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GEOCARBON

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1. Introduction

1.1 Short summary

This deliverable presents a summary of the work on cost-benefit assessment of the benefits accruing from improvement in information about carbon fluxes. Three streams of work are described that have emerged under the different tasks of CMP7/WP21: (1) Valuation of benefits that come from being able to better manage a carbon management policy. The new methodology is illustrated with the example of Reduced Emissions from Deforestation and Degradation (REDD), where better carbon monitoring helps to avoid the costly implications of under- and over-reporting. A positive net benefit is found. (2) Valuation of the benefit accruing from more stable climate policy enabled by better information on actual carbon fluxes. It is shown that this creates investor certainty, thus helping to achieve policy goals (here: emissions reductions) more effectively. An add-on to this analysis is a game-theoretical application, which acknowledges that large-scale monitoring would involve joint investment and operation of equipment by different countries/regions. As these differ in the parameters of their energy sectors that are to be decarbonized (cost structure, emissions intensity), their incentives to engage in joint monitoring differ as well. We compute the equilibrium as the intersection of those countries' response functions. Again, better carbon flux information has a positive net benefit. (3) A positive net benefit in land-based climate change mitigation policy is most importantly related to biomass (bioenergy, REDD, etc). An improvement in such information can be effected by making – in addition to monitoring equipment and modelling – use of crowd-sourcing and consolidation and analysis of existing products. A biomass geo-wiki has been set up leading to substantial progress in achieving this objective thus providing large benefits compared to relatively modest costs.

1.2 Rationale for this deliverable

This deliverable describes an important component within the GEOCARBON project. While other components and work packages are mostly occupied with the actual improvement of carbon flux information, this WP goes a step further and tries to assess the (net) benefit of doing so. This is important, as it (a) uses the project's results to demonstrate their use to stakeholders, which in the case of the work done so far are mostly policymakers, and (b) sets the cost of operationalizing a Global Carbon Observation system into context when it comes to the usage of the products it will generate. While there are theoretically some applications of value of information studies, which can partially transferred here, there was a substantial need for further method development, which has been mainly carried out in the WP. First results demonstrate the net benefit, while the next deliverable will use more data from the project (as it becomes available) and test the methods, which will then be linked to more heavy modelling machinery (linking a land use with an integrated assessment model, cf. D21.2) as well to enable us to draw spatially differentiated conclusions. These results will be contained in D21.2, while D21.1 will focus more on methods and first (general) results.

1.3Problems encountered and envisaged solutions

Relatively little problems were encountered. An interdisciplinary task force was set up in order to coordinate work between the carbon experts and the researchers occupied with developing economic methods of benefits evaluation. One problem was a delay in data provision on uncertainty reductions in carbon flux measurements, but we can still demonstrate the potential magnitudes of the net benefit in this deliverable report based on the task force's expert estimates. The papers based on work streams 1 and 2 will still be extended upon data availability before their submission to peer-reviewed journals.

2 Full description

In this report we will present the three work streams in which different methods for benefit valuation have been developed, where the third is less focussed on the measurement of the benefit, but more on the creation of the same at low cost. Section 2.1 starts with the benefits of avoiding costly deviations from the emissions reduction target due to over- and underreporting, which remains undetected without the Global Carbon Observation System. Section 2.2 presents the benefit in terms of achieving policy goals (here: emissions reductions in the energy sector, where uncertainty about actual fluxes necessitates frequent adjustments in incentives thus deterring investment in less carbon-intensive energy technologies). Section 2.3 presents the biomass geo-wiki concept, which is a low cost way of improving decision-relevant information with huge benefits.

2.1 GEOCARBON – Cost-Benefit Analysis of Carbon Monitoring Systems

The work performed in this stream was done in collaboration between CMCC and IIASA with colleagues from IPSL – LSCE. In this report we describe the methology developed for the assessment to be carried out in the coming months, but we also offer some illustrative results in order to help developing a feeling for the magnitudes of the benefits considered here.

Background and motivation

Decision makers are increasingly demanding systematic, consistent and transparent data, information and tools, for an independent and reliable verification system of greenhouse gas (GHG) emissions and absorptions, and to enable them to address mitigation and adaptation policies in a timely way. Therefore, coordination for a global integration of the current carbon monitoring efforts and their datasets and an expansion of those is needed.

The objective of this paper is to assess the benefit of an improved global carbon monitoring system. The literature on valuing the benefit of better information – or short, the value of information (VOI) - usually derives this value from either the willingness of decision-makers to pay, which is closely related to evaluating gains in productivity or output enabled by better-informed decisions or from hedonic approaches, where the impact on markets is measured (e.g. through changes in wages or house prices) (McCauley 2006). Laxminarayan and Macauley (2012), present a number of applications in the area of Earth Observation, where the chapter by Fritz et al. (2012) develops a methodology for analyzing portfolios of mitigation options when land cover and thus the cost of the land-based mitigation option become less uncertain. The closest to our approach is the study by Durant et al (2011), which will be further reviewed below.

In this paper we estimate the benefit of an enhanced carbon monitoring system by the gains it can imply in terms of mitigation costs. In a nutshell, having better information on carbon fluxes enables decision-makers to make better-informed plans for the reduction of CO_2 emissions. In contrast to Durant et al. (2011), we focus on the second carbon component, the emissions from land use changes such as deforestation. In particular, there are two (costly) errors, which can be avoided through more exact carbon monitoring:

The first error relates to overshooting: for example, if we try to achieve a reduction in emissions from deforestation, but cannot be sure whether we will achieve the right reduction level, we have to reduce more than the expected value in order to reduce the risk of not achieving the target. This creates a case of over-compliance, with additional cost. However, these extra costs might be justified if decision-makers are averse against crossing (unknown) thresholds triggering irreversible damages (see e.g. Keller et al. (2004), who find that considering thresholds beyond which irreversible damages occur (in their case a collapse of the thermohaline circulation) significantly raises near-term abatement levels). Cost savings from the reduced need to over-comply constitute an economic benefit, which can be measured. This reasoning is in line with the European Union's firm commitment to the 2^{o}C target.

