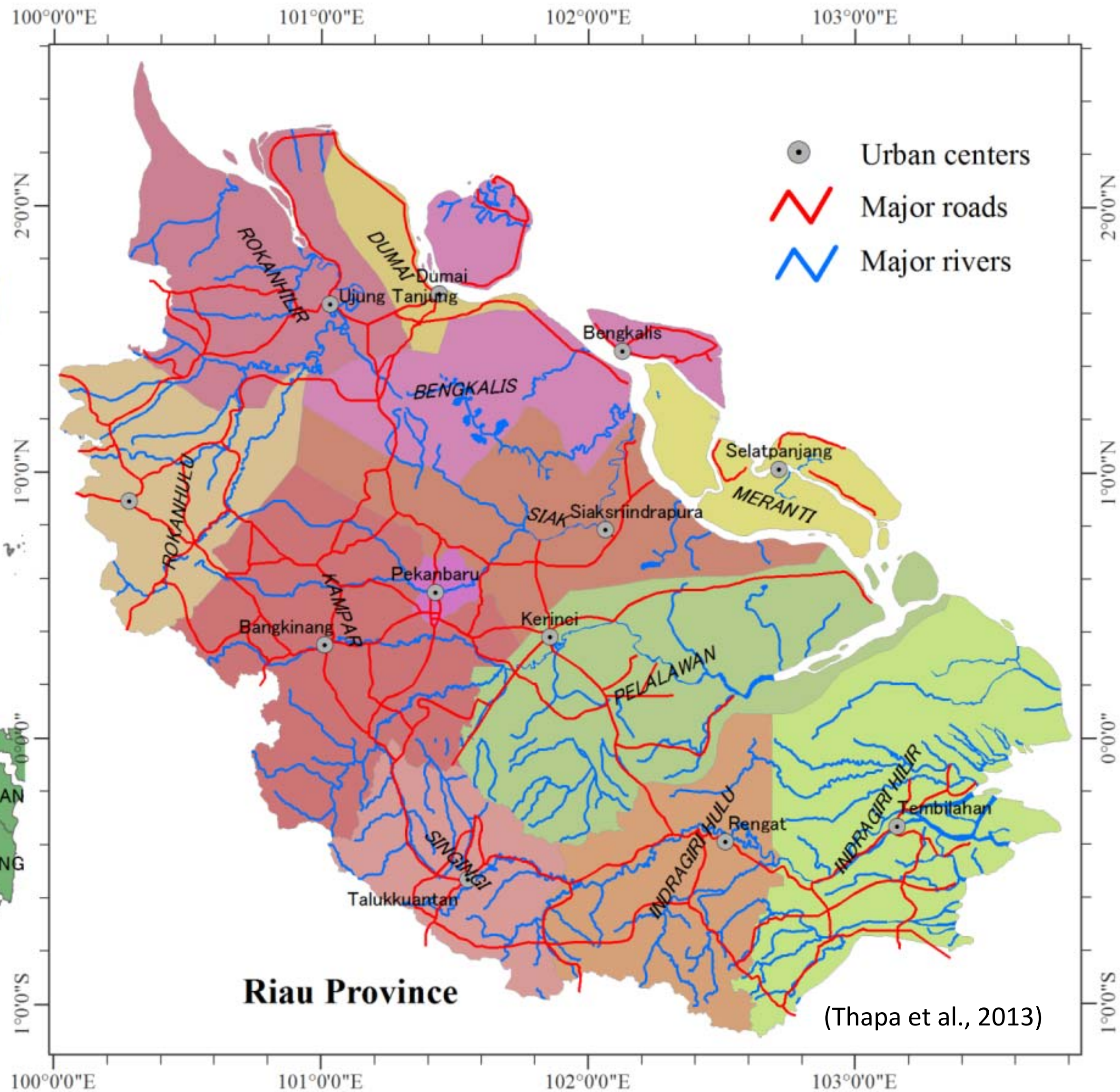
1. Introduction (study area: Riau, Indonesia)

CO_2 emission from deforestation in Indonesia (2000-2005)



Source: Compiled from Table 6. of IFCA Consolidation report (MoFor, 2008).

