The CLIMSAVE Project

Climate Change Integrated Assessment Methodology for Cross-Sectoral Adaptation and Vulnerability in Europe

Overview of the meta-models within the CLIMSAVE Integrated Assessment Platform

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1. Introduction

The CLIMSAVE Integrated Assessment Platform (IAP) is a web-based exploratory tool that stakeholders can use to interactively investigate climate change impacts and adaptive responses of relevance to themselves. In order to deliver the fast web-based response time demanded by this participatory application, a process of meta-modelling has been carried out on a set of tried and tested desktop models to abstract the leanest representation for inclusion within the IAP that is consistent with delivering both functionality and speed.

The spatial scale of the IAP represents a compromise between the scale of available harmonised datasets, model runtime and spatial detail of the outputs. The higher the resolution at which the IAP operates, the greater is the number of times that the meta-models have to run and hence the greater the overall runtime of the IAP. The European and Scottish CLIMSAVE IAPs therefore operate at resolutions of 10' x 10' (10 minute by 10 minute) and 5km x 5km, respectively, consistent with the available baseline climatologies.

The CLIMSAVE IAP contains a suite of meta-models describing key European sectors (agriculture, forests, water, coasts, biodiversity and urban) which each simulate a range of stakeholder-relevant impact and ecosystem service indicators. Once the User has selected the model inputs (scenario selection and slider/button settings), the IAP runs the series of linked meta-models (Figure 1) which are described in the following sections.

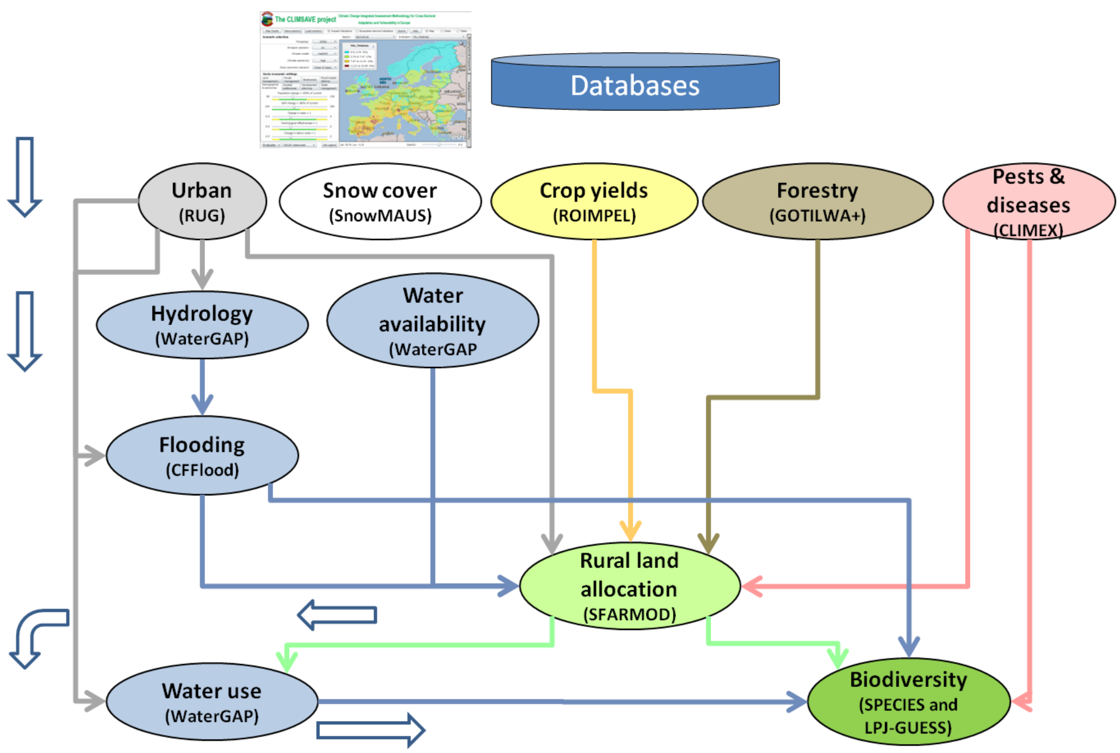


Figure 1: Overview of the meta-model linkages within the CLIMSAVE IAP [Names of the models used to generate the meta-models are given in parentheses].

2. Overview of the snow cover meta-model

The snow cover meta-model is based on the detailed SnowMAUS snow cover simulator (Trnka et al., 2010), whose core algorithms were proposed by Running and Coughlan (1988) and modified by Trnka et al. (2010). The snowMAUS model operates on a daily time step, with seven key parameters that govern snow accumulation and melting. Two datasets were used for calibration and validation of SnowMAUS; 65 sites across Austria with data from 1948-2002, and 83 sites across Europe with 1971-2000 data from the COST734 database (Trnka et al., 2011). The snowMAUS model effectively captured daily values of snow cover in terms of snow water equivalent and snow duration across a large altitudinal gradient. The model was able to explain an average of 73% of the variability in the number of days with snow during individual seasons and, an average of 81% of the variability in the seasonal volume of snow between 1948 and 2002 (Figure 2.1).

The SnowCover meta-model was based on an Artificial Neural Network that was calibrated and tested against outputs from SnowMAUS. The meta-model was calibrated on a training set of data that was sampled to cover the range of predictors and the predicted variable, i.e. number of days with snow. The meta-model was then independently tested on the complementary validation set. The performance of the snow cover meta-model was statistically evaluated using the Pearson correlation coefficient (r), mean bias error (MBE) and root mean square error over the validation dataset. The meta-model fit is good for both days with more than 1 cm of fresh snow (Figure 2.2; MBE of close to 0, RMSE of 2.1 days, and with more than 99% variability explained) and days with more than 10 cm of fresh snow (MBE = 0 day; RMSE = 2.6 days and R^2 = 0.99).

