Project Number 017841

NitroEurope IP

The nitrogen cycle and its influence on the European greenhouse gas balance.

Sixth Framework Programme

Priority 6.3

Global Change and Ecosystems

D3.4.3

Updated PCML protocol

Due date of deliverable: **01/07/2008**

Actual submission date: **00/00/0000**

Start Date of Project: **01/02/2006**

Duration: **60 months**

Organisation name of lead contractor for this deliverable :
UNIABDN

Revision: **final**

Project co-funded by the European Commission within the Sixth Framework Programme (2002-2006)		
Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	☐
RE	Restricted to a group specified by the consortium (including the Commission Services)	☐
CO	Confidential, only for members of the consortium (including the Commission Services)	☐

Protocol for testing response to climate change, land use change and mitigation measures to be used by NitroEurope core models at site level analysis

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Introduction:

This document is the protocol for testing the impact of climate change, land use change and mitigation options on GHG emissions at plot scale. This protocol will be followed by the modellers in NEU, and will be referred to as "Protocol – PCLM". This document identifies different variables and provides a quantitative measure of uncertainty, which will be used in sensitivity analysis for plot scale models.

Model processes / outputs included in the sensitivity analysis to mitigation measures

Nitrous oxide emissions
Methane and CO_2 (Optional)
N leaching
Mineralization
Denitrification / nitrification rate
Total soil N

Climate variables to be included:

From an impacts perspective, it is usually desirable to have a fair amount of regional detail of future climate and to have a sense of how climate variability may change in next few decades or centuries. Simply defining a single climate future is insufficient and unsatisfactory; different scenarios would provide adequate quantitative measures of uncertainty at particular site. The analysis of model response to different IPCC emission scenarios at site level may be cumbersome and redundant, compared to regional runs. We picked two IPCC emission scenarios (A1, B1) to represent the entire range of uncertainty of climate variables. The models can be run up to 2100 for suggested IPCC scenarios and results can be used for model inter-comparison.

Change in Land use to be included:

Current and future land use practices are critical in determining the GHG emissions. The models can be run to the year 2100 for different land use types (i.e., Arable, grassland and forest) depending on model feasibility. Future possible land use changes can be construed based on the existing (baseline) land use as follows.

Base line land use (Existing land use)	Future land use	Ecosse	DayCent	DNDC			
Cropland	Grassland	X	X	X			
Cropland	Forest	X	X	X			
Grassland	Forest	X	X	X			
Grassland	Cropland	X	X	X			
Forest	Grassland	X	X	X			
Forest	Cropland	X	X	X			

(Please mark it as ‘X ‘if you can run the model)

The management data from the core sites (cropland, grassland and forestry) used in the Bayesian calibration exercise can be used to drive the model for each of the land use transitions listed in the table above.

Mitigation scenarios to be tested:

The structure of a mitigation assessment will vary depending upon its goals and scope. We have provided a list of mitigation options in different ecosystems. We propose that the sensitivity of each of the models be tested to each of the following potential mitigation measures. The mitigation measures were selected base on the mitigation potential

Proposed mitigation options from different ecosystems at site level:

Measure	Mitigation option
Croplands	
	Nutrient Management : N – fertilizer application (no fertilizer, recommended and double the recommended fertilizer application) Organic – N fertilization
	Tillage and no tillage systems
Grasslands	
	Nutrient Management : N – fertilizer application (no fertilizer, recommended and double the recommended fertilizer application)
	Grazing intensity
Forest	
	Forest Management : 1. thinning 2. Cutting

In NEU, all modellers are recommended to:

Carry out sensitivity analysis (SA) of their model and report: (1) The chosen SA method, (2) Output uncertainty. The SA method is chosen by the modeller but can be one of the recommended methods described in the following sections.

Possible approaches for conducting the sensitivity analysis (from Smith & Smith, 2007)

Approaches that have been used to provide information about the uncertainty of Projections have included model sensitivity analysis, model calibration, and model intercomparison. Model sensitivity can be used to assess uncertainty if the model structure is accurate and if there is sufficient information about model parameters.

***1. One-at-a-time* or *local* sensitivity analysis:** In its simplest form, sensitivity analysis entails adjustment of model input components one-at-a-time, whilst all others remain constant, and the influence of each input on the model outputs is examined. This form of sensitivity analysis is termed, not surprisingly, *one-at-a-time* or *local* sensitivity analysis. The input can be varied by an arbitrary amount (e.g. by 50% of the estimated or mean value), or by a function of its variability, if known (e.g. by a function of its standard deviation). If the variability of the input is known or can be estimated, the actual range of the input can be entered.

