The **CLIMSAVE** Project
Climate Change Integrated Assessment Methodology for Cross-Sectoral Adaptation and Vulnerability in Europe

Report describing the development and validation of the sectoral meta-models for integration into the IA platform

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1. Introduction

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1.1 Background to Deliverable 2.2

Deliverable 2.2 reports on one of the Tasks associated with the development of the CLIMSAVE Integrated Assessment Platform (IAP):

- Task 2.4 - Development and validation of the meta-models within the IA platform.

However, because the development of the meta-models is so intrinsically linked to Task 2.2 (Development of the meta-model specifications), the outcomes from this Task which were reported in D2.1 (Holman & Cojocaru, 2010) are first summarised.

Given the participatory approach to the design and development of the CLIMSAVE Integrated Assessment Platform (van Asselt & Rijkens-Klomp 2002), we anticipate that the IAP and the associated meta-models will undergo modifications throughout the duration of the project in response to progressive stakeholder feedback from the activities of Work Packages (WP) 1 and 3 and from direct stakeholder engagement via the CLIMSAVE website. As such, the activities described in this report represent ‘works in progress’, rather than being ‘set-in-stone’.

1.2 References


2. Summary of the development of the meta-model specifications (Task 2.2)

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2.1 Summary of Deliverable 2.1

A meta-modelling approach is being used in CLIMSAVE whereby computationally-efficient or reduced-form models that emulate the performance of more complex models are being developed to deliver the fast run times required by the IA Platform. For efficient development of the CLIMSAVE IAP, each of the meta-models (described in the proceeding sections) are designed to be modular, independent and capable of replacement at any time. A meta-model specification was therefore developed to ensure successful linkage and integration of the meta-models, irrespective of the final algorithms inside each of the meta-models. The specifications have been defined in relation to anticipated stakeholder needs (CLIMSAVE WP1), the vulnerability framework (WP5), the scenario methodology and climate and socio-economic scenario variables (WP3) and the requirements of the adaptive capacity methodology (WP4), plus some redundancy for future development.

The development of the specification went through five distinct stages:

1. Defining the spatial resolution of the data to be transferred between meta-models;
2. Identifying and prioritising meta-model inputs and outputs;
3. Identifying points of contact between the meta-models;
4. Specifying the data dictionaries for each meta-model;
5. Standardising the data dictionaries across all of the meta-models.

For the European scale case study application of the CLIMSAVE IAP, the spatial scale of data transfer between the meta-models 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. It was agreed that the European CLIMSAVE IAP would operate at a resolution of 10’ x 10’ (10 minute by 10 minute), using the same grid as the Climatic Research Unit’s baseline 1961-90 baseline climatology (CRU CL 2.1- Mitchell et al., 2003). This represents over 23,000 land-based grid squares across the CLIMSAVE European case study area. It has similarly been agreed that the Scottish IAP will use a resolution of 5km x 5km.

In order to deliver the fast web-based response time demanded by this application, a process of meta-modelling is being carried out on a set of tried and tested desktop models to abstract the leanest representation consistent with delivering both functionality and speed. Based upon the state-of-the-art sectoral impact models available to the consortium (as outlined in the Description of Work), model inputs and output were identified by the modellers and rated for stakeholder-relevance by the wider CLIMSAVE consortium. For the model inputs, the prioritisation was based on their relevance to adaptation responses, whilst the model outputs were prioritised according to perceived stakeholder relevance (e.g. areas at risk of flooding
and flood damages) and/or policy relevance (e.g. rural land-use allocation for intensive agriculture, extensive agriculture, abandoned land, etc).

Points of contact were also identified between the meta-models (Figure 2.1) – these are the linkages and influences between sectors, and represent data transfers between the models. For example, following the flow arrows from the RUG model in Figure 2.1, the simulated area, location and type of urban development (“artificial surfaces” and “residential/non-residential development” from the urban model – RUG) affects the population exposed to flood risk (“People affected” as estimated by the Flood Model), river basin hydrological response (“Basin flow” from WaterGAP-H), the land available for agriculture and forestry (“landuse allocation” from the land allocation model – SFarmMod) and consequently habitat availability (biodiversity model – SPECIES and LPJ-GUESS).