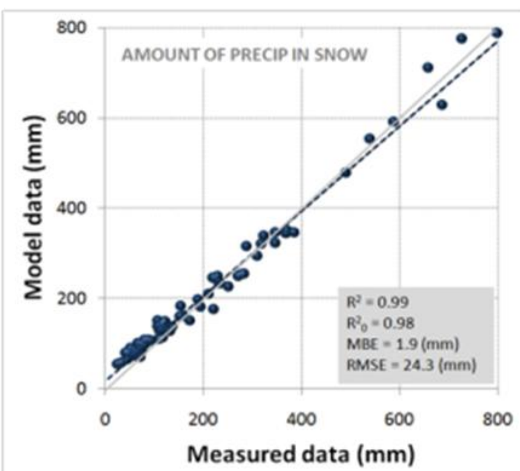


Figure 2.1: Validation of the SnowMAUS model at 61 sites in terms of long-term climatology (1948-2002) of snow cover.

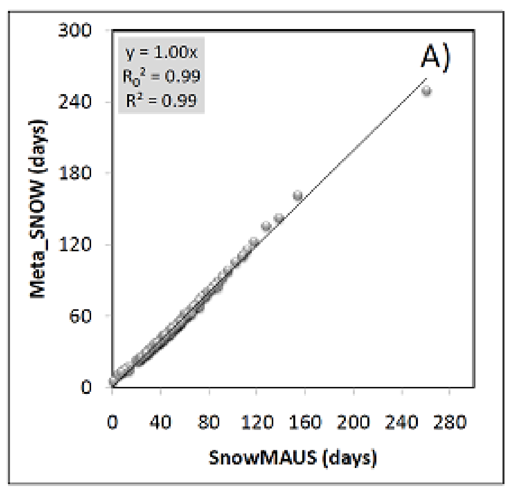


Figure 2.2: Comparison of the validation runs of the snow meta-model against SnowMAUS for snow days with more than 1 cm of fresh snow.

References

Running SW and Coughlan JC (1988). A general model of forest ecosystem processes for regional applications: I. Ecological Modelling, 42: 125-154.

Trnka M, Kocmánková E, Balek J et al. (2010). Simple snow cover model for agrometeorological applications, Agricultural and Forest Meteorology, 150: 1115-1127.

Trnka M, Olesen J, Kersebaum CK et al. (2011). Agroclimatic conditions in Europe under climate change. Global Change Biology (in print).

3. Overview of the RUG Urban meta-model

The RUG urban meta-model is based on the Regional Urban Growth (RUG; Rickebusch et al. in prep.) model, which simulates urban growth as a function of changes in socio-economic variables and societal values. The full model also takes into account the local geography, travel times with the existing infrastructure and city typology (e.g. mono- versus polycentric). It first calculates the expected quantity of artificial surfaces for each NUTS2 region, based on the linear regression model developed by Reginster and Rounsevell (2006), which links the proportion of artificial surfaces to the population and gross domestic product per capita. RUG uses two additional factors, urban type (large city versus smaller city/rural region) and country, in this regression model. RUG then evaluates the potential for settlement in each 1km x 1km grid cell within the region, based on the cell's characteristics (e.g. existing artificial surfaces, distance to the coast) and parameters reflecting planning and household preferences (e.g. strictness of planning constraints, attractiveness of the coast).

The RUG meta-model in the IA platform consists of a look-up table of maps of the proportion of artificial surfaces per 10' x 10' grid cell, based upon aggregated outputs of runs of the full RUG model on the 1 x 1 km grid with all possible combinations of input values.

