EU-wide spatial down-scaling of results of regional economic models to analyze environmental impacts

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Abstract

Major environmental indicators require data at a spatial resolution below administrative units as found in economic models. The CAPRI-Dynaspat project added spatial results for EU27 to the CAPRI model allowing for linkage to bio-physical models and calculation of novel indicators. The layer consists of clusters of 1x1 km cells exhausting the agricultural area, uniform in soil parameters, slope class, land cover and administrative unit. Crop and irrigation shares, stocking densities and yields are estimated per cluster along with intermediate input demand including crop specific fertilizer application rates. Those estimates drive statistically estimated meta-models from the bio-physical crop growth model DNDC to derive the nitrogen and water cycle. Indicator calculators allow estimating further impacts as e.g. different gaseous emissions or economic performance of agriculture. The results are available for the base year, for projection or scenario results, thus allowing analyzing environmental impacts in a spatial context.

Key words: Spatial dis-aggregation, agri-environmental indicators

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1. Background

Since 2001, the EU directive 2001/42/EC on Strategic Environmental Impact Assessment and the subsequent communication COM(2002)/276 as well as the impact assessment guidelines (SEC(2005) 791) shall ensure that economic, social and environmental consequences of certain plans and programmes are identified and assessed during their preparation and before their adoption. More specifically, the recent reforms of the Common Agricultural Policy claim to promote the so-called multi-functional model of European agriculture linked to the different pillars of sustainability. However, it is obvious that data availability often hinders calculation of the necessary agri-environmental indicators for impact assessment, e.g. those proposed in the Common Evaluation and Monitoring Framework for Rural Development. That is especially true for Pan-European forward looking analysis of the CAP due to the spatial resolution and result coverage of the available agricultural sector models. The EU funded research project CAPRI-Dynaspat aimed therefore at the development of down-scaling methodologies for the regional result layer of the economic model CAPRI to drive environmental indicator calculators and bio-physical models at an appropriate spatial resolution. That seemed necessary as agricultural management and its impact on the environment depend on local factors as climate and soil, and the underlying relations are often highly non-linear.

Several other research projects or approaches deal with linking economic models and their results for larger administrative units to (agricultural) land use at sub-administrative regional scale as e.g. SENSOR (Jansson et.al. 2007), EURURALIS (Verburg et.al. 2007), INSEA (Adler et.al. 2007), GENEDEC (Chakir 2007) or LUMOCAP (van Delden and Luja 2007). However, the combination of Pan-European coverage, the rather dis-aggregated list of crops, inclusion of stocking densities and output and input coefficient estimates per activity render the CAPRI-Dynaspat rather unique, along with some novel statistical methodologies.

A spatial down-scaling of CAPRI results was deemed to be especially promising as the data ex-post and scenario and projection results ex-ante are available for EU27, Norway and Western Balkans at the level of NUTS II regions. Those regional data sets comprise crop areas, animal herds, input and output coefficients for a rather detailed list of crop and animal production activities, and are based wherever possible on official harmonized data sources. CAPRI has been widely used in policy impact analysis and research projects, and already covers environmental indicators at NUTS II level as nitrate balances or Green House Gas inventories. The structure of the regional programming models in CAPRI which combine a Leontief technology for intermediate inputs with an econometrically estimated cost function is a good starting point for model extension allowing scenario analysis of agri-environmental legislation. Additionally, the transparent link inside CAPRI between the programming models and its large-scale global trade model for agricultural products ensures a consistent integration of price feedback as well as of market and border policies.

