USE OF REMOTE SENSING PRODUCTS IN A TERRESTRIAL ECOSYSTEMS VERIFIED FULL CARBON ACCOUNT: EXPERIENCES FROM RUSSIA

Anatoly Shvidenko (1), Dmitry Schepaschenko (1,2), Ian McCallum(1), Maurizio Santoro(3), Christine Schmullius(4)

(1 International Institute for Applied Systems Analysis, A-2361 Laxenburg, Austria, Email: shvidenk@iiasa.ac.at;
(2 Moscow State Forest University, Mytischi-5, Moscow region, Russia, Email: schepd@iiasa.ac.at
(3) Gamma Remote Sensing, CH-3073 Gümligen, Switzerland, santoro@gamma-rs.ch
(4) Friedrich-Schiller University, D-07743 Jena, Germany, c.schmullius@uni-jena.de

ABSTRACT

The paper considers the specifics, strengths and weaknesses of available remote sensing products within major steps and modules of a verified terrestrial ecosystems full carbon account (FCA) of Russia's land. The methodology used is based on system integration of all available information sources and major methods of carbon accounting using IIASA's landscape-ecosystem approach for overall designing of the account. A multi-sensor remote sensing concept is a corner stone of the methodology being substantially used for (1) georeferencing and parametrization of land cover and its change, (2) assessment of important biophysical and ecological parameters of ecosystems and landscapes, and (3) assessment of the impacts of environmental conditions on ecosystem productivity and disturbance regimes. System integration and mutual constraints of remote sensing and ground information allow for substantially decreasing uncertainty of the FCA. In the Russian case-study, the net ecosystem carbon balance of Russia for an individual year (2009) is estimated with uncertainty at 25-30% (CI 0.9), that presumably should satisfy current requirements to the FCA at the national (continental) scale.

1. INTRODUCTION

High uncertainties surrounding assessment of the impacts of terrestrial ecosystems on global and regional carbon cycling hinder the reasonable inclusion of the terrestrial biosphere in the post Kyoto international negotiations. Overcoming this problem requires assessment of the uncertainties and their reduction to a level that would be acceptable for policy-makers. It leads to a need for a *verified* terrestrial ecosystem full carbon account (FCA) as a methodology that would comprise all ecosystems and all processes in a spatially explicit fashion and continuously over time, would allow to comprehensively and reliably assess uncertainty, and present information for management of uncertainties, particularly if they do not provide a preliminary settled level [1]. The major idea beyond this approach is the understanding of the FCA as a "full complexity" problem, i.e. ill-defined and quasi-manageable task, that is (1) structurally, functionally and dynamically intricate; (2) non-separable from context, observation and interest; (3) multi-objective/subjective; (4) inherently uncertain due to incomplete knowledge and (5) is practically non-verified by any strict formal methods (cf. [2]). It leads to a principal conclusion: it is not possible to estimate uncertainty of the FCA at national or continental scales in a reliable and comprehensive way if any of the major methods of FCA (i.e. landscape-ecosystem approach; dynamic vegetation models; direct measurements of ecosystem-atmosphere carbon exchange; and inverse modeling) are used individually.

In our attempt to provide a FCA for Russian terrestrial ecosystems, we developed a methodology that takes into consideration (1) the fuzzy character of the studied system; (2) strengths and weaknesses of major individual approaches to carbon accounting; (3) possibility to provide synergetic combination of different information sources of different details and reliability, particularly for remote territories of polar and boreal zones; (4) abundance of vast territories with rapid changes, mostly after natural and human-induced disturbances; (5) lack of knowledge of some important processes; and (6) availability of temporal trends and substantial seasonal variability of major components of the carbon budget. The guiding idea of such a methodology is that only system integration of relevant information sources and different methods of the account, which are obtained independently, are able to extract maximum information on the ecosystem carbon budget. A landscape-ecosystem approach (LEA) is used as a system background and for overall designing of the FCA and defining intra- and inter-system boundaries. The FCA within LEA is provided as a complimentary combination of pool-based and flux-based methods. Estimates received by other methods of carbon accounting are used for comparative analysis, harmonization and multiple constraints of the results and corresponding uncertainties. The information environment of LEA is organized in the form of an Integrated Land Information System (ILIS) of Russia, for 2009. The ILIS integrates all relevant information sources - cartographical materials (digitized maps of vegetation, land use – land cover, soil, landscapes, administrative maps etc.), data of different inventories and surveys (State Land Account, State Forest

