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Forest carbon change in Uganda 2000-2012 estimated with InSAR

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Summary: A novel approach for forest carbon monitoring is demonstrated wall-to-wall for Uganda. Forest height changes over time are used to estimate change in forest carbon stock. The height changes are derived from two data sets covering Uganda, i.e. the SRTM in 2000 and Tandem-X around 2012. These heights are derived from interferometric SAR, i.e. an advanced radar sensor system. Both forest height decreases from logging and forest height increases from growth are seen over Uganda. On average the height decreased by 2.6 cm per year during 2000-2012. This decrease corresponds to an annual CO2 emission of 20.7 million t. The uncertainty of this estimate is given by a 95% confidence interval of ±8.5 million t. If this is used as a Reference Emission Level it means that if Uganda reduced its forests carbon stock change to zero, Uganda might claim a REDD credit of 105 million US$ per year from a donor country.

Introduction

A novel approach for the estimation of CO_2 emissions from deforestation and other forest changes in the tropics is being developed based on InSAR. The idea is to estimate changing carbon stocks from forest height changes derived from InSAR, rather than based on land cover changes based on Landsat-like satellite data. The advantages are (i) detection of gradual changes like forest degradation and growth; (ii) more accurate carbon estimation because highly uncertain and fixed 'emission factors' assigned to various land cover types are not required, and (iii) cloud cover does not prevent data acquisition.

The REDD+ is an initiative for paying tropical countries for maintaining forest carbon stocks. The more they reduce the forest carbon losses the more they get paid. In order to make this happen a tropical country needs a reference emission level (REL) for a given time period in the past and regular surveys of emissions to be compared to the REL.

Objective

This study aims at estimating the forest carbon stock change for Uganda for the period 2000 to ~2012 based on SRTM and Tandem-X.

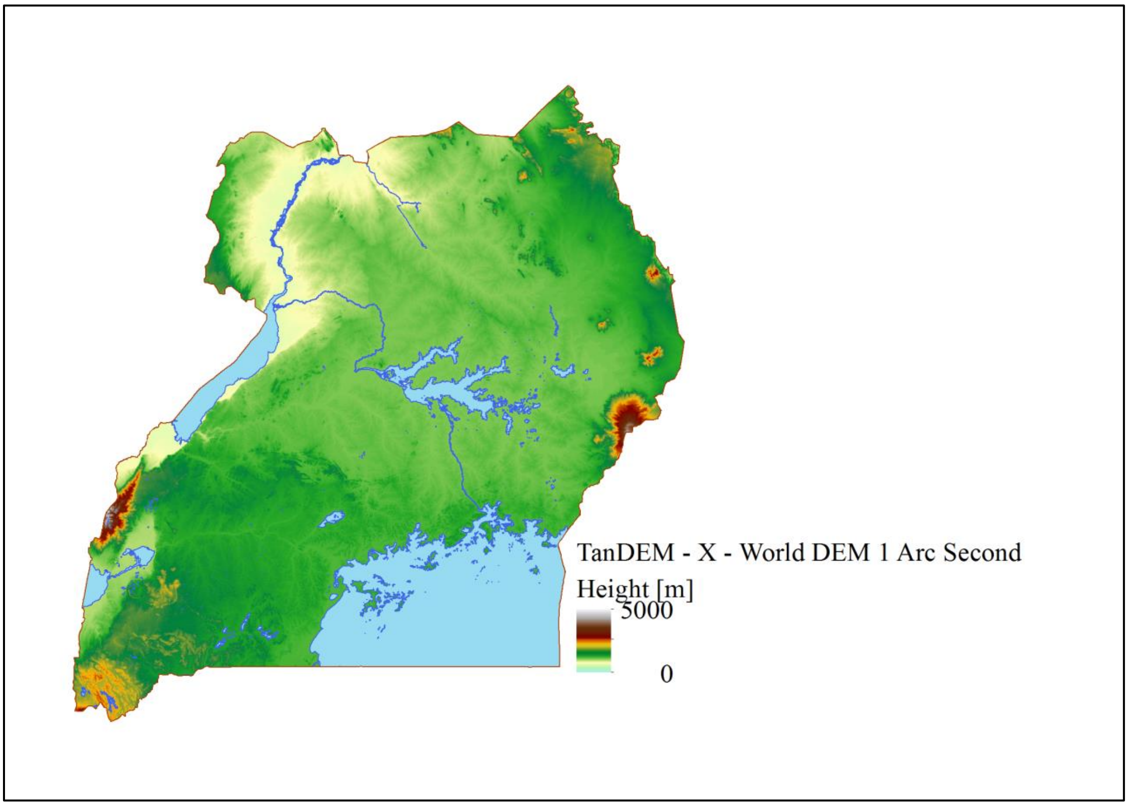
Materials

This study is based on height changes in Digital Surface Models (DSMs) over a 12 –year period. One data set was acquired around the year 2012 (Tandem-X) and another in the year 2000 (SRTM). The data are obtained with radar sensors, or Synthetic Aperture Radar (SAR), and the DSMs are produced using interferometric processing (InSAR). These core data were supplemented with auxilliary data on land cover types, Landsat-based forest cover estimates and their changes over time, water-masks as well as external models obtained from other studies on the conversion between variables.

TanDEM-X

TanDEM-X is a SAR satellite mission operating with two TerraSAR-X satellites in bistatic mode. Both satellites are operated by the German Aerospace Center (DLR). During their flight around the earth they form a crossing helix orbit, allowing them to cover one and the same spot on earth from two angles. TanDEM-X was launched on the 21.06.2010 and supports the TanDEM-X – TerraSAR-X mission for 5 years (DLR, 2010). The main objective of Tandem-X is to provide data for a global DEM; - the WorldDEM™, - a global DEM with unprecedented accuracy (Krieger et al. 2007). However, the present study will demonstrate that the data are excellent for forest monitoring applications. The satellites operate in the short wavelength, i.e. X-band, which is echoed from high in the forest canopy (Chen et al., 2007) and provides information about forest height and its changes over time.

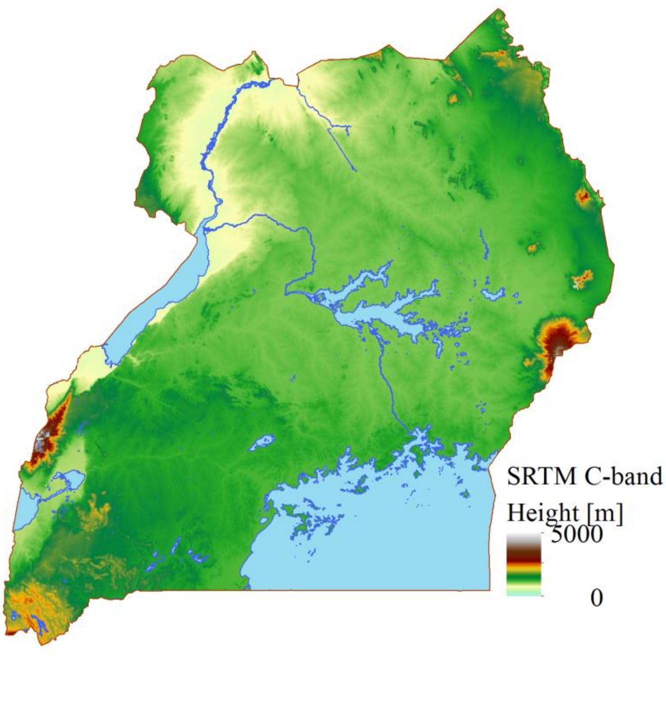
In the present study we did not use the WorldDEM data as it is normally purchased, but another version having a coarser spatial resolution, i.e. 1 arc second (~ 30 m) and slightly coarser resolutioin in height, i.e. meters without decimals. The data were provided by Airbus DS as 37 1° x 1° tiles covering Uganda, wheere pixels outside Uganda were blanked. The data were given as ellipsoidal heights in WGS84-G1150 latitude/longitude projection Each tile was derived from 13 to 64 acquisitions within the timeframe of December 2010 to November 2014, with an average acquisition time being the year 2012. We mosaicked the tiles together and obtained a seamless data set using the 'mosaic to new raster' tool in ArcGIS 10.3.

