USING MULTIPLE LINEAR REGRESSIONS TO DERIVE CROPLAND AND PASTURE PROPORTION MAPS IN ROMANIA

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Abstract. The spatial pattern of agricultural lands is an important part of the assessments regarding land management and its societal consequences, especially when considering the increasing demand for food and stronger environmental change impacts. As a subsequence, integrative studies based on complex spatial models simulating biogeochemical and physical processes that estimate yield gaps, crops efficiency or agricultural water resources use are relevant for providing trustful information required by stakeholders from different governance levels, and whose interests center on land use and its societal implications. The present paper is about the creation of a dataset representing the distribution of cropland and pasture proportions at 1 km resolution grid cell in Romania, around the year 2012. The geospatial dataset was developed by fusing the statistical agricultural data provided by the TEMPO Online Service of the National Institute of Statistics with the CORINE 2006 Land Use / Land Cover geospatial data. The two input datasets were linked through multiple linear regressions using a backward selection method. In this way, the statistical proportion of croplands and pastures of each Local Administrative Units (LAU2) is explained by all significant CORINE Land Use / Land Cover classes. The results show a high agreement between the observed proportions and the linear models' estimates, particularly in the case of croplands (i.e. 94% of the proportions are correctly estimated) as well as for pastures (i.e. 84% of the observed values). Moreover, the graphical representation of the difference between the estimated values and the observed proportions, at LAU2 level, shows that such differences, either overestimated or underestimated, are below 10 percentage points in most of the cases. The newly developed geospatial dataset could be particularly useful as an input dataset for integrative models of atmosphere-plant-soil processes simulation as well as for a wide range of specific topic-oriented syntheses and assessments on agricultural land use issues.

1. INTRODUCTION

Agricultural sustainability is framed by effective integrative management of both internal and external factors to agriculture. The internal drivers relate to land productivity, climatic conditions and variability, yields, farmers' options, etc., while external factors have been identified as economic (including the influence of global market, food security, prices and production costs on agriculture), environmental (referring to land and water resource use efficiency, soil and water quality preservation, biodiversity), and territorial (aspect that is connected to the social-economic development and integration of rural areas) (European Union: Agricultural Policy Perspectives Brief, 2013; European Union: Agriculture, 2014).

Sustainable management of agricultural land is of even more importance by, firstly considering future climatic conditions and, secondly, the population demand for food and their changing diets. In Romania, climate change is already posing threats to crop productivity and yields in areas increasingly affected by long and persistent droughts (e.g. south and south-eastern part of Romania), while fragmentation of the agricultural land in still many parts of the country and land property confusions and market transactions imperil the economic viability and growth of farms (Popescu, 2013; Popovici *et al.*, 2013; Sandu and Mateescu, 2014). These problems do not only reflect themselves in current farming practices and land management measures, but impact the farmers' responses and stakeholders'

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decisions regarding the future development pathways of the farms. To this end, sustainable management strongly emphasizes investment and research in new technologies, particularly with respect to irrigation infrastructures and drought-resistant crop seeds as well as to decision support tools that would better evaluate the trade-offs between increased yields and environmental conditions (JRC, 2013; Foley *et al.*, 2013).

Secondly, meeting peoples' demands in terms of food and individual nutritional preferences, is an issue that is strongly correlated to the welfare and economic conditions of the countries. In this respect, one of the most relevant research topics refers to the extent and intensity resources' exploitation, particularly land and water, and to the production and consumption of goods in relation with the socio-economic regional differences and with agricultural markets, food trade and resource governance aspects (World Resources Institute: Millennium Ecosystem Assessment, 2003).

The analyses concerning agricultural-related issues are tightly connected to integrative approaches that would account for both aspects climate change consequences and agricultural management on agriculture. In this respect, research projects and studies are based on the application of complex models which are able to simulate biogeochemical and physical processes and socio-economic trends alike, generating estimations on crop yield potentials and gaps, croplands environmental quality and use, agricultural water use and supply, etc.