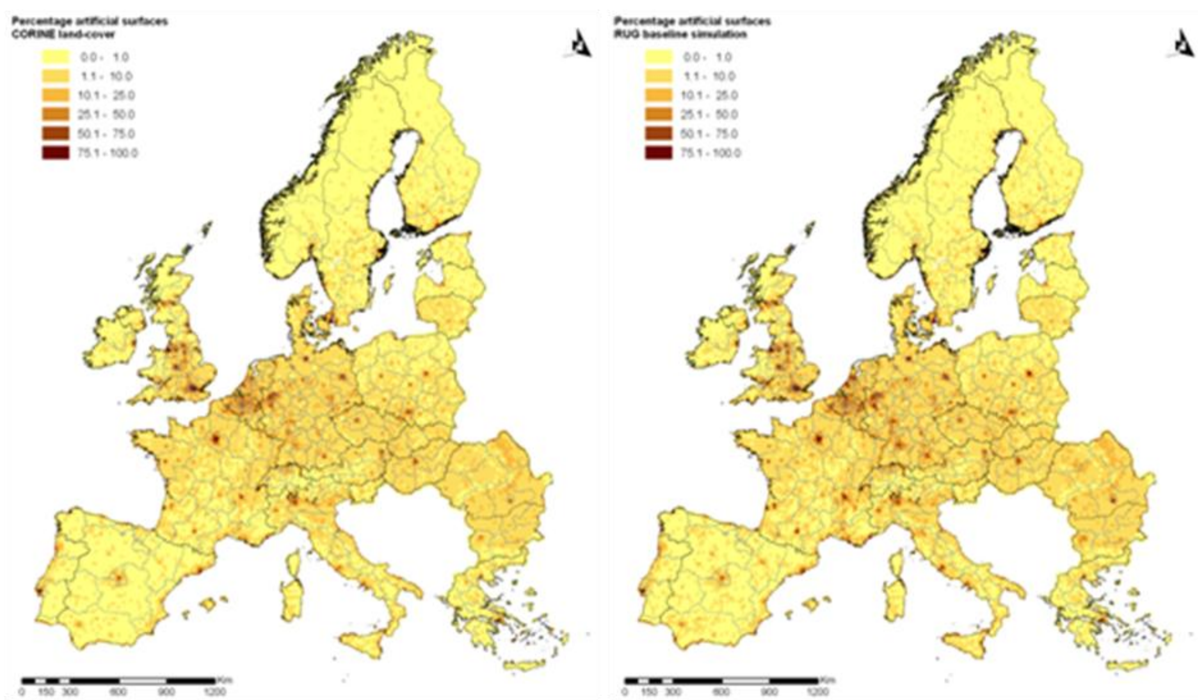


Figure 3.1: Artificial surfaces derived from the CORINE land-cover map (left) and produced by RUG with baseline parameters (right).

References

Reginster I and Rounsevell M (2006). Scenarios of future urban land use in Europe. Environment and Planning B-Planning & Design, 33: 619-636.

Rickebusch S, Fontaine CM and Rounsevell MDA (in prep.) Scenario analysis of urban growth in Europe. Computers, Environment and Urban Systems.

4. Overview of the metaGOTILWA+ forest meta-model

The forest MetaGOTILWA+ meta-model is based on the GOTILWA+ (Growth Of Trees Is Limited by WAter, http://www.creaf.uab.cat/gotilwa+/) model, which simulates carbon and water uptake and fluxes through forests of different tree species and in changing environmental conditions, due to either climate or management regimes. Processes are described in GOTILWA+ that integrate the results of simulated growth and evolution of the whole tree stand through time (hourly calculations integrated at a daily time step). The GOTILWA+ model has been extensively applied in different European projects such as LTEEF-II, ATEAM, SILVISTRAT and ALARM, compared with other process-based models (see Morales et al., 2005) and been applied European-wide (see Schröter et al., 2005).

The forest MetaGOTILWA+ meta-model is based on artificial neural networks which have been developed to reproduce GOTILWA+ outputs as a function of GOTILWA+ inputs for around 1000 cells, selected across Europe to explore the response of GOTILWA+ across all ranges of environmental and climate conditions. The predictions of the neural network were tested against data from cells which have not been used for training (Figure 4.1). Although there is inevitable scatter in the example results for *Pinus sylvestris* (Figure 4.1), there is a strong 1:1 relationship between the outputs of metaGOTILWA+ and GOTILWA+. Figure 4.2 shows example spatial results across those climate zones in Europe in which *Pinus sylvestris* grows for the baseline (1961-90) climate.

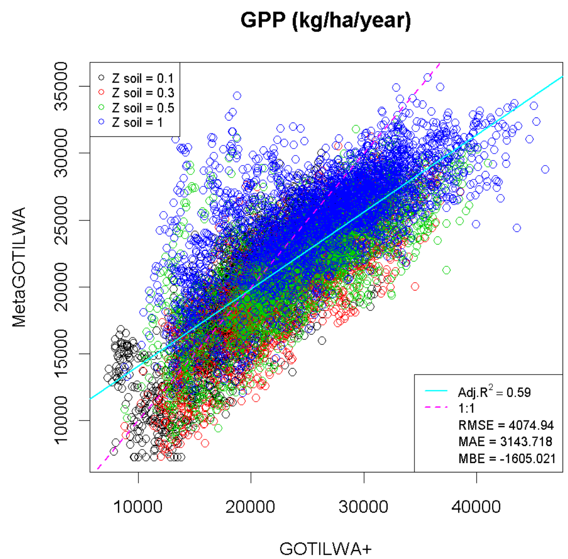


Figure 4.1: Comparison of Gross Primary Production (GPP) outputs from GOTILWA+ and metaGOTILWA+ for *Pinus sylvestris.*

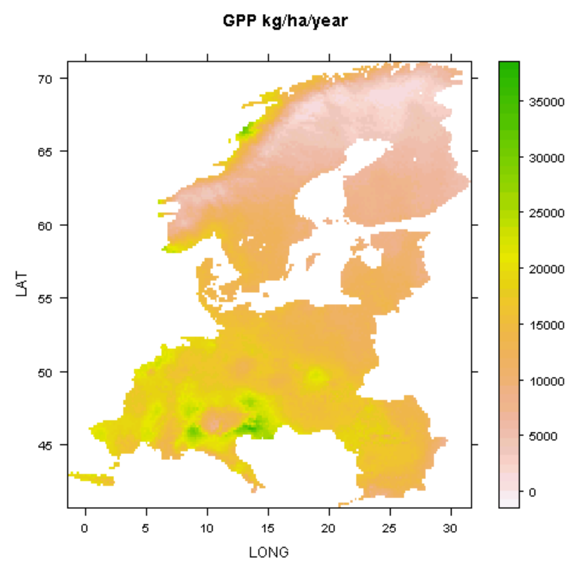


Figure 4.2: Baseline GPP outputs from metaGOTILWA+ for *Pinus sylvestris* for the boreal, continental and alpine regions.

References

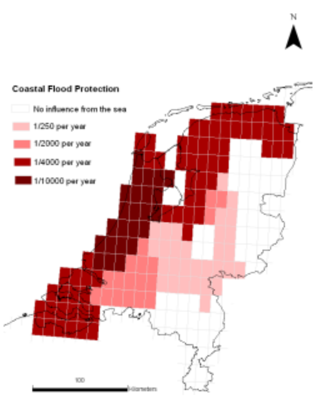
Morales P, Sykes MT, Prentice IC et al. (2005). Comparing and evaluating process-based ecosystem model predictions of carbon and water fluxes in major European forest biomes. Global Change Biology, 11-12: 2211-2233.