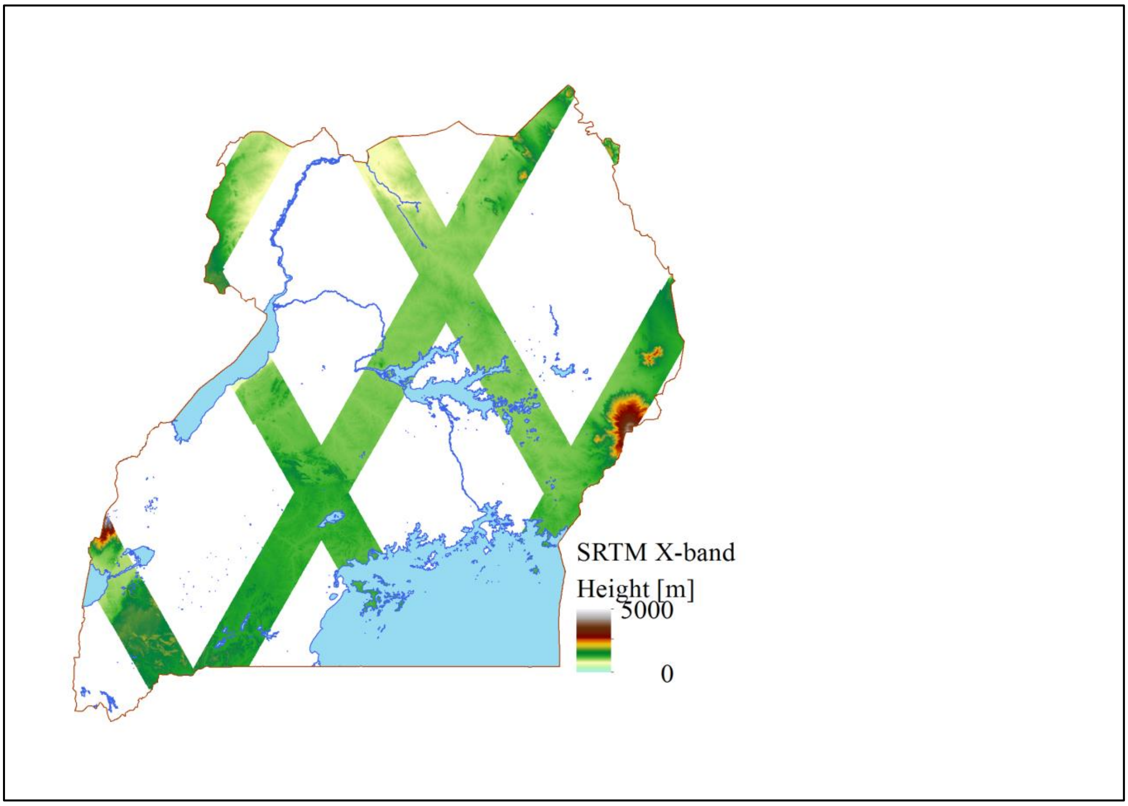


SRTM C- and X-band

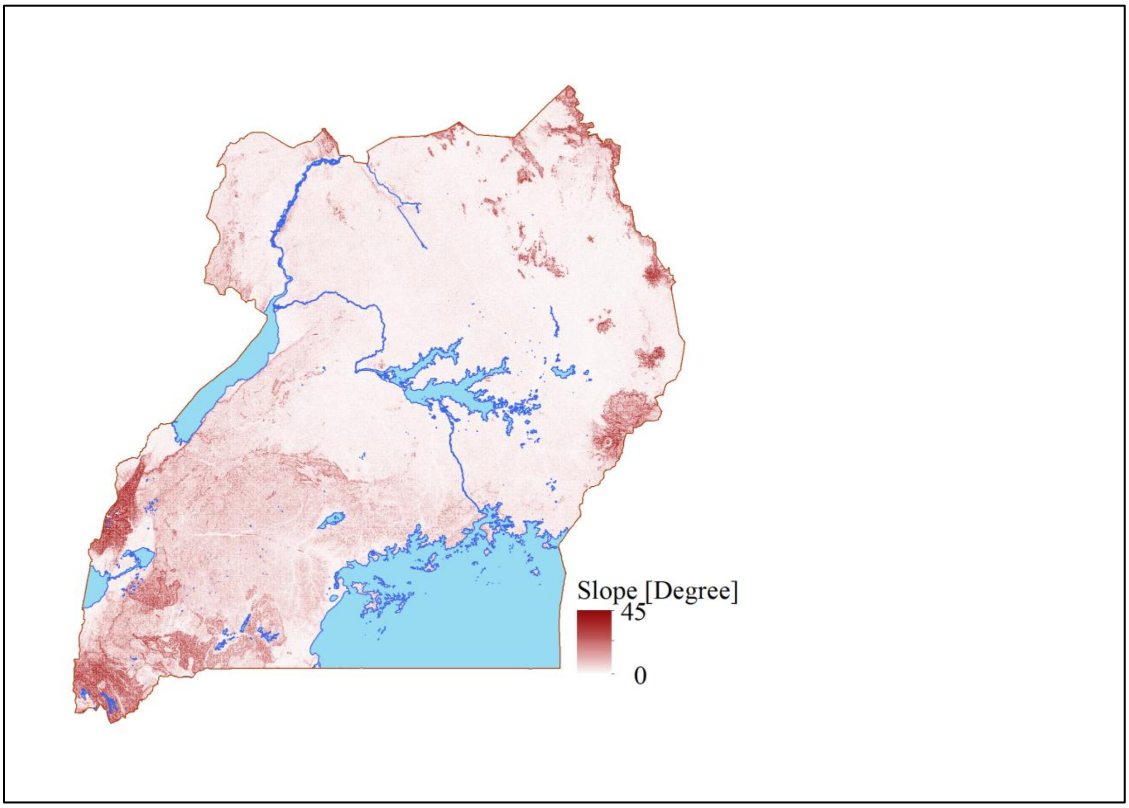
We used both the X- and C-band InSAR DSMs from SRTM, which were acquired in February 2000 (Rabus et al. 2003). The SRTM mission acquired bi-static data by mounting SAR sensors both in the space shuttle body and on the tip of a 60 m extended boom. The C-band data were acquired with a scanSAR system of the Spaceborne Imaging Radar-C (SIR-C) hardware, while the X-band data were acquired with a stripmap system. The C-band data had full areal coverage, while the X-band provides partly coverage (~30%) only, making up an X-shaped coverage pattern over Uganda. The data were in geographic (lat/lon) projection in meters above sea level with a spatial resolution of 1 arc sec. We downloaded the data as DEM tiles. The C-band data were downloaded from USGS and the X-band from the German Aerospace Centre (DLR). The tiles were mosaicked together to one C-band and one X-band DSM file over Uganda. We converted the elevation data to elliposidal heights using ENVI / Sarscape software. In the C-band two small mountain areas contained void areas making up 0.24% of the country area.

A particular issue with obtaining height changes from SRTM C-band to Tandem-X X-band is that they used different wavelengths, and the penetration depth into vegetation is influenced by wavelength. The wavelength is 3.1 cm for X-band and 5.6 cm for C-band. The longer the wavelength the deeper is the penetration into a vegetation volume, which means that the radar echo from C-band will be somewhat deeper down in the canopy than the X-band echo. Hence, before we can compare the two data sets, and extract height changes over time, we corrected the C-band DSM, i.e. we lifted it upwards to a simulated X-band DSM. We have our own patent-applied methodology for this depending on forest cover and forest type. The idea is that no correction shall occur in treeless areas, while it should be a maximum correction in dense forests.





From the SRTM C band DEM we derived a slope map to discard extreme values. InSAR data is sensitive to steep slope angles that cause random extreme values due to irregularities in the signal reflection. The slope data set was employed to support the exclusion of false information in further processing steps.



Land Cover Type

U.S. Geological Survey provided an open source raster product derived from MODIS data (MCD12Q1) between 2001 and 2010 (Modis, 2012). Since the data product had a global coverage with 17 land cover types, the spatial resolution was with 15 arc seconds respectively low (Broxton et al., 2014). Further processing steps required equal extent and resolution as found for the TanDEM-X DSM and SRTM C-band data sets. Therefor the land cover type data set (LCT) was resampled to 1 arc second, using ‘nearest neighborhood’ and clipped to the rectangular extent of the SAR products. Like the prior data sets, also the LCT data was downloaded in latitude/longitude WGS84 geographic projection.

Among those 17 land cover types, 10 of which were found in Uganda, and we further reduced this to 8 types by combining land cover types of small extent:

Table x. Land cover types

Initial land cover type	Re-classified land cover type
Water	Water
Evergreen Broadleaf Forest	Evergreen Broadleaf Forest
Open Shrubland	Others
Woody Savanna	Woody Savanna
Savanna	Savanna
Grassland	Grassland
Permanent Wetlands	Permanent Wetlands
Croplands	Croplands
Urban	Others
Cropland and Natural Vegetation Mosaic	Others

Savanna regions dominated in northern Uganda, while cropland and natural vegetation was the main land cover type in the remaining country (Fig. x). On the south-western corner and more southern country borders in general, evergreen broadleaf forests were found in larger patches.