Proc. 'Earth Observation for Land-Atmosphere Interaction Science', Frascati, Italy
3 –5 November 2010 (ESA SP-688, January 2011)

Account, fire maps etc.), diverse databases of *in situ* measurements (live biomass, net primary production, heterotrophic respiration and many others), spatially distributed climate data, relevant remote sensing products, numerous auxiliary models for assessment of biophysical indicators of ecosystems etc. This information is organized around a hybrid land cover land cover at the spatial resolution of 1 km^2. A multi-sensor remote sensing concept is a corner stone of the methodology of the FCA being substantially used for (1) classification, georeferencing and parametrization of land cover and its change, (2) estimation of important biophysical and ecological parameters of ecosystems and landscapes, and (3) assessment of the impacts of environmental conditions on ecosystem productivity and disturbance regimes.

2. DEVELOPMENT OF HYBRID LAND COVER

Current ground information on land cover and state of terrestrial ecosystems for vast, mostly sparsely populated territories of Northern Eurasia is not satisfactory. Official statistics systematically report obsolete data of unknown accuracy for large parts of the region. The region is represented by substantial areas of rapid change (burnt forest area, industrially transformed territories etc.). Thus, remote sensing remains the most important tool for representing the updated land cover. However, there is an evident trade-off between a need to cover large territories, required minuteness of the FCA, and technical capabilities of remote sensing products.

The major idea, realized in development of the hybrid land cover, was combining the different sources of information for georeferencing and parameterizing hierarchical classification of land classes with stepwise inclusion of remotely sensed and ground information of known reliability. At the first stage, two land cover datasets were used: the GLC2000 (GLC) [3] and MODIS land cover. GLC seems to be the most reliable product, validated by regional experts [4]. MODIS land cover on the other hand provides the most up to date information. The MODIS Vegetation Continuous Fields (VCF) product is an annual representation of percent tree, herbaceous/shrublands and barren cover for each pixel [5]. The VCF provides the necessary flexibility, allowing us to prioritize the assignment of statistical data to land cover data. These three products allowed for identifying aggregated land classes – unproductive land, agricultural land, forest, wetlands, grasslands, and shrubs.

A number of key GIS datasets was used to assign data from different statistical inventories - administrative region coverage (81 regions) and forest enterprises map (about 1600 polygons) updated for 2009. A soil database was one of the key components for selecting the appropriate area of arable land and wetlands. It contains a total of 292 unique soil types across the country with 21,988 polygons. The digitized soil map was developed by V.V. Dokuchaev Soil Science Institute (Moscow) in 1996 (1:2.5 Mil scale), edited by [6]. A vegetation dataset was also utilized to provide broad vegetation classes and bioclimatic zones (derived from the dataset titled Vegetation of the former USSR), produced at a scale of 1:4 Mil [7]. The dataset includes georeferencing of 101 vegetation classes and 8 bioclimatic zones (polar desert; tundra; forest tundra, northern & sparse taiga; middle taiga; southern taiga; temperate forests; steppe; deserts and semi-deserts). In order to account for data not captured in the above datasets due to small areas of individual polygons, but which could have substantial total areas (e.g.,. linear features; small waterbodies; harvested areas, etc), we relied on the Russian 1:1 Million Planimetric dataset to account for "*virtual polygons*". All of these virtual polygons (not presented on the map, but taken into account for the area balance and further calculations) were then tabulated per administrative region.

The State Forest Account (SFA) (http://www.roslesinforg.ru) contains statistics for approximately 1600 forest enterprises. The SFA data contains areas and growing stock by dominant forest species distributed by age, site index and relative stocking. There are approximately 50 sets of records for each enterprise on average [8]. The State Land Account (SLA) is provided annually by the State Committee of Land Resources of Russia based on land statistics. Originally, the SLA is provided by administrative districts (about 3000 for Russia) and contains areas by (approximately 50) land classes. The SLA contains a two-dimensional official Russian land-use and land-cover hierarchical classification. Land cover classes are defined by their dominant use and are based on natural and historical characteristics. They include agricultural (arable; fallow; hayfields; pastures; and perennial vegetation) and non-agricultural land classes (forest lands and lands under tree and shrub vegetation; built-up land; lands under roads; land of water fund; disturbed land – mining operations, earthmoving, etc.; and other land – ravines, sand, dumps etc.) [9].