Schröter D, Cramer W, Leemans R et al. (2005). Ecosystem Service Supply and Human Vulnerability to Global Change in Europe. Science, 310 (5732): 1333—1337.

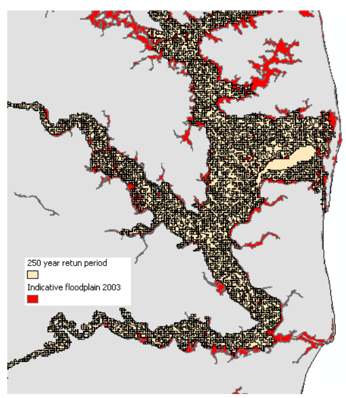
5. Overview of the fluvial and coastal flood zone meta-models

The **C**oastal **F**luvial **Flood** meta-model (CFFlood) provides estimates of the impacts of future flooding attributed to climate change and sea-level rise in Europe's coastal and fluvial floodplains. CFFlood contains three main sub-model components: (1) Coastal flood, (2) Fluvial flood and (3) Habitat change/loss components which are developed from Mokrech et al. (2008).

The coastal flood component assumes that the Standard of Protection (SoP) of flood defences decreases and flood frequency increases with a rise in extreme sea levels (from astronomical tides, storm surges, and sea-level rise). Food risk zones (based on topography and extreme sea levels) and estimated future SoP determine the extent of flooding, the number of people affected (based on population within the flooded areas) and the residential flood damages (based on damage curves by Linham et al. (2010)). The results are also used as a constraint on agricultural land use – arable and pastoral farming are precluded from areas flooded more often than once every 10 and 1 years, respectively (Mokrech et al., 2008). The fluvial flood component follows a similar approach, but uses flood maps for the rivers in Europe produced by the JRC Institute using LISFLOOD simulations (Feyen et al., 2011). Changes in the area of flood plain habitats (saltmarsh, intertidal flats, coastal grazing marsh and fluvial grazing marsh) are also assessed (Richards et al., 2008). The direct impact of sea-level rise on coastal wetlands follows the broad scale model of McFadden et al. (2007). Habitats can be either lost or can experience transition, considering the three influencing factors of accommodation space, sediment supply and rate of relative sea-level rise. The outputs of the CFFlood meta-model are being validated using existing studies and results (Figure 5.1) – for example, by comparing against regional results from the RegIS2 model outputs for the East Anglia region in the UK (Richards et al., 2008; Mokrech et al., 2008).



a) Coastal flood protection in the Netherlands.



b) The 250 year flood map and the 200 year indicative flood map for an area in eastern England.

Figure 5.1: Calibrating/validating the input parameters into the CFFlood meta-model.

References

Feyen L et al (Submitted). Fluvial flood risk in Europe in present and future climates. Climatic Change.

Linham M and Nicholls RJ (2010). Technologies for Climate Change Adaptation: Coastal Erosion and Flooding. TNA Guidebook Series, UNEP Risø Centre on Energy, Climate and Sustainable Development, Roskilde, Denmark.

McFadden L, Spencer T and Nicholls RJ (2007). Broad-scale modelling of coastal wetlands: what is required? Hydrobiologica, 577: 5-15.

Mokrech M, Nicholls RJ, Richards JA, et al (2008). Regional impact assessment of flooding under future climate and socio-economic scenarios for East Anglia and North West England. Climatic Change, 90: 31-55.

Richards J, Mokrech M, Berry PM and Nicholls RJ (2008). Regional assessment of climate change impacts on coastal and fluvial ecosystems and the scope for adaptation. Climatic Change, 90: 141-167.

6. Overview of the WaterGAP water resources and water use meta-models

The WaterGAP meta-model (WGMM) used in the IAP is designed to be a surrogate for the global hydrology and water use model WaterGAP (Water - Global Assessment and Prognosis; Alcamo et al., 2003; Döll et al., 2003; Verzano, 2009) which consists of two main components: a global hydrology model and a global water use model.

The WGMM hydrology meta-model makes use of a look-up table populated with the results of 273 pre-run daily WaterGAP3 simulations for river flow parameters (Figure 8.1 and 8.2) and water availability assessments, aggregated for about 100 spatial units or river basins larger than 10,000 km^2. The WGMM output parameters related to river flow, i.e. Q_{95}, Q_{avg}, Q_5 and Q_{med}, are downscaled to the 10' x 10' grid cells by multiplying the grid cell values for baseline conditions by the changes in the matching river basin relative to baseline conditions.

The WGMM water use meta-model is based on the WaterGAP3 results for sectoral water withdrawals and consumption in the base year 2005 (EU FP6 project SCENES) for both countries and river basins. For a given scenario, WGMM first computes the changes of sectoral water uses per country relative to the base year taking into account scenario input data on Gross Domestic Product, population, Gross Value Added, Thermal Energy Production and technological change. In a second step, the country-level changes are applied to water uses at the river basin scale.