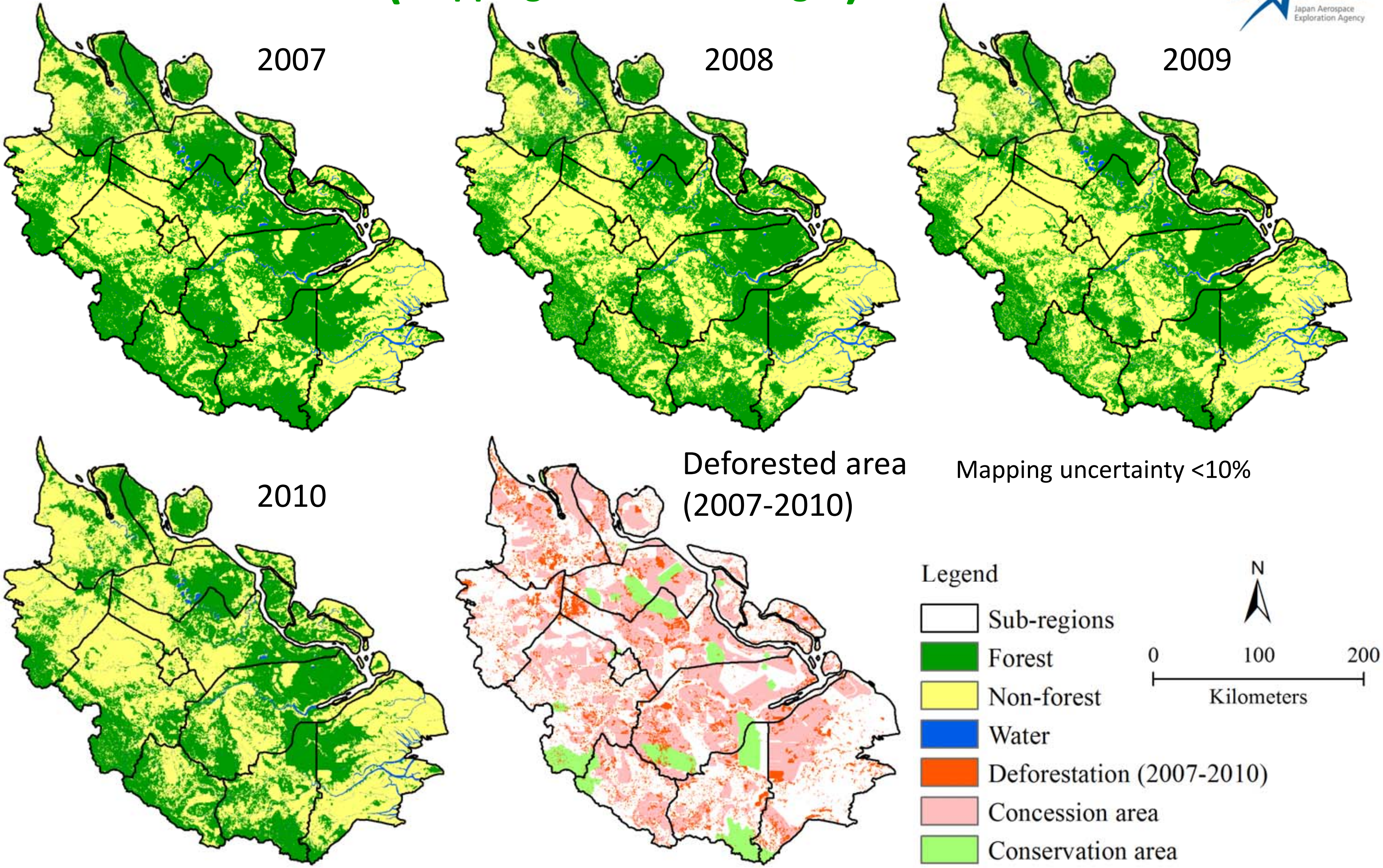
1. Introduction (a brief geography of Riau, Indonesia)



(Thapa et al., 2013)

- Sub-regions: 12
- Population: 5.5 million, (PGR 3.6%/yr)
- Landscape: 9 million ha.
- Elevation: ~1200m
- Atmosphere: Mostly cloudy and hazy through out the year

1. Introduction (mapping the forest changes)



Mapping process: Thapa et al. (2014) and Shimada et al. (2014), <u>Remote Sensing of Environment</u>, 155 (K&C Special Issue)

1. Introduction (Deforestation trend in Riau province)

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The tropical forest in south east Asia: Monitoring and scenario modeling using synthetic aperture radar data

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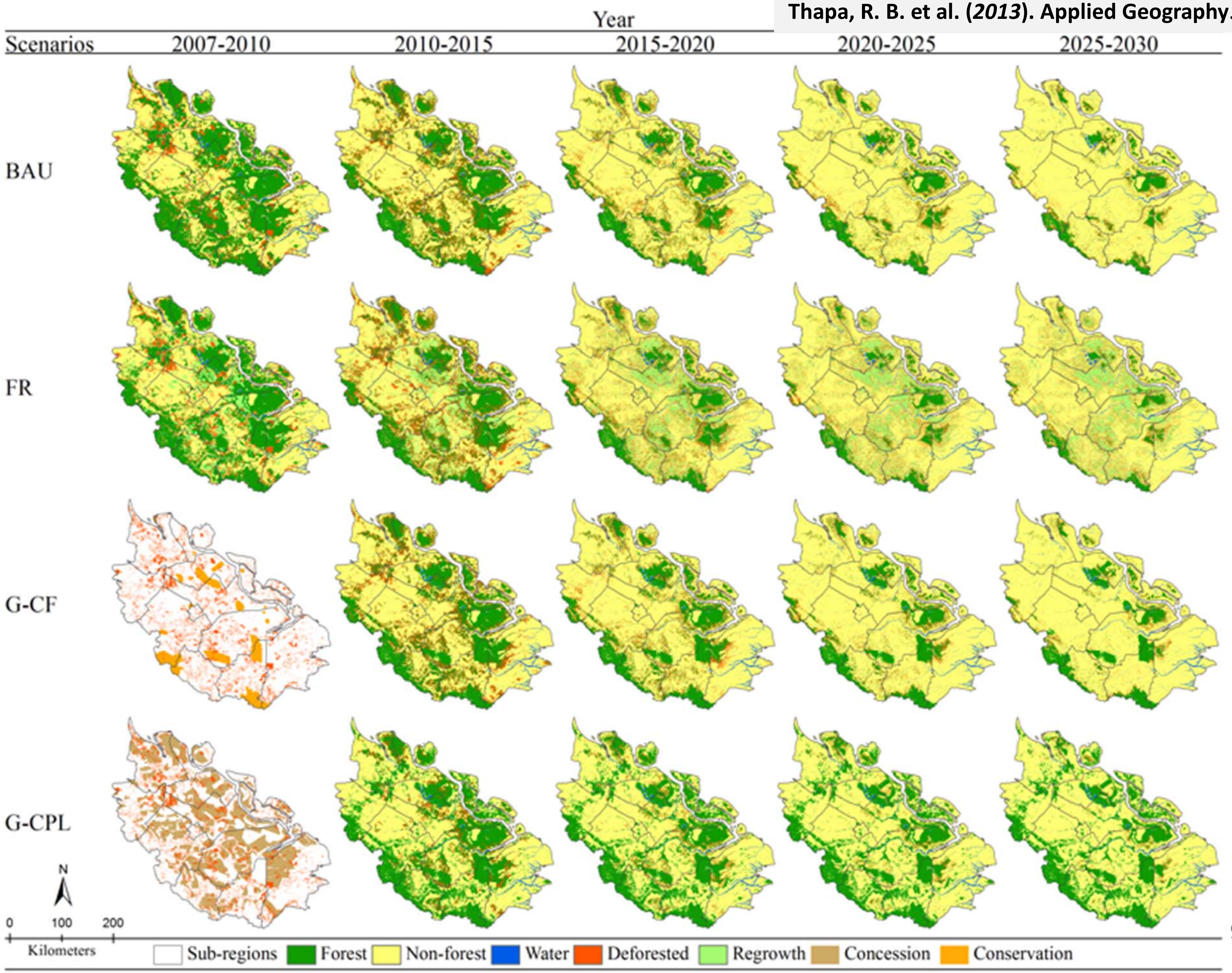
Keywords:
PALSAR
Land cover change
Deforestation
Scenario analysis
LULUCF
Weights of evidence
Sumatra
REDD+