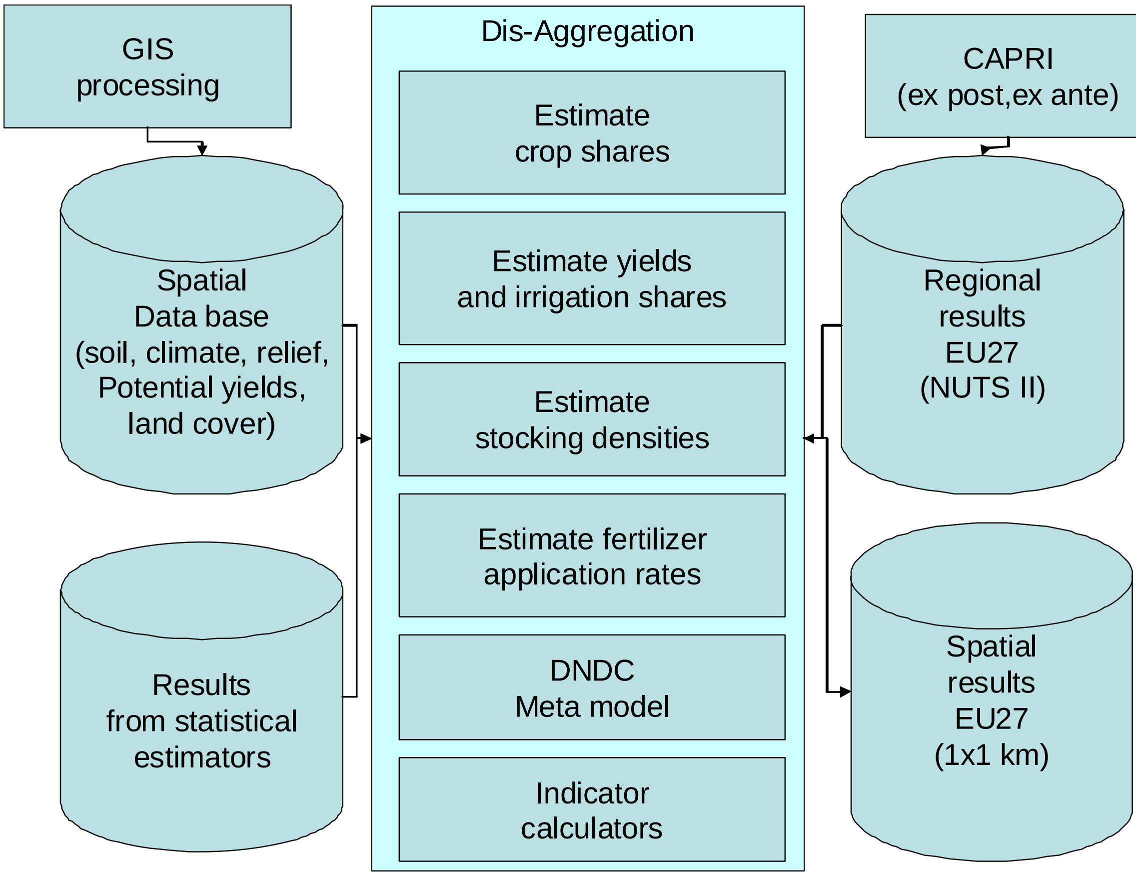
2. Methodology and data sources

2.1. Overview on down-scaling process

The down-scaling process dis-aggregates all major elements of the regional data set from CAPRI, ex-post or ex-ante to clusters of 1x1 km grid cells for the agricultural area of EU27. The process consists of working steps which build onto each other. Each step ensures that the spatial results are consistently down-scaled from NUTS II level, and is based on the combination of spatially explicit data as e.g. soil or climatic parameters and either statistically estimated or engineering relations. The approach is motivated by the assumption that market conditions and the policy implementation for agricultural production activities are a rather homogenous inside NUTS II regions, so that the spatial distribution of regional characteristics can be derived from local factors as soil type, relief or surrounding land cover. The different steps are discussed in detail below. The estimation of cropping shares, yields and irrigation shares and stocking densities is based on Highest Posterior Density (HPD) estimators (Heckelei et.al. 2005).

For crop shares and stocking densities, the Farm Structure Survey (FSS) is used in addition to the CAPRI NUTS II data during the generation of the spatial base year layer. FSS provides data at NUTS III resolution in countries where NUTS II regions are rather large. The resulting estimates at 1x1 km resolution for the base year are then used as anchor for dis-aggregation of ex-ante results at NUTS II level.

Figure 1: Overview on dis-aggregation process



2.2. Definition of the sub-regional processing unit

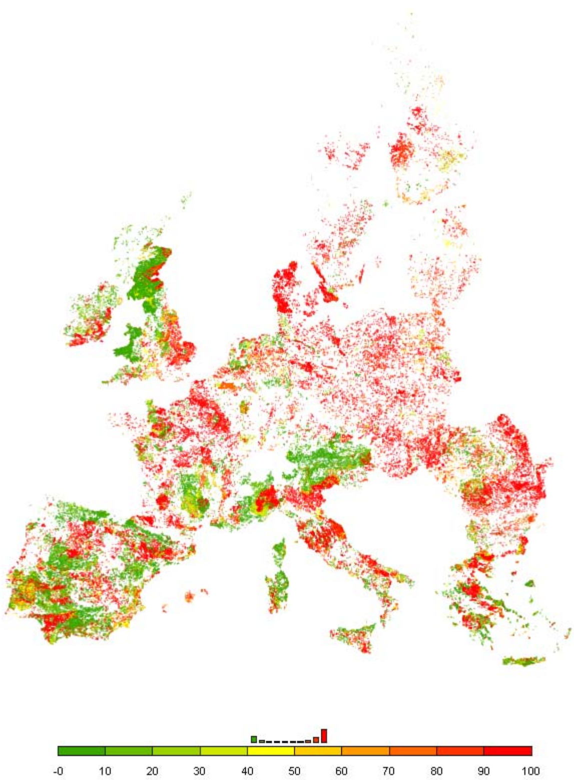
The processing units are sub-regional geo-referenced entities to which the regional results are dis-aggregated. They are defined as to produce a manageable number of sites which are as far as possible uniform. The latter refers to those characteristics deemed most important from a point of view of environmental impact analysis: soil, climate, slope and land cover. For soil, the publicly available European Soil Map was used, climate data were provided by MARS, slope and elevation data by DEM 250 and CORINE 2000 provided land cover information. All the input data were first rastered to 1x1 km grid cells. Grid cells of the same soil type, in the same slope class, CORINE Land Cover class and administrative units were then combined to pixel clusters building so-called Homogenous Soil Mapping Units (HSMU). Climate was not used as a delineation factor given the 50x50 km resolution for the daily weather time series. Each HSMU may consist of several polygons not necessarily connected, and feature an area between an individual 1x1 km cell to several thousand square kilometres, depending on the spatial variability of the delineation factors. Additional data beyond the delineation features, as climate or soil parameters, were defined per HSMU and stored in data base. Those processing steps were handled by the Climate Change Unit of the JRC (for details on data sources and methodology see: Leip et.al. 2007).