We calculated the quantitative correspondence of statistics (forest and land account) and spatial (remote sensing, GIS) data – agreement index of land suitability (S_{ts}) for each pixel-pair (grid of territory (t) and statistics record (s)) within the territory unit (forest enterprise, administrative region).

$$S_{ts} = \frac{1}{q}\left(\sum_{j=1}^{q}(x_{tj}^{norm} - x_{sj}^{norm})^2\right)^{1/2}$$

where q - number of parameters;

$x_{tj}^{norm}, x_{sj}^{norm}$ - normalized value of parameter j for territory pixel t and j;

$$x_j^{norm} = \frac{x_j - x_{j\min}}{x_{j\max} - x_{j\min}}$$

where $x_{j\max}, x_{j\min}$ - maximum and minimum values of parameter j within the certain area (forest enterprise, administrative unit).

Data on a nominal scale, i.e. GLC land cover classes were ranked with respect to a certain vegetation class in the statistics.The resultant agreement index S varies from 0 to 1. It can be interpreted as a distance between objects (grid of territory and statistics record) within the space of parameters. The lower the index value, the higher agreement of initial datasets and more suitable is the current piece of territory for the given statistical data.

The final stage involved the optimization of distribution statistics data on the territory based on the agreement index results. The assignment of ground data to the most suitable grid for *forests* was provided using SFA data within each forest enterprise. SFA data were assigned to the 1-km grid applying the following parameters: GLC/MODIS to place species from the SFA in the most appropriate GLC/MODIS classes; VCF: to assign the highly stocked forests to cells with a high VCF_trees; NPP: to compare NPP derived from statistics and measured from Space; and Soil and vegetation zone maps to assign the most productive forests to the most appropriate soils and landscape elements.

For some administrative units, both remote sensing products (VCF, GLC) indicated forested area which exceeds the forested area found in the SFA. Generally these areas correspond to territories with obsolete forest inventory data (time since inventory more than 15 years) or areas of abandoned agriculture. We distinguish these kinds of forests using GLC "vegetation" classes and VCF_trees ≥ 21% (for Tundra, Forest-tundra and Sparse & Northern Taiga) and VCF_trees ≥ 35% (for forests situated southward of the middle taiga zones). For these areas we assign the most representative SFA records within the respective administrative units and forest enterprises. The productivity parameters (i.e. growing stock volume, NPP) of such forests were corrected by regional regressions in accordance with the VCF_trees level and controlled for some regions based on radar images (ASAR, PALSAR).

Appropriate procedures of combining remote sensing and ground data have been applied to other land classes. The State Land Account (SLA) contains the following *agricultural land* categories by administrative regions: arable land; hayfield; pasture; and fallow. Areas of these categories have been used for independent control. An "abandoned arable land" category was also introduced in accordance with estimates done by the Russian Academy of Agricultural Sciences and the Federal Service of State Statistics [10]. We also used the following sources to distribute agricultural land: GLC (Cropland, Cultivated area, Herbaceous cover and mosaics); MODIS land cover (croplands, cropland/natural vegetation mosaic); VCF_Herbaceous (maximum value exceeds 50%); and the Soil map (soil was ranked in order of potential agricultural productivity). The highest priority has been ascribed to arable land, then to abandoned arable, then other agricultural land. The final control was provided based on areas of currently cultivated land.