A B S T R A C T

Tropical forests play a major role in storing large carbon stocks and regulating energy, and water fluxes, but such forest cover is decreasing rapidly in spite of the policy attention on reducing deforestation. High-resolution spatiotemporal maps are unavailable for the forests in majority of the tropical regions in Asia because of the persistent cloud cover and haze cover. Recent advances in radar remote sensing have provided weather-independent data of earth surface, thus offering an opportunity to monitor tropical forest change processes with relatively high spatiotemporal resolutions. In this research, we aim to examine the tropical deforestation process and develop a spatial model to simulate future forest patterns under various scenarios. Riau Province from central Sumatra of Indonesia is selected as the study area;

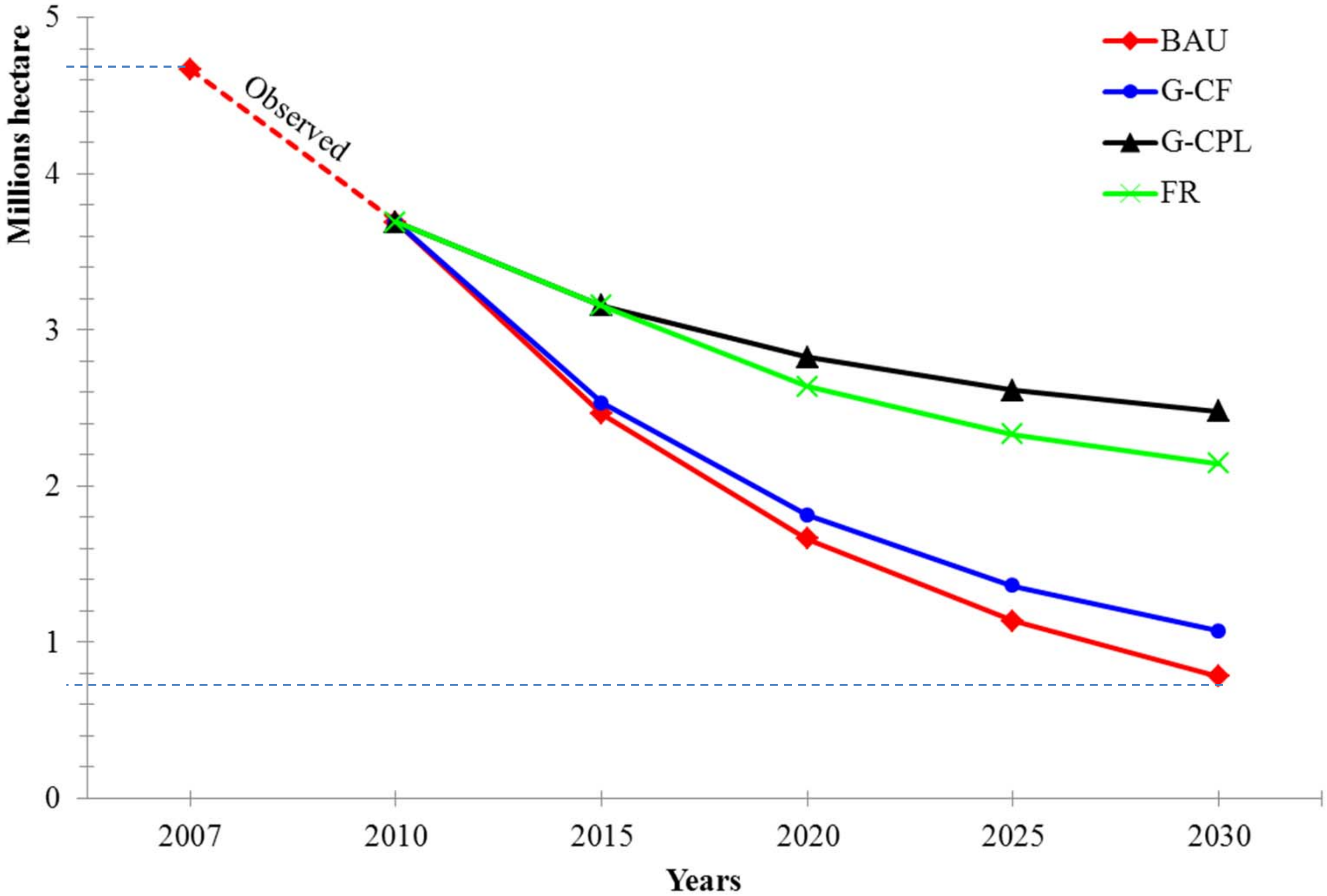
1. Introduction (Deforestation trend in Riau province)

Thapa, R. B. et al. (*2013*). Applied Geography.