2. Global sensitivity analysis: Sensitivity analysis can also involve adjustment of more than one input at a time. In its simplest form, multiple sensitivity analysis takes the form of a *factorial analysis*, which involves choosing a given number of samples for each input, and running the model for all combinations. Computationally, both one-at-a-time and factorial analysis can be performed by a *grid search*, whereby a grid of values is used to run the model for multiple runs.

This type of sensitivity analysis in which the effect of varying all inputs simultaneously is examined is known as a *global sensitivity analysis*. Global sensitivity analysis has the advantage of assessing input sensitivity in the context of other varying inputs. If the ranges and distributions of the inputs are known or can be measured, a *probability density function* can be defined for each input. The probability density function gives distribution of the possible values of an input, and so can be used to randomly select input values from within these distributions, allowing the full range of potential model outputs to be examined. This can be used to define input sensitivity as described for one-at-a-time sensitivity analysis, by comparing how changes in the inputs affect model results. If the variation in the outputs is compared to the variation in the inputs, a global uncertainty analysis is performed.

Metrics for assessing and comparing model sensitivity (from Smith & Smith, 2007)

Sensitivity can be determined qualitatively by plotting outputs against inputs. A very convenient quantitative expression of sensitivity is then given by the correlation coefficient between inputs and outputs. Expression of sensitivity to variation in more than one input at a time can be calculated using regression analysis between inputs and outputs.

A major drawback of using the correlation coefficient to define sensitivity is the inherent assumption that the relationship between inputs and outputs is linear. Also, the possibility that input parameters are strongly correlated to each other can result in apparent correlations between inputs and outputs that do not exist. If non-linear relationship between inputs and outputs or correlation with other inputs is likely, other less powerful methods of expressing sensitivity must be used.

Other ways of expressing the sensitivity include the *sensitivity coefficient*, which is the ratio of the change in the output to the change in one input whilst all other inputs remain constant. Model outputs are compared to the base case output, which is the model result with all inputs held constant (Hamby, 1994). This gives the sensitivity of the model but only to a fixed change in a single input.

The sensitivity of the model over the entire possible range of an input can be expressed using the *sensitivity index*. By varying the parameter from its minimum to its maximum and examining the minimum and maximum output values, the sensitivity index for a parameter is given by the maximum output value minus the minimum output value, all divided by the maximum output value.

Quantitative expression of model sensitivity to variation in one input (assuming linear relationship between inputs and outputs).

$$\text{e.g. Sample correlation coefficient, } r = \frac{\sum_{i=1}^{n}(I_i - \bar{I})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(I_i - \bar{I})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}$$

Where Ii is the *i*th input value, $\bar{I}$ is the average measured value, Pi is the i^{th} output value, and $\bar{P}$ is the average output value.

Quantitative expression of model sensitivity to a fixed change in a given input

$$\text{Sensitivity coefficient } = \frac{(P_i - \bar{P})}{(I_i - \bar{I})}$$

Where I_i is the *i*th input value, $\bar{I}$ is the average measured value, P_i is the *i*th output value, and $\bar{P}$ is the average output value.

Quantitative expression of model sensitivity to a range of changes in a given input

$$\text{Sensitivity index } = \frac{\max(P_i) - \min(P_i)}{\max(P_i)}$$

Where max(Pi) is the maximum output value, and min(Pi) is the minimum output value from the range of input value used.

A range of other approaches to expressing sensitivity exists. Hamby (1994) and Saltelli et al. (2000) have reviewed many of these approaches.

Factor importance analysis:

Sensitivity analysis determines the level of correlation between model result and the value of a given input component. In the case of a high correlation the model is termed sensitive to the input. However, not all sensitive factors are necessarily important. A sensitive factor can be known with a very high precision and accuracy and consequently with a low uncertainty and is therefore not important for the variance of the output (Hamby, 1994; Saltelli, 2000). It is therefore important to not only identify sensitive factors but also to classify their importance. This can be done by assessing the global uncertainty and the contribution of each input factor to the global uncertainty, which is referred to as the "factor importance" in which case a factor is both, sensitive and uncertain (Gottschalk et al. 2007).