2.3. Crop shares

Unfortunately, there exists no publicly available land use/cover map at European scale which identifies in sufficient detail crop shares at a resolution below rather large administrative units. Therefore, an estimation framework was developed which is able to break-down land uses classes from the Pan-European publicly available CORINE land cover (CLC) map to individual crop shares. CLC shows pre-dominant land cover distinguishing a few agricultural classes only, where e.g. all arable crops are aggregated. CLC is based on photo interpretation of satellite images where the resolution did not allow distinguishing features smaller then 25 ha. Accordingly, shares of agricultural cover are systematically found in other land use classes, and agricultural classes often comprise sizeable shares of non-agricultural cover (see Gallego 2007). Further on, it is almost impossible from photo interpretation to distinguish between certain extensive forms of grassland and certain types of natural vegetation. The same holds quite clearly for stationary and to lesser extent for rotational set-aside. And last but not least, the Utilizable Agricultural Area as used in CAPRI to define agricultural areas is linked to private ownership to farm land as defined by the FSS, so that e.g. common grazings are not comprised in the CAPRI definition, but clearly found in CLC. The combination of those factors can lead to differences in the range of 20% for NUTS II or III regions between CLC and the FSS even with all types of agricultural land cover aggregated in one class. As environmental impacts depend heavily on the crop mix even inside arable crops, it was deemed necessary to build an agricultural land cover map for single crops consistent to the FSS and further regional agricultural statistics and to develop a methodology which would allow updates based on projections and scenario results. Similar efforts for a base year are e.g. undertaken by the FATE project (Grizetti etl.al.2007).

In Land Use Cover Change (LUCC) models, land use as in CLC is typically expressed as pre-dominant land cover per raster cell (Verburg et.al. 2006). If that representation is used to map and store the results of a dis-aggregation procedure, a rounding error is introduced, depending on the number of cover classes and the grid resolution. As arable cropping is for its largest part characterized by crop rotations, and the spatial result layer was set up as to have the same level of detail as the regional one in the CAPRI data base, a pre-dominant land cover presentation was therefore not deemed advisable. Instead, a cropping shares representation was chosen. This allows consistency in downscaling according to numerical machine accuracy combined with a number of processing units determined by the spatial accuracy of the delineation features used.

Figure 1: Arable crop share [%]



The crop shares were estimated in a two stages process (see for details: Kempen at.al. 2005). The LUCAS data provided geo-referenced point observations for a large observation sample where single crops had been identified per location based on field visits and photo interpretation. Those data were input into a binary Maximum Likelihood estimator per crop, using a spatially widened regression, to derive probability density functions per crop and HSMU as the first step in the process. The second step then scales the crop areas at administrative level consistently down to the cluster of grid cells. For each FSS Region, a HPD estimator chooses the combination of crop shares for each HSMU which simultaneously exhaust the given regional crop area and maximizes the joint probability density given the density functions estimated from LUCAS. The resulting crop share map at Pan-European level alone was already an important outcome of the project, and is used in different EU funded research projects. It has been successfully evaluated with out-of-sample observations (see e.g. Elbersen et.al. 2006, Leip et.al. 2007).

2.4. Crop yield and economic indicators for crops

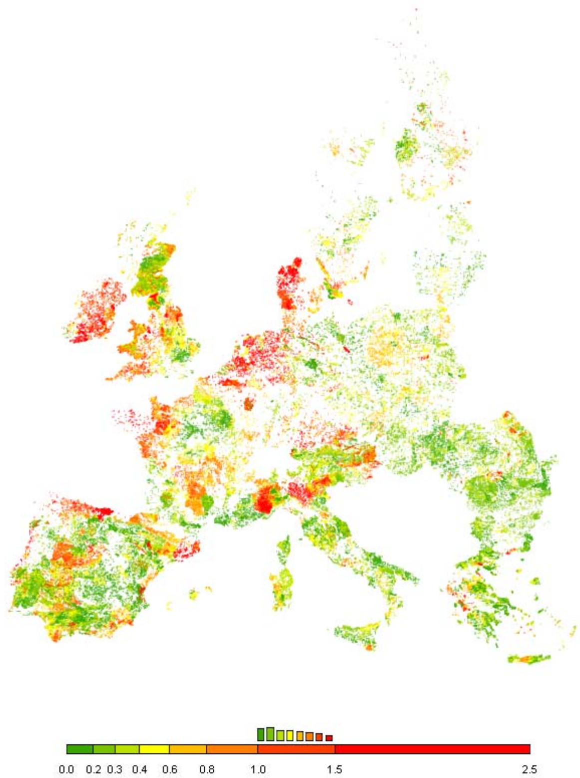
The crop yield estimation combines three different types of a priori information in a HPD estimation framework to derive simultaneously spatially explicit yield estimates and irrigation shares per crop. A first input data set in the estimation process is the irrigation map from FAO used to provide per HSMU an estimate of the share of irrigated agriculture. Secondly, the FSS delivers data for irrigated areas for certain crops at administrative level and, thirdly, MARS offered potential yields for rainfed and fully irrigated agriculture. The FSS data about irrigated hectares at regional scale had been used via regressions to find some basic relations between soil properties and climatic parameters and the irrigated share per crop or crop group. From those regression models, forecasts are derived at the level of single HSMUs about the irrigated share per crop. The HDP framework minimizes simultaneously deviations from the estimated crop specific irrigation shares per HSMU, from the irrigation shares per HSMU derived from the FAO map and from the potential yields. Constraints ensure that firstly the area weighed average of the yields per HSMU is equal to the one found in regional statistics, and secondly that the irrigated area per HSMU exhaust the irrigated area at regional level found in the FSS.

