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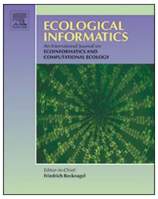

Modelling of the carbon sequestration and its prediction under climate change

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ABSTRACT

The aim of the presented study is to quantify the total carbon stock of habitats in addition the estimation of aboveground and belowground biomass, necromass, and soil organic carbon. Prediction of carbon storage under climate change is based on future land-use changes, identification of new land-use distribution, and evaluation of changes in human impacts on biomass production and carbon storage. Widely used InVEST model was applied to determine the existing carbon stocks and the amount of carbon captured over time. Changes in the carbon storage were calculated from aboveground biomass, belowground biomass, necromass, and soil organic carbon pools. The original model was modified to vector space to better identify land heterogeneity. The values of the four carbon pools for individual land-use categories were derived from literature and experimental investigation. Land Change Modeller was then used to model future land use by applying business-as-usual scenario on data derived from 1990, 2000, 2006, and 2012 Corine Land Cover data. In this contribution, land cover predictions are calculated using three CORDEX climate models and two emission scenarios (RCP 4.5 and RCP 8.5). Results describe current carbon stock by basic carbon pools and prediction of the total amount of carbon stored in four reservoirs in three time period. Results show that the difference in predictions between specific scenarios in each period is increasing and in all predictions, roughly the same proportional carbon ratio is maintained between the individual stocks.

1. Introduction

Ecosystems regulate Earth's climate by adding and removing greenhouse gases such as CO_2 from the atmosphere. Forests, grasslands, peat swamps, and other terrestrial ecosystems collectively store much more carbon than does the atmosphere (Lal, 2004). By storing this carbon in wood, other biomass, and soil, ecosystems keep CO_2 out of the air, where it would contribute to climate change (Watson et al., 2000). Beyond just storing carbon, many ecosystems also contribute to its accumulation in plants and soil over time, thereby “sequestering” additional carbon each year. Disturbing these systems with fire, disease, or vegetation change through land use/land cover (LULC) conversion, significant amounts of CO_2 is released into the atmosphere (Kareiva et al., 2011). Therefore, information on current soil carbon stocks and possible changes are needed in the context of the United Nations Framework Convention on Climate Change. Managing landscapes for carbon storage and sequestration require information about volume and location of already stored carbon, quantity of carbon sequestered or lost over time, and relationship between land use change and its effect on carbon storage and sequestration over time (Oulehle et al., 2011). A terrestrial-based carbon sequestration process is perhaps the most widely recognized of all ecosystem services (Canadell and Raupach, 2008; IPCC, 2006; Pagiola, 2008; Stern, 2007).

Determination of carbon stocks in the aboveground biomass can be accomplished by a variety of methods, including both contact field measurements and contactless measurement using remote sensing. Contact measurement methods always provide more accurate results but they are costly and time consuming (Brown, 2002; Coomes et al., 2002; Gibbs et al., 2007; Machar et al., 2016). Therefore, for large areas, the contact methods are almost unusable. That is why in present time numerous studies are devoted to incorporate remote sensing technology for quick and contactless determination of carbon stocks (Goodenough et al., 2005; Mandal and van Laake, 2005; Vicharnakorn et al., 2014).

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The fundamental methods based on contact approaches include forestry inventory, the method of table production, and Eddy Covariance method. Production table method is based on linking self-classified areas and pre-prepared tables of carbon stock production for each category according to preset classification. Tabulated values are derived from previous contact measurement and literary data. This method is also used in the documents of the Intergovernmental Panel on Climate Change (IPCC) and it implements several software models including Invest or NLLUF-KP10 (Cruickshank et al., 2000, Kareiva et al., 2011; Kuldeep, 2011; Sanga-Ngoie et al., 2012). Eddy covariance method is based on direct measurements of energy flows. The method is very accurate but it is only intended for the direct measurement of the CO_2 flow for a small area (Hunt et al., 2002; Zhang et al., 2012).

Land-use change is considered one of the most critical processes when attempting to understand and model the global change. It is a result of complex interactions between human and environmental driving factors (Schaldach and Priess, 2008) and it may impact soil, water, and atmosphere. Changes in land use may affect the climate while climate change will also influence opportunities for future land use (Dale, 1997). Lawler et al. (2014) studied land-use change using an econometric model to predict spatially specific changes in land use across the continuous United States from 2001 to 2051. The model estimated the probability of conversion among major land-use categories based on observations of past land-use change, land parcels characteristics, and economic return. Huang et al. (2015) used Markov-based cellular automata model for simulating and forecasting urban land change in Wuhan City, China, using satellite images captured between 1999 and 2005. The change in land use and land cover in Kermanshah City, Iran, was accomplished by utilizing Markov Chain model, Landsat satellite images, and site information (Razavi, 2014). Mishra et al. (2014) have employed IDRISI Land Change Modeller and Landsat satellite images to update the prediction and forecast map for years 2025 and 2035. Korateng and Zawilla-Niedzwiecki (2015) have utilized Cellular Automata and Markov Chain (Cellular Automata-Markov) to predict a land-use cover change for 2020 and 2030 for forest modelling of Ashanti Region, Ghana.