Monte Carlo techniques are a common tool to analyse model uncertainty and the associated factor importance (Kleijnen, 1997; Heath and Smith, 2000; Zaehle et al., 2005; Verbeeck et al., 2006, Gottschalk et al. 2007). To generate the necessary samples of input factor probability density functions (PDFs) Latin Hypercube Sampling (LHS) can be applied. LHS is a stratified sampling technique where the distributions are divided into equal probability intervals. Samples are drawn from these intervals rather than randomly from the entire factor space. This ensures that all portions of the distribution are represented equally (McKay et al., 1979) with a smaller number of samples necessary compared to pure random sampling. This has the advantage of reducing the number of model runs, and it requires a small number of samples to establish a stable output distribution (Smith and Heath, 2001). LHS has been successfully applied by Heath and Smith (2000) and Zaehle et al. (2005) to assess uncertainties of a forest carbon budget model and the dynamic global vegetation model Lund-Potsdam-Jena (LPJ) respectively. Multiple model runs allow the assessment of model behaviour under a wide range of reasonable input combinations, to give estimates of output uncertainty and the contribution to global uncertainty from each input factor.

The contribution index can be chosen as the measure for expressing uncertainty. This index represents the importance of each input factor for the global uncertainty that takes factor interaction into account (Smith and Heath, 2001; Ogle et al., 2003; Hall, 2006). The contribution index is calculated by running a Monte Carlo simulation, consisting of multiple executions of the model, with all input factors sampled from the probability density functions. The Monte Carlo simulation is then repeated for the number of assessed input factors, each time holding one of the input factors constant at its default value, whilst allowing all others to vary within their defined range. The standard deviation of the distribution of the model output (NEE in this case) from the first Monte Carlo simulation represents the global uncertainty. The variation of the output distributions of the following simulations gives a quantitative estimate of the contribution of each input factor to the global uncertainty. The contribution is expressed as the normalized percentage change in standard deviation with respect to the standard deviation of the global uncertainty (Vose, 2000). The contribution index is the measure of the importance of each factor in the overall uncertainty of the model output, a high percentage indicating that the factor is important in determining output uncertainty, a low percentage indicating a low importance. The contribution index was calculated using the following equation:

$$c_i = \frac{\sigma_g - \sigma_i}{\sum_{i=1}^{i_{\max}} (\sigma_g - \sigma_i)} \cdot 100 \qquad \text{Contribution index}$$

where ci is the contribution index in % of factor (i), imax is the total number of model input factors considered and i the specific input factor of interest at a time, σg is the standard deviation of the global uncertainty, σi is the standard deviation of the simulations with setting factor (i) to its default value (Gottschalk et al. 2007).

References

Gottschalk, P., Wattenbach, M., Neftel, A., Fuhrer, J., Jones, M., Lanigan, G., Davis, P., Campbell, C., Soussana, J.-F. and Smith, P., 2007. The role of measurement uncertainties for the simulation of grassland ecosystem NEE in Europe. Agric. Ecosyst. Environ.

Hall, J.W., 2006. Uncertainty-based sensitivity indices for imprecise probability distributions. Reliability Engineering & System Safety 91, 1443-1451.

Hamby, D.M., 1994. A review of techniques for parameter sensitivity analysis of environmental models. Environmental Monitoring and Assessment, 32: 135-154.

Heath, L.S. and Smith, J.E., 2000. An assessment of uncertainty in forest carbon budget projections. *Environmental Science & Policy*, 3(2-3): 73-82.

Kleijnen, J.P.C., 1997. Sensitivity analysis and related analyses: A review of some statistical techniques. *Journal of Statistical Computation and Simulation* 57, 111-142.

McKay, M.D., Beckman, R.J., Conover, W.J., 1979. A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. *Technometrics* 21, 239-245.

Ogle, S.M., Breidt, F.J., Eve, M.D., Paustian, K., 2003. Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997. *Global Change Biology* 9, 1521-1542.

Saltelli, A., Chan, K., Scott, E.M., 2000. *Sensitivity analysis*. John Wiley & Sons Ltd, Chichester, 467 pp.

Smith, J.E., Heath, L.S., 2001. Identifying influences on model uncertainty: an application using a forest carbon budget model. Environmental Management 27, 253-267.

Smith, J.U. & Smith, P. 2007. Environmental Modelling. An Introduction. Oxford University Press, Oxford. 180pp.

Verbeeck, H., Samson, R., Verdonck, F. and Lemeur, R., 2006. Parameter sensitivity and uncertainty of the forest carbon flux model FORUG: A Monte Carlo analysis. Tree Physiology, 26(6): 807-817.

Vose, D., 2000. Risk Analysis: A Quantitative Guide. Wiley, New York.

Zaehle, S., Sitch, S., Smith, B. and Hatterman, F., 2005. Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics. *Global Biogeochemical Cycles*, 19(3): 1-16.