For instance, models simulating atmosphere-plant-soil processes (e.g. DSSAT, CERES, CropSyst, LPJ, GEPIC, AquaCrop, CROPWAT, etc.) are based on plant growth algorithms, data on farming practices and land management, climate and soil parameters. They are widely applied to analyze biomass production and yield potentials, blue and green water consumption in different environments (van Wart *et al.*, 2013; Liu, 2009; Liu *et al.*, 2009; Folberth *et al.*, 2012), climate change effects on crop yields (Supit *et al.*, 2012; Bocchiola *et al.*, 2013) or on plant stress conditions (Pfister *et al.*, 2011; Heyder *et al.*, 2011).

Most of such models are particularly designed and applied to global level analyses (Hoff *et al.*, 2010), showing relatively well performances of the undertaken evaluations. Narrowed down to national or regional scale applications, they require fine resolution input datasets and local-specific calibrations of sensitive parameters. Therefore, all integrative models are based on comprehensive input datasets, including geospatial and tabular data, at various resolutions, depending on the scale of the analysis, which need to be processed and harmonized to properly feed the respective model.

The scope of the present paper is the development of a geospatial dataset on croplands and pastures in Romania, which could serve as input data for some spatial (complex) models as well as for particular syntheses on Romanian land use / land cover issues. For this purpose, statistical data of agricultural land categories at local level (LAU2), from the National Institute of Statistics (INS), were correlated with the CORINE Land Use / Land Cover geospatial dataset in order to estimate the proportion of cropland and pasture coverage in Romania, at 1 km resolution grid cell, around the year 2012.

2. MATERIALS AND METHODS

2.1. Spatial Data from the CORINE Land Cover Project

CORINE Land Cover (CLC) is a database of the European environmental landscape derived from the interpretation of satellite imagery: Landsat 4/5 TM (in a few cases, Landsat MSS), SPOT 2/3, Landsat 7ETM, SPOT4 and IRS LISS III images (Bossard *et al.*, 2000; Feranec *et al.*, 2012). In this study we used CORINE Land Cover database for the reference year 2006 (scale 1:100,000) produced by the method of visual interpretation of SPOT 4 and/or IRS LISS III images. The complete classification, nomenclature and methodology are available in the official CORINE portal (http://www.eea.europa.eu/publications).

A number of 33 in the CLC nomenclature were identified within Romania, being further grouped into 15 classes (level 2) and 5 classes (level 1). To account for cropland and pasture areas in Romania, all the identified CLC classes have been used in the analysis, except for the artificial areas, wetlands and water bodies categories. Therefore, we used all *agricultural forest and semi-natural areas* (12 classes – level 3), included in 6 classes (level 2) (Table 1). Worth mentioning that the forest CLC classes (311, 312 and 313) were considered in the analysis as some portions of their edging lands and/or some open canopy areas within can be used for grazing and thus contributing to the proportion of pastures as explained later in the methodological part of the study. Figure 1 shows the spatial representation at 100m resolution of the aggregated agricultural and forest CLC classes, according to CORINE level 1 nomenclature.

Table 1

CLC dataset used in this study, classified by the nomenclatures identified for Romania

LEVEL 2	LEVEL 3
21 Arable land	211 Non-irrigated arable land 213 Rice fields
22 Permanent crops	221 Vineyards 222 Fruit trees and berry plantations
23 Pastures	231 Pastures
24 Heterogeneous agricultural areas	242 Complex cultivation patterns 243 Land principally occupied by agriculture, with significant areas of natural vegetation
31 Forests	311 Broad-leaved forests 312 Coniferous forests 313 Mixed forests
32 Scrub and/or herbaceous vegetation associations	321 Natural grasslands 324 Transitional woodland-scrub