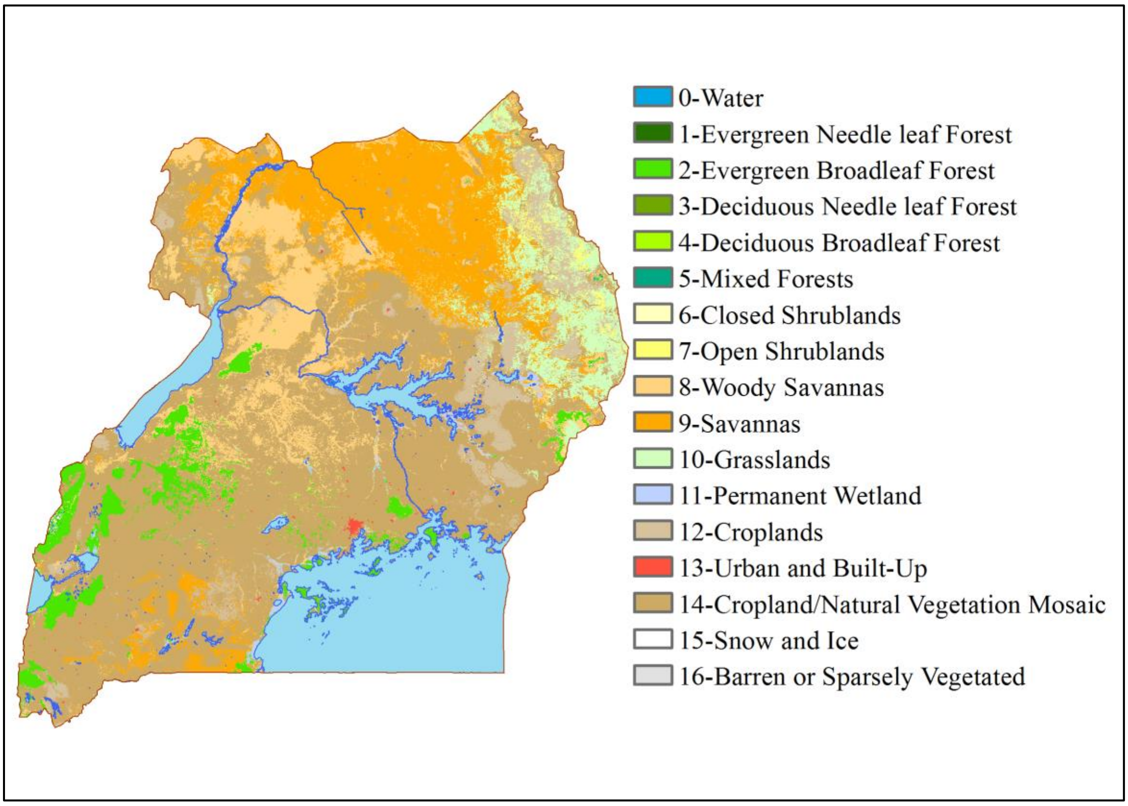


Fig. x. Land cover types.

From this we derived:

Uganda area (including water):	241 278	km2
Water area:	36 707	–“-
Uganda terrestrial area:	204 571	km2

Country Boundaries (and watermask)

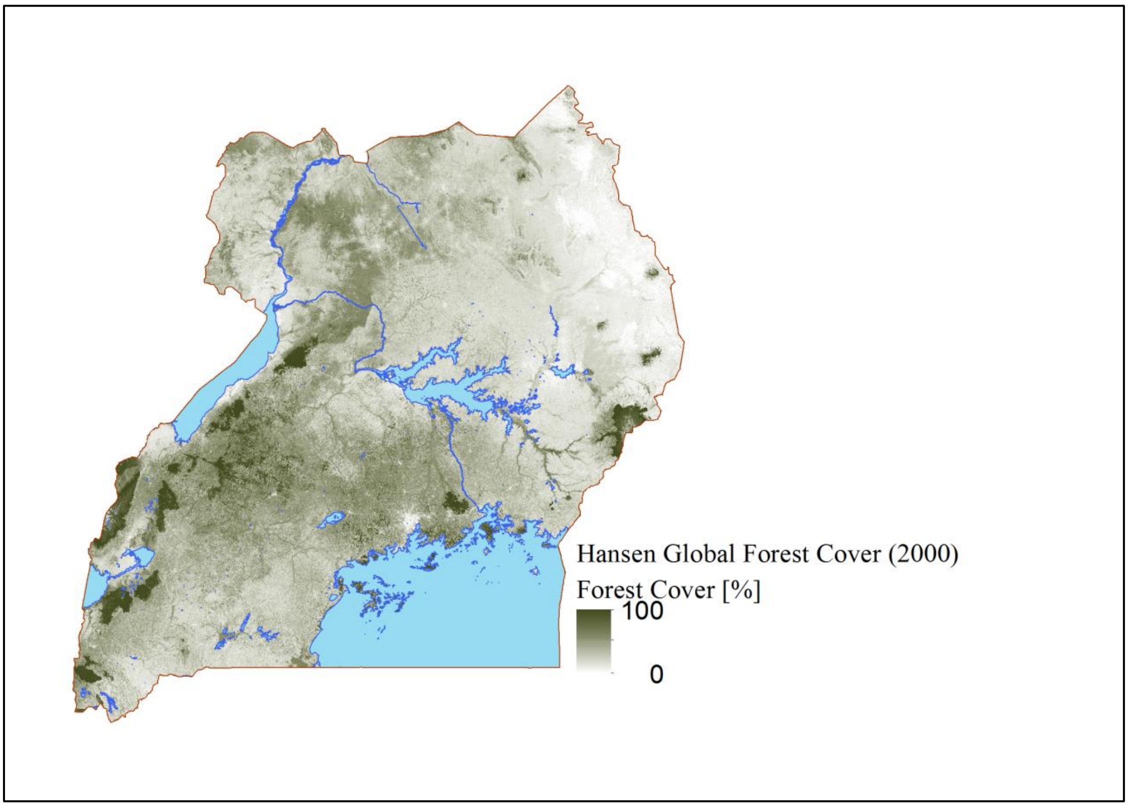
The country boundaries, as well as the watermask were provided by the open source spatial GIS data platform Diva-GIS.org. Both were vector data sets in geographic projection WGS84. (Diva-GIS, 2011). The data provided in their data bases was derived from existing public domain data bases and thereby could be considered as relatively accurate. (Hijmans et al., 2001)

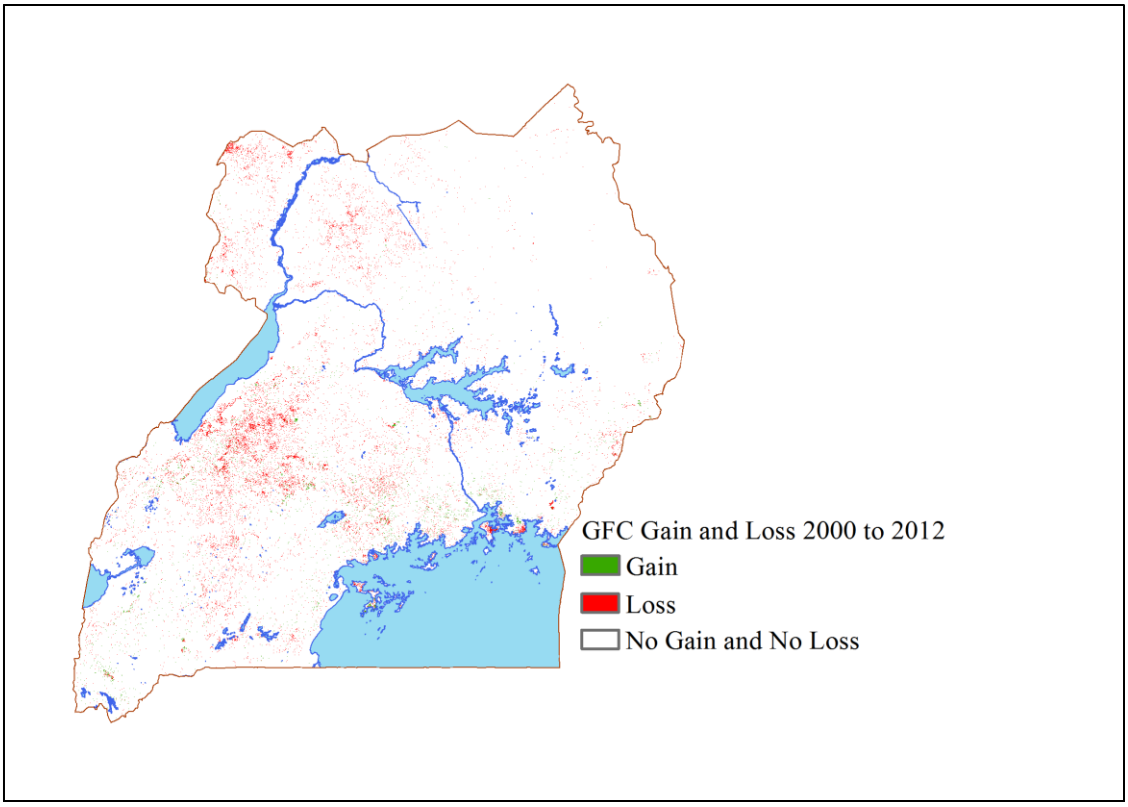
Global Forest Cover and Change 2000 – 2013

The University of Maryland provided the Hansen Global Forest Change data set, which was a raster product derived from a Landsat 7 ETM+ time series between 2000 and 2012. Each tile covered an area of 10 by 10 degrees on a global scale. The extent of Uganda was covered with four tiles. Three different data products were downloaded, containing information about the tree canopy cover in 2000 from 0 to 100 % for all trees with a height more than 5m, the forest gain and forest lost from 2000 to

2012 as a 8-bit tiff file where 0 represents no gain (or no loss respectively) and 1 represents gain (or loss). All tiles were provided in geographic projection (WGS84) and could be downloaded in the 'download_v1.0' version with 1 arc second spatial resolution. (Hansen et al., 2013)

Each of those 4 tile consisting data sets were mosaicked and clipped to the SAR data's rectangular extent.