Wetlands were basically identified based on the soil map. Soils with a considerable peat layer (thickness >30 cm) as well as wet meadow and tundra soils were ranked with high probability, excluding the areas which had been classified as other above land classes based on remote sensing data (GLC, VCF). The SLA typically overestimates wetland area due to the definitions used, and the SFA typically underestimates regional wetland area because indicated only treeless bogs. The final wetlands area was assigned in the range of both land and forestry statistics based on the appropriate soil types. Finally, nine wetland classes were assigned according to vegetation zone, landscape peculiarities and soil type: polygon mires; palsa mires; aapa mires; raised string bogs; pine bogs; reed and sedge fens; marshes; flood plain wetlands; and eutrophic fens. *Open woodlands* were identified using the correlation between canopy closure and relative stocking of stands by tree species and vegetation zone. This area was distributed over remaining land with percent tree cover (VCF) in the range of 13-34%. For some regions and vegetation zones, area of open woodland proved to be higher than the area indicated by the SFA, particularly for the regions outside of the forest fund area. For such regions the entire area with a VCF_trees level in the range of 13-20 % were shifted to open woodland. Burnt area is presented in the SFA by forest enterprise. We combined burnt area in the SFA with that from remote sensing, and assigned it to the appropriate GLC class (10 – tree cover, burnt). The remaining area was distributed according to areas of low VCF_trees value, not previously assigned to other vegetation classes. The assignment of *shrub* and *grassland* was the final step in the assignment of vegetative land cover. There are no appropriate statistics recorded for this land class. Thus we used remote sensing data (VCF, GLC) to define the area. The vegetation dataset was used to classify shrub and grassland types. The GLC water class was used to assign water to the resultant coverage. Additionally we calculate virtual polygons: small water bodies and rivers which are not captured by remote sensing at the resolution 1 km. Unproductive polygons for our dataset were derived from the GLC coverage.

Application of the methodology described above has resulted in the new hybrid land cover/land use map of Russia at 1km resolution (fig.1) A total of six major land cover types were identified, namely: forest, agriculture, wetlands, shrubs/grasses, water and unproductive land. These are further subdivided into the following classes: forest – each grid links to the SFA database (the SFA data contains areas and growing stock by dominant forest species distributed by age, site index and relative stocking), containing 78639 records; agriculture – 6 classes, parameterized by 81 administrative units; wetlands – 8 classes, parameterized by 83 zones/regions; and shrub/grassland – 58 classes, parameterized by 321 zones/regions.

Figure 1. Land cover of Russia 2009

Direct validation of the Russian hybrid land cover dataset is rather difficult and we were able to do it only for some regions with a highly detailed and verified land cover (e.g., regions covered by previous projects SIBERIA and SIBERIA-II). As a validation procedure, we attempted to assess spatially the level of confidence in the assignment, based on the assessed agreement between the input datasets [11]. As a result, 52% of the country's area infers a high degree of confidence in the agreement among the remote sensing products and the statistics. Another 18% of the territory has good and 24% acceptable agreement between initial datasets. High disagreement has only about 5% of area. This is mostly sparse vegetation with typical forms of disagreement such as wetland-grassland in West Siberia and forest-tundra ecotones in East Siberia and the Far East. A large portion of this class ($36 \cdot 10^6$ ha) is situated in dry steppe and semi dessert zone of European Russia. In GLC it is indicated as "bare areas", but VCF shows herbaceous cover in the range of 61-98%. In accordance with the SLA data, we assigned "pasture" to this area. High disagreement also appears in mountains and on the outskirts of large cities where 1 km grid cannot perform better because of mosaic. Forest statistics incompleteness appears on about 1% of area. Most of the area lies in the European southern taiga (assumed to be abandoned agricultural area which is afforested) or in the north (outside of inventoried forest area). Overall, the confidence map showed a satisfactory confidence in the agreement between the various remote sensing and statistical datasets. Finally, the hybrid land cover was assigned on a per-pixel basis (1km) across the entire country following the general principle that the most accurate and updated information has priority in assignment.

3. ASSESSMENT OF BIOPHYSICAL INDICATORS AND PROCESSES

Limited size of this paper does not allow presenting here any detailed description of development of diverse layers of biophysical and other indicators included in the ILIS and used in the FCA (live biomass, NPP, HR, coarse woody debris among many others). Here we limit the consideration by several different typical examples. Some additional information on this could be found in publications (e.g., [12]).

Forests contains above 85% of live biomass (LB) of the country's vegetation. Thus the accuracy of estimation of forest LB is important within the FCA. For territories with reliable forest inventory data, assessment of LB is provided based on a system of multi-dimensional regressions which combine biomass extension factors with inventory indicators $R_i = \varphi(A, RS, SI)$, where $R_i = M_i/GCV$, $i = 7$, M_i denotes *LB* of stems, branches, foliage, roots, understory and green forest floor, and *GSV, A, RS* and *SI* are growing stock volume, age, relative stocking and site indexes, respectively, for stands of individual species by ecological region [13]. However, this approach cannot be directly applied to forests with outdated forest inventory data among which growing stock volume (GSV) is most important.