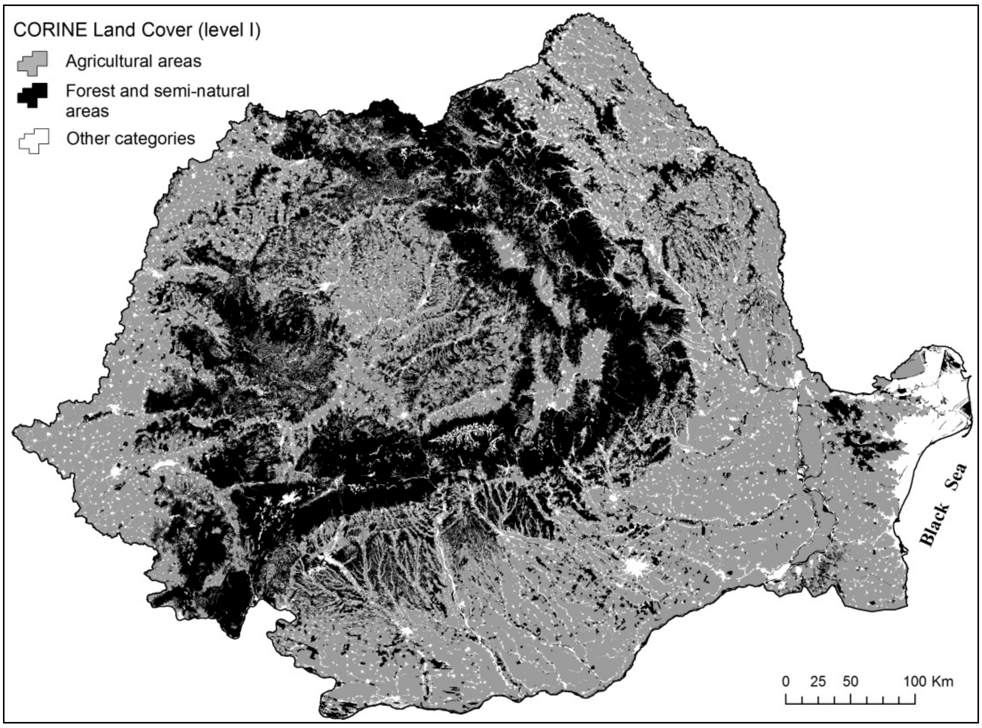

Fig. 1 – CLC classes used in the study aggregated at level 1.

2.2. Agricultural statistical data from the National Institute of Statistics (INS)

We used the agricultural data from INS (the TEMPO Online Service) at locality level (i.e. 3181 LAU2) for the period 2010 – 2013. The adopted classification of the dataset was according to the INS definition of "Agricultural surface area". This consists in the lands used for agriculture by individuals or agricultural legal entities and are grouped as arable land, natural pastures and meadows, vineyards and vine nursery, orchards and fruit tree nursery. As such, the proportions of cropland within each LAU were compiled of arable land, vineyards and vine nursery, orchards and fruit tree nursery categories, while pastures proportions are formed by natural pastures and meadows. However, the INS does not distinguishes between the natural pasture and forest lands used for grazing, this being the reason why forest CLC classes were taken into account in the analysis. The dataset was averaged around the year 2012.

2.3. Methodology

To create the present geospatial dataset of the proportion of cropland and pasture at 1 km grid cell for Romania we followed the methodological framework developed by Ramankkuty *et al.*, 2008 for obtaining the spatial distribution of croplands and pasture at global level using high-resolution satellite derived land-cover datasets which were calibrated against agricultural census data.

The process of creating the map of croplands and pastures for Romania consisted in two sequential steps, first, to determine the link between the geospatial CORINE Land Cover data and the INS statistical agricultural data, and second, to use the connecting determinants in the calculation of the proportion of cropland and pasture for each 1 km grid cell.

To this end, the CORINE Land Cover classes (Table 1) are used to spatially locate the agricultural lands within an administrative unit (LAU2), but the total area of agricultural land in the respective administrative unit is given by the INS statistical data. In this case, the CORINE Land Cover data are linked to the INS agricultural statistical data through linear models (Eq. 1 and Eq. 2), where the CLC classes (level 3) are used as predictors, while the INS statistical data are the dependent variables. Worth mentioning that, due to the slight difference of temporal representation of the two datasets, we assumed that no changes occurred in the spatial extent of the CLC classes between 2006 and the beginning of the 2010s.