2. Material and methods

2.1. Carbon storage

The concept of model InVEST 3 - Carbon was applied to determine the existing carbon stocks and its future development using four carbon pools (aboveground biomass, underground biomass, dead organic matter and soil carbon) (Kareiva et al., 2011). This concept of InVEST model was implemented in ArcGIS for better identification of land heterogeneity and use data in the national coordinate system (EPSG: 5514). Individual carbon pools were identified for each analysed landscape segment based on the mapping of current land cover and topography. In each segment (pixel), the percentage representation of natural, near to nature, and more anthropically influenced habitats was analysed. According to percentage representation of habitats in each pool, the relevant carbon coefficient (amount of carbon per square meter) was assigned. The carbon coefficient for all four pools of natural and anthropically influenced habitats was derived from literature and experimental measurements (Stará et al., 2011). Coefficients were multiplied by the area of individual pools, and finally summed for each segment.

Prediction of the future carbon stocks was based on the changes in future land cover. An innovative element of this work is the interconnection of this model for the calculation of ecosystem services with the land cover prediction model using advanced modelling techniques including Markov chain for calculating the trend of change and Cellular automata for modelling the behaviour of the neighbours.

2.2. Prediction of land use

Historical land cover data describing the evolution of land cover in the Czech Republic comes from Corine Land Cover (CLC) database inventory mapped in 1990, 2000, 2006, and 2012. The CLC data were provided by the Czech Environmental Information Agency in a vector format (polygons) at scale 1:100,000 and supplemented with topography information including road and rail networks. The source of topographical data is Data200 geodatabase which represents a digital geographic model of the Czech Republic with accuracy and degree of generalisation to map scale of 1:200,000. The updated CLC vector layers were transformed to ETRS-89-LAEA coordinate system and then converted to raster format with a cell size of 500 × 500 m using dominant share rule. Dominant share rule assigns a pixel value of the feature that occupies the largest proportion of that pixel (Liu and Mason, 2016). TerrSet's Land Change Modeller (LCM) software was selected by authors for its ability to analyse land cover change, empirically model relationship between land cover and its explanatory variables, and project future changes (Eastman, 2016). It provided tools to perform spatio-temporal analysis of spatial CLC data to determine the difference in representation of each land cover category and subsequent evaluation of trends in land coverage for each category and location for the periods 2012–2030/2050/2090 on business as usual (BaU) scenario. First, LCM was used to assess dominant land use changes between time 1 (T1) and time 2 (T2) of two CLC maps (Fig. 1). The land-use changes identified between the two maps represent transitions from one land cover state to another and are used to evaluate losses and gains for each land-use class (Eastman, 2016). Then, transition potential model was created using multi-layer perceptron (MLP) neural network based on a set of explanatory variables, also called drivers. The model combined eight drivers and one barrier for selected periods. The drivers used in the development of the model included altitude, slope, distance to the urban area, distance to water streams, distance to roads, population density, average daily temperature and average daily precipitation sum.

The last two drivers were the only features that changed with time and were calculated using three climate models with Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 emission scenarios (Collins et al., 2011; Meinshausen, 2011). RPCs are greenhouse gas concentration trajectories that describe possible climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come (Weyant et al., 2009). Three selected climate models CORDEX (EC-Earth - RACMO22E, MOHC-HADGEM2-ES - RCA4, MPI-ESM-LR - CLM4.8.17) with two emission scenarios (RCP 4.5 and RCP 8.5) were adopted for Czech Republic territory in the frame of the CzechAdapt project (Climate change in CR, 2016). Results from climate models were obtained in a spreadsheet without geometric information. Therefore, a process of full integration of data from climate models into the GIS environment had to be developed. In the ArcGIS environment, a reference spatial layer based on forest typology maps and digital terrain model has been created and, by using this layer the climate tables, geocoded and transformed into a suitable spatial layer. Then, the layer was imported into LCM and loaded as a driver.

The other six drivers were set constant. The model also considered one barrier which defines the presence of large specially protected areas such as national parks and protected landscapes. The transition potential model was based on a given climatic model and emission scenario and interpolated for each land cover category. It expressed time-specific potential for land cover change. In the final step, a future scenario for a detailed data was predicted using the historical rates of change and the transition potential model. The simplified flowchart of the used methodology is presented in Fig. 1. Outputs display spatial distribution and quantification of particular forms of land cover change that is a result of predicted relations. Predicted land cover enters to model for calculation of new carbon stock. Carbon coefficients remain