The crop yields are used as explained below as explanatory factor in the estimation of animal stocking densities and drive as well the estimate of crop specific fertilizer application rates. Using simple linear input demand function per crop activity for the different inputs (plant protection, repair costs etc.) and assuming uniform prices for output and inputs insides the administrative units, the crop yields at HSMU level are also used to derive economic indicators per crop (revenues, variable costs, gross value added, gross value added plus CAP pillar I premiums). It is planned to add soon estimates about CAP pillar II payments.

2.5. Animal stocking densities

Unfortunately, in opposite to the LUCAS sample for crops, no high resolution observation sample for animal stocking densities at Pan-European level is available. Additionally, especially for area independent animal production activities as pigs and poultry, a weak relation between local natural factors as soil and climate and stocking densities can be expected. Therefore, the estimation of stocking densities builds on a cross-sectional estimation from the Farm Structure Survey for a mix of NUTS II and NUTS III administrative units with overall about 500 observations for EU27 per animal category. Regression models for the different animal activities in CAPRI as well as aggregates for ruminant and non-ruminants were estimated, using crop and land cover shares (forest, shrubs, total UAA, non-agricultural land cover, cereals, grassland, fodder maize, all type of fodder production), fodder maize and cereals yields as well as revenues and GVA plus premiums per ha for Grandes Cultures and cereals, altitude and slope along with climate data (annual rain fall, temperature sum, length of the vegetation period) as explanatory variables. All variables were offered untransformed, as squares and square roots to the estimator. The estimators then used a backward elimination, removing explanatory variables as long as the adjusted R squared was increasing or a variable was not significantly different from zero at the 5% level. In order to account for specific national legislation and market conditions, either the FSS regions of a country were estimated separately (France, Italy) or national dummies we used in the estimation for group of countries (Group 1: Germany, The Netherlands, Belgium; Group 2: Spain, Portual and Greece; Group 3: Denmark, Sweden, Finland, UK, Irland and Austria; Group 4: EU12). Such grouping ensured sufficient degrees of freedom during estimation. Not surprisingly, the explained variance for the ruminants was general high in the range of 80% and above, whereas for pigs and poultry, R^2 were in some instances as low as 40%.

Figure 2: Livestock Density [LU/ha]



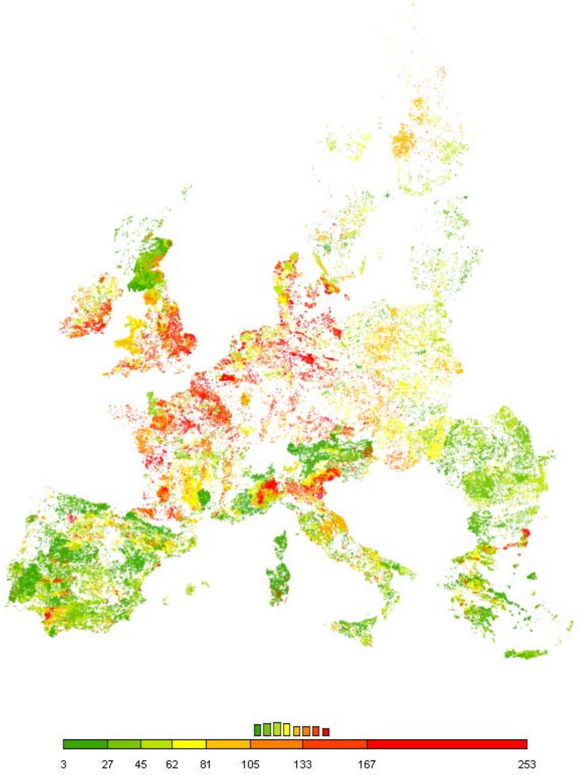
As own produced fodder and organic fertilizer may be transported easily even over several kilometres, it was decided to base the estimation of local stocking densities not on the explanatory variables per HSMU, but rather on a distance and area weighted average of the area around each pixel cluster. Those locally weighted averages per HMSU were then used to estimate the expected mean and its forecast error for each animal category, and livestock unit aggregates for ruminants, non-ruminants and all types of animals, providing a priori distribution for the stocking densities per HSMU. A HPD estimator chooses then those combinations of stocking densities per HSMU which exhaust the regional herd sizes. During estimation, bounds prevent the generation of very large stocking densities. In order to stabilize the results, the estimation included also the mentioned aggregates for ruminants, non-ruminants and all type of animals expressed in livestock units.

The resulting data set was evaluated against out-of-sample from France showing stocking densities for 35.000 single communes based on the FSS. The comparison revealed that the estimation was doing significantly better compared to a solution assigning average regional stocking densities per fodder area for ruminants and average stocking densities per ha for the non-ruminants (Leip et.al. 2007).

The stocking densities allow is also to include economic performance indicators for animal activities in the calculation at sub-regional level.