The equations' variables are given by: 1) the proportion of each CLC class *j* within the corresponding administrative unit *i*, notated $\lambda_{j,i}$, and with the sum of the proportion of CLC classes (level 3) in *i* being 1 ($\sum_{j=1}^{n_\lambda} \lambda_{j,i} = 1.0$, where n_λ is the number of CLC classes), and 2) the proportion of cropland and pasture area from the INS statistical data, $p.C_i$ and $p.P_i$, out of the total LAU2 area (A_i).

$$p.C_i = \sum_{j=1}^{n_\lambda} (\alpha_j \times \lambda_{j,i}) + \varepsilon_{i(C)}, \quad \text{(Eq. 1)}$$

and

$$p.P_i = \sum_{j=1}^{n_\lambda} (\beta_j \times \lambda_{j,i}) + \varepsilon_{i(P)}, \quad \text{(Eq. 2)}$$

where α_j and β_j are the unknown parameters of each land cover class *j*, and $\varepsilon_{i(C)}$ and $\varepsilon_{i(P)}$ are the error terms (residuals) representing the difference between the INS statistical observations and the estimations of the linear model of cropland and pastures proportions respectively.

To solve the unknown parameters α_j and β_j, we started from a full linear model considering that all CLC classes are potentially cropland or pasture within the administrative unit. We then applied the stepwise regression method using backward selection, eliminating at a time those predictors that are not significant in the process of explaining the proportion of cropland and pasture, respectively, identifying the best fit model (the elimination criteria are explained below).

The following steps were taken to solve the unknown parameters and reach the best fit models (Ramankkuty *et al.*, 2008):

1. The standard approach of least-squares minimization method is used to solve the regression equations (i.e. LSE = $\sum_{i=1}^{m}[(\varepsilon_{i(C)})^2 + (\varepsilon_{i(P)})^2]$, where m_i is the number of administrative units). However, to minimize the sum of squared residuals, a weighting term (ω_i) was specified to weight the data in each administrative unit by its area normalized by areas' maximum value ($i.e.\ \omega_i = \frac{A_i}{max(A_{[1..m]})}$).

2. The proportions of cropland and pastures in any grid cell (when the estimations are needed for the calculations at grid cell level) need to be between 0 and 100% and their sum less than or equal to 100%. Therefore, we have:

$$0 \leq \alpha_j \leq 1;$$
$$0 \leq \beta_j \leq 1;$$
$$\alpha_j + \beta_j \leq 1.$$

These three particular conditions lead to the following criteria of eliminating the predictors that were not significant in explaining the proportion of cropland and pasture, respectively:

– we removed, one at a time, any CLC class with negative parameter values, starting from those with significant P-value at levels ≥ .05, and re-estimated the model;

– whether the sum of cropland and pasture estimated parameters exceeded 1 for a particular CLC class, we set the pasture parameter at $1 - \alpha_j$ and moved the respective CLC class on the other side of the equation, thus changing the dependent variable, and re-estimated the model;

– whether the value of cropland estimated parameter exceeded 1 for a particular CLC class, we set the cropland parameter to 1, moved the respective CLC class on the other side of the equation, thus changing the dependent variable, and re-estimated the model;

– we removed any left CLC category with a P-value that was not significant at least at .05 level and re-estimated the model.

Finally, having α_j and β_j parameters determined, we calculated the proportion of cropland and pasture at grid cell level, as follows:

– for each 1 km grid cell, x, y (latitude by longitude) we calculated the proportion of each CLC class, $\lambda_{j,x,y}$, within the 1 km grid cell.

– using the α_j and β_j estimates of the linear models, we calculated the cropland and pastures proportions in each 1km grid cell, $p.C_{x,y}$ and $p.P_{x,y}$, by the formula: $p.C_{x,y} = \sum_{j=1}^{n_\lambda}(\alpha_j \times \lambda_{j,x,y})$ and $p.P_{x,y} = \sum_{j=1}^{n_\lambda}(\beta_j \times \lambda_{j,x,y})$.

3. MAPS OF CROPLAND AND PASTURES PROPORTIONS AND LINEAR MODELS' ACCURACY ASSESSMENT

3.1. Cropland and pasture maps

In order to obtain robust results and to better operationalize the application of the above explained methodology, it was deemed necessary to split the data into several parts of high variability and run the models for each single such entity. In this respect, the development regions of the country were considered appropriate for the partition of the data as within each, the land cover is heterogeneously patterned and of various extensions. As well, an adequate number of observations corresponds to each region, with the note that Bucuresti-Iflov was added to the South development region, totaling 608 observation in this case. The resulted maps represent the proportion of cropland and pasture in each grid cell of 1 km resolution around the year 2012 (Fig. 2).