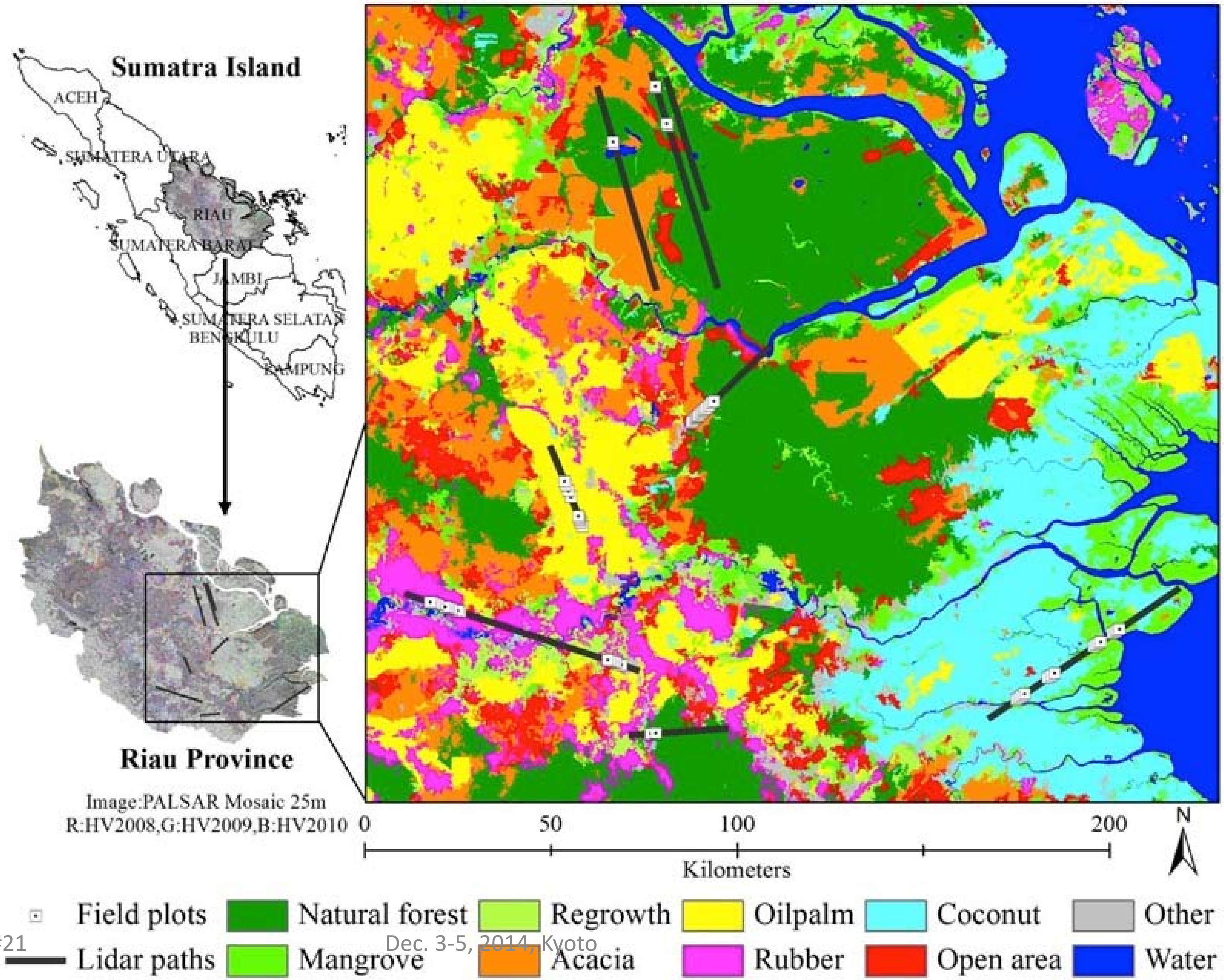
1. Introduction (Deforestation trend in Riau province)

Thapa, R. B. et al. (*2013*). Applied Geography.



2. Method (Field campaign: lidar and field measurement)

Field plots: 87
LiDAR paths: 8



2. Method (AFCS modeling)

Field data AGB (AFCS = AGB*0.47)

Land use	# Plots ha	%Plots	Mean AGB ton	AGB Range ton
Acacia plantation	9	10.34	68.92	44.77 – 98.68
Coconut plantation	7	8.05	34.04	14.61 – 58.72
Mangrove forest	8	9.20	56.50	19.20 – 91.47
Natural dry forest	9	10.34	421.48	227.00 – 710.84
Oil palm plantation	20	22.99	17.59	2.51 – 44.56
Peat swamp forest	19	21.84	242.69	148.29 – 369.40
Regrowth	5	5.75	266.28	179.96 – 349.97
Rubber	10	11.49	82.61	40.64 – 125.27
Total	**87**	**100.00**	**140.51**	**2.51 – 710.84**

*Thapa et al. (2014), **IEEE J-STARS**, and Thapa et al. (submitted)**, Remote Sensing of Environment***

2. Method (LiDAR data acquisition)

LiDAR System	Phase 1 Feb 2012	Phase 2 Nov-Dec, 2012
Laser sensor	LM-5600	Optec ALTM 3100EA
Orthophoto system	Hasselblad	Trimble 60M
Scan angle (degree)	20	37
PRF (kHz)	100	70
Platform height (m)	1000	600
Swath (m)	200	200
Data type	Discrete returns	Discrete returns and full waveform
Average point density (sq. m)	1.2	3.6
Vertical error (m)	0.15	0.12
Horizontal error (m)	0.55	0.2
Paths	3	5
Coverage (ha)	3600	4472

Calibration of Aboveground Forest Carbon Stock Models for Major Tropical Forests in Central Sumatra Using Airborne LiDAR and Field Measurement Data

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***Abstract*—Despite substantial policy attention, tropical forests in Southeast Asian region are releasing large amount of carbon to the atmosphere due to accelerating deforestation. Accurately determining forest statistics and characterizing aboveground forest carbon stocks (AFCSs) are always challenging in the region. In order to develop more accurate estimates of AFCS, the present study col-**

and Forest Degradation in Developing Countries (REDD+), and the global forest assessment of Food and Agricultural Organization (FAO), are underway to explore the impact of GHG emissions on global climate change and to reduce deforestation and forest degradation in tropical countries [3]–[8].