Within any single simulation of the CLIMSAVE IAP, there will be five components of data reading and transfers:

1. Data transfers from the user to the meta-models, representing the communication of input parameter values from the user (slider bars, timeslice, scenarios, etc) to the models, via the Running Module;
2. Data transfers between the meta-models, where the simulated output from one meta-model is an input to other meta-models;
3. Data transfers from the IAP database to the meta-models containing, for example, the input data for a user-selected scenario;
4. Data transfers between the meta-models and the user Interface, as outputs are selected by the user for display;
5. Data that is read into a meta-model from the meta-model’s own internal dataset.

With the exception of (5), all of the above represent transfers of data which need to be clearly defined in a transparent way for the consortium. Data dictionaries have therefore been developed for data associated with (1) – (4), which unambiguously define each variable or parameter and its characteristics. The final step in the process is the standardisation of the data dictionaries across all of the meta-models, so that each end (IAP, database or meta-model) of a data transfer (for example, meta-model to meta-model; or IAP to meta-model) uses the same data dictionary. This then allows the data transfers in terms of model variables and parameters to be defined (Figure 2.2).

The meta-models themselves are implemented as Dynamic-Link Libraries (DLL) developed in various software languages: Microsoft C++, Microsoft C#, Microsoft VB, and Delphi as both managed and unmanaged code. They will be embedded in the main Running module, working as one piece of software. The Running module will feed the DLLs with data, run the DLLs and collect the outputs. The exchange of data will be made available based on structures of data transferred by pointers to minimise the time required for data exchange. In this approach, the meta-model is told where to point data within the internal memory, rather than the data being physically transferred to the model, with consequent time savings given the number of grid cells (>23,000).

2.2 References

Figure 2.1: Draft schematic of the data interactions between the meta-models [Ovals - meta-models; open rectangles – data inputs from the databases; shaded rectangles – meta-model outputs; numbering and large open arrows – order of operation of the meta-models].
Figure 2.2: Schematic of the data transfers according to model variable and parameter name [numbers and open arrows indicate the order in which the server will prioritise the processing of the meta-models within the 4 core processors].
3. Introduction to Task 2.4 - Development and validation of the meta-models within the IA platform

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3.1 Summary of Task 2.4

The CLIMSAVE consortium brings together a number of participants with expertise in developing participatory integrated assessment platforms, such as the Regional Impact Simulator (Holman et al., 2008a;b), CLIMPACTS (Kenny et al., 2000) and SimCLIM (Warrick et al., 2005). Participatory IA platforms are a vehicle for communication, training, forecasting and experimentation (Welp, 2001, Kasemir et al., 2003, Jäger et al., 2008), whose usefulness is enhanced by the integrated assessment approach which enables stakeholders to explore / understand the interactions between different sectors, rather than viewing their own area in isolation. An assessment of stakeholder needs for, and perspectives on, integrated assessment platforms showed that stakeholders desired to be able to perform their own integrated assessment - investigating the impacts and adaptive responses of relevance to themselves, rather than having to rely on the restricted outputs generated from a limited number of simulations chosen arbitrarily by researchers (Holman et al., 2005; 2008a). However, stakeholder involvement is discouraged in most IAs by the complex software and unacceptably long runtimes (Wolfe et al., 2001). Holman et al. (2008a) developed the use of computationally simpler modelling techniques, so called ‘meta-models’ or ‘reduced form models’ (Carmichael et al., 2004), within a user-friendly interface and evaluated stakeholder experience (Holman et al., 2008b).