Spaceborn optical and short wave synthetic aperture radar (SAR) backscatter data (particularly limited by X and C bands) are not optimal for assessment of LB or GSV. However, a novel GSV retrieval approach from SAR data in the case of C-band Envisat ASAR images acquired in ScanSAR mode (100 m and 1 km spatial resolution) reported very promising results [14] based on the BIOMASAR algorithm. The BIOMASAR algorithm is implemented in a three-step procedure: (i) a SAR processing block to obtain co-registered stacks of SAR images, (ii) a Water-Cloud modeling solution expressing the backscatter as a function of GSV and (iii) a multi-temporal combination of individual GSV estimates. The retrieval of GSV showed no saturation, up to 300 m^3/ha, which represented the entire range of GSV in remote regions of the boreal zone with outdated inventories. The accuracy was between 34 and 48% using one year of ASAR data. The relative root mean square error (RMSE) improved substantially when averaging GSV estimates over neighboring pixels. The 25% level was reached for a pixel size of 1 km when starting from 100-m spatial resolution estimates. These results allowed to use the retrieved forest GSV from hyper-temporal stacks of C-band backscatter data for improving the assessment of forest LB. Note, that availability of the above mentioned system of interdependences of different components of LB with biometric indicators of stands allows to use different SAR bands for assessing certain components of biomass (e.g., the use of X band for estimating mass of foliage and twigs) and a following calculation of the entire LB including "hidden" components like below ground biomass. However, the resulted accuracy of such estimations depend on accuracy and adequacy of regional regressions included in the system.

Integration requires careful professional analysis of all components of the estimation procedures. The following example illustrates how substantial unrecognized biases could be. Based on results of measurements on about 5,000 sample plots, it has been recognized that during recent decades (1960-2000s) the structure of LB in Northern Eurasian forests has changed significantly [15]. Fig. 2 shows dynamics of ratio between dry mass of above ground wood, green parts and roots to GSV for all Russian forests normalized for values of 1983: the green parts have the highest rate of the change. An interesting fact is that average NDVI for this region is highly correlated with relative amount of the green parts. Taken into account the change of LB structure, the estimate of carbon sequestered by Russian forests is very close to the result following from forest inventories; disregarding these dynamics and using NDVI as the only proxy for changes in the total LB of Russian forests leads to overestimation of the carbon sequestration of about 3-fold during the 1982-1999 period [16].

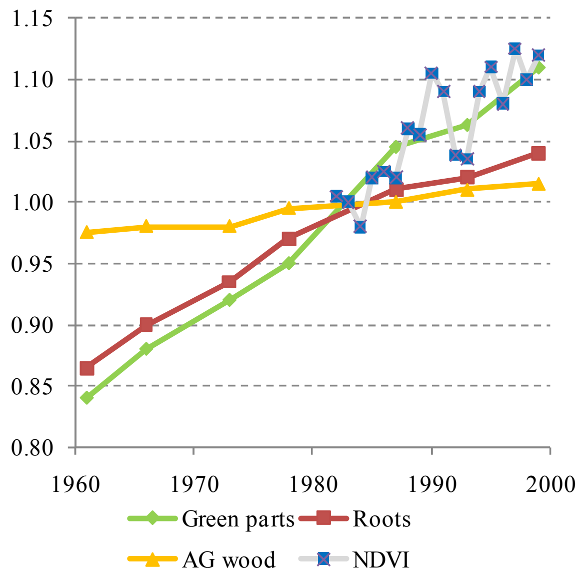

Figure 2. Alteration of live biomass structure in Russian forest 1961-1998

The MODIS net primary production (NPP) product [17] presents up to date estimation of vegetation productivity. Fig. 3 shows comparison of forest MODIS NPP with empirical assessment of NPP for ~1600 forest enterprises across Russia. The NPP by the individual enterprises was defined with uncertainty at 10-12%. Weighted mean MODIS NPP (310 g C m^{-2} yr^{-1}) and Empirical NPP (316) are almost identical for the whole country (the difference is in limits of 2%), there are substantial bias in MODIS NPP for low productive and high productive forests. Likely, these differences follow from substantially different physiognomic characteristics of forest canopy (mostly larch forests in the first case and dark coniferous forests in the second).