$$\begin{aligned}\mathrm{AFCS} = {} & 259.488 - (146.373 \times \mathrm{MCH}) \\ & + (4.738 \times \mathrm{MCH2}) - (4.881 \times \mathrm{Cover}) \\ & + (3.513 \times \mathrm{MCH\_cover}) - (0.0954 \times \mathrm{MCH2\_cover}) \\ & - (1.583 \times \mathrm{QMCH\_cover}) + (22.568 \times \mathrm{P50}) \\ & + (26.118 \times \mathrm{P90}). \qquad \text{(Model-5)}\end{aligned}$$

Thapa et al. 2014, IEEE J-STARS

2. Method (AFCS mapping…)

% AFCS plots (2803) for
Calibration: 50, Validation: 50

PALSAR Data: 25m slope corrected mosaics
HH&HV 2009, 2010

Predictive function: Maximum likelihood probability

$$g_i(x) = \ln p(\omega_i) - \frac{1}{2}\ln\left|\sum\nolimits_i\right| - \frac{1}{2}(x - m_i)^t \sum\nolimits_i^{-1}(x - m_i)$$

Where:
i = AFCS; x = n-dimensional data (where n is the number of polarizations in PALSAR data); $p(\omega_i)$ = probability that AFCS ω_i occurs in the image and is assumed to be the same for all AFCS; $|\Sigma_i|$ = determinant of the covariance matrix of the data in AFCS ω_i; t = transposition of matrix; Σ_i^{-1} = inverse matrix; m_i = mean vector

Source:
Richard and Jia (2006), RS Digital Image Analysis, Springer
http://www.exelisvis.com/docs/MaximumLikelihood.html

Uncertainty and similarity measures

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n}$$

$$\mathrm{Adj.\,RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i - Bias)^2}{n}}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

d: Index of Agreement
Range: 0 – 1, Disagreement to Perfect Agreement between the Predicted and Observed AFCS values.
Willmott et al. 1980, 2012

2. Method (linking AFCS maps to forest policy)

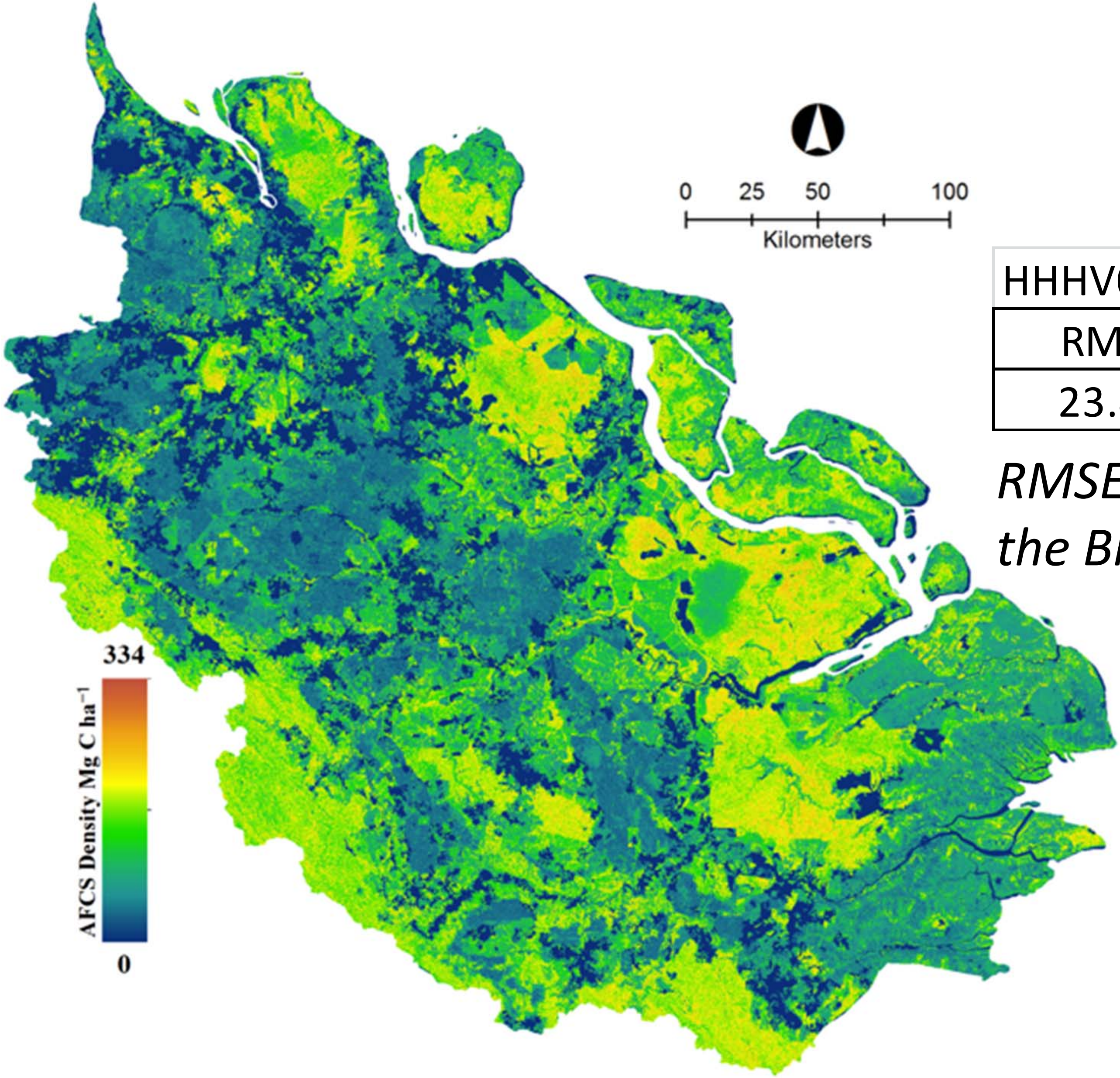
Forest policies and assumptions:

Business as usual (BAU): the deforestation process will continue the past trend everywhere in the province, so release the AFCS in deforested areas.