2.6. Crop specific fertilizer application rates

Figure 3: Estimated Mineral Nitrogen Fertilizer Input [kg/ha Nitrogen]

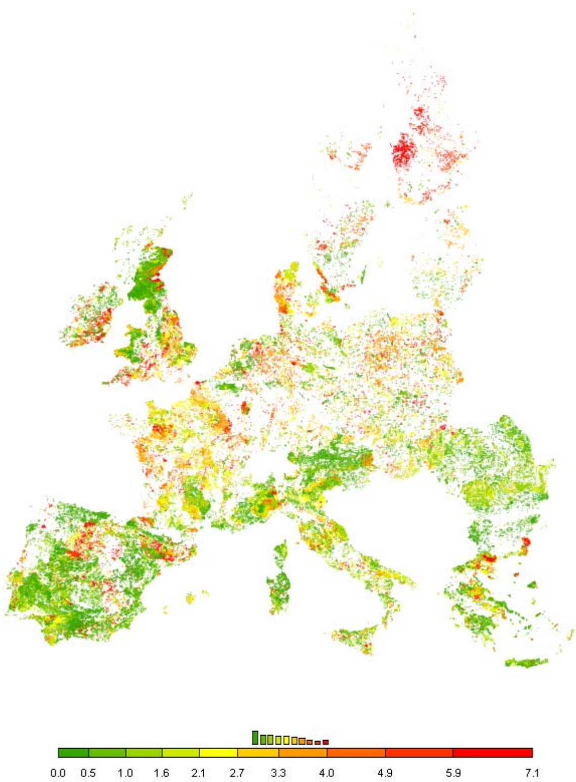


Organic and mineral fertilizer application rates are a highly relevant factor for environmental impacts of agricultural production as they dive realized crop yields and nutrient surpluses, and consequently the whole nutrient and carbon cycle in agriculture. Unfortunately, even at Member State level, data on typical organic and inorganic fertiliser application rates for crops are not available from harmonized European statistics. However, the International Fertilizer Manufacturer Association (IFMA) kindly agreed to let the project team access the results of expert surveys on inorganic application rates for crops or group of crops at Member State level. Those data are used in the process of building the regional data base of CAPRI to define regional fertilizer application rates per crop, taking into account regional yields, manure availability, average regional soil parameters and emission factors lined up with the MITERRA and RAINS models (Oenema et.al. 2007).

At sub-regional level, the organic and inorganic application rates per crop are defined as to recover in average the ones at regional level. Firstly, organic application rates per crop and HSMU are estimated by increasing and decreasing the organic application rate for the crop at regional level depending on two factors. The first factor is the estimated local crop nutrient uptake in relation to the regional one, derived from the crop yield. Crop uptakes are derived from yields. A second factor increase or decreases the rate according to the estimated organic nutrient availability derived from stocking densities and manure excretion coefficients. Here again, as in the case of the estimation of the stocking densities, distance and size weighted averages of the organic nutrient availability around the HSMU are used rather than spot observations. The resulting estimated organic application rates per crop are then scaled in order to recover as the area weighted mean the given regional rate per crop. In a similar manner, inputs from crop residues, biological fixation and atmospheric deposition are calculated. Finally, the estimated mineral rate are based on the difference between the crop nutrient need and all non mineral sources, corrected by typical loss rate, and a factor based on soil properties. Those estimates per crop are then again scaled to deliver in average the regional mineral application rates.

2.7. Meta-model of DNDC

Figure 3: Estimated N2O output [kg/ha Nitrogen]



DNDC (Liu et. al. 2006) for denitrification and decomposition is a bio-physical model for crop growth with a focus on the nitrate and carbon cycle. As often with bio-physical models, many processes in DNDC are simulated with a daily or even sub-daily time resolution, and runs cover several decades, yielding tremendous processing times for Pan-European applications requiring many site-crop combinations. In order to keep processing time and storage needs in a manageable range, there are two tactics to derive a manageable system layout for large-scale applications of bio-physical models: either simulation of selected crops for larger processing units – e.g. in FATE were the five dominant crops for 10x10 km grid cells are simulated with EPIC – or the development of a statistical response surface from the bio-physical model for the results of interest as e.g. average yearly leaching. The latter does not only reduce dramatically processing time, but also eases the integration into another IT structure. Many bio-physical models communicate with other applications by input and output files in specific formats, requiring then software to generate and read those files in order to interface with e.g. an economic model. A meta-model however can be easily integrated in the reporting part of an economic model, or if necessary, even linked into its equation system.

There is also a further more subtle argument to use a meta-model. In the application presented in the paper, fertilizer rates from the economic model and ex-post consistent to statistical data are used to drive the bio-physical model. Those fertilizer application rates are inter alia derived from the observed yields at NUTS II and, as explained above, from differences in yield potentials at sub-regional scale. Unfortunately, there is no guarantee that the simulated yields from a bio-physical model even in average over all sites in a region would match the regional average. But as the input of nutrients at regional level in the system is fixed via the fertilizer application rates per crop, an error in average simulated crop yields will hence lead to an error in the average estimated nutrient balance, and in nutrient fate (leaching, gas emissions, change in soil stocks). Already a 10% error in crop yields will lead to a substantial percentage error in nutrient balance positions.