The development of the CLIMSAVE integrated assessment platform, and its constituent meta-models, has learnt from this unique process. The following sections describe the development and validation of each of the meta-models describing key European sectors (agriculture, forests, water, coasts, biodiversity and urban). The meta-models each simulate a range of stakeholder-relevant impact indicators and indicators which translate the outputs from the integrated sectoral models into ecosystem services indicators (Table 3.1). Ecosystem services cover all key European sectors, such as cultivated ecosystems, forest ecosystems, inland water ecosystems, coastal ecosystems, natural ecosystems and urban ecosystems. They closely correspond to the key sectors studied by Working Group II of the IPCC Fourth Assessment Report (IPCC, 2007) and enable climate change impacts to be linked directly to human well-being.

After the following sections which describe each of the meta-models in turn, Section 14 concludes by summarising (Table 14.1) how the stakeholder-relevant indicators simulated by the meta-models link to the ecosystem services in Table 3.1.
Table 3.1: List of ecosystem services according to the Millennium Ecosystem Assessment (MA).

<table>
<thead>
<tr>
<th>MA category</th>
<th>Ecosystem service</th>
</tr>
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<tbody>
<tr>
<td>Provisioning services</td>
<td>Food</td>
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<tr>
<td></td>
<td>Fibre</td>
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<tr>
<td></td>
<td>Fuel/energy</td>
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<tr>
<td></td>
<td>Genetic resources</td>
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<tr>
<td></td>
<td>Biochemical/natural medicines</td>
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<tr>
<td></td>
<td>Ornamental resources</td>
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<tr>
<td></td>
<td>Fresh water</td>
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<tr>
<td>Regulatory services</td>
<td>Pollination</td>
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<tr>
<td></td>
<td>Seed dispersal</td>
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<td></td>
<td>Pest regulation</td>
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<tr>
<td></td>
<td>Disease regulation</td>
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<tr>
<td></td>
<td>Climate regulation</td>
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<td></td>
<td>Air quality regulation</td>
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<td></td>
<td>Water regulation</td>
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<td></td>
<td>Erosion regulation</td>
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<tr>
<td></td>
<td>Natural hazard regulation</td>
</tr>
<tr>
<td></td>
<td>Invasion resistance</td>
</tr>
<tr>
<td></td>
<td>Water purification/waste treatment</td>
</tr>
<tr>
<td>Cultural services</td>
<td>Spirit and religious values</td>
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<tr>
<td></td>
<td>Education and inspiration</td>
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<tr>
<td></td>
<td>Recreation and ecotourism</td>
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<tr>
<td></td>
<td>Cultural heritage</td>
</tr>
<tr>
<td></td>
<td>Aesthetic values</td>
</tr>
<tr>
<td></td>
<td>Sense of place</td>
</tr>
<tr>
<td>Supporting services</td>
<td>Primary production</td>
</tr>
<tr>
<td></td>
<td>Photosynthesis</td>
</tr>
<tr>
<td></td>
<td>Provision of habitat</td>
</tr>
<tr>
<td></td>
<td>Soil formation and retention</td>
</tr>
<tr>
<td></td>
<td>Nutrient cycling</td>
</tr>
<tr>
<td></td>
<td>Water cycling</td>
</tr>
</tbody>
</table>

3.2 References

Holman, I.P., Rounsevell, M.D.A., Cojocaru, G., Shackley, S., McLachlan, C., Audsley, E., Berry, P.M., Fontaine, C., Harrison, P.A., Henriques, C., Mokrech, M., Nicholls, R.J.,


4. Development and validation of the snow cover meta-model

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4.1 Snow cover model description

The snow cover meta-model is based on the SnowMAUS snow cover simulator (Trnka et al., 2010). The core algorithm used in the snow cover model for agrometeorological use (snowMAUS) was proposed by Running & Coughlan (1988) and was 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. Snow melting is usually facilitated by other factors, such as sublimation, sun-driven ablation and often combined with the influence of wind. These factors cannot be directly considered due to the nature of the available input data and were summed into a single empirical factor.