The second type of error, on the other hand, is related to the risk of underestimation: if we cannot monitor the decrease in carbon fluxes from reduced deforestation precisely, there will be an incentive to under-comply (=over-report), as it will not be detected. The lower end of the distribution will be the lower bound of this under-compliance. By comparing the potential for under-compliance for the first set of information (which will be relatively high) and the potential for under-compliance for the set of information with lower uncertainty (more narrow distribution or lower standard deviation), we will be able to derive the benefit from having the latter set of information in terms of emissions, which would otherwise not have been avoided. An example of the implications of under-compliance can be found in Obersteiner et al. (2000), who find that any emissions trading scheme is destined to disintegrate if uncertainty and unverifiable emissions reductions enable over-reporting. [1]

In the case of the first type of error, a more narrow distribution would obviously reduce the amount of over-compliance and similarly lead to savings in terms of avoided policy costs. An example of a study measuring the benefits of reducing the second type of error through improved carbon monitoring can be found in Durant et al (2011), who use the integrated assessment model PAGE to estimate that if 5% of global CO_2 emissions go unreported and undetected, the associated marginal economic impacts could reach approximately US$20 billion each year by 2050. This number could reach up to US$20 billion each year by 2050, which accumulates to a net present value (NPV) aggregated until 2200 and discounted back to the present of more than US$10 trillion, which clearly

[1] The solution the authors offer is a penalty on uncertainty, which will lead to an incentive to reduce uncertainty to achieve the verifiable emission reduction target at least cost.

exceeds all suggested measures' cost that would be employed for better monitoring and would reduce cheating (over-reporting).

In this paper, we focus on the decision of how many tons of CO_2 should be abated through the use of avoided deforestation measures and estimate the cost savings in the face of improved carbon flux information, which requires less over-compliance to meet the reduction target with complete certainty (i.e. the first type of error described above).

Benefit concept

In Figure 1 below, we present a sketch on how the benefit from having more precise information on carbon fluxes is measured. In particular, we focus on the cost savings from needing less over-compliance to meet the (pre-defined) target with 100% certainty. Multiplying the emissions savings with the corresponding carbon price gives us the monetary benefit, which can then readily be compared to the cost of installing, maintaining and operating the monitoring system.[2]

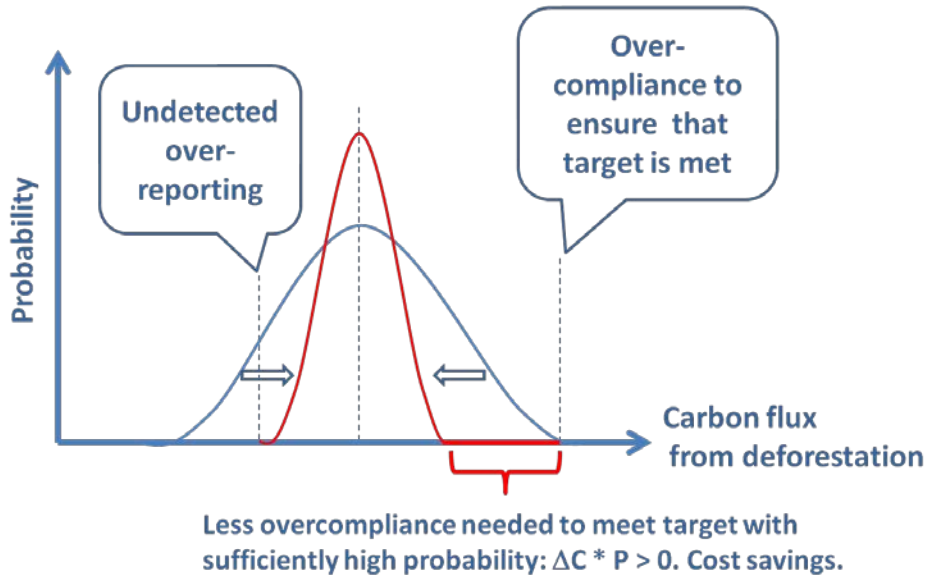


Figure 1: Benefit Assessment of Improved Carbon Monitoring

The change in the shape of the distribution (or the narrowing of the corresponding confidence interval (CI)) can be determined through inverse modeling, although in this case it is hard to attribute the fluxes to different activities. Therefore, this paper relies on expert estimates, which are described in further detail below.

Uncertainty reduction and costs

Deforestation CO_2 flux estimates are affected by uncertainties in 1) deforested areas, 2) biomass stocks impacted, 3) legacy emissions from soil C consecutive to deforestation (roughly one third of immediate deforestation emissions), 4) re-growth and NPP of secondary ecosystems. While it is beyond the scope of this paper to separate the contributing sources of uncertainty associated with

[2] Note that the other type of error – avoiding undetected over-reporting – would be determined analogously at the other side of the distribution.

each term, biomass stocks differences (from two recent RS products, Saatchi et al. and Baccini et al.) have been used as well as modeled LUC CO_2 fluxes from DGVMS used for the IPCC AR5.

Concerning biomass, an uncertainty of 80% on standing stocks (estimated 95% CI range) is estimated from visual comparison of biomass difference between Saatchi et al. (2011) and Baccini et al. (2012). The nature of such an uncertainty is mostly bias.

For pan-tropical average LUC CO2 emissions, we have a 1-sigma uncertainty of +/- 0.5 Pg C yr^{-1} for a mean flux of 0.9 Pg C yr^{-1} averaged over tropical continents (i.e. 60% of the mean) in the IPCC AR5. The nature of this uncertainty about the mean tropical LUC CO_2 emissions is likely to be mostly a bias. Therefore, a bias of 60% in the mean tropical flux translates into a bias of 60% on the mean LUC CO_2 emission of each deforested pixel.

The error reduction associated with more / better measurements in the future for biomass stocks is very difficult to project. Based on preliminary insights, at the RAINFOR inventory sites where the best possible in-situ data are collected, the biomass estimation bias is 50 t C ha^{-1}. For the purpose of this paper, we thus make the assumption that remote sensing estimates of biomass will not perform any better than this "limit". So we consider 50 t C ha^{-1} as our error on biomass. This implies a 15% mean bias in the future as compared to a mean bias of 80% today. This 15% error is also the one independently estimated from the design studies of the BIOMASS P-band radar mission under Phase-A at ESA.

For LUC CO_2 fluxes, the reductions in uncertainty are very difficult to project as well. We assume that with high resolution images, like in place over Brazil with the PRODES system, the forest loss area could be very accurately monitored in the future (the forest area loss) within a few %, hence this will not be the limiting error term in the uncertainty budget. For biomass stocks impacted, we have the above value of 15% uncertainty. It will be very difficult to reduce errors on soil C emissions consecutive to deforestation (soil C data will be slow to collect and very heterogeneous). Re-growth and NPP of secondary ecosystems could be assumed to be constrainable within 15% from biomass stock change estimates. Altogether, assuming a 15% uncertainty on gross deforestation fluxes (loss and re-growth) which are 2/3 of the total LUC flux, and a 60% uncertainty unchanged from today on legacy soil CO_2 emissions which are 1/3 the total LUC flux gives a rough estimate of 30% for net LUC CO_2 flux uncertainty at the pixel level in the future, as compared to 60% today. Again, this is mostly a bias.