It is deemed hence important to ensure as far as possible a match between the simulated yields and the ones used to determine the fertilizer application rates. The meta model offers an elegant way to achieve that by adding both plant specific and other parameters typically used to calibrate the bio-physical model as additional explanatory variable in the regressions. The yield egression equation can may now determine those values for the calibration parameters which lead to an exact estimate of the yield at the inputted fertilizer application rates and other farm management parameters. That solution should naturally be combined with a careful calibration of the crop growth model, in which case has then the potential to reduce possible errors from coupling the different data layers to its minimum.

For the linkage to DNDC, first a large observation sample per crop was generated, by systematically changing the organic and mineral application rates for typical crop-site combination across Europe. That observation sample was then used to estimate per crop independent linear regression models for crop yield expressed in N removal, different gas losses, leaching and the elements of a water balance as percolation and transpiration. The map above shows the estimated output of N2O per ha of land, which given its CO2 equivalent of 310 is an important source of Green House Gases emissions from agriculture. The very high values in some cases as e.g. in Finland are however questionable as the soil map may over-estimates the soil organic carbon content for agricultural land cover in those locations, albeit arable cropping on peat lands is common in Finland (for details: Leip et.al. 2007).

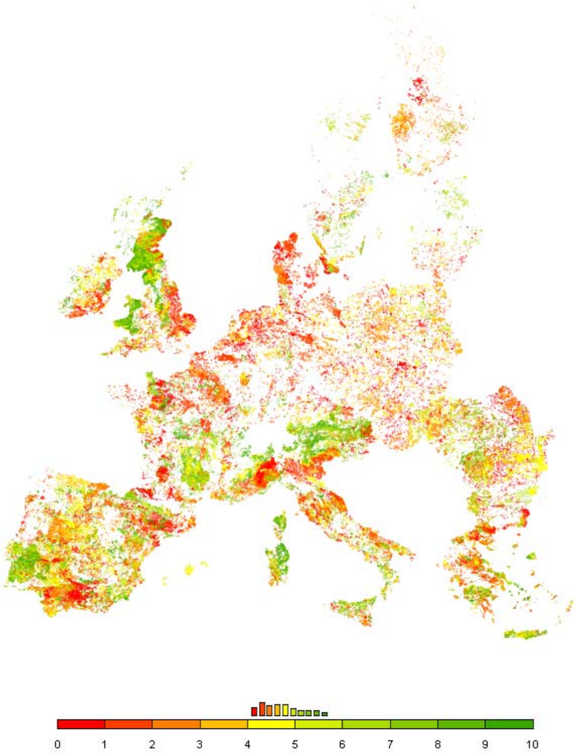
3. Indicators derived from the results

The combination of crop shares, animal stocking densities, and activity specific input and output coefficients including application rates of mineral and organic fertilizer can be linked to many different indicator calculators. The following table lists the indicators currently implemented and the results from the different steps stored in the final data set at 1x1 km resolution at EU27 scale. Those data can be exploited e.g. as interactive maps.

Table 1: Results stored and Indicators

Topic	**Results and Indicators**
Economic performance (expressed per ha of UAA)	Agricultural revenues Intermediate input cost Gross value added at market prices plus CAP pillar I premiums
Driving forces	Livestock densities (total, ruminants, non-ruminants) Crop shares (about 30 crops, and aggregates of those) Mineral fertilizer consumption (per ha, crop specific and for UAA) Irrigation water use per ha UAA Intensity index for High Nature Value Farmland characterization
Pressures and benefits (per ha UAA)	Nitrogen balance Phosphor balance Ammonia Emissions Green House Gas emissions in CO2 equivalents
Nitrogen Fate (based on DNDC meta-model, in kg N per ha UAA)	Change in soil content Emission of N2O, of NO, of N2 Leaching
Water balance (based on DNDC meta-model, in l per ha UAA)	Rainfall and Irrigation Leaching Transpiration Evaporation