Governance – forest conservation (G-FC): the deforestation process will discontinue the past trend and will only occur beyond the conservation area, so release AFCS outside the conservation areas.

Governance – concession for industrial plantations and selective logging (G-CPL): the future deforestation process will discontinue the past trend and confine in the concession areas only, so AFCS untouched outside the areas.

3. Results (AFCS map…)



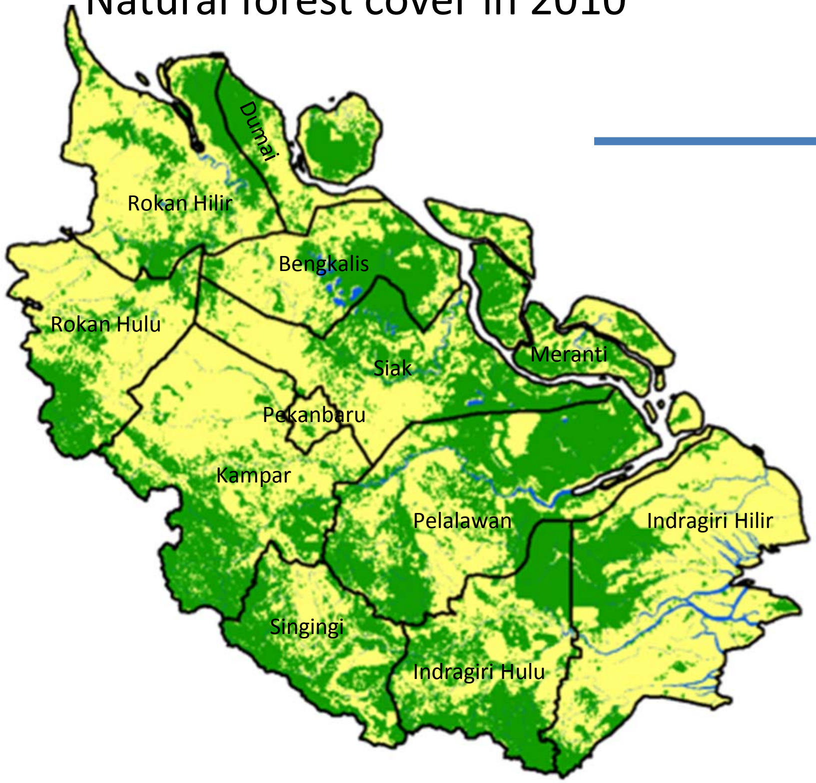
HHHV0910		
RMSE	Bias	d
23.49	1.13	0.843

RMSE after adjusting the Bias: 23.47 Mg C ha^{-1}

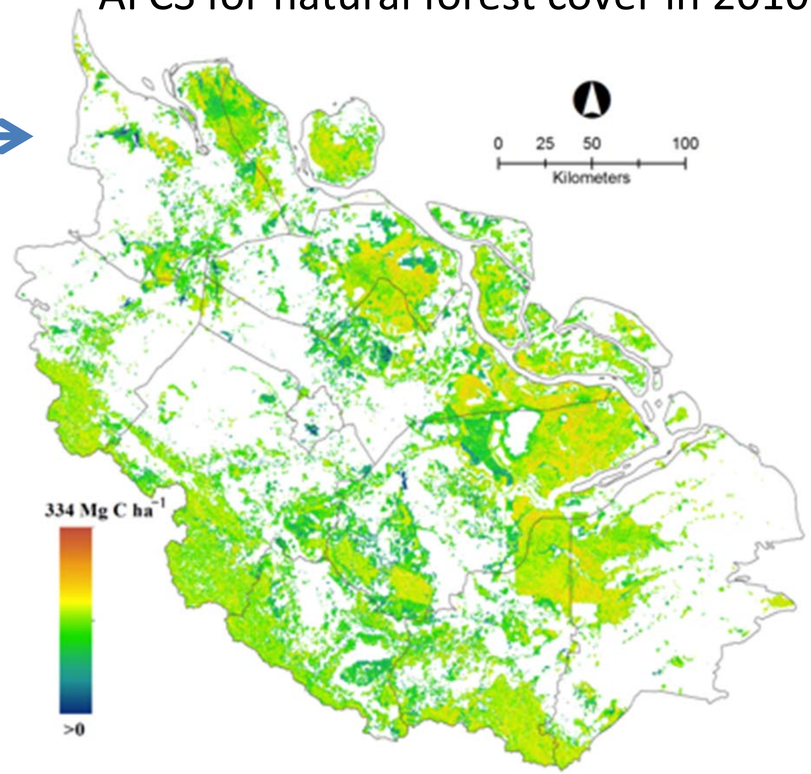
(Validation N=1397)