As there is even more uncertainty as to how technology is going to evolve to measure biomass and to provide data to estimate LUC CO_2 fluxes in the long-term, these estimates are based upon planned satellite missions and existing observing capabilities. So the horizon for achieving the error reduction is 2025.

Table 1 gives an overview of possible ways how infrastructure (considered in the GEOCABON project) could help improving the monitoring of emissions from deforestation:

	Deforestation Immediate flux = biomass loss	Deforestation legacy flux = soil C loss following deforestation event	Degradation biomass loss
Disturbance scale (1 ha)	RS of biomass (radar, lidar) Annual revisit	RS of biomass RS of NPP of 2ndary ecosystem Model for 2ndary ecosystem C Flux tower Chronosequence data	< Ha RS of biomass (airborne lidars, radar)

REDD project scale (1000 ha)	RS of biomass	RS of biomass Flux tower forest C model - if sink of intact forest required	< Ha RS of biomass (airborne lidars, radar)
Regional scale (106 ha)	RS of biomass with regional coverage (radar, lidar) Annual revisit	RS of biomass with regional cov RS of NPP of 2ndary ecosystem Model for 2ndary ecosystem C Regional drivers data Perhaps atmospheric sampling (e.g. OCO, or many stations)	< Ha resolution RS Forest disturbance C model Perhaps atmospheric sampling (e.g. OCO, or many stations)

Table 1: Potential for improving monitoring of deforestation emissions

Forest model, inputs and results

In order to assess the benefit of the outlined uncertainty reductions according to the method outlined above, we use the IIASA model framework combining the interlinked global economic land use model GLOBIOM, the global forestry model G4M and results from other models (EPIC, POLES, WEO) (Gusti et al. 2012). Three POLES scenarios of population GDP and bioenergy (POLES base, high and low GDP) combined with WEO bioenergy scenarios are implemented in GLOBIOM (Bottcher et al. 2011) [3]. G4M supplies GLOBIOM with spatial information on the potential amount of wood in forests and initial prices of wood and agriculture land. GLOBIOM, in particular, returns to G4M regional data on wood demand.G4M (Kindermann et al., 2006 and 2008, Gusti and Kindermann, 2011) is designed to estimate impacts of forestry activities (afforestation, deforestation and forest management) on biomass and carbon stocks. A comparison of the net present value of managed forest (difference between wood price and harvesting costs, income by storing carbon in forests) to the net present value of alternative land uses is the basis for decisions concerning optimal activities. The model is spatially explicit and is used on a 0.5° x 0.5°resolution in this application.

Wood prices, agricultural land rents, wood demand and prescribed land use change are exogenous, assumptions are in line with minimum nutritional constraints, land for urban development and other assumptions. Forest area change, carbon sequestration and emissions in forests, impacts of carbon incentives and biomass supply for bioenergy and timber are endogenous.

Forest age structure[4] is initialized using country scale statistics (see Table 2, which is a reproduction of Table 1 in Gusti et al., 2012). The model performs final harvests such that all age classes occupy an area of equal area after one rotation. Increment is determined by a potential net primary productivity (NPP) map (see Table 1) and translated into net annual increment (NAI). In this application we use a static increment map, even though this can be changed to a dynamic growth model.

[3] The mentioned work was done for the Secretary of State of Energy and Climate Change, London, UK under Contract Offer dated 11 January 2011, IIASA Contract No. 11-107. As new data become available in the ongoing IPCC processes (e.g. the Shared Socioeconomic Pathways, short SSPs), this analysis will be updated. This will also enable us to perform the necessary sensitivity analysis with respect to different drivers (population, GDP, etc).
[4] Forest age classes have one year width.

Parameter	Resolution	Reference
Net annual increment, forest age structure	Country	MCPFE http://forestportal.efi.int/view.php?id=1895&c=E1
Land under infrastructure, secured cropland	0.5x0.5 deg	Tubiello and Fischer (2007)
Potential NPP	0.5x0.5 deg	Cramer et al. (1999)
Potential vegetation	0.5x0.5 deg	Ramankutty and Foley (1999)
Forest biomass, litter and coarse woody debris	0.5x0.5 deg	Kindermann et al. (2008b), Gallaun et al. (2010)
Protected forest	0.5x0.5 deg	WDPA Consortium (2004)
Landcover	0.5x0.5 deg	GLC2000 [JRC 2003], CORINE [CLC2000]

Source: adapted from Gusti et al. (2012)
Table 2. Main data used by the models

Forest management options included are (1) variations of thinning and (2) changes in rotation length. The model gradually adjusts rotation length within maximum and minimum rotation lengths to harvest the demanded amount of wood.

Mitigation occurs in response to credits (carbon price) for storing carbon. Mitigation measures in forestry in G4M occur through (1) reduced rates of deforestation, (2) an increase in afforestation, (3) adjustments of rotation length of existing managed forests, (4) adjustments of the ratio of thinning to final fellings, (5) changing the harvesting intensity.

Assigning an increasing price to the carbon stored in the living forest (biomass and soil) over the three 'baseline' scenarios the marginal abatement cost curves in Fig. 2 are obtained.

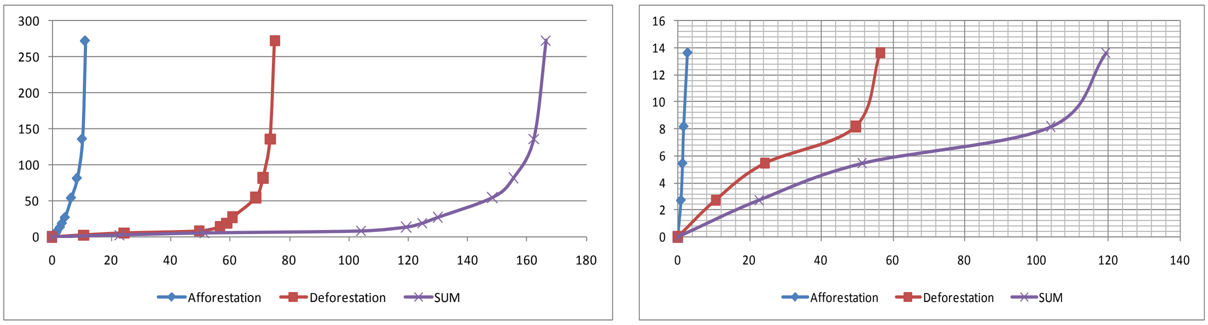


Figure 2: Marginal abatement cost curves from G4M

The gains in terms of less costly achievement of the carbon reduction target through avoided deforestation with 100% probability have been estimated running the G4M model with both the more uncertain and the less uncertain information[5] (in Figure 1 above that would correspond to the

[5] For this estimate total (total biomass + soil) net deforestation emissions (afforestation+reforestation-deforestation) have been used.

wider and the more narrow distribution (blue and red) respectively, Table 3 below summarizes the values used in this study). In a similar way, we could estimate the costs we would avoid at the other side of the distribution that comes from undetected underreporting. With the squeezed distribution, underreporting is not possible anymore, i.e. would be detected immediately!