Figure 4: Intensity index [0-10] to characterize HNV probability

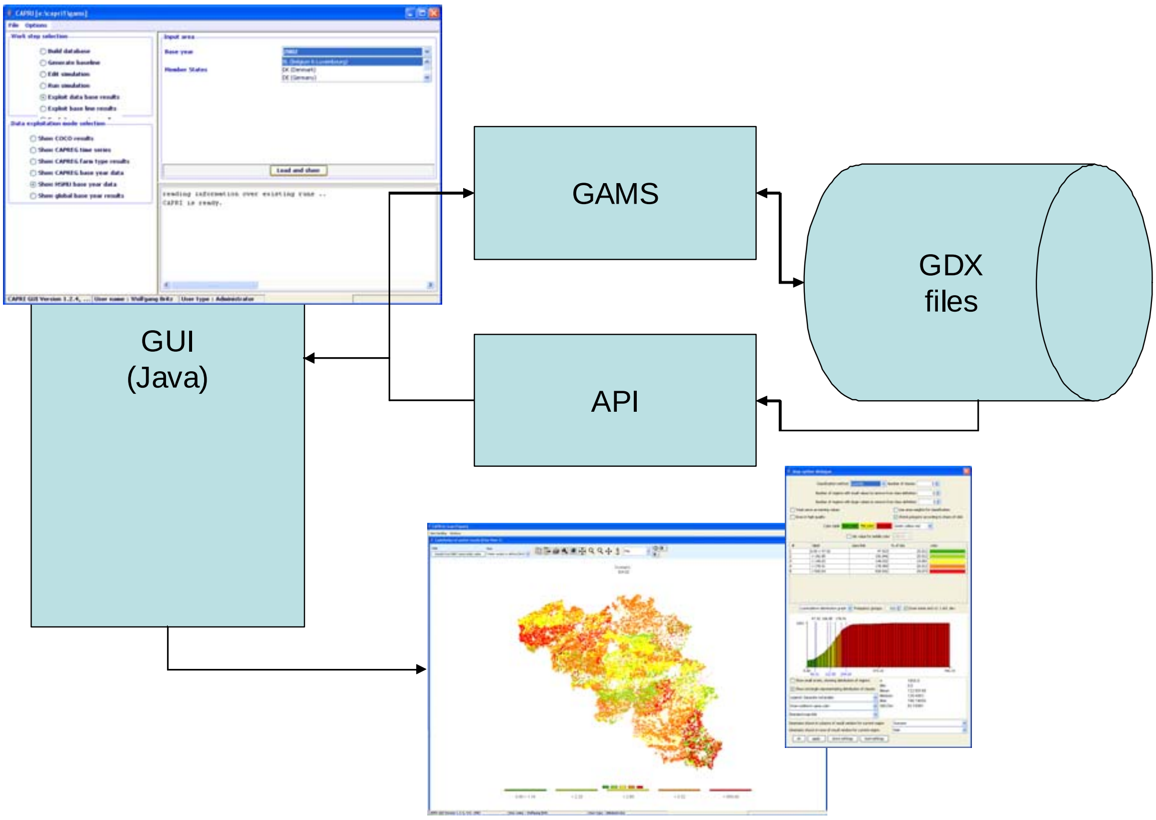


There is a growing concern about loosing the so-called High Nature Value (HNV) farmland (Hoogeveen et.al. 2004) and HNV in combination with biodiversity is one of the priorities in axis 2 of the rural development programs until 2013. JRC and EEA have produced in the period 2005-2007 a Pan-European HNV farmland map on the basis of a regional stratification of CORINE land cover data, biodiversity data (NATURA 2000, Important Bird Areas, Prime Butterfly Area) and national data sets where available. (Paracchini et.al. 2006). A complementary approach discussed here is based on deriving an index characterizing the probability of HNV presence. The index is an area weighted average of sub-indices for arable crops, fodder areas, olive groves and other permanent crops. The sub-index for arable crops is based on the average application rates of mineral and organic nitrogen per ha and a Shannon index characterizing simultaneously the number of crops grown and their distribution. The index for fodder areas uses a potential yield estimate for fodder under rainfed agriculture in combination with stocking densities to characterize the intensity of fodder production. For olive groves, remote sensing based characterization of the intensity of cultivation could be used (Weinsteiner et.al. 2007), whereas for the rest of permanent cultures, again mineral and organic nitrogen input characterize the intensity. The different elements were all mapped into 0-10 indexes, and then aggregated into the final index.

4. Technical implementation

ArcGIS was used to host the spatial data base with soil, climate, land cover, relief data and administrative borders, to generate 1x1 km raster from thje layers and to define the pixel clusters. As the economic core model of CAPRI and the module building up its data base are realized in GAMS, it seemed natural to realize the down-scaling modules in GAMS as well. That especially allowed basing the core down-scaling steps (crop shares, yields, animal stocking densities) on HPD estimators which are most easily represented as an explicit optimization problem under constraints. In order to keep the IT structure rather simple, it was decided to store all input and output data in the generic GDX-format of GAMS, and use an Application Programming Interface (API) provided by GAMS to access the GDX files from the CAPRI graphical user interface (GUI) which is realized in Java. The GUI allows visualizing the results from the spatial layer as maps, and was used to produce the maps shown above.

Figure 5: Technical implementation of the Spatial Dis-Aggregation



5. Summary and outlook

Given the increasing need for integrated policy impact analysis building on economic, social and environmental indicators, economic models need interfaces to indicators calculators, to bio-physical models and/or land use models at an appropriate geographical resolution below their typical administrative simulation units. The CAPRI-Dynaspat project has proven that the necessary data bases, methodologies and IT structures are available or can be developed to down-scale results from economic models to a sufficiently high geographic resolution on a large scale. Taking into account soil, relief, climate and land cover data, robust estimates for cropping shares, stocking densities and input use in agriculture can be generated from CAPRI results, allowing for environmental analysis and linkage to bio-physical models. This clearly offers the chance to improve the understanding of the environmental consequences of current or simulated farming practices on the environment, and opens up the way to novel indicators as the one presented to characterize the probability for High Nature Value Farmland.

A challenge remains the low amount of publicly available high resolution data on agriculture which could improve down-scaled results or replacing estimates by real world observations. The FSS, to name a prominent example, offers data on crop shares and stocking densities even at the level of single municipalities based on a harmonized methodology at Pan-European scale, but is currently only available aggregated to rather high administrative units (NUTS II/III). Here, new distribution layers (e.g. 10x10 km grid cells instead of administrative boundaries) could be developed by the statistical offices to overcome confidentiality issues currently hindering the usage of such data sources in research projects.