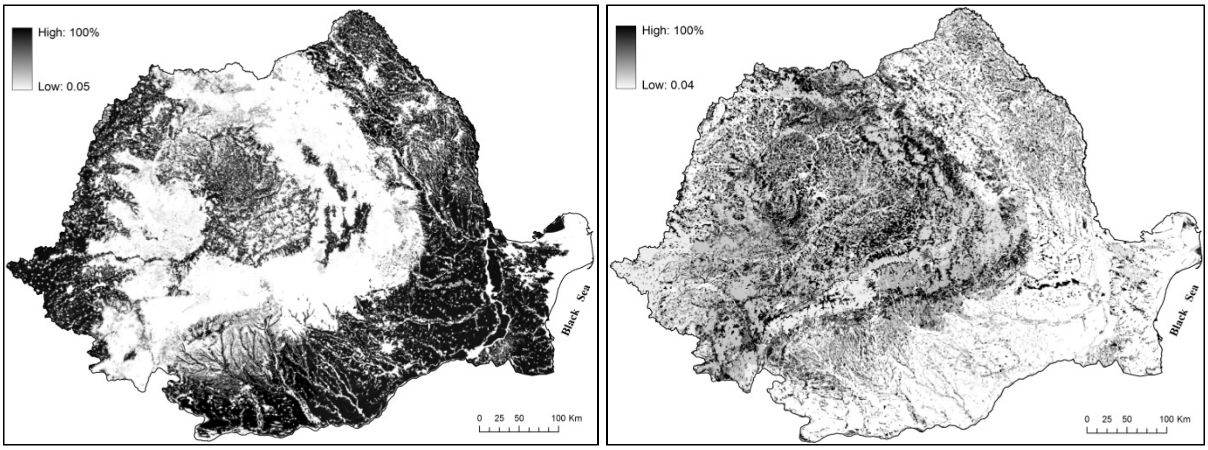

Fig. 2 – Spatial distribution of cropland (left) and pasture (right) proportions at 1 km grid cell, around the year 2012.

3.2. Linear models' accuracy

The accuracy of the estimates is shown by the good agreement between the observed and the predicted proportions of cropland and pastures for each region for which the multiple linear regression with the backward selection method was applied. This is expressed by the Pearson's correlation coefficient between the observed and the predicted proportions for the two land cover groups, showing a very high correspondence level (i.e. Pearson's correlation coefficient between 0.83 and 0.99) for most regions (Table 2). The exceptions are the South-West region and the croplands of the North-East region whose lower Pearson's coefficient values could be due to a greater variety of the relief in the first case and a high degree of fragmentation in the second. Similarly, a high correlation between the observed proportions and the linear models' estimates is shown by the scatterplots made for the entire data, particularly in the case of croplands (i.e. Pearson's coeff. = .94) as well as for pastures (i.e. Pearson's coeff. = .84) (Fig. 3).

Table 2

Pearson's correlation coefficient between observed and predicted proportions of cropland and pastures for each region

CORRELATION BETWEEN OBSERVED DATA AND LINEAR MODELS' PREDICTIONS BY REGIONS				
REGION	**Number of administrative units**	**Cropland**	**Pastures**	**Significance level+**
SE	390	0.99	0.88	***
S	608	0.97	0.94	***
SW	448	0.69	0.66	***
V	323	0.99	0.77	***
NW	446	0.97	0.78	***
NE	552	0.63	0.91	***
CEN	414	0.93	0.83	***