Methods

Overview of the processing steps:

The first part of the processing is to extract the forest height difference over time. The difference between the Tandem-X DEM and the SRTM C-band DEM contains three different sources:

a) Real height changes over time (logging, forest growth)
b) Errors, mainly or only errors in the SRTM C-band DEM
c) The penetration difference of X- and C-band into the forest canopy

The processing steps were as follows:

- Forest height change from year 2000 to year 2012 derived as $\Delta H_1 = DEM_{TDX} - DEM_{SRTM}$
- Processing step 1, Correcting errors (artifacts) of the SRTM C-band DEM, obtaining ΔH_{corr1}
- Checking for remaining bias and ramp: No correction needed.
- Processing step 2, Correcting for C-band to X-band penetration difference, including removal of errors (artifacts) of the SRTM X-band DEM, obtaining ΔH_{corr2}
- Processing step 3, Filling of voids and illegal, extreme values, obtaining ΔH_{corr3}

The second part is to recalculate the height changes to biomass and carbon stock changes.

- Processing step 4: Recalculating ΔH_{corr2} to Above Ground Biomass (AGB) change, ΔAGB_{corr2}
- Processing step 5: Recalculating ΔAGB_{corr2} to ΔCO_2 emissions
- Processing step 6: Uncertainty description and estimation

Preprocessing

All data sets were available with geographic coordinates, referring to WGS 84 ellipsoid, with 1 arc second spatial resolution and pixel alignment, - a few of them after resampling from other coordinate systems or from orthometric heights. The resampling was carried out with ENVI / Sarscape and ArcMap software. The data sets were clipped to a rectangular extent covering Uganda. All raster data sets were transformed to tables, and statistical analyses were carried out using SAS (Statistical Analyses Software).

Filtering away artifacts of the SRTM C-band DEM

The errors occurring as line and band artifacts were clearly visible in the difference between the Tandem-X DEM and the SRTM C-band DEM, and were assumed to be errors in the SRTM C-band DEM (Fig. 2a). We successfully removed these artifacts using an Analysis of Variance (ANOVA) model to make a tailored filter, and by subtracting this we obtained a difference image representing real height changes (Fig. 2b). In the ANOVA we excluded real changes, by excluding pixels having height changes larger than 10 m, as well as pixels classified as 'gain' or 'loss' in the Global Forest Cover change dataset based on Landsat data (Hansen et al. 2013). This left about 400 million pixels which were entered into the ANOVA model.

Checking for bias and ramp

We selected pixels having no forest cover and no forest cover change evenly around Uganda, and calculated the mean and slope of these pixels. This was to possibly make a final large-scale correction of the ΔH_{corr1}.

Combined filtering away artifacts of the SRTM X-band DEM and C- to X-band correction

We developed a model for a height correction between the C-band and the X-band DEMs, representing the difference in penetration depth into the forest canopy. First, we assumed that the artifacts estimated in step 1, above, were errors in the C-band DEM, and we used them to correct the C-band DEM. The height difference between the X-band DEM and the corrected C-band DEM has two components, - penetration differences and artifacts of the X-band DEM. It was crucial to estimate these two sources of difference simultaneously with one model. The model type we used was based on the assumption that the penetration difference increase from zero in non-forest pixels linearly with the density of the forest canopy, and we used forest cover from the GFC data set as a proxy for canopy density. The X-band artifact removal and penetration difference were estimated with a GLM model. With this we derived specific correction models were made for 8 land cover types, i.e. Evergreen Broadleaf Forest; Woody Savanna; Savannas; Grasslands; Permanent Wetlands; Croplands; Urban and Built-Up; and Cropland/Natural Vegetation Mosaic. With these models the corrections varied from zero in no-forest pixels up to some decimeters in densely forested pixels.

Filling of voids and unreliable data occurrences

There were certain void areas in the SRTM C-band data, and as well some extreme values outside the range of plausible values. We discarded such pixel values and replaced them with plausible values. First, the pixels to be discarded were identified in steep areas. Such pixels were found mainly in steep terrain and near water bodies indicating inaccuracy in the outline of water bodies. A careful and visual examination of these occurrences revealed that pixels in terrain steeper than about 30° had unreliable height change values. We discarded pixels above the 99% quantile of slopes, i.e. pixels having a slope > 29.6 degrees. Furthermore, we discarded height change values exceeding +-25 m, which made up 0.56 ‰ of the observations. The +-25 threshold was found after careful examination of extreme values. Large and real changes were seen as clear-cut areas, fitting well with the 'loss' category in

GFC changes, and as well in some cases forest growth was evident e.g. following exactly the outline of protected areas. The maximum height changes found in these cases were ±20, while a few cases of height changes up to ±25 m were found.

These pixels were replaced in the following way: There were assigned with the mean height change of pixels in the same land cover type and the same Global Forest Cover (GFC) change category. This means for example that a given void pixel occurring in a woody savannah and tagged as 'forest loss' in GFC was assigned the mean value of all woody savannah pixels tagged as 'forest loss' in GFC. In this GLM model we discarded pixels having a slope steeper than 30° or having a height change more than 25 m.

Recalculating ΔH to ΔAGB

The conversion was based on proportionality, i.e. that ΔAGB = 18.4 * ΔH for an evergreen broadleaf forest and ΔAGB = 14.1 * ΔH for all other land cover types. This stems from 2 regression analyses from similar forest types in Tanzania. Altogether, we have 4 relationships from different case studies (Fig. 1), where the relationship between AGB and InSAR is described as proportionality. The slope varies fairly little, i.e. AGB = 14.1 * H in a Tanzanian woodland, AGB = 18.6 * H in a Tanzanian evergreen forest in the mountains with exceptionally high biomass values, AGB = 14.8 * H in a Norwegian spruce forest, and AGB = 13.0 * H in a virgin rainforest in Brazil. The slopes are remarkably similar, with an average of AGB = 15.1 * H. So, what separates these forest types is not so much the slope of the relationship, but the height above-ground of the radar echo. The Tanzanian woodland is characterized by scattered trees and groups of trees, - a very open forest with very low biomass. Here, the radar echo is typically some 5 m above ground, which corresponds to 7 * 14.1 = 70 t/ha in above-ground biomass. On the other end of the scale we have the Tanzanian evergreen mountain forest, which has perhaps the highest above-ground biomass density in the world, with values up to about 1000 t/ha. This corresponds to a radar echo of about 55 m above ground * 18.4 = 1000 t/ha. It is unlikely that the forests of Uganda would be more different from the Tanzanian forests than a Norwegian spruce forest is, and a Brazilian rainforest is. It is likely that the mean Ugandan forest is also around 15.1, or about 14 in the savannah-like forest types and about 18 in the mountain evergreens. However, using a mean value of 15.1 all over is hence one reasonable alternative, since the evergreens make up a smaller part of the country.