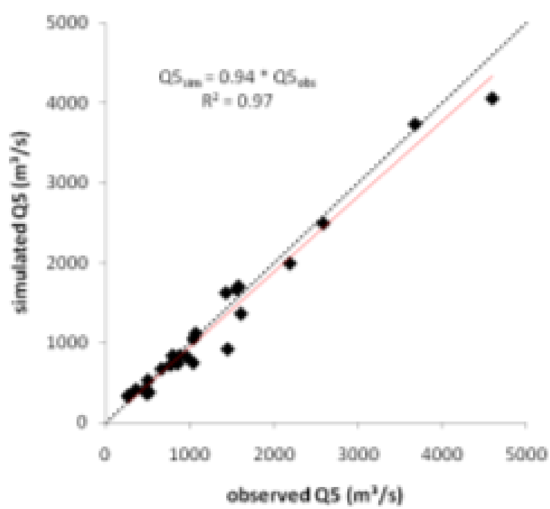


Figure 8.1: Simulated vs. observed high flow parameter Q_5 for 25 gauging stations across Europe, dashed line = 1:1 line, red (solid) line = linear fit.

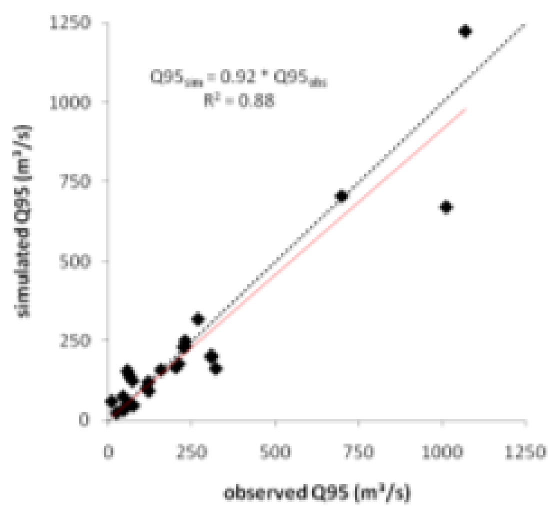


Figure 8.2: Simulated vs. observed low flow parameter Q_{95} for 25 gauging stations across Europe, dashed line = 1:1 line, red (solid) line = linear fit.

References

Alcamo J, Döll P, Henrichs T, Kaspar F, Lehner B, Rösch T and Siebert, S (2003). Development and testing of the WaterGAP 2 global model of water use and availability, Journal of Hydrological Science, 48: 317-337.

Döll P, Kaspar F and Lehner B (2003). A global hydrological model for deriving water availability indicators: model tuning and validation. Journal of Hydrology, 270: 105-134.

Verzano K and Menzel L (2009). Hydrology in Mountain Regions: Observations, Processes and Dynamics, IAHS-Publication 326, chap Snow conditions in mountains and climate change - a global view, pp 147–154.

7. Overview of the crop yield meta-models

The crop yield meta-models within the IAP are based on the results from the full agricultural model ROIMPEL (Rounsevell et al., 2003; Audsley et al., 2008), which simulates the daily dynamics of development stages, and water-, temperature-, and nitrogen stresses. Biomass accumulation is based on radiation use efficiency (which is sensitive to CO_2 concentration) and net photosynthetically active radiation. Biomass increases and yields are corrected for temperature, water and nitrogen stresses. ROIMPEL results for actual, potential and irrigated crop yields and crop sowing and maturity dates are available for a wide range of crops (winter wheat and spring wheat, winter barley and spring barley, winter oil seed rape, potatoes, grain maize, sunflower, soybean, cotton, grass, olives) across Europe.

The crop yield meta-models have been developed by training artificial neural networks (ANNs) to calibration datasets which adequately cover the whole range of both predictors (soil and climate parameters) and predicted variables e.g. sowing date or actual yield. Each model was then independently tested on the complementary validation set in order to assess its performance accuracy (e.g. Figure 7.1). The outputs from the 5 best ANNs models are combined together in order to generate a final composite projection. The meta-models show excellent performance for sowing and harvest dates (with usually more than 90% of the variability explained), the RMSE for the yield estimates is in most cases below 0.5 t/ha and the MBE is close to 0 indicating that there is low/no systematic bias.

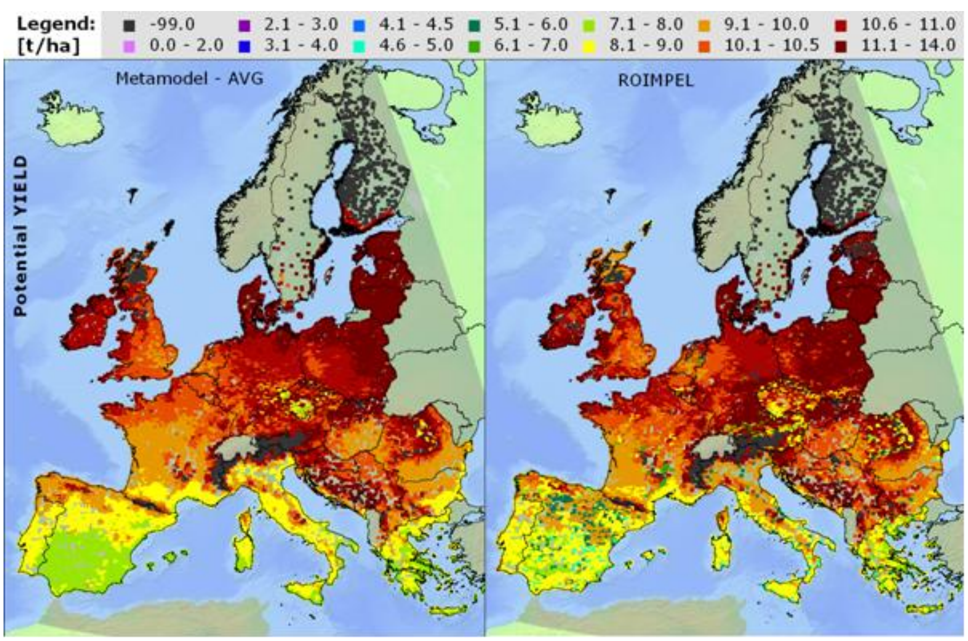


Figure 7.1: Comparison of potential (water and nutrient unlimited) yield for winter wheat as predicted by (left) the mean of the meta-model ANN ensemble and (right) ROIMPEL.