Current estimate of uncertainty	**Expectations (with better EOS)**
Biomass	
80% (comparison Saatchi et al 2011 vs. Bacchini et al. 2012	15% (RAINFOR inventory sites, Biomass p-band mission under Phase A at ESA)
Deforestation	
60% (IPCC AR5)	30%

Table 3. Uncertainty reductions used

The results for saving costs by not having to overcomply as much anymore indicate benefits substantially in excess of zero: we can achieve 60% accumulated emission reductions for 2026-2050 (19,000 mtCO2) at approximately 6$/tCO2 for which the countries must pay 6$/t CO_2 x 19,000 mt CO_2= 114,000 million $. However, after the reduction in uncertainty due to more precise carbon flux measurements, we only need to achieve 30% (9,500 mt CO_2) emission reductions by avoiding deforestation after the uncertainty reduction (at a carbon price of 3.25 $/t CO_2), i.e. 3.25 x 9,500 = 30,875 million $. We can thus save 83,125 million $.

2.2 The Benefits of Investment into Improved Carbon Flux Monitoring

Operationalizing a Global Carbon Observing and Analysis System[6] would obviously provide a sound basis for monitoring actual carbon fluxes and thus getting quantities right when pricing carbon – be it in a cap-and-trade scheme or under a tax regime. However, such monitoring systems are extremely expensive and – especially in times of economic crisis – budgets for science and environmental policy are under particular scrutiny. In this study we attempt to demonstrate the magnitudes of benefits involved in improved information about actual carbon fluxes, which comes from its ability to better inform policymaking and thus paves the way for a more secure investment environment when decarbonizing the energy sector. Furthermore, we add a game-theoretical layer to the study acknowledging that an engagement in global carbon observation and analysis would be a multi-country effort. While the numerical results obviously rely on a number of assumptions, they give a robust indication of a positive value of improving carbon monitoring systems when compared to their cost. In this section, we present the method developed for capturing and evaluating these benefits, developed together with colleagues from FASTOPT and University of Bristol. We also give some illustrative results to put the potential benefits into perspective. In the next report, the integrated framework will be used to give more detailed results on benefits.

Background and concepts

The current knowledge about climate change is plagued by uncertainties. There are major uncertainties about climate sensitivity and about the thermal lag of the climate system (Roe and Baker (2007); Caldeira et al. (2003); Hansen et al. (2005); Forest et al. (2002) and Hansen et al. (1985)). Further down in the causal chain there are perhaps even larger uncertainties about impacts both from low probability threshold events (O'Neill and Oppenheimer, 2002) and from gradual

[6] www.geocarbon.net

changes in the climate. Thus the resulting climate policies are invariably vague and volatile as well. This has been observed also in the European Union's Emission Trading Scheme (EU ETS), where the over allocation of emissions allowances for EU ETS Phase I drove the carbon price down to zero in 2007 (CCC, 2008). This over allocation reflects the difficulty in precisely quantifying current CO_2 fluxes and predicting future emissions, which is necessary in setting a cap (Carbon Trust, 2009). It has been shown that this leads to large fluctuations in the resulting CO_2 price (Point Carbon, 2008). Therefore, it may very well be of economic value to improve the existing monitoring system to provide more precise measurements resulting in a better allocation and a more stable CO_2 price.

In this study we plan to focus on the question how the investment decisions into carbon-neutral technologies are affected by future CO_2 price uncertainty and to which extent a decrease in CO_2 price volatility affects the resulting investment cost and behavior and thus the success of the policy to decarbonize the energy sector. This serves to quantify the economic value from having a better monitoring system, i.e. we can use these estimates to derive the benefits (or the maximum investment cost that can be justified) of an observation system as well.

First, we adopt a social planner's perspective and formulate a stylized real options model (Dixit and Pindyck, 1994) to find the optimal timing and the resulting cost of a shift to a carbon-neutral technology in the presence of a stochastic carbon price. We model the price as a Geometric Brownian Motion (GBM), which, with additional assumptions (e.g. constant emission intensity of the incumbent, more carbon-intensive technology), will enable us to derive the solution analytically as a function of the underlying parameters (price process parameters, technology cost etc.). The assumption of increasing carbon prices is in line with shadow price trajectories underlying stabilization targets analyzed by all major integrated assessment frameworks (e.g. GEA, 2012).

We will use then use the model to assess if (and to what extent) it is optimal for society to invest into improved monitoring of carbon quantities. Following the approach outlined in Kryazhimskiy et al. (2008) and Chladná et al. (2006), we introduce the possibility to invest an arbitrary amount into an improved monitoring system at the beginning of the planning horizon, which will result in a decrease in the resulting carbon price volatility. Using the solution of the stylized model we will be able to derive analytically the amount, which results in the lowest cost to the society. The analytical solution will enable us to further analyze the impact of the underlying parameters and assumptions on its qualitative properties and identify its robust elements. This will give us an answer what would be optimal for the society as a whole (a more detailed formulation is given in the methods section).

However, in reality such an investment is not undertaken by one player individually, but is in fact a corporate decision undertaken by a coalition of countries or regions – especially given the cost and considerations of precluding any form of cheating (i.e. over-reporting). We therefore extend our analysis by introducing a game theory layer on top of the real options model to analyze the optimal investment in the case where two economies have the possibility to invest jointly into such a monitoring system.

In such a case, each economy can decide independently how much will be invested into the monitoring system in the beginning of the planning horizon. The sum of the contributions of each economy will be thus invested into the joint monitoring system resulting in a decrease in the volatility of the CO_2 price. At the same time, each economy faces the same optimization problem from the first layer, i.e. to find the optimal timing of the switch to carbon neutral technology.

Using the solution from the first layer we will be able derive the best response function for each economy and further also the resulting Nash equilibrium (if existent) analytically (see Kryaszhimskiy et al. (2008) and Chladná et al. (2006) for mathematical details). This, in turn, will enable us to analyze different qualitative behavior of different types of economies based on the underlying parameters and compare to what would be optimal for the society as a whole.