3. Results (AFCS map …)

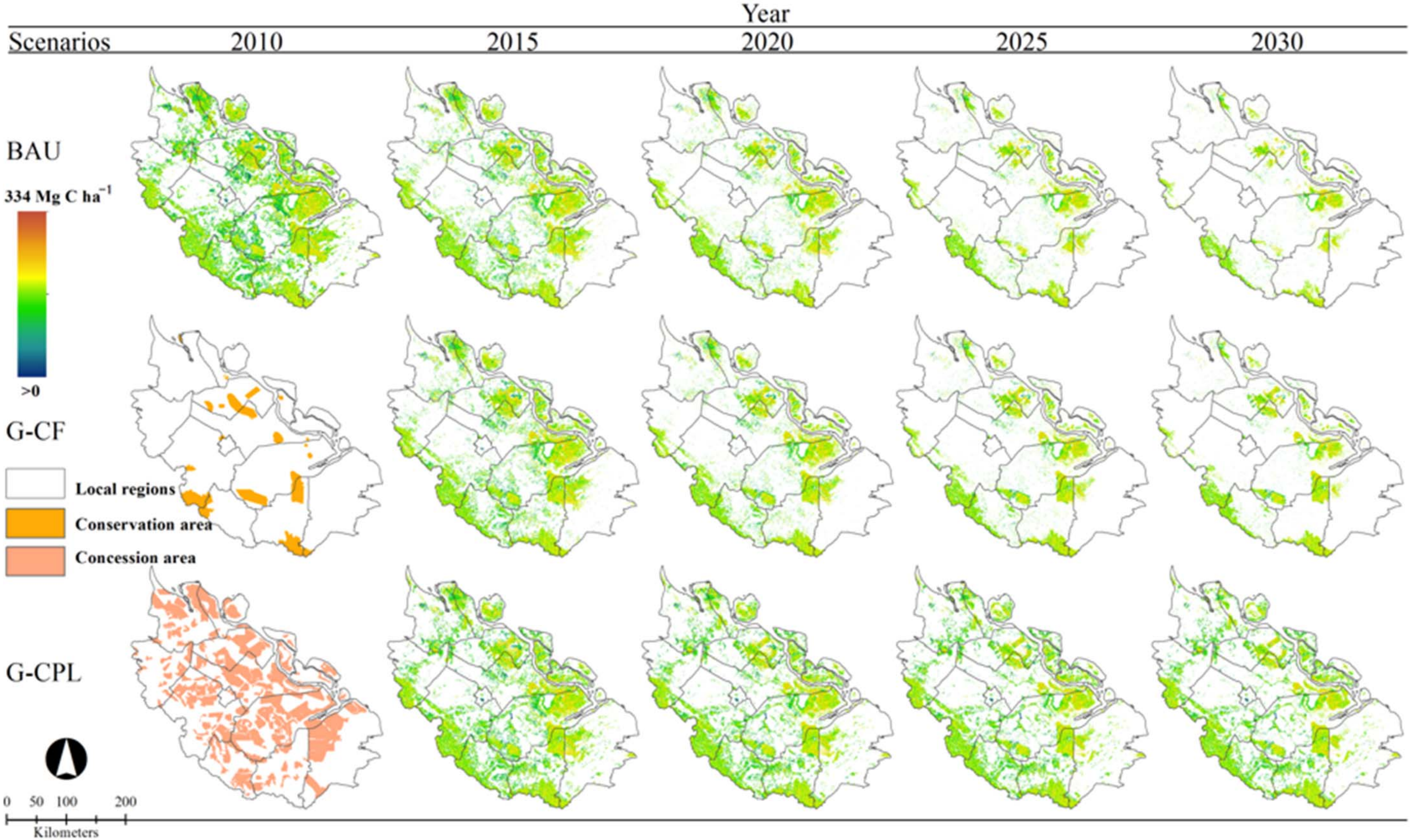
Natural forest cover in 2010



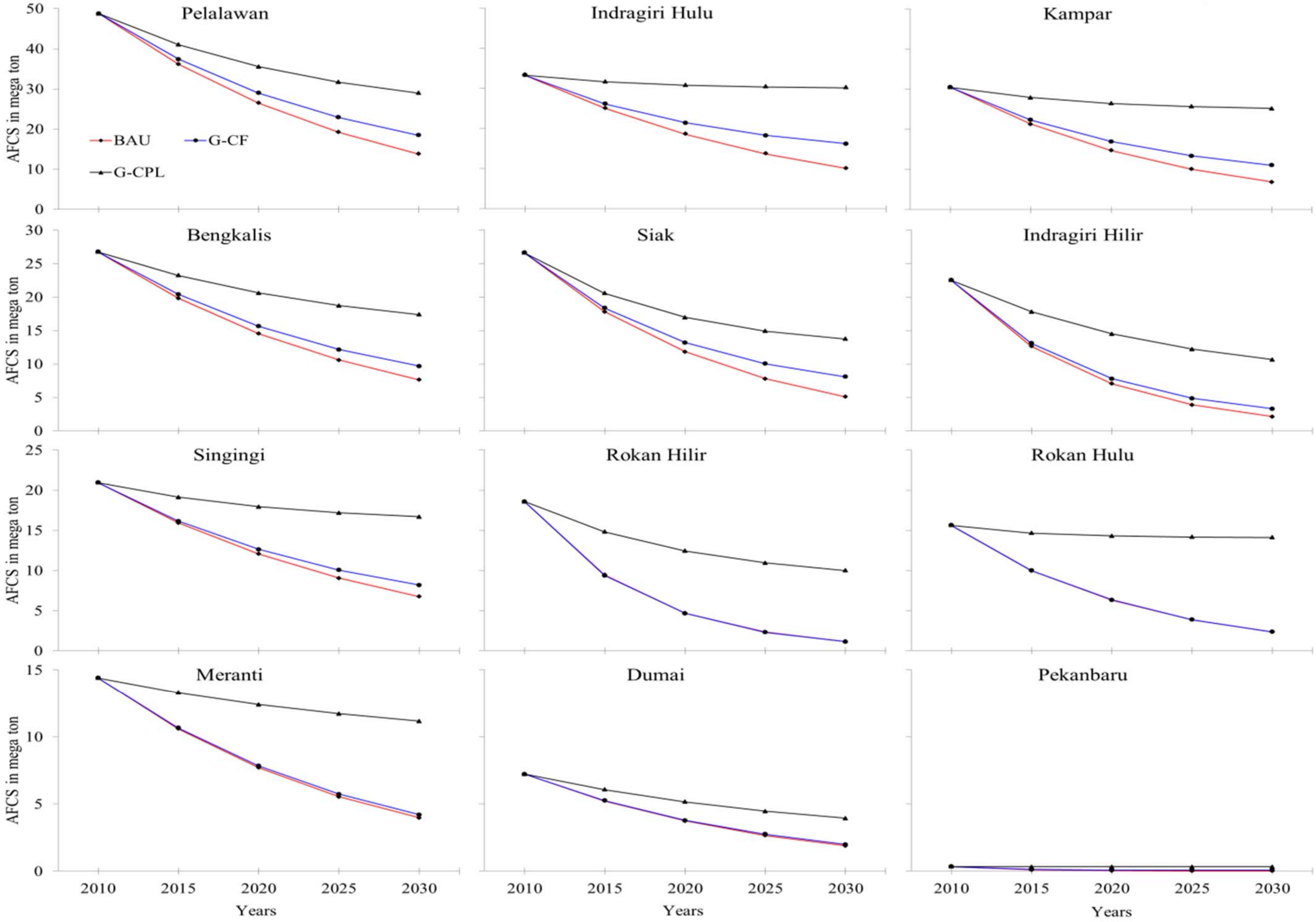
AFCS for natural forest cover in 2010



3. Results (expected AFCS trend by policy)

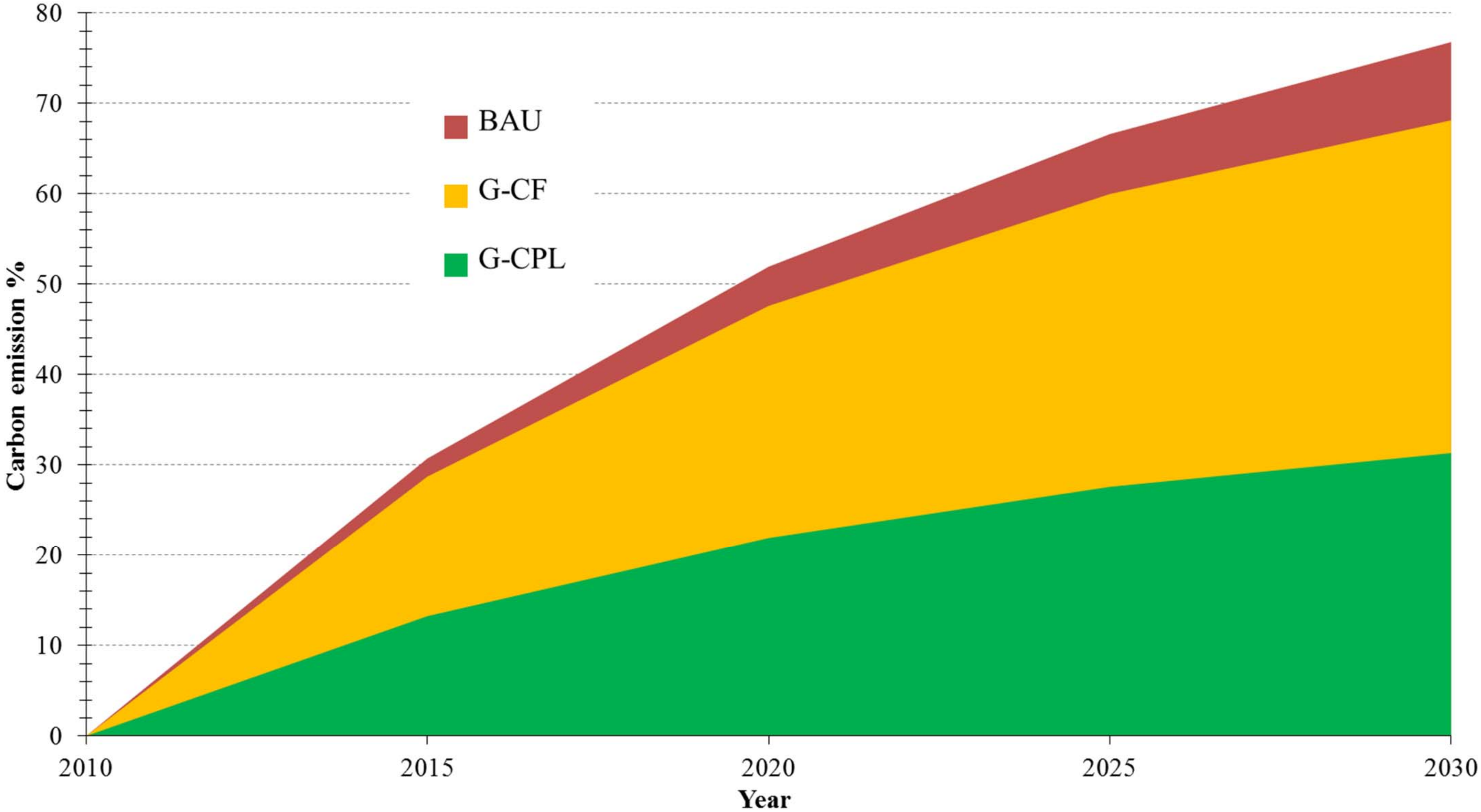


3. Results (sub-region wide expected AFCS by policies)



3. Results (expected AFCS emission by policy in the province)

Natural forests AFCS in 2010: 265.57 million tons



4. Summary

- High spatial resolution AFCS baseline map with an uncertainty of 23.47 Mg C ha^{-1} for Riau Province
- Natural intact forest alone stores 265 million tons of AFCS.
- Extrapolation of future AFCS trends with three forest polices for the next two decades.
- Scenario-wide spatially explicit AFCS storylines at local and provincial level
- AFCS emission risk from land use activities in next two decades: 75%
- Conservation may lower the risk by 8.5%
- Concession likely save 44%.

Questions/Comments?

Thank you!

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1. Introduction (Deforestation trend in Riau province)

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New global forest/non-forest maps from ALOS PALSAR data (2007–2010)

CrossMark

Masanobu Shimada [a], Takuya Itoh [b], Takeshi Motooka [a], Manabu Watanabe [a], Tomohiro Shiraishi [a], Rajesh Thapa [a], Richard Lucas [c]

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Evaluation of ALOS PALSAR sensitivity for characterizing natural forest cover in wider tropical areas

CrossMark

Rajesh Bahadur Thapa [a,*], Takuya Itoh [b], Masanobu Shimada [a], Manabu Watanabe [a], Motohka Takeshi [a], Tomohiro Shiraishi [a]