References

Audsley E, Pearn KR, Harrison PA and Berry PM (2008). The impact of future socio-economic and climate changes on agricultural land use and the wider environment in East Anglia and NorthWest England using a metamodel system, Climatic Change 90: 57-88.

Rounsevell MDA, Annetts JE, Audsley E, Mayr T and Reginster I (2003). Modelling the spatial distribution of agricultural land use at the regional scale. Agriculture, Ecosystems and Environment, 95(2-3):465-479.

8. Overview of the SFARMOD rural land use allocation meta-model

The SFARMOD meta-model is based on the Silsoe Whole Farm Model (SFARMOD) of whole farm planning. SFARMOD (Holman et al., 2005; Annetts and Audsley, 2002; Audsley, 1981) is a mechanistic farm-based optimising linear programming model of long-term strategic agricultural land use allocation, based on profit maximisation subject to the constraints of soil, precipitation, and sound agronomic practice. It has been extensively used in European and UK applications. Within SFARMOD, the soils available for agriculture and forestry in each 10' x 10' grid cell are first constrained by urbanisation and protected areas of natural and semi-natural habitats. The potential profit of the remaining soils for each potential land use is then estimated. Each soil within each grid will be allocated to the most profitable option.

Meta-models were developed to relate the input parameters to the SFARMOD outputs across the systematically modelled input parameter space of 20,000 SFARMOD simulations. A neural network meta-model was derived for each modelled crop (winter wheat, spring wheat, winter barley, spring barley, winter oil seed rape, potatoes, grain maize, sunflower, soybean, cotton, grass, olives) to predict the proportion of the potential agricultural area allocated to the crop (Figure 8.1), based on inputs such as crop gross margin, soil type and effective precipitation. Given these crop areas and using gross margins and workability, a further neural network meta-model calculates the farm profit (Figure 8.2). It is assumed that each soil within each grid cell will be used for the most profitable option, with the land use based on lower thresholds of €350/ha for intensive agriculture and €150/ha for extensive agriculture. If forestry is more profitable than agriculture, then forestry is allocated.

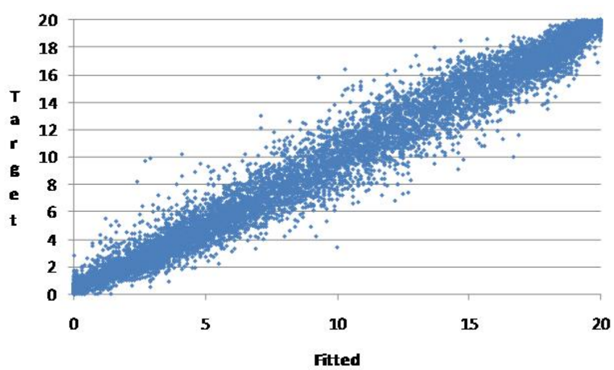


Figure 8.1: Comparison of the performance of the SFARMOD meta-model with the results for the full SFARMOD for the percentage allocated to potatoes.

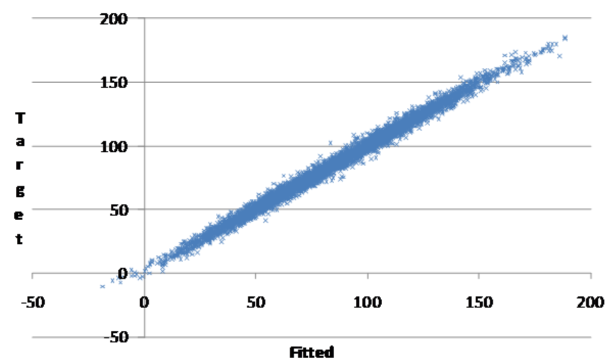


Figure 8.2: Comparison of the performance of the SFARMOD meta-model with the results for the full SFARMOD for profit (1000€/100 ha).

References

Annetts JE and Audsley E (2002). Multiple objective linear programming for environmental farm planning. The Journal of the Operational Research Society, 53(9): 933-943.

Audsley E (1981). An arable farm model to evaluate the commercial viability of new machines or techniques. Journal of Agricultural Engineering Research, 26(2): 135-149.

Holman IP, Rounsevell MDA, Shackley S, Harrison PA, Nicholls RJ, Berry PM and Audsley E (2005). A regional, multi-sectoral and integrated assessment of the impacts of climate and socio-economic change in the UK. Climatic Change, 71(1): 9-41.

9. Overview of the pest meta-models

The pest meta-models were designed based on the outputs of the climate-matching software program CLIMEX (Sutherst et al., 2000) that estimates the geographical distribution of a species based on the climate conditions of a given location. CLIMEX is based on the premise that it is possible to define climates which directly affect populations on a short time-scale. CLIMEX outputs were produced for 7 species - Codling moth (*Cydia pomonela*), European grapevine moth (*Lobesia botrana*), Cereal leaf beetle (*Oulema melanopus*), Colorado Potato Beetle (*Leptinotarsa decemleniata*), European corn borer (*Ostrinia nubilalis*, Bird cherry-oat aphid (*Rhopalosiphum Padi*) and the English grain aphid (*Sitobion Avenae*). Model outputs were compared with presence data in the CAB International database, Fauna Europea and published studies. CLIMEX was also compared to the detailed model ECAMON (Trnka et al., 2007) using a database of European corn borer (ECB) occurrence spanning the Czech Republic. Both models demonstrated very good agreement with the observed data, and both properly recorded the ECB expansion of the last decade of the 20th century. Overall CLIMEX reproduces the regional and local presence/absence suitability for the above pest species.