Our contribution to the literature is thus firstly theoretical in formulating a framework, which covers both the investment decision into monitoring equipment, which will reduce uncertainty and thus influence investment behavior in the energy sector, and then linking this with a game-theoretical approach to study the problem in a two-country setting. On the other hand, we also want to demonstrate the magnitudes for the analytical results to derive tangible policy conclusions regarding the financing of such equipment in reality. Using data from Quantitative Network Design (see the following section for more detailed information) gives us a quantitative assessment of the potential of monitoring systems to reduce uncertainty. Combined with the qualitative analysis of the benefit of coalitions and the resulting emissions savings, this will give a comprehensive assessment of the overall benefit of carbon monitoring systems in the climate change mitigation context.

In the next section we explain in more detail what Quantitative Network Design is and how it can be used to assess the uncertainty reduction potential in carbon flux management. It also gives an introduction to the data, which will be used in the model described in the following section, which is divided into two sub-sections, where the first one is dedicated to the first layer of the problem and the second one introduces the game-theoretic layer to the problem formulation. Results are presented in the final section.

Quantitative Network Design

Quantitative Network Design (QND) is a technique that allows to evaluate potential observational networks (for an introduction see Kaminski and Rayner, 2009) providing measurements of a given system. It exploits the capability of modern data assimilation systems to propagate uncertainties from observations to the system's control variables and then forward to target quantities of interest (see Scholze et al., 2007). It is worth noting that this technique only requires the sampling times and locations, an estimate of the combined uncertainty reflecting observational and model errors, and the sensitivity of the simulated observation with respect to the model's control variables. It does not require actual observations and is thus suitable to evaluate potential networks. We apply a QND framework (Kaminski et al., 2012) that is built around the Carbon Cycle Data Assimilation System (CCDAS, Rayner et al., 2005) and is suitable to evaluate networks observing the atmospheric and terrestrial carbon cycle. The CCDAS is set up in a configuration with 57 control variables, which are parameters in the process description of the terrestrial biosphere model BETHY (Knorr, 2000) and an initial value of the atmospheric CO_2 concentration. BETHY composes the global vegetation of 13 Plant Functional Types (PFTs). As the target quantity we use the 20-year average of the annual mean Net Ecosystem Production (NEP) simulated on the model’s 2 by 2 degree global grid.

Evaluation of a network example

As an example, we define an observational network that consists of 41 sites collecting monthly samples of the atmospheric CO_2 concentration and 10 sites providing direct flux measurements on an hourly time resolution, covering all PFTs that are available to BETHY over Europe. Both component networks are described by Kaminski et al. (2012), where they are respectively denoted as 'flask' and 'flux'. Their combined network is sampling over a period of 20 years. By contrast to that study, in the simulation of the target quantity we use a model error of 5% of the simulated annual mean Net Primary Production (NPP). The uncertainty reduction achieved by the network relative to the prior uncertainty, i.e. a nil network without any measurements, is displayed in Figure 1. The uncertainty for a nil network is calculated by mapping our prior information on the BETHY process parameters to the target quantitiy. There is a debate about the number of PFTs required in a model to allow a realistic assessment. Kaminski et al. (2012) have tested configurations with higher number of PFTs. For quadrupling their number of PFTs from 13 to 52, for example, they found only a moderately weaker performance of the network 'flask' and for a flux network sampling 4 times the number of PFTs as the original network 'flux' they found almost the same performance as the network 'flux' has in the original 13 PFT configuration.

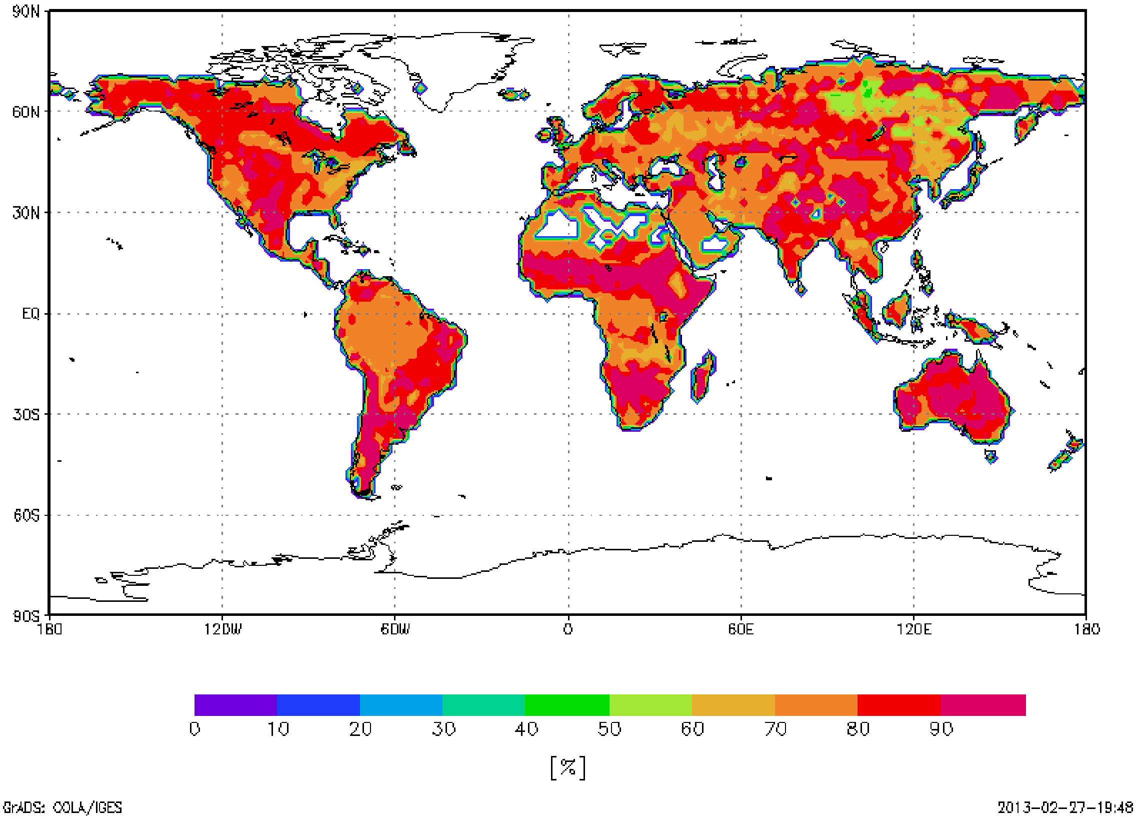


Figure 3: Uncertainty reduction in 20-year average NEP/year relative to prior uncertainty

Cost of an observational network

The observational network evaluated above is composed of two types of measurements, atmospheric flask samples and direct flux measurements. The respective costs can be divided into installation costs and operating costs. The installation of an analysis laboratory for atmospheric flask samples (with a lifetime of 10 years) is estimated to cost about 2.5 Million Euro and its operation is estimated to cost about 1.5 Million Euro per year (ICOS stakeholder handbook, 2012). The annual costs for the operation of a flask sampling site can be estimated to amount to 10 thousand Euros on average (M. Heiman, personal communication). For the ecosystem network, on average per site, installation costs are estimated to amount to 48 thousand Euros (for a lifetime of 7 years), and the operation about another 30 thousand Euros per year (A. Lindroth, personal communication). Since our simulations assume observations over 20 years, we double the investment costs for the atmospheric measurements and triple them for the ecosystem measurements. The of cost operating 41 flask sampling and 10 ecosystem sites over 20 years amount to about 43.2 Million and 7.3 Million Euro respectively. The total cost of the combined network is thus just over 50 Million Euro. If we had used a network of 40 (100) instead of 10 ecosystem sites it would be just below 73 Million Euro (117 Million Euro).