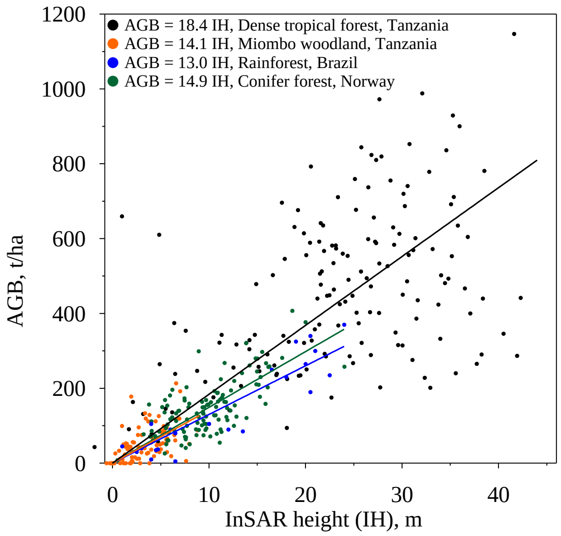


Fig. 1. Above-ground biomass plotted against mean InSAR height for four different data sets and with linear, no-intercept model fits. This includes an evergreen, mountain forest in Tanzania, (black dots) a miombo woodland in Tanzania (orange dots) (Solberg et al. 2015); a rainforest in Brazil (blue dots) (Neeff et al. 2005); and a conifer forest in Norway (green dots) (Solberg et al. 2014).

There is a tendency to heteroscedasticity, although there are points with severe residuals also at low InSAR height values. We decided that heteroscedasticity is likely not to be an important part of the total uncertainty.

Recalculating ΔAGB to ΔB

The recalculation, or expansion of above ground biomass to total biomass was based on standard IPCC guideline values found in IPCC's Emission Factor Data Base (EFDB). We used two models (Table ?).

Table ?.

IPCC guidelines

IPCC main category	Sub-category	Model	Used in Uganda	ref
Tropical / sup - tropical forest	Primary tropical/sub-tropical moist forest	B = 1.24*AGB ±0.03	Evergreen Broadleaf Forest	33, 57, 63, 67, 69
Other	Woodland/savanna	B = 1.48*AGB ±0.19	All other types	10-12, 21, 27, 49, 65, 73, 74

Recalculating ΔB to ΔC and CO_2 emissions

It was assumed that 50% of the biomass was C with a 95% confidence interval of 2%. This is the IPCC default factor (IPCC 2006, Vol.4 AFOLU, p. 5.17). The conversion of C to CO_2 emissions is based on stoichiometry and atomic masses of C and O. We calculated ΔC and CO_2 emissions for entire Uganda, including urban areas and farmlands, assuming that trees are present also in these categories of land cover. The surface height in villages and cities may change over time due to non-forest changes, e.g. due to construction of new buildings, however; these changes will cover negligible areas.

We have here estimated carbon change from biomass change, while soil carbon changes are not included as they would make up a minor and uncertain fraction. Available literature consistently suggest that soil carbon losses would make up about 5 - 10% of total carbon losses if a savannah is converted to a cropland (Table 3). This is the land cover conversion type having the most severe soil carbon loss. If we consider that Uganda's overall decrease in forest biomass is only partly made up of such severe conversions, the expected fraction of soil carbon loss would be about 2-5%.

Table 3. The relative contribution of soil carbon loss in a conversion from savannah to cropland

	Before	After	Loss	Relative loss	Comment
Biomass C	60	0	60	86%	Don et al. 2011, worst case

Soil C	40	30	10	14%	
Total	100	30	70		
Biomass C	60	0	60	91%	Don et al. 2011, worst case
Soil C	40	34	6	9%	
Total	100	34	66		
Biomass C	85	0	85	97%	IPCC guidelines
Soil C	15	10	5	3%	
Total	100	10	90		

<u>Uncertainty estimation</u>

For REDD+ purposes it is required to describe and quantify uncertainty. There are 3 main uncertainty issues with our estimated carbon change (ΔC) for Uganda. First, the height measurements we use were imperfect, in the sense that the SRTM data had considerable errors (artifacts) which had to be removed prior to the modeling. Second, our ΔC was a synthetic estimate, in the sense that our measurements were not of ΔC but rather of the auxiliary variable ΔH, and we used a model to convert from ΔH to ΔC. Finally, we used external models, in the sense that the models were not developed and calibrated with field data from Uganda. The conversion from ΔH to ΔAGB was based on studies in Tanzania, while the other steps were based on several studies in various countries (IPCC guidelines). Altogether, there was a sequence of processing steps, each of which had an uncertainty. Rather than deriving the overall uncertainty by combining the uncertainty of each step, we estimated the uncertainty with Monte Carlo (MC) simulation. We generated 45 random samples; each containing approximately 4 million pixels which corresponded to 1% of the total data set of about 400 million pixels. We processed each of these 45 samples 5 times, i.e. 225 processing batches. In each process the initial ΔH value was sequentially corrected and used to estimate ΔC. The sequence of processing consisted of 6 steps:

1. error removal of C-band SRTM,
2. correction from C to X-band SRTM,
3. replacing voids and extreme, illegal values with values specific the given land cover and forest change category,
4. recalculating ΔH to ΔAGB,
5. expansion of ΔAGB to ΔB,
6. recalculating ΔB to ΔC (IPCC GPG LULUCF 2006, p. 5.17).

Between each of the 225 batches we varied the parameter estimates of each step, letting them vary according to their standard error assuming a Gaussian distribution. This means that each of the parameters got 225 different values. From this we obtained 225 ΔC values. The variation between the 225 MC simulations was attributable to two sources:

1. the sampling error, i.e. the mean value of each of the 45 sample's deviation from the overall mean, and
2. the variation attributable to uncertainty in the 6 processing steps.

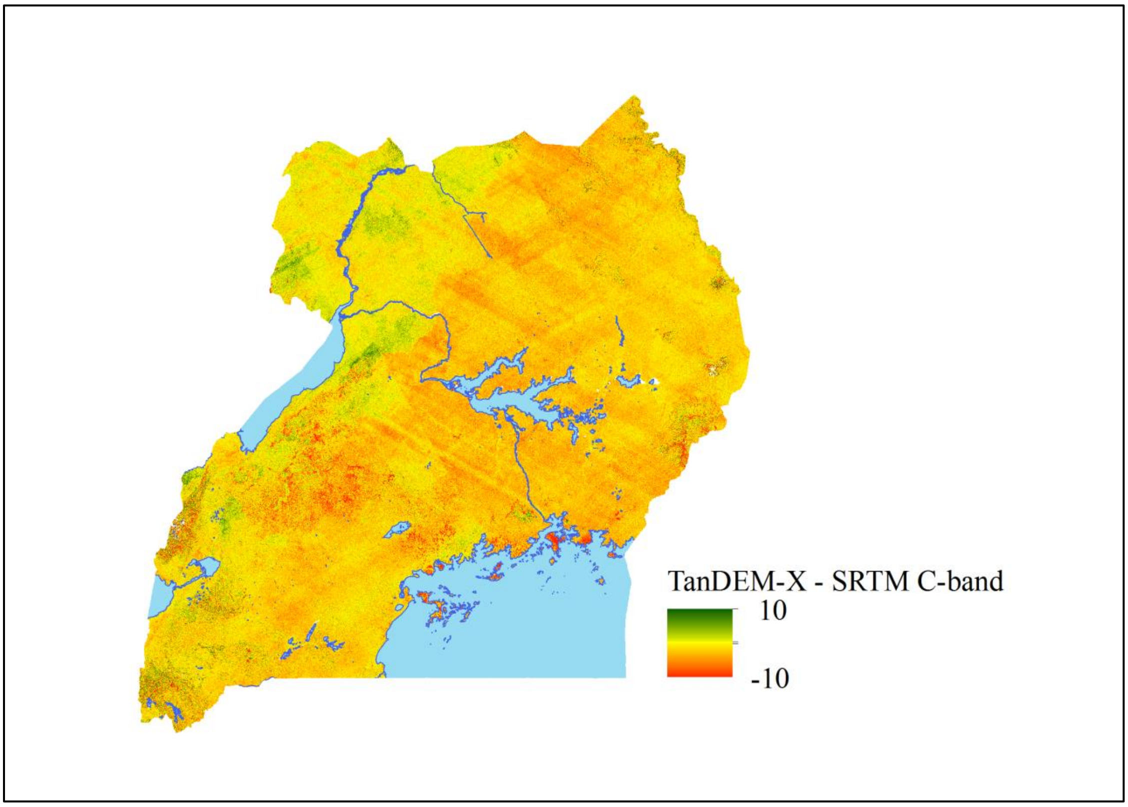
The latter is the uncertainty we wish to quantify. We could have run the MC on the entire data set, however, it turned out to be very time consuming and less feasible from a technical point of view. We would then avoid the sample error. However, by having 5 replicates of each sample, we can separate the two sources of variability in the MC from each other using an ANOVA:

(4) $\Delta C_{ij} = \text{Sample}_i + e_{ij}$,

where i = 1…45, j=1…5, and *e* was the residual error i.e. the estimate of the uncertainty due to the 6 processing steps.