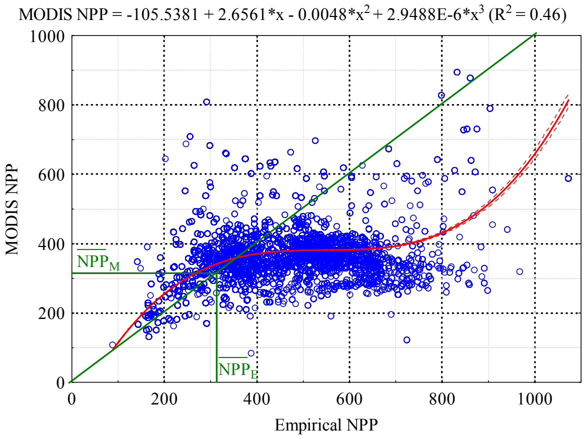

Figure 3. Empirical NPP vs. MODIS NPP (average by forest enterprises)

Natural disturbance plays a large role in shaping the landscape of northern Eurasia. Wildfire is responsible for large areas of annual land cover change. There are several RS sources for assessing burnt areas and severity of fire. Two major remote sensing products used in Russia for detection of vegetation fire - VGT and AVHRR - have a similar temporal resolution and nadir spatial resolution. VGT has better geometric fidelity, radiometric calibration, multi-spectral registration, multi-temporal registration, and absolute geolocation, but has no thermal channels. The latter is important for Russian forests with the dominance of ground fire. It leads to substantial seasonal variation of the number of fires and area burnt defined by these two products. However, detection of large fires (>200 ha), which comprise about 90% of burnt areas in the country, particularly for long periods, are rather similar. Burnt areas defined by VGT, AVHRR and indicated in GFED3 (e.g., [18-19]) have similar attitude and uncertainty – the difference between total burnt area during the last decade does not exceed 15%. However, the diversity of reported burnt areas in Russia (and, consequently, emissions of greenhouse gases) remains. The average area of vegetation fire from 2003-2007 in [20] is reported to be 19.6 million ha included 6.9 million ha in forest. The estimate [21] of burnt area in forest is 3.9 million ha for the same period. Both of these assessments are based on the same remote sensing products (Terra-MODIS).

In this study, wildfire data were acquired based on the Advanced Very High Resolution Radiometer (AVHRR) (hot spots) with control of burnt area by the LANDSAT Thematic Mapper [22]. The dataset contains burnt area and the date of fire for each 1 km^2 pixel. The average burnt area in 1998-2009 is estimated to be 9.0 million ha that is closed to GFED3 estimate (9.2 million ha). These data are assumed substantially more reliable than official fire statistics [23]. The second crucial indicator for assessing fire emissions is severity of fire. Following a number of studies (e.g., [24-25]), fire radiative power (energy) seems to be a very promising indicator for assessing fire severity. However, quantification of this approach requires development of regional empirical models which would connect amount of consumed fuel with fire radiative power signal for different types of fire, particularly peat and steady ground fire on in forests. Our estimate of the amount of carbon consumed by fire in all ecosystems in 1998-2009 was estimated at 20% more than the estimation of GFED3 for the same period (127 Tg C yr^{-1}).

4. DISCUSSION

This study has demonstrated the ability and benefits of system integration of different information sources into an integrated information system for solution of complicated ecological problems, like assessment of carbon cycling on large areas. Every source of information has its advantages and shortcomings. Multi-sensor remote sensing supplies the most up-to-date information, but a lack of parameterization and interpretation. Land statistics are the best parameterized product, but lack spatial distribution and are partially out-of-date. GIS datasets are explicit spatially, well parameterized, but also often out-of-date. The ILIS uses the advantages of all sources, supplies up-to-date geographically explicit and well parameterised information, thus allowing for reduction of all source's uncertainties. The main advantage of the methodology is the ability to link on-ground data and models to the remote sensing products. The algorithm presented in this study for hybrid land cover development is flexible, allowing for the inclusion of additional existing datasets or newly created datasets in the future (i.e. elevation, lidar biomass, and more).