The impact of improved carbon flux monitoring on investment into carbon-free technology

First layer

Problem formulation

As has already been described, the first layer should assess the benefit of having an improved monitoring system in finding the optimal timing of the switch to a carbon-neutral technology. We adopt a social planner's perspective and assume the decision maker is facing a stochastic carbon price, modeled as a geometric Brownian motion[7]

$$dP_t = \mu P_t dt + \sigma P_t dW, \tag{1}$$

μ and σ representing its trend and volatility respectively, dW denoting the increment of Wiener process. We will denote the original price as P^0. We assume an infinite planning horizon, where the decision maker has two options at his disposal. Firstly, in the beginning, he can decide on the level I of investment into an improved monitoring system. This investment leads to a decrease in the volatility of the carbon price, based on the level of investment, i.e. we assume σ is a decreasing function of I, $\sigma = \sigma(I)$. Secondly, he can choose the timing of the switch to a carbon-neutral technology. We assume a constant emission intensity Q of the incumbent (more carbon-intensive) technology. Thus the switch to the carbon-neutral technology results in yearly savings QP_t of carbon payments (E.g. in an EU ETS type of scheme or in the form of taxation) but is connected with capital (and unit operational) costs of investment C (c). We denote r the discount rate. We assume the decision maker is risk neutral and seeks to minimize the underlying present value of costs of both decisions

The described problem can be formulated as an optimal control problem

$$\min_{\tau,I} I + E \int_0^\tau e^{-rt} Q P_t dt + C e^{-r\tau} + \int_\tau^\infty e^{-rt} Qc\, dt \tag{2}$$

$$dP_t = \mu P_t dt + \sigma(I) P_t dW,$$

where τ is the stopping time.

Real options step solution

The formulated problem can be transformed into a two-step optimization problem

$$\min_I \left[I + Q \frac{P^0}{r-\mu} - F(P^0) \right] \tag{3}$$

$$F(P^0) = \max_\tau e^{-r\tau} \left(Q \frac{P_\tau}{r-\mu} - C - Q \frac{c}{r} \right)$$

$$dP_t = \mu P_t dt + \sigma(I) P_t dW.$$

where the second step is a standard real options problem, $F(P^0)$ denoting the value of the option to switch to the carbon-neutral technology if the present carbon price is P^0. It formulates the problem of the optimal timing of the switch to a carbon-neutral technology, $F(P^0)$ expressing the present value of such an investment if it is carried out optimally. The first step, on the other hand, formulates the problem of the optimal level of investment into an improved carbon monitoring system assuming the switch to the carbon-neutral technology will be timed optimally. Deriving the solution of the second step and substituting this into (3) will enable us to analyze the two decisions

[7] This is in accordance with rising shadow prices for carbon under any stabilization target.

separately. Following Dixit and Pindyck (1994) we see that the solution is to switch to the carbon-neutral technology as soon as the carbon price hits the threshold

$$P \quad = \frac{\beta}{\beta-1}(r-\mu)\left(\frac{C}{Q}+\frac{c}{r}\right), \tag{4}$$

where β is the positive root of the quadratic equation

$$\frac{1}{2}\sigma^2(I)\beta(\beta-1)+\mu\beta-r=0,$$

and thus

$$\beta=\frac{1}{2}-\frac{\mu}{\sigma^2(I)}+\sqrt{\left(\frac{\mu}{\sigma^2(I)}-\frac{1}{2}\right)^2+2\frac{r}{\sigma^2(I)}}>1. \tag{5}$$

The option value can be further expressed as

$$F(P^0)=\left[Q\frac{P}{r-\mu}-C-Q\frac{c}{r}\right]\left(\frac{P^0}{P}\right)^{\beta} \tag{6}$$

First step solution

Substituting (6) into (3) we get a following formulation of the first step optimization problem:

$$\min_I\left[I+Q\frac{P^0}{r-\mu}-\left[Q\frac{P}{r-\mu}-C-Q\frac{c}{r}\right]\left(\frac{P^0}{P}\right)^{\beta}\right] \tag{7}$$

$$P \quad = \frac{\beta}{\beta-1}(r-\mu)\left(\frac{C}{Q}+\frac{c}{r}\right),$$

$$\beta=\frac{1}{2}-\frac{\mu}{\sigma^2(I)}+\sqrt{\left(\frac{\mu}{\sigma^2(I)}-\frac{1}{2}\right)^2+2\frac{r}{\sigma^2(I)}}$$

Since $\beta>1$ we see that the objective is a differentiable function of I and thus, formally, we can find the set of its extremes as solutions of the first order condition. However, the expression is too complex to enable a simple analytical solution; moreover, it is not obvious whether any solutions exist.

From a mathematical point of view, it is of interest to find a set of conditions that would ensure the existence of solutions to the first order condition. But from a practical point of view – and to fulfill the objective of this study - it is more desirable to visualize the behavior of the objective for real data and see what it implies for the optimal investment into the improved monitoring system. Furthermore, the optimal level of investment can be found as a numeric solution of the first order condition. This, of course will require extensive sensitivity analysis with respect to the underlying parameters to ensure the robustness of the obtained findings and enable us to derive any qualitative results. The results can be found in Section 4.

Second layer

In the second layer, two players (regions, in this example Brazil and Russia) enter a game, as depicted in the scheme in Figure 4, which jointly invest into the carbon monitoring system leading to better policy coordination and more stable carbon prices. Both players benefit from this by increasing their ability to optimize the shift to the carbon-neutral technology. However, they differ in regional parameters such as their emission intensity, cost structure of the energy sector etc, which means that the value of their net benefits will also differ.