What are possible new research avenues? Firstly the project did not take into consideration how the indicators calculated at a 1x1 km resolution could be up-scaled to a regional scale and/or integrated into indices to ease their application in policy impact analysis. Here, SENSOR (Kristensen et.al. 2006) may provide guidelines. Secondly, the project was dealing with agricultural land use, only, and an integration with a land use model and linkage with economic models dealing with other sectors would be promising, as e.g. in EURURALIS (Verburg et.al. 2006). And thirdly, quite clearly, further comparison between downscaled results and real world observations is necessary to improve the methodology and develop uncertainty estimates.

References

Adler et.al. (2007), INSEA (Integrated Sink Enhancement Assessment), Final Report, IASSA

Chakir R. (2007): Spatial downscaling of Agricultural Land Use Data: An econometric approach using cross-entropy method. Toulouse: Inra.

Elbersen, B., Kempen, M., van Diepen, K., Andersen, E., Hazeu, G. and Verhoog, D. (2006): Protocols for spatial allocation of farm types. SEAMLESS report no. 19

Gallego, J. and Bamps, K. (2007). Using CORINE Land Cover and the point survey LUCAS for area estimation. *International Journal of Applied Earth Observation and Geoinformation*, in print

Grizzetti, B., Bouraoui, F. and Aloe (2007), F. Spatialised European Nutient Balance. Ispra: European Commission Joint Research Centre, Institute for Environment and Sustainability EUR 22692 EN.

Heckelei, T, Mittelhammer, R.C. and Britz W. (2005). A Bayesian Alternative to Generalized Cross Entropy - Solutions to Underdetermined Models. Contributed paper presented at the 89th EAAE Symposium "Modelling agricultural policies: state of the art and new challanges", February 3-5, Parma, Italy.

Hoogeveen, Y., Petersen, J.E., Balazs, K, and Higuero I. (2004). High nature value farmland - Characteristics, trends and policy challenges. EAA-Report 1/2004.

Jansson, T., Bakker, M., Hasler, B., Helming, J., Kaae, B., Neye, S., Ortiz, R., Sick Nielsen, T., Verhoog, D. and Verkerk H. (2007). Description of the modelling chain. SENSOR Deliverable 2.2.1. In: Helming K , Wiggering H, (eds.): *SENSOR Report Series 2006/5*, http://zalf.de/home_ip-sensor/products/sensor_report_series.htm, ZALF, Germany

Kempen, M., Heckelei, T. and Britz, W. (2005). A Statistical Approach for Spatial Disaggregation of Crop Production in the EU. In Arfini F. (ed), *Modelling Aricultural Policies: State of the Art and New Challenges*”. Parma: Monte Universita: 810-831

Kristensen, P., Frederiksen, P., Briquel, V. and Parachini, M.L. (2006). SENSOR indicator framework, and methods for aggregation/dis-aggregation – a guideline. In: Helming K , Wiggering H, (eds.): *SENSOR Report Series 2006/5*, http://zalf.de/home_ip-sensor/products/sensor_report_series.htm, ZALF, Germany

Leip, G., Marchi, R., Koeble1, M., Kempen, W., Britz, W. and Li, C. (2007). Linking an economic model for European agriculture with a mechanistic model to estimate nitrogen losses from cropland soil in Europe. In: Freibauer, A., Valentini, R., Dolman, H. and Janssen I. (eds). *Greenhouse gases in the northern hemisphere. Biogeosciences.* Special Issue

Liu, Y., Yu, Z., Chen, J., Zhang, F., Doluschitz, R., and Axmacher, J. C. (2006). Changes of soil organic carbon in an intensively cultivated agricultural region: A denitrification-decomposition (DNDC) modelling approach. *Sci. Total Environ*., 372, 203–214

Oenema, O., Oudendag, D.A., Witzke, H.P., Monteny, G.J., Velthof, G.L., Pietrzak, S., Pinto, M., Britz, W., Schwaiger, E. , Erisman, J.W., de Vries, W. , van Grinsven J.J.M. and Sutton M. (2007). Integrated measures in agriculture to reduce ammonia emissions. Final summary report. Wageningen: Alterra

Paracchini, M.L., Terres, J.M., Petersen, J.E. and Hoogeveen, Y., (2006). Background document on the methodology for mapping High Nature Value farmland in EU27. European Commission Directorate General Joint Research Centre and the European Environment Agency.

Van Delden, H. and Luja P. (2007). Integration of multi-scale dynamic spatial models for land use change analysis and assessment of land degration and socio-eonomic processes. In: Proceeding from the conference on Soil protection strategy - needs and approaches for policy support, Polawy, Poland 9-11th March 2006.

Verburg PH, Schot PP, Dijst MJ, Veldkamp A (2004) Land use change modelling: current practice and research priorities. Geojournal 61:309–324

Verburg, P.H., Schulp, C.J.E., Witte, N. and Veldkamp A (2006). Downscaling of land use change scenarios to assess the dynamics of European landscapes. *Agriculture, Ecosystems & Environment*: Volume 114, Issue 1, 39-56

Weissteiner, C. J., Sommer, S., and Strobl, P. (2007). Time series analysis of NOAA AVHRR derived vegetation cover as a means to extract proportions of permanent and seasonal components at pixel level. *EARSeL eProceedings*, in press.