Meta-model ensembles of the best performing 5 artificial neural networks (ANNs) were developed for the Ecoclimatic Index (which describes the overall suitability of climate conditions for the establishment and long-term presence of a pest population) and the number of generations, with at least 91% of the variability explained. Figure 9.1 shows the excellent spatial comparison between CLIMEX and the ANN.

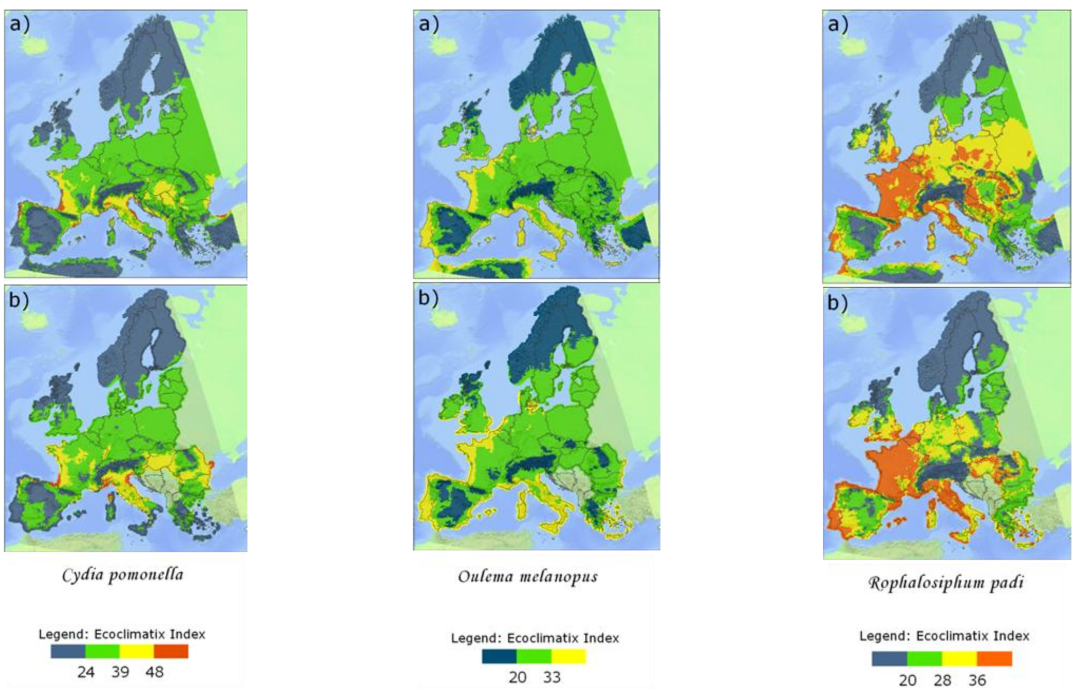


Figure 9.1: Comparison of the Ecoclimatic Index for *Cydia Pomonella*, *Oulema melanopus* and *Rophalosiphum padi* according to (a) CLIMEX and (b) the mean of the 5 ANN meta-models.

References

Sutherst RW, Maywald GF, Bottomley W et al. (2001). CLIMEX v2 User's Guide. CSIRO Entomology, 12-13: 281-99.

Trnka M, Muška F, Semerádová D et al (2007). European corn borer life stage model: Regional estimates of pest development and spatial distribution under present and expected climate. Ecological modeling, 207: 61-84.

10. Overview of the LPJ-GUESS biodiversity meta-model

The LPJ-GUESS meta-model is based on outputs from LPJ-GUESS, a complex dynamic global vegetation model. It simulates successional vegetation dynamics on different scales while modelling the atmosphere-vegetation carbon and water fluxes, plant physiology, establishment, mortality, and disturbance due to land use and fire (Sitch et al., 2003).

As it is impracticable to run LPJ-GUESS on a reduced functionality, it was decided to construct the meta-model using look-up tables of LPJ-GUESS model outputs for each time slice and scenario. Given the extensive previous validation of LPJ-GUESS (e.g. Gritti et al., 2006; Morales et al., 2007), the LPJ-GUESS meta-model was not further calibrated or validated during CLIMSAVE. Within the baseline setting in the IAP, the number of combinations of slider positions (for annual temperature change, summer and winter precipitation change and CO_2 concentration) is too great to create look-up tables for every combination. Hence, a sensitivity analysis of LPJ-GUESS has been undertaken to define relationships between the climate variables and the outputs of LPJ-GUESS (Figure 10.1).

For each combination of user choice (emissions scenario, GCM, climate sensitivity and timeslice), the matrix of the look-up tables has the dimensions of number of species (22) times number of land use types (4) times number of grid cells (23781) times number of output variables (Net Primary Production-NPP, biomass, Leaf Area Index, timber).