As a result obtained within the landscape-ecosystem approach, the Net Ecosystem Carbon Balance of Russia was estimated at 0.6±0.25 Pg C yr^{-1}. This value is subject to changes in limits of ±10-15% dependently on different account's boundaries. The application of an ensemble of different Dynamic Global Vegetation Models which are substantially based on remote sensing products showed a rather good consistency of estimates of major carbon fluxes (e.g., NPP) for the entire country; however the estimates for large regions (e.g., bioclimatic zones) are less reliable and often substantially biased. Recent results for Russian land received from four different inversion approaches gave a mean -0.65±0.12 PgC yr^{-1} (inter-model variability) and a median -0.61 Pg C yr^{-1} [26]. Overall, the methodology used allowed assessing the Net Ecosystem Carbon Balance for Russia with uncertainty of 25-30% (CI 0.9) likely suitable for decision making in the post Kyoto world [1].

However, there are evident validation and verification problems. The major problem that the users face is unknown reliability of the majority of RS products as applied to an individual region. On-ground regional validation of global RS products remains poor and thresholds of estimated indicators substantially depend on the algorithms used. A fundamental solution of the problem is development of a unified system on on-ground truth in different zones and regions of the globe. An attempt to generate such a system for boreal Asia has been done within the EU Project SIBERIA (SAR Imaging for Boreal Ecology and Radar Interferometry Applications) [27]. The project developed 82 test territories with a GIS at scale 1:50,000 of the total area of about 3 million ha and detailed quantification of each land cover polygon. Evidently, information from such test territories requires periodical updating.

Major directions of future improving the reliability of the results of the FCA for Russian ecosystems include *inter alia*: (1) introduction of more detailed hybrid land cover for regions with more accurate available ground and remote sensing information; (2) more complete implementation of models and remote sensing products for correction of many year empirical ecological indicators using climatic and environment characteristics of individual growth seasons; (3) development of empirical models for regional correction of remotely sensed biophysical indicators (like NPP, fire radiative energy, et.); (4) further improvements of ecological models which combine remotely sensed and “hidden” components of ecosystem; some others.

In addition to regional and continental applications, the possibility to apply this methodology over the globe now exists, with the majority of input datasets used being global. The method allows use of not only the fixed set of data, but all existing relevant information. We consider some other remote sensing products (e.g. GlobCover, elevation models, lidar data, and others) as very promising for use in this methodology. In addition, it is possible to place weights on datasets (i.e. favouring data with low uncertainty) or recently updated statistics.

REFERENCES

1. Shvidenko, A., Schepaschenko, D., McCallum, I., et al. (2010). Can the uncertainty of full carbon accounting of forest ecosystems be made acceptable to policymakers? *Climatic Change*. **103**, 137-157.
2. Schellnhuber, H.J. (2003). Integrated assessment of adaptation and mitigation options. In Proc. *World Climate Change Conference*. Moscow.
3. Bartholome, E. & Belward, A.S. (2005). GLC2000: A new approach to global land cover mapping from earth observation data. *International Journal of Remote Sensing*. **26**(9), 1959-1977.
4. Bartalev, S.A., Belward, A.S., Erchov, D.V., et al. (2003). A new SPOT4-VEGETATION derived land cover map of Northern Eurasia. *International Journal of Remote Sensing*. **24**(9), 1977-1982.
5. Hansen, M.C., DeFries, R.S., Townshend, J.R.G., et al. (2002). Towards an operational MODIS continuous field of percent tree cover algorithm: examples using AVHRR and MODIS data. *Remote Sensing of Environment*. **83**(1-2), 303-319.
6. Fridland, V.M. (1989). Soil map of the USSR. Committee on Cartography and Geodesy, Moscow, Russia.
7. Stolbovoi, V. & McCallum, I. (2002). Land Resources of Russia. [CD-ROM] [cited 01/02/09; Available from: http://www.iiasa.ac.at/Research/FOR/.
8. Shvidenko, A., Schepaschenko, D., McCallum, I., et al. (2007). Russian Forests and Forestry. [cited 01/02/09 01.02.2009]; Available from: http://www.iiasa.ac.at/Research/FOR/forest_cdrom.
9. FACRE'RF (2009). State (national) report about the state and use of lands of Russian Federation in 2008.: Federal Agency of Real Estate Cadastre Report, Moscow, Russia, 220 pp.
10. Kevesh, A.L., ed. 2008. Russian regions. Social-economic indicators. 2008: Statistics collection. Rosstat: Moscow. 999 pp.
11. Schepaschenko, D., McCallum, I., Shvidenko, A., et al. (2010). A new hybrid land cover dataset for Russia: a methodology for integrating statistics, remote sensing and in-situ information. *Journal of Land Use Science*. **TLUS-2009-0005.R1**.
12. Shvidenko, A., Schepaschenko, D., & Maksyutov, S. (2010). Impact of terrestrial ecosystems of Russia on the global carbon cycle from 2003-2008: An attempt of synthesis. In Proc. *Int. conf. on Environmental Observation, Modeling and Information Systems. Enviromis'2010.* Tomsk.
13. Shvidenko, A., Schepaschenko, D., Nilsson, S., et al. (2007). Semi-empirical models for assessing biological productivity of Northern Eurasian forests. *Ecological Modelling*. **204**(1-2), 163-179.
14. Santoro, M., Beer, C., Cartus, O., et al. (2010). Retrieval of forest growing stock volume in