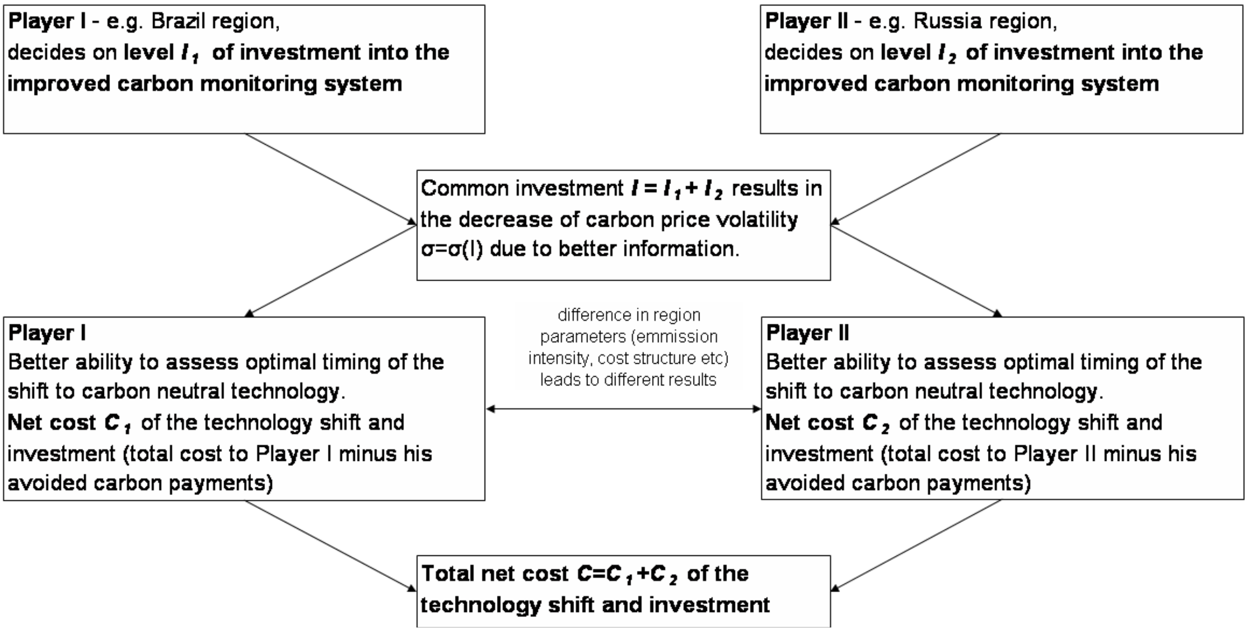


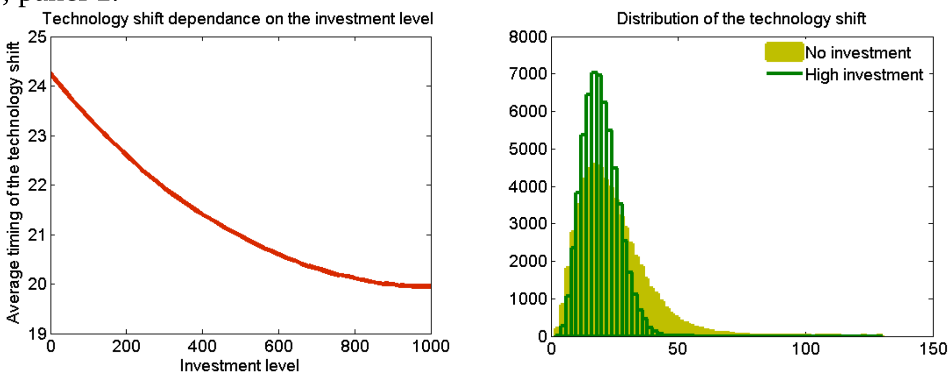
Figure 4: Structure of Layer 2

Formally, we derive for each player the optimal response functions I1(I2), I2(I1), which at their intersection give us the equilibrium investment levels.

Results

Layer 1

First results for the first layer show that indeed adoption of carbon-free technology occurs earlier for a higher investment level into better observation and thus lower CO_2 price volatility, see Figure 5, panel 1.



Panel 1 *Panel 2*

Figure 5: The impact of reduced carbon price volatility

Also, the distribution is much narrower with better information, avoiding the extremely late technology shifts that CO_2 cost uncertainty would imply for the private investor, see Figure 5, panel 2.

The benefit of an improved observation system can be thus expressed by the value of the avoided emissions, i.e. in this case the success indicator of the (emission-reducing) policy. In Figure 6, we show the carbon savings for an increasing investment level into carbon monitoring, where a more advanced and bigger system leads to more precise measurements and thus a more stable CO_2 price. We see that carbon savings increase sharply, but at a diminishing rate illustrating that after a certain size additional improvements in the carbon monitoring system will only lead to marginal gains in terms of emission reductions. In order to find the optimal level, we have to compare our results for the value with the costs of installing and operating the system.

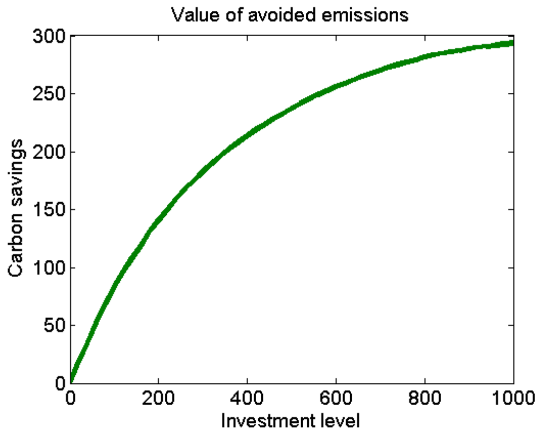


Figure 6: Value of avoided emissions

Layer 2

In Figure 7, the best response in terms of investment level of player 2 is on the y-axis and the same for player 1 on the x-axis. The more player 1 invests, the less the pressure for player 2 to invest and vice versa. Due to the differences in the players' energy sectors (emissions intensity, cost structure etc), these two curves differ in slope and intercepts and equilibrium investment will occur at their intersection only. In the example in Figure 7, this occurs at a somewhat lower investment level for player 2 than for player 1.