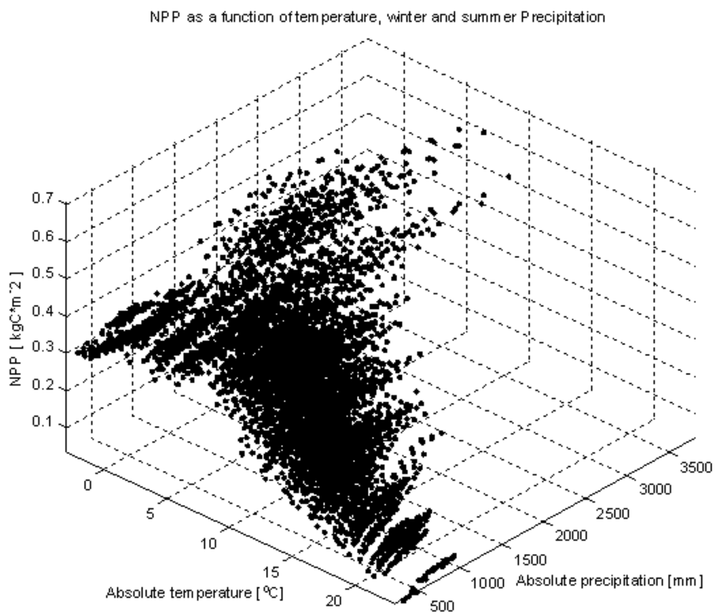


Figure 10.1: Three dimensional scatter plot of NPP as a function of temperature and precipitation.

References

Gritti ES, Smith B and Sykes MT (2006). Vulnerability of Mediterranean Basin ecosystems to climate change and invasion by exotic plant species. Journal of Biogeography, 33: 145-157.

Morales P, Hickler T, Rowell DP, Smith B and Sykes MT (2007). Changes in European ecosystem productivity and carbon balance driven by regional climate model output. Global Change Biology, 13: 108-122.

Sitch S, Smith B, Prentice IC et al. (2003). Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. Global Change Biology, 9: 161-185.

11. Overview of the SPECIES biodiversity meta-model

The SPECIES model (Spatial Estimator of the Climate Impacts on the Envelope of Species; Pearson et al., 2002) is used in the IAP to simulate the impacts of climate change on the suitable climate space of 116 species. The species were selected to interact with the agricultural, forest, coastal and water sectors and to indicate a range of ecosystem services (pollination, berries for food from wild plants, charismatic or iconic wildlife for aesthetic enjoyment, and species for hunting). SPECIES is based on ensembles of artificial neural networks (ANN), which integrate bioclimatic variables of relevance to birds and other taxa for projecting the distribution of species through the characterisation of bioclimatic envelopes.

The model is trained using existing empirical data on the European and North African (north of 15°N) distributions of species to enable the full climate space of a species to be characterised and to ensure that the model does not extrapolate outside its training dataset when used to project the distribution of species under potential future climates in Europe. The SPECIES model ANNs are calibrated and tested using an ensemble forecasting approach whereby projections are derived by constructing and training *multiple* ANNs for a single species (O'Hanley, 2009). The outputs from each of these models are then combined together in order to generate a final composite projection.

Validation of the models showed that all species had 'Area Under the Receiver Operating Characteristic Curve' (AUC) statistics greater than 0.89, indicating good discrimination ability and 84% has AUC statistics greater than 0.95, indicating excellent model performance. Kappa values are slightly lower, but this is to be expected as the index ranges from 0 to 1. Values were greater than 0.7 for 66% of species indicating very good agreement between observed and simulated distributions, and between 0.4 and 0.7 for 30% of species indicating reasonable agreement.

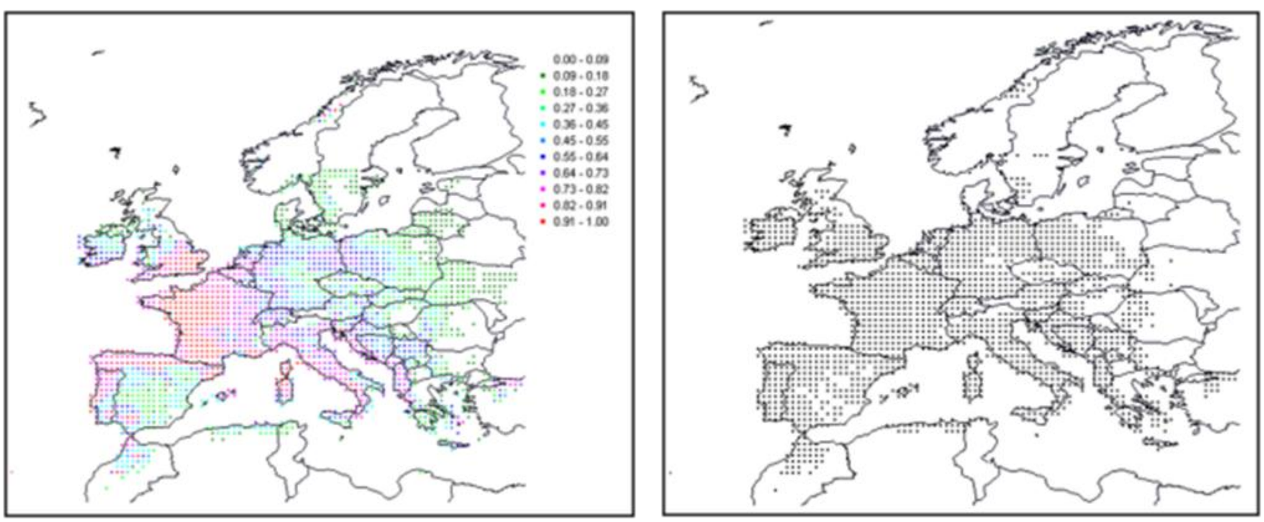


Figure 11.1: Illustrative results for *Silene gallica* (small-flowered catchfly) for Europe: (left) simulated climate suitability surface; (right) observed presence/absence distribution.

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