Results and discussion

The artifacts (errors) of the C-band DEM was successfully removed using the ANOVA modeled filter. These errors occurred visibly in the height change from SRTM to tandem-X DEM. The artifacts were clearly visible at the country scale, and the results of the filtering is shown in Fig2. No further adjustment for bias or ramp was required, as such trends were negligible. Based on 18728 no-forest points evenly selected over Uganda we found that the remaining bias was 0.9 mm, and we found a 16 mm upslope from west to east and an 8 mm upslope from North to South.



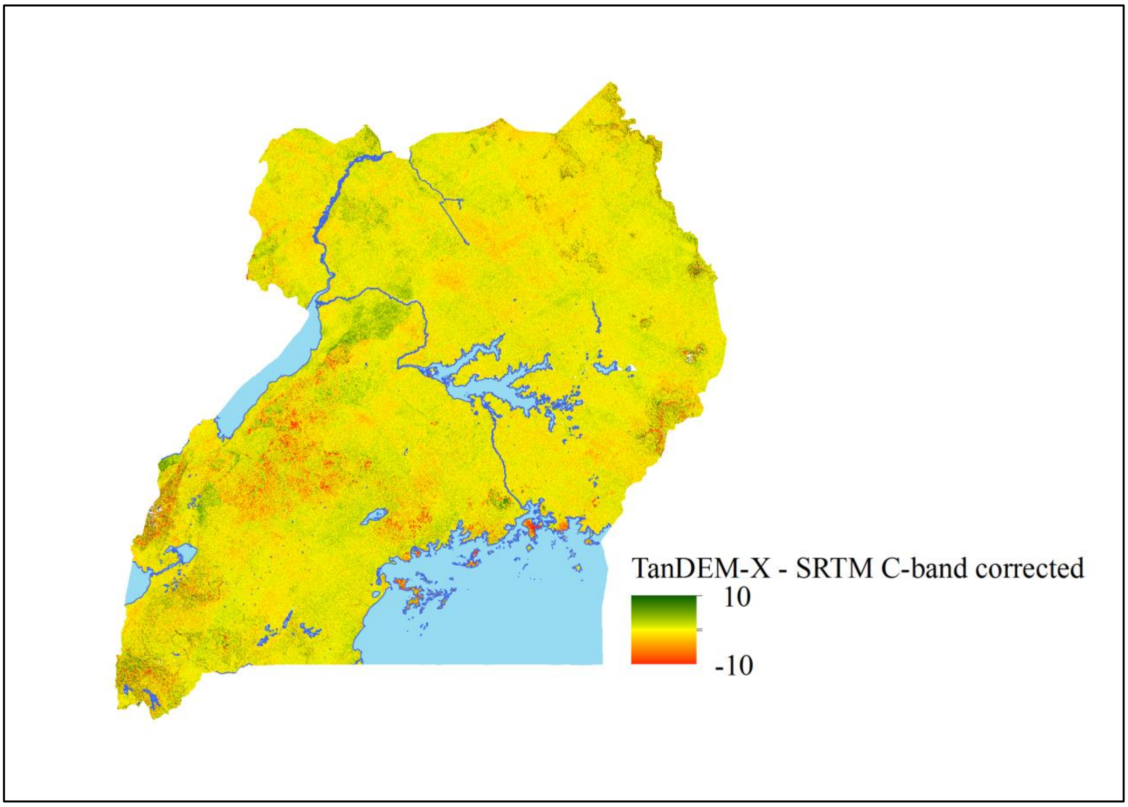


Fig. 2. Removal of artifacts of the SRTM C-band DEM demonstrated for the 2000-2012 difference image for entire Uganda. 2a. ΔH_{corr1}, 2b. the corrected height change $\Delta H_{corr1.}$

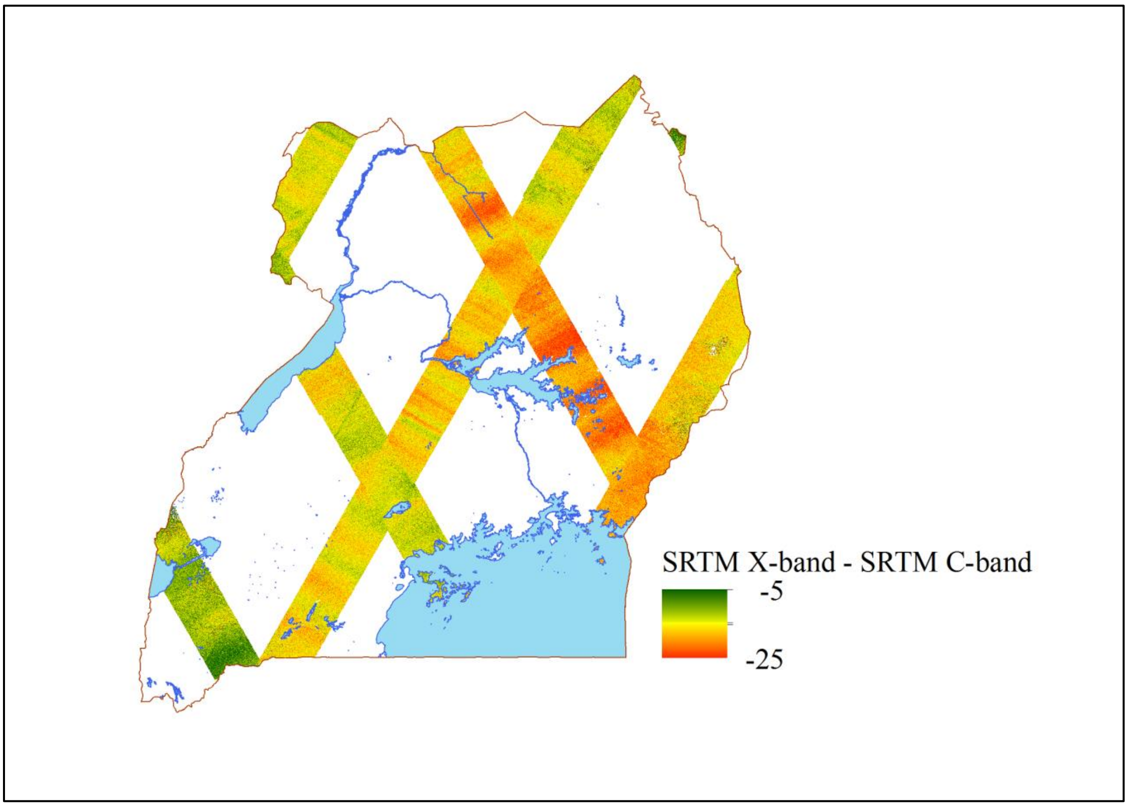
The artifacts of the X-band were successfully removed by the GLM model, and at the same time we fitted the penetration difference between X and C-band into the forest canopy depending on land cover type. The obtained parameter estimates for the penetration difference varied somewhat between land cover types, however; they were all on the same order of magnitude, and fairly similar values, and reasonable magnitudes. This model assigned no change for no-forested areas increasing up to about 30 cm – 1.5 m increase in a dense forest (Table 3).

Table 3. Parameter estimates for height correction going from C- to X-band, given in m per % forest cover, and by land cover type

land cover	Estimate	Standard Error	correction (m) at 100% forest cover
Evergreen Broadleaf Forest	0.0059	2.71E-05	0.59
Woody Savanna	0.0096	3.21E-05	0.96
Savannas	0.0029	5.13E-05	0.29
Grasslands	0.0147	9.31E-05	1.47
Permanent Wetlands	0.0134	7.75E-05	1.34
Croplands	0.0049	9.26E-05	0.49

Cropland/Natural Vegetation Mosaic	0.0042	3.29E-05	0.42
others / mixed	0.0018	1.70E-04	0.18

The GLM model is visualized on the entire Uganda land area (Fig. 3). The artifacts clearly occurred as lines across the X-band belts. As demonstrated in Fig. 3c, the model residuals occurred as a minor random noise.