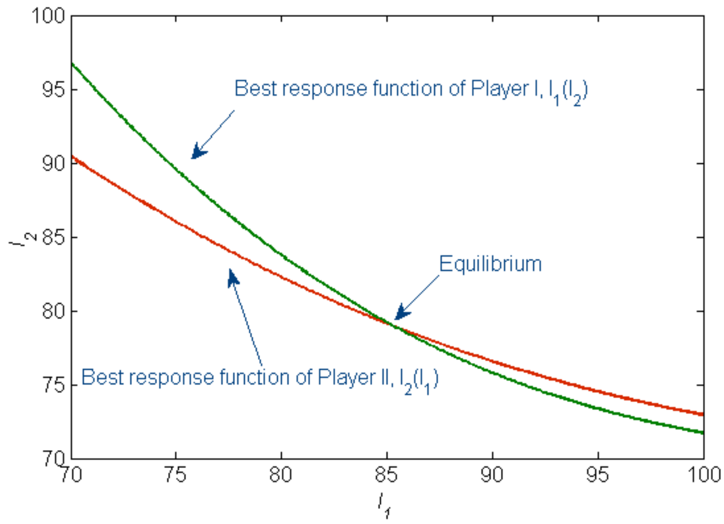


Figure 7: Solution, Layer 2

2.3 Biomass geo-wiki

Section 2.3 presents the biomass geo-wiki concept, which is a low cost way of improving decision-relevant information with huge benefits. Accurate estimates of terrestrial biomass and its dynamics are crucial for a wide variety of applications. For example, biomass is an important indicator of land use and land use change, and it provides one critical input to the development of climate change mitigation policies such as REDD+. Carbon budgeting is another important area that requires biomass monitoring. One more point of recent global interest has been biofuels and the food vs. fuel debate (e.g. Pimental et al., 2009). These are just a few examples that illustrate the importance of biomass datasets.

Remote sensing is one of the most effective ways to monitor land resources in a timely manner, in particular the monitoring of vegetation productivity, carbon stocks and land use dynamics (e.g. deforestation). However, many of the spatial datasets produced show discrepancies when compared with one another, and they have been subject to limited validation, which remains the most serious problem that requires attention. More recently, new opportunities (Doan et al., 2011) have arisen to collect additional spatial information via the Internet and mobile devices, which could aid in the validation process.

Geo-wiki was originally a single crowd-sourcing system for land cover validation (Fritz et al. 2009, 2012) but has now evolved into a family of tools with different branches. Biomass is only one branch along with agriculture, urban, human impact, competition and many others. The core datasets in Geo-Wiki are registered in the geo-portal and it represents one of many ongoing GEO activities, which contribute to building a Global Earth Observation Systems of Systems (GEOSS) (Christian, 2005). Following the principles of GEOSS, Biomass Geo-Wiki provides a broad range of information on biomass to a wide variety of users in the form of global, regional and local biomass datasets. In addition to visualization, volunteers are encouraged to validate datasets using Google Earth as well as share their own data, measurements and opinions.

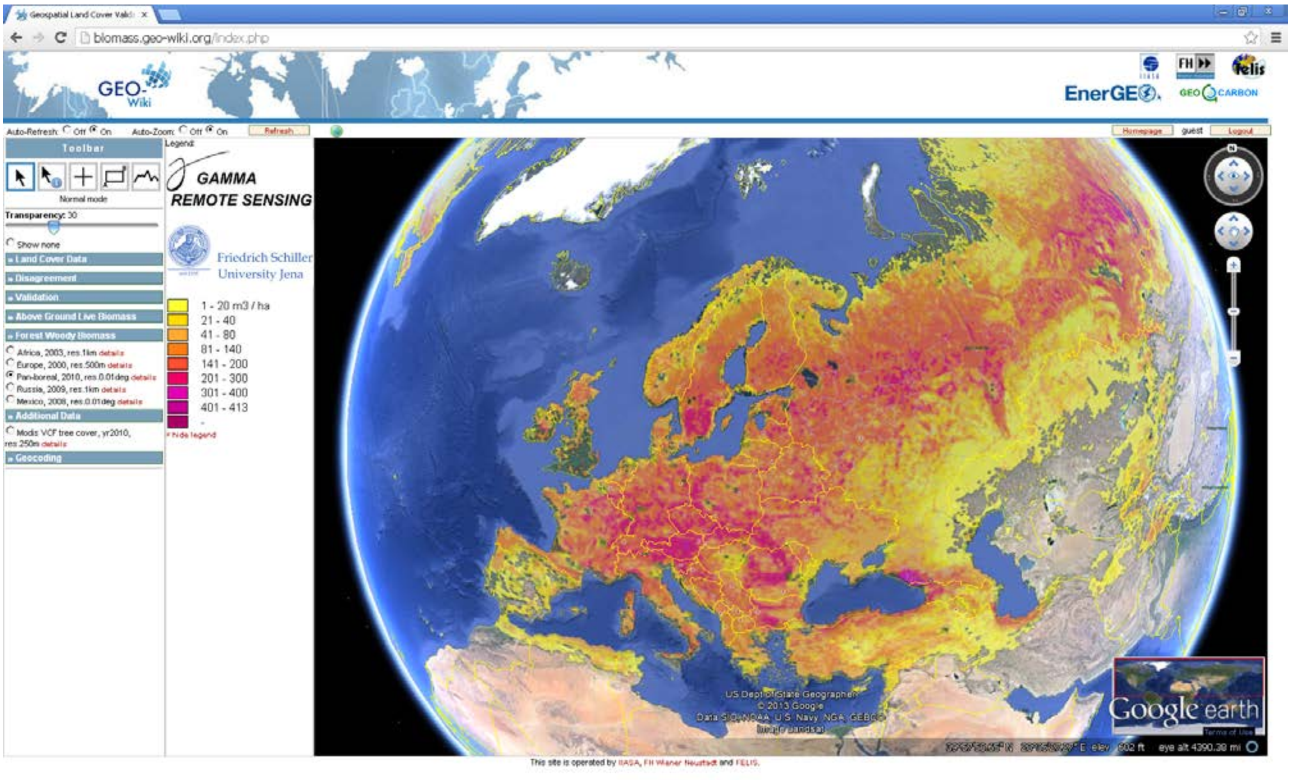


Figure 8: Screenshot of Biomass.geo-wiki.org, showing pan-boreal 2010 forest woody biomass layer

While a great deal of work has gone into producing biomass datasets in recent years, there is a need to begin harmonizing these efforts. Existing products do not yet provide a consensus on the spatial distribution or the amount of biomass. This disagreement becomes very apparent when the different products are compared with one another. One product might show a high biomass value while another product suggests a low or no biomass pool. The availability of different datasets is confusing to the users of these products, who have no idea which product is the best one to choose for their particular application nor is there much guidance available to aid their choice. Another issue is independent validation, which is a crucial task. Consequently, the main drivers behind the development of are on the one hand: the large amount of disagreement between the different biomass maps but also the lack of good validation data.

Biomass Geo-Wiki will ultimately lead to the provision of better information on global biomass, which is a necessary component to the development of national and international level REDD+ policies. Biomass inputs are also critical to Monitoring, Reporting, and Verification (MRV) frameworks of carbon inventories and will therefore provide a valuable resource for national governments in the future.

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