+The significance level is at .0001

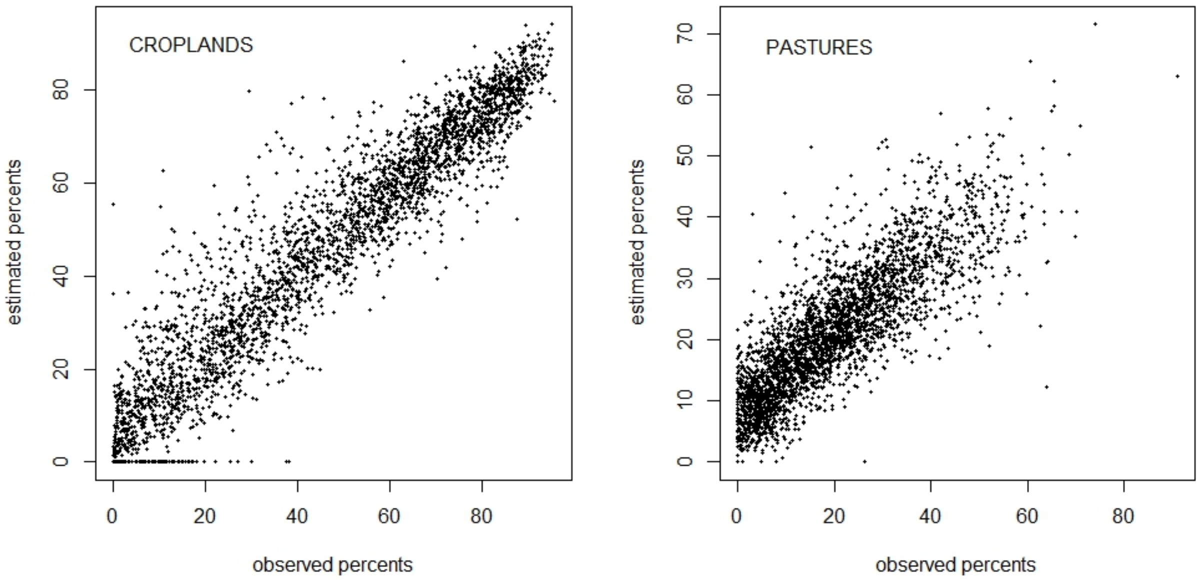

Fig. 3 – Linear models' performances expressed by scatterplots of the observed proportions of croplands and pastures against estimated proportions of the two agricultural categories.