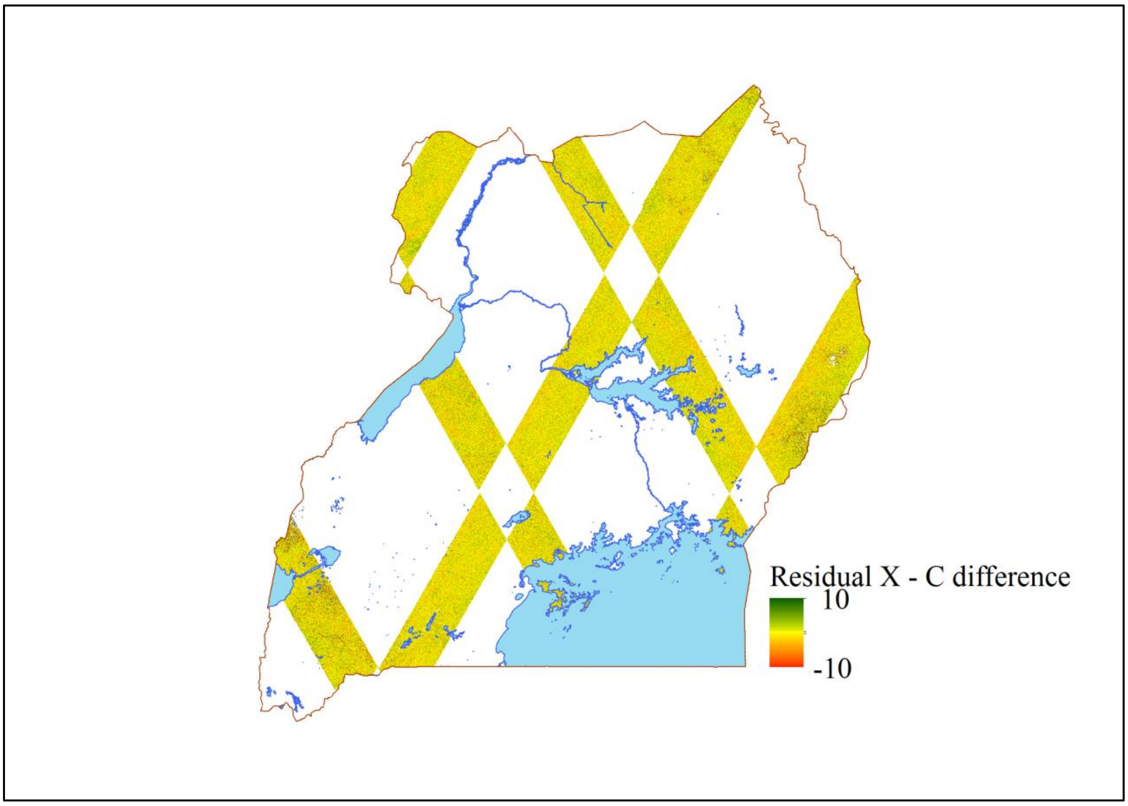


Fig. 3. Removal of artifacts (errors) in the X-band DEM and estimation of corrections for difference in penetration between X- and C-band. 2a. difference, 2b. the residual.

Applying the correction model from C- to X-band resulted in a lifting of the C-band DEM up to a simulated X-band DEM. The lifting varied from zero up to about 1.5 m. Clearly, the lifting was mainly confounded to some dense forest areas around Uganda (Fig. 4).

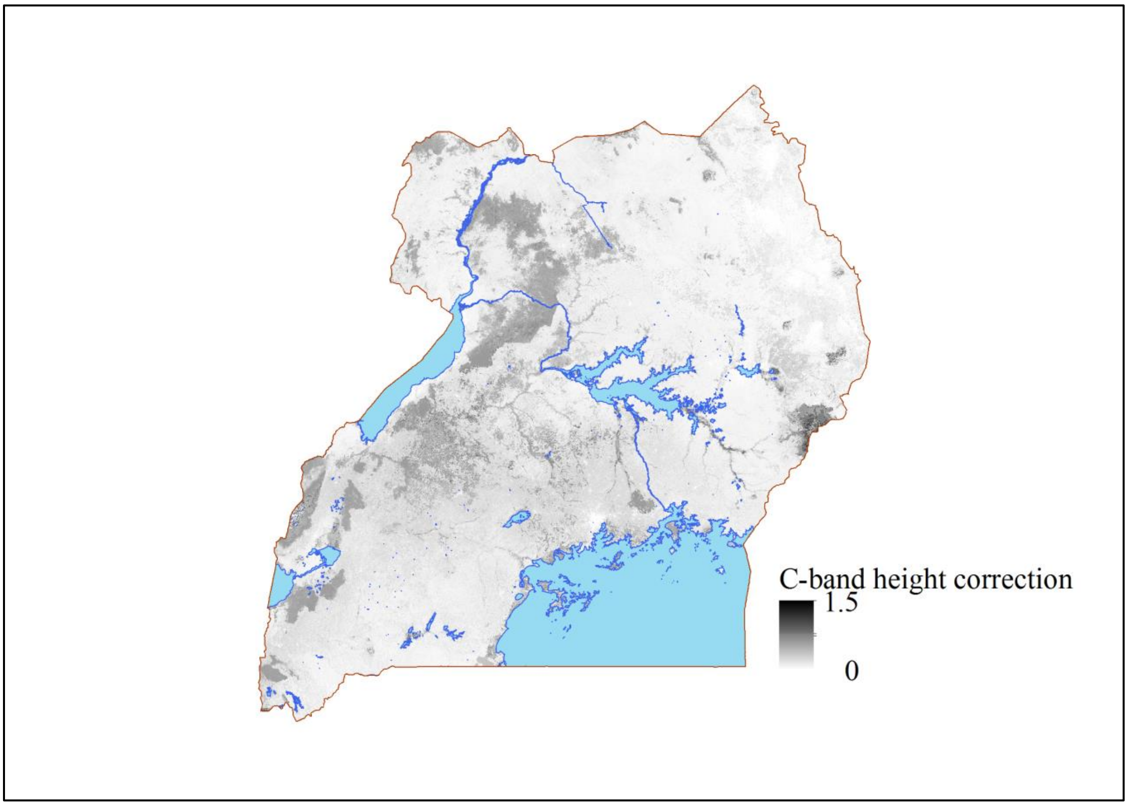


Fig. 4. The lifting of the C-band DEM based on the GLM model (2).

After these corrections we obtained the corrected height change ΔH_{corr2} as shown in Fig. 5.

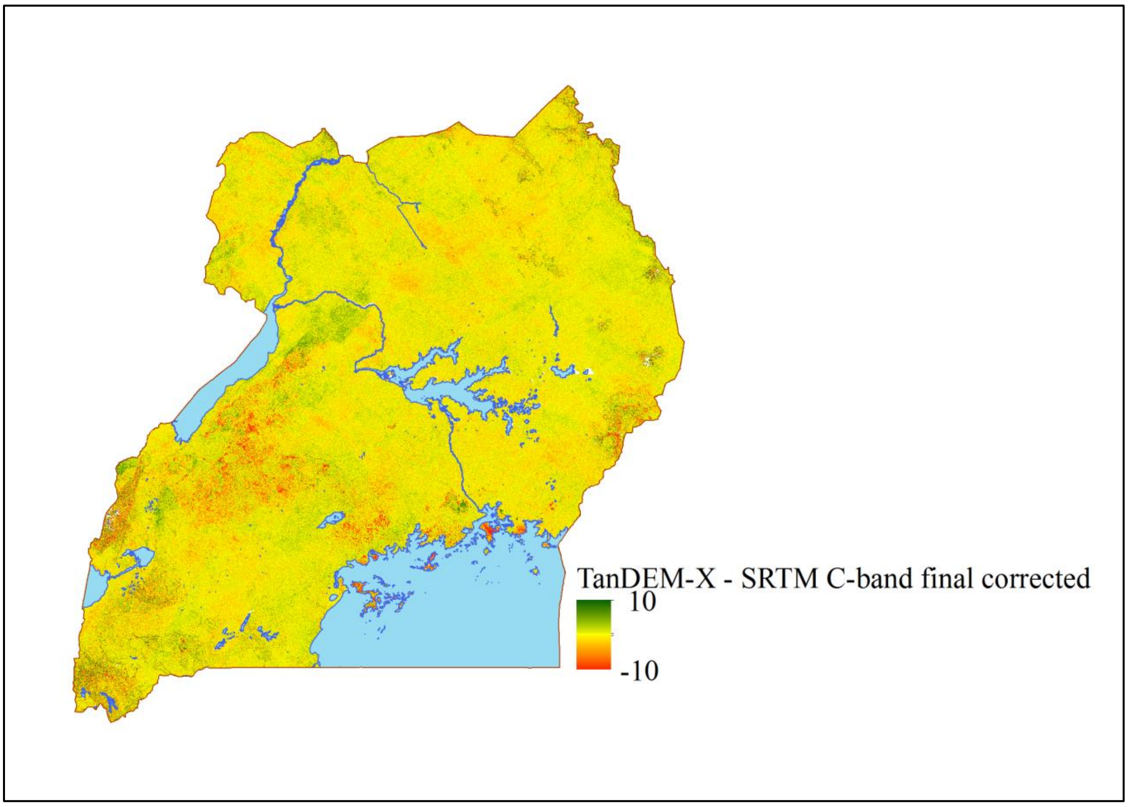


Fig. 5. The corrected height change ΔH_{corr2}

No further adjustment for bias or ramp was required, as such trends were negligible. Based on 18728 no-forest points evenly selected over Uganda we found that the remaining bias was 0.9 mm, and we found a 16 mm upslope from west to east and an 8 mm upslope from North to South.