Data was gathered from 1948-2002 from 65 sites across Austria (Figure 4.1), which exhibited considerable variability in elevation (155-3111 m a.s.l.). Of these stations, 65% were located at altitudes below 800 m, where most agricultural activity takes place. Four of these sites within the crop-growing altitude range (Irdning [A], Pabneukirchen [B], Gleisdorf [C] and Hohenau [D]) were randomly selected and the model calibrated for the period 1948-2002 (Figure 4.1). In order to test newly introduced routines and to verify the stability of the selected thresholds, an extensive sensitivity analysis including Monte-Carlo method was carried out.

Figure 4.1: Area within which SnowMAUS model was originally calibrated and validated.

The remaining sites served as independent tests of model performance and included several high elevation stations where agriculture production was limited to hay production and/or grazing. The datasets consisted of quality-controlled and homogenized daily surface weather records, including observations of daily maximum and minimum air temperatures at 2 m
above the surface, total daily precipitation, precipitation type, daily values of snow cover height and continuity of the snow cover. Precipitation that was recorded as ‘trace’ was replaced with 0.0 mm, which had no significant effect on the precipitation totals. The snow cover volume was expressed in terms of water equivalent in mm. Years with incomplete observations of snow cover or precipitation during the winter season were excluded from the analysis. An overview of the station locations is provided in Figure 4.1.

The snowMAUS model effectively captured daily values of snow cover in terms of snow water equivalent (Figure 4.2) across a large altitudinal gradient. The model was able to explain, on average, 73% (ranging from 42 to 89%) of the variability in the number of days with snow during individual seasons and, on average, 81% (ranging from 31 to 97%) of the variability in the seasonal volume of snow between 1948 and 2002. The snowMAUS model captured over 96% and 98% of the between-site variability in the number of days with snow and the volume of precipitation in the form of snow, respectively (Figure 4.2). Despite acceptable overall performance, the model overestimates snow cover at lowland stations and underestimates snow cover at high elevations for some seasons; however on the level of long-term means (as applied in CLIMSAVE) this has marginal importance.

![Graphs showing model validation](image)

**Figure 4.2:** Results of the SnowMAUS model validation at 61 sites in terms of long-term climatology (1948-2002) of snow cover.

### 4.2 Development and validation of the SnowCover meta-model

In order to develop a snow cover meta-model based on SnowMAUS that would be applicable over the wider CLIMSAVE European domain, new datasets were acquired based on the COST734 database (Trnka et al., 2011). In this database, 83 sites with the high quality daily weather data needed for SnowMAUS runs were available both for the baseline (1971-2000) climate, for the period around 2050 (using three global circulation models runs) and for an assumed global warming of 5°C (Figure 4.3).

The SnowCover meta-model was based on artificial neural networks (ANNs; Qnet, 2000) that were calibrated and tested using outputs of the more detailed SnowMAUS model. The model was calibrated on a training set of data that was sampled to cover the whole range of predictors and the predicted variable, i.e. number of days with snow. The sampling of the calibration dataset took into account values outside ± 1 standard deviation from the mean of each parameter. This model was then independently tested on the complementary validation
dataset in order to calculate statistics of its performance accuracy. In total, 12 different ANN designs were tested with the most suitable one being selected on the basis of the variability explained (R²) and the root mean square error (RMSE). For the final design, 20 different initiations for the ANN were tested, but no significant difference in the outputs was found.

![Image](image.png)

Figure 4.3: Location of the 83 sites (black dots) used for the development of the SnowCover meta-model laid over the environmental stratification of Europe of Metzger et al. (2005) and Jongman et al. (2006).

Two snow cover meta-models were developed - the first for days with more than 1 cm of fresh snow (i.e. 1 mm of snow water equivalent) and the second for days with more than 10 cm of fresh snow (i.e. 10 mm of snow water equivalent) which would allow leisure activities and provide frost protection for crops. The performance of both snow cover meta-models were evaluated using the explained variability (R²), mean bias error (MBE) and root mean square error (RMSE) over the validation dataset (Figure 4.4). For days with more than 1 cm of fresh snow (i.e. 1 mm of snow water equivalent), the fit is good, with a MBE of close to 0, a RMSE of 2.1 days and more than 99% of the variability explained. The second meta-model for days with more than 10 cm of fresh snow (i.e. 10 mm of snow water equivalent) shows similar accuracy (MBE = 0 day; RMSE = 2.6 days and R² = 0.99).