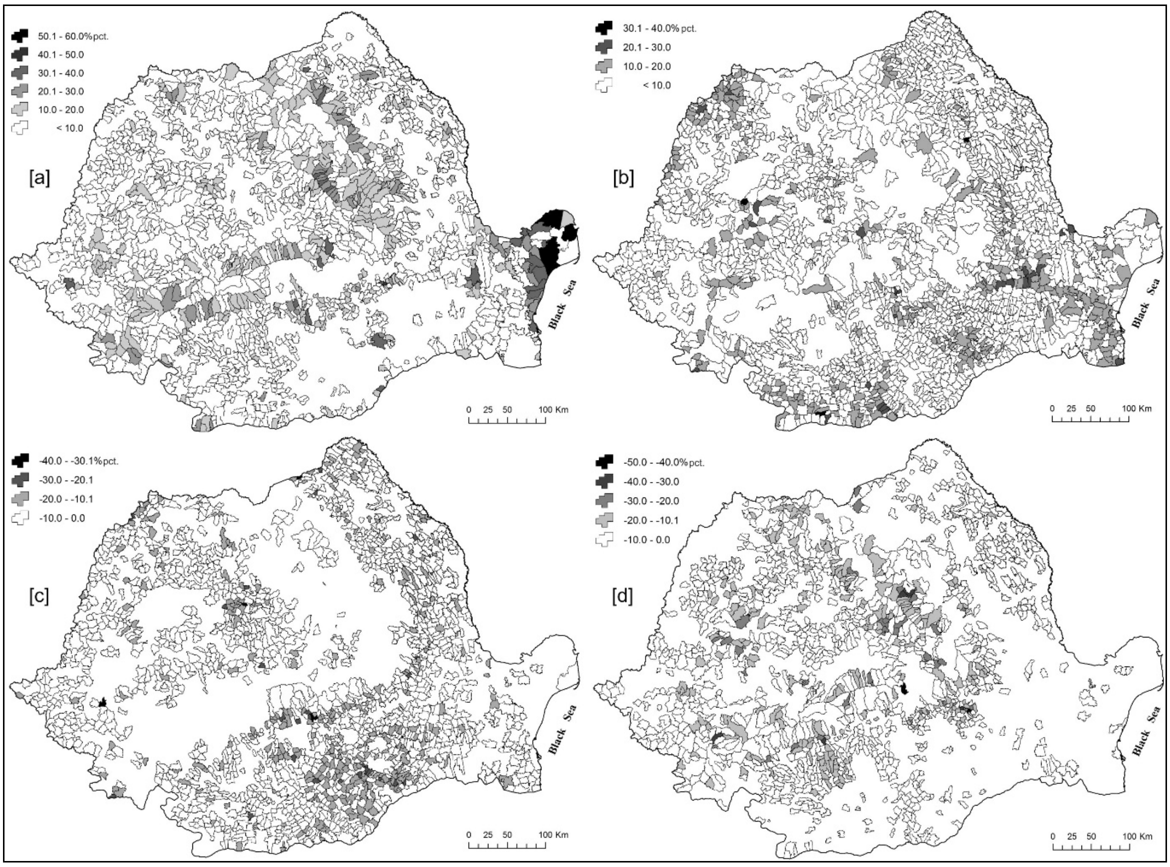

Fig. 4 – Predicted vs. observed proportions for croplands and pastures at LAU2 level: 4.a) overestimations of cropland proportions; 4.b) overestimations of pasture proportions; 4.c) subestimation of cropland proportions; 4.d) subestimation of pasture proportions.

Moreover, the graphical representation of the difference between the estimated values and the observed proportions, at LAU2 level, shows that these differences, either overestimated or underestimated, are below 10 percentage points in most of the cases (Fig. 4). It is only the communes located in the Danube Delta Biosphere Reserve that show higher overestimated values for croplands, possibly as a consequence of the particular farming regimes and status postulated for the lands here, for which the land use categories cannot be clearly delineated and/or counted up.

4. DISCUSSIONS

The present cropland and pasture proportion maps were obtained by merging two different datasets, the CORINE Land Cover / Land Use dataset, a geospatial dataset englobing satellite-derived information on the land cover classes, and the INS statistical agricultural data, which accounts for the areas occupied by crops and pastures at locality level on a yearly time span. The maps describe the spatial extent of croplands and pastures within 1km resolution grid cells in latitude by longitude, around the year 2012, thus forming themselves two comprehensive geospatial datasets of croplands and pasture proportions in Romania. The national cropland area estimated in this study is 91,123 km^2, i.e. 6.95% lower than the INS registered data of 97,929 km^2, while the pastures are predicted to total an area of 44,552 km^2, i.e. 7.57% below the area reported by INS which is 48,202 km^2.

Although the estimates of the distribution of cropland and pasture proportions do fairly agree with the observed corresponding data, several uncertainties related to the accuracy of the produced maps have to be considered and, potentially, dealt with in the future. First, the CORINE Land Cover / Land Use data might be subject to some locally confined inadequacies between the information withdrawn from satellite images and the terrain realities. Second, the period between the two datasets used in this study is slightly different (i.e. the CORINE dataset is updated to the reference year 2006, while the INS statistical data is averaged around the year 2012); in this case the assumption of the present study was that no changes in the spatial extent of the CLC classes had been occurred between the two time slots. Then, the resulted maps are better suited for regional or country level approaches or modeling rather than for large geographic scale analyses, due to their inherited resolution of 1km grid cell. As a consequence, undertaking investigations on the uncertainties of the linear models used to produce the maps, by applying appropriate statistical methods and/or by validating the geospatial datasets by ground truth analyses, might be advisable to reduce some of the limitations of the present study.

The cropland map could be further used to represent the spatial distribution of different crop types, provided census data of the area covered by the respective crop types is available at fine administrative unit scale (Monfreda *et al.*, 2008; Portmann *et al.*, 2010). In this sense, the geographical representation of wheat and maize in Romania will be undertaken by a forthcoming analysis using the spatial distribution of croplands and the area cultivated by the two crops around the year 2003, the period for which the necessary input data are freely available. Moreover, an approach to the dynamics of land use change in Romania will be possible, by overlaying and comparing the 2012 and 2003 cropland distributions. Furthermore, such geospatial datasets could serve as inputs for a variety of integrative complex models (hydrological, biomass growth and economic) that enable spatially-explicit and process-based assessments of different environmental and water and land resources consumption aspects, at different scales and within different thematic contexts.

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available for download from European Environment Agency site: http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2006-raster-3, and from the National Institute of Statistics, the TEMPO Online Service site: http://statistici.insse.ro/shop/, respectively.

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