Correction of voids and unreliable values

The gain and loss categories of GFC corresponded to reasonable height change values, - at least in most cases. The evergreen broadleaf forest typically containing tall trees had the largest height decrease estimate for forest loss, i.e. an 8.8 m decrease. The other land cover types had height decreases in the range 1.2 (savannah) to 3.7 m (woody savannah). The height changes estimated for no change and gain were generally minor, with values ranging from -1.0 to 1.8 m. For three land cover types the estimated height increase for the category 'gain' was slightly smaller than that for 'no change'. This is unreliable, and is interpreted as a possible effect of random errors. However, we kept all parameter estimates in the further analyses.

Overall result

The mean forest height change for entire Uganda was - 0.309 m, i.e. an annual decrease

ΔH = - 2.6 cm.

The mean carbon stock change was ΔC = -3.31 t/ha, i.e. an annual decrease of 0.28 t/ha. If we aggregate the carbon stock change for entire Uganda we get an annual decrease of

$\underline{\Delta C}$ = 0.28 t/ha * 204 571 km2 * 100 ha/km2 = 5 642 750 t = <u>5.6 million t/year</u>

Which corresponds to an annual CO_2 emission of

$\underline{\Delta CO_2}$ = 5 642 750 t/year * 44/12 t_{CO2}/t_C = 20690084 t/year = <u>20.7 million t/year</u>

Hence, the 2.6 cm corresponded to an annual CO_2 emission of 21 million tons, and further to a payment value of 105 million US$. The meaning of this is that if Uganda managed to stop the CO_2 emissions from forests by increasing forest growth or reducing logging it would earn a REDD+ credit of 105 million US$ per year from a donor country. The conversion from CO_2 emissions to payment value is here done by multiplication of the CO_2 emission by 5 US$. This value has been mentioned several times by the Norwegian government as the target payment value. In Brazil, however, the Norwegian government pays only 0.5 US$ per ton CO_2, simply because Brazil is so large that our government cannot afford more. In addition, it is a careful and low value because the CO_2 emissions estimated from Landsat-data is very uncertain.

The strength of the InSAR approach for forest carbon monitoring is apparent in some areas containing protected areas. Certainly, there has been a carbon stock gain in some protected areas, surrounded by deforestation in their vicinity (Fig. 6, left). These carbon gains occur through forest growth and cannot be detected by Landsat-like satellite data, as seen in the Global Forest Cover databases (Fig. 6, right). There is a very clear correspondence between the losses as seen by InSAR and as seen by Landsat, likely because the losses has occurred as deforestation which is easily detected by Landsat.

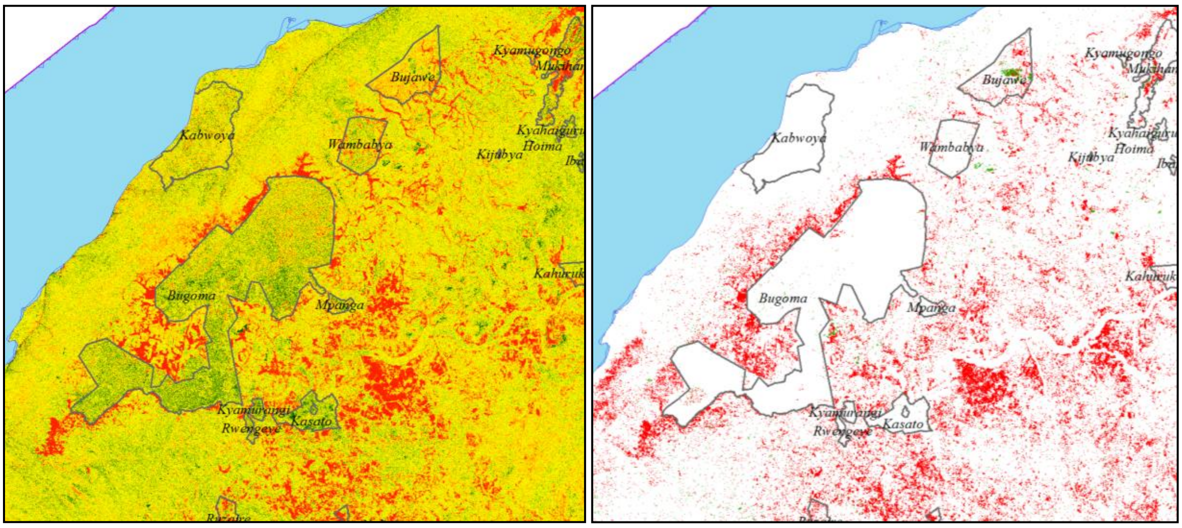
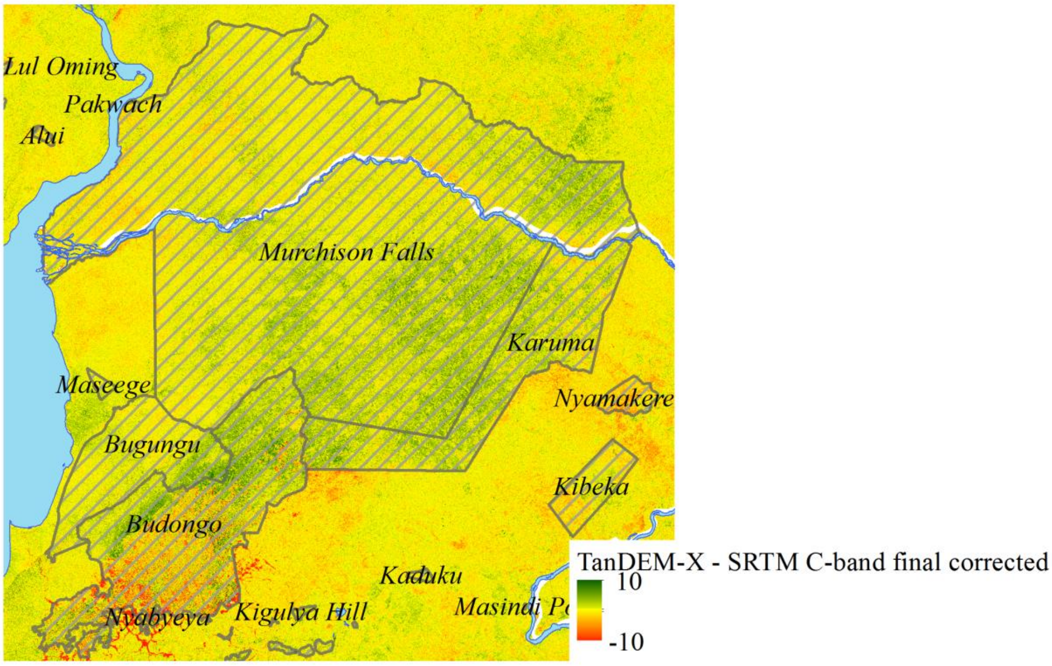


Fig. 6. Forest height changes 2000 to 2012 inside and outside of some protected areas (left). To the right is shown the Global Forest Cover data based on Landsat, i.e. gains (green) and losses (red) for the same area, where the real gains inside the protected areas are hardly detected, while the losses correspond well to the InSAR data.



Uncertainty

For the 12 year change in carbon stock the ANOVA on the Monte Carlo analyses produced a Mean Square on the residuals (MSe) to be 0.494 (Table x), corresponding to a

95% confidence interval = 1.96 * SQRT(0.494) = 1.378 t/ha.

This corresponds to

95% confidence interval (%) = 1.378/3.31 = 0.416 = 41.6%.

The ΔC 95% confidence interval for annual changes on entire Uganda is then = ±41.6% * 5.6 million t/year = ±2.33 mill t/year.

Similarly, the ΔCO_2 95% confidence interval for annual CO_2 emissions for entire Uganda, is then ±2.33 mill t/year * 44/12 = ±8.5 million t/year.

Altogether, the estimated annual CO2 emission with 95% confidence interval is

ΔCO_2 = 20.7 ±8.5 million t/year

Table x. ANOVA results from Monte Carlo analyses:

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	44	24.8306247	0.5643324	1.14	0.2691
Error	180	88.8865987	0.4938144		
Corrected Total	224	113.7172234			

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The work is carried out at NIBIO (the Norwegian Institute Bioeconomy, - former Norwegian Forest and Landscape Institute) of based on InSAR. A company, Forest Vision, has been established for possibly providing services on a commercial basis. The innovation center Kjeller Innovasjon has established the company, which is tightly linked to NIBIO. The Norwegian Research council has funded this study as one among some large scale demonstration cases with the method. The present study is the first, and covers Uganda. The next study will be on Tanzania. A strong co-operation is established with Airbus Defense and Space and the German Aerospace Center. The results of the Uganda demonstrator are to be presented at the FAO world congress in Durban, South Africa September 2015, and possibly at the COP meeting in Paris later in the autumn.

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Appendix 1. SAS program

Appendix 2. Other programs