UK NCEO work on Global Forest

SDCG-10: Reading, 7-9 September, 2016











Examples from NCEO-University of Leicester









ESA DUE GlobBiomass

- Improved quantitative biomass maps at regional and global scale
- Provision of associated uncertainty maps
- Validation including major user organisations and establishing common practices and standards
- Contribution of new scientific results with respect to biomass stock and change estimation
- Identification of the limitations of current data and methods to estimate biomass by historical, recent and future global Earth observation data (Sentinels, BIOMASS, SAOCOM, ALOS-2)









ESA DUE GlobBiomass



- Produce a global map for 2010
- Produce 5 regional maps for 3 epochs
 - -Epoch 1: 2005
 - -Epoch 2: 2010
 - -Epoch 3: 2015
- Spatial resolution < 150 m
- Map the uncertainty of the estimates
- Biomass change maps between Epochs







GlobBiomass Regional Mapping

Partner/ Region	Method	Datasets
UniLeicester Mexico	MaxEnt	ALOS PALSAR dual polarization, Landsat Surface Reflectance, Landsat Percent Tree Cover, SRTM, Field data
CESBIO South Africa	WCM + MIPERS	ALOS PALSAR dual polarization, Landsat Percent Tree Cover, SRTM, Field data
IGIK Poland	Random Forest Regression	ALOS PALSAR dual polarization, SRTM, Landsat, Field data
RSS Kalimantan	Regression	ALOS PALSAR dual polarization, SRTM, Airborne LiDAR, Field data
SLU/GAMMA Sweden	knn / Biomasar	SPOT 4 and SPOT 5, Field data / ALOS PALSAR dual polarization







Focus: Mexico regional





Model Prediction Geographical Space

Maximum probability weighted mean for each pixel

$$\widehat{AGB} = \frac{\sum_{i=1}^{N} P_i^n AGB_i}{\sum_{i=1}^{N} P_i^n}$$

 P_i is the MaxEnt probability estimated for each biomass range class AGB_i (median value of the range), and \widehat{AGB} is the predicted value of AGB for each pixel

Prediction Error:

$$\begin{split} \varepsilon_{prediction} &= \sigma_{\widehat{AGB}} / \widehat{AGB} \, x 100 \\ \text{where} \quad \sigma_{\widehat{AGB}} &= \sqrt{\frac{\sum_{i=1}^{N} (AGB_i - \widehat{AGB})^2 P_i}{\sum_{i=1}^{N} P_i}} \end{split}$$

$$\varepsilon_{AGB} = (\varepsilon_{measurement}^2 + \varepsilon_{allometry}^2 + \varepsilon_{sampling}^2 + \varepsilon_{prediction}^2)^{1/2}$$

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Aboveground Biomass and Uncertainty maps at 25m spatial resolution for the reference year 2010 for the regional sites of Central Mexico and the Yucatan peninsula















Biomass change







On-going project: REDD+ Monitoring Services with Satellite Earth Observation - Community Forest Monitoring Pilot

- Kenya's economy is losing US\$ 68 million annually from deforestation and aims to achieve afforestation to 10% forest cover by 2030.
- To protect forest resources, capacity is needed for timely deforestation monitoring
- 360° communication: Users have to be able to add photos, text annotation, feedback on validation and other local information to the deforestation alerts
- The Sentinel-1&2 and Landsat data (in future potentially also NovaSAR-S) enable much more frequent event detection
- The edge of our product is the customisable mobile app combined with satellite-derived and user-entered information







Satellite optical and radar data acquisition

Smartphone app deforestation alerts and forest information

> Community / field based response to illegal logging and deforestation





Initial results







Initial results





2 3 4 km 0 1 3 - Al

2 3







Clearance Probability 0.000000 0.138750 0.277500 0.416250 0.555000 Change classification Cleared forest Stable forest Stable non forest veg Stable low veg/impervious Non forest veg change Cloud 2





EODIP Project: Sentinel-1 C derived Forest Cover Map



Forest cover and disturbance map of Aberfoyle area in Scotland



Specific objectives:



Measuring Forest Degradation in Colombia

OBJECTIVE: Explore the capabilities of SAR bands L (Alos PalSAR, Alos 2) and C (Sentinel 1A and 1B), in order to measure forest degradation in Colombia:

- Understand the intrinsic characteristics of forests and its changes in structure and carbon stocks.
- Recognize patterns of forest degradation and forest regeneration to improve the carbon emissions estimates from forest loss and regrowth?
- Analyse temporal series complemented with field data observations.







Thanks





Mapping tropical forest processes using Earth Observation data



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Sentinel (1 and 2) and L-band SAR (ALOS-2 PALSAR-2, SAOCOM, NISAR) imagery, together with the long-term Landsat archive, offer an unprecedented opportunity to build a pan-tropical system capable of tracking forest processes, such as:

- secondary forests establishing on abandoned farmland
- wildfires occurring over peatland dominated regions

Mapping non-forest, age of secondary forest, and mature forest in the Amazon with single-date Landsat TM and ALOS PALSAR data



- Discriminating non-forest, secondary forest and mature forest with overall accuracy of 98%
- Retrieving the age of secondary forests with RMSE = 3.84 yr and bias = -0.06 yr

In combination with biomass accumulation curves, this approach offers an alternative source of information to estimate the carbon stocks and fluxes in the above-ground biomass pool of tropical secondary forests

Carreiras et al. (2016). *Remote Sensing of Environment* (under review)

Mapping the 2015 burnt areas in Central Kalimantan with monthly time-series of Sentinel-1A (VV+VH) data



Sentinel-1A data acquired between March – December 2015



- Burnt area mapping with overall accuracy between 75-95%
- 11% of the study area burnt in
 2015, with the majority (75%) in
 a 7-week period
 (6 Sep 24 Oct)

In highly cloud-covered tropical forest regions, monthly time-series of C-band SAR data can play a unique role at estimating not only the annual burnt area extent but also its time-dependent distribution

Forest Monitoring from Earth Observation: Examples from Aberystwyth University

SDCG-10: Reading, 7-9 September, 2016

Peter Bunting, Richard Lucas, Ake Rosenqvist, Nathan Thomas, Sizwe Mabaso, Joshua Jones and Joao Carreiras







THE LAY

A

Carnahan Classification Based on Height and Cover





No Data Grassland Grassland with shrubs Grassland with trees Grassland with tall trees Grassland with verv tall tr Very low open woodland Low open woodland Open woodland Tall open woodland Very tall open woodland Very low woodland Low woodland Woodland Tall woodland Verv tall woodland Very low forest Low forest Forest Tall Forest Verv tall forest Very low closed forest Low closed forest Closed forest Tall closed forest Very tall closed forest







Product at 25m resolution and is the integration of ALOS PALSAR, Landsat and ICESat. Segmentation of PALSAR and Landsat products, populate segments with intersecting ICESat footprints, interpolate ICESat profiles using PALSAR and Landsat = forest height for Australia.

Mapping Forest Growth Stages







Maps of forest regrowth stage generated using Landsat-derived Foliage Projective Cover (FPC) and Advanced Land Observing Satellite (ALOS) PALSAR HH and HV data. All mapping is based on the response relative to that of remnant forest for different regional ecosystems

Global Mangrove Watch





Global monitoring system for changes in mangrove extent. Built using the Giri et al 2000 product and ALOS PALSAR, PALSAR-2 and JERS-I SAR data. Change is identified using an innovative map-to-image change method.

Forest Regrowth Biomass: Amazon



Thanks

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