boreal forest using hyper-temporal stacks of Envisat SAR ScanSAR images. *Remote Sensing of Environment (in press)*.

15. Lapenis, A., Shvidenko, A., Shepaschenko, D., et al. (2005). Acclimation of Russian forests to recent changes in climate. *Global Change Biology*. **11**(12), 2090-2102.
16. Myneni, R.B., Dong, J., Tucker, C.J., et al. (2001). A large carbon sink in the woody biomass of northern forests. *Proceedings of the National Academy of Sciences of the United States of America*. **98**(26), 14784-14789.
17. Running, S.W., Nemani, R.R., Heinsch, F.A., et al. (2004). A continuous satellite-derived measure of global terrestrial primary production. *BioScience*. **54**(6), 547-560.
18. Van Der Werf, G.R., Randerson, J.T., Giglio, L., et al. (2006). Interannual variability of global biomass burning emissions from 1997 to 2004. *Atmospheric Chemistry and Physics Discussions*. **6**(2), 3175-3226.
19. Zhang, Y.H., Wooster, M.J., Tutubalina, O., et al. (2003). Monthly burned area and forest fire carbon emission estimates for the Russian Federation from SPOT VGT. *Remote Sensing of Environment*. **87**(1), 1-15.
20. Vivchar, A. (2010). Wildfires in Russia in 2000-2008: estimates of burnt areas using the satellite MODIS MCD45 data. *Interntional Journal of Remote Sensing (in review)*.
21. Ershov, D.V., Kovganenko, K.A., & Sochilova, E.N. (2009). GIS-tecnology for estimation of fire carbon emissions based on Terra-MODIS data and State Forest Account. *Current Problems of Earth Observation from Space*. **6(II)**, 365-372 (in Russian).
22. Sukhinin, A.I. (2008). Satellite data on wild fire. Russian Forests and Forestry [cited 01/02/09; Available from: www.iiasa.ac.at/Research/FOR/forest_cdrom/index.html.
23. Shvidenko, A. & Goldammer, J.G. (2001). Fire Situation in Russia. *International fire news* **24**, 41-59.
24. Wooster, M.J. & Zhang, Y.H. (2004). Boreal forest fires burn less intensely in Russia than in North America. *Geophysical Research Letters*. **31**(20), L20505 1-3.
25. Xu, W., Wooster, M.J., Roberts, G., et al. (2010). New GOES imager algorithms for cloud and active fire detection and fire radiative power assessment across North, South and Central America. *Remote Sensing of Environment*. **114**(9), 1876-1895.
26. Ciais, P., Canadell, J.G., Luyssart, S., et al. (2010). Can we reconcile atmospheric estimates of the Northern terrestrial carbon sink with land-based acoounting? *Current Options in Environment Sustainability*. **2**, 1-6.
27. Schmullius, C., Baker, H., Baltzter, H., et al. (2001). SIBERIA-SAR Imaging for Boreal Ecology and Radar Interferometry Applications. European Commission 4th Framework Project ENV4-CT98_0743 (DG12-EHKN), Final Report, September 2001.