4.3 SnowCover meta-model illustrative results

4.3.1 Baseline climate

Once the meta-model was trained and validated, it was then applied across the CLIMSAVE 10’ European grid to produce a surface of mean snow cover days (Figure 4.5).
Figure 4.4. Comparison of the validation runs of the snow cover meta-models for snow days with more than (a) 1 cm of fresh snow and (b) 10 cm of fresh snow.

Figure 4.5: Illustrative results for mean number of days with more than 10cm of snow during the period 1961-1990.
4.3.2 Climate sensitivity

In order to test the newly developed meta-model routines, an extensive sensitivity analysis was carried out against changes in temperature (across the range from -2 to +6°C) and precipitation (from -40 to +40%). The results indicate that in terms of snow cover days, temperature is the main driving factor. Figure 4.6 illustrates the profound impacts of changes in temperature on the number of days with snow (without any change in precipitation), whilst Figure 4.7 shows the lesser effect of precipitation changes.

Figure 4.6: Sensitivity analysis of the snow cover meta-model (>10 cm of fresh snow) over the temperature range -2°C to +6°C.
Figure 4.7: Sensitivity analysis of the snow cover meta-model (>10 cm of fresh snow) over the precipitation range -40 mm to +40 mm per month.

4.4 Integrating the SnowCover meta-model with the other sectoral meta-models

Currently, the present version of the SnowCover meta-model is considered as stand-alone, providing indicators for ecosystem services related to recreation/tourism (Table 3.1). Outputs may be used to “trim” the results of SFARMOD for particular crops or to define areas that could be used for winter tourism.
4.5 References


5. Development and validation of the RUG urban meta-model

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5.1 RUG model description

The Regional Urban Growth (RUG; Rickebusch et al., in prep.) model simulates urban growth as a function of changes in socio-economic variables (population, GDP per capita) and societal values (strictness of planning constraints, household location preferences). The model also takes into account local geography, travel times with the existing infrastructure and city typology (e.g. mono- versus polycentric).

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. The appropriate map is selected according to the slider values set by the user for percentage change in population and GDP per capita, household preference for proximity to green space versus social amenities, attractiveness of the coast (scenic value versus flood risk) and strictness of the planning regulations to limit sprawl. The RUG meta-model then calculates the relative change in artificial surfaces compared to the baseline map derived from CORINE land-cover 2006 (CLC) and the area of residential and non-residential properties (which are in the same proportion as in the baseline map). The artificial surface maps were produced by running the original RUG model (on a 1 x 1 km grid) with all possible combinations of input values and aggregating the data to the 10’ grid.

The original European-wide RUG model (Rickebusch, 2010; Rickebusch et al., in prep.) runs on one NUTS 2 region at a time. It first calculates the expected quantity of artificial surfaces for the region, based on the linear regression model developed by Reginster & 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 grid cell within the region, based on the cell’s characteristics (e.g. existing artificial surfaces, distance to the coast) and the parameters entered by the user for planning and household preferences (e.g. strictness of planning constraints, attractiveness of the coast). Table 5.1 summarises the internal variables and those set by the user. The new percentage of artificial surfaces returned for each cell depends on its potential for settlement and on the total amount of artificial surfaces expected in the region.

The RUG model currently runs on a “growth-only” assumption, so it cannot simulate shrinkage. If the projected proportion of artificial surfaces is lower than the baseline value, it returns the latter.
Table 5.1: Input variables and parameters for the RUG (meta-)model.

<table>
<thead>
<tr>
<th>Set by user in IA platform</th>
<th>Internal to model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in population</td>
<td>Population</td>
</tr>
<tr>
<td>Change in GDP per capita</td>
<td>GDP per capita</td>
</tr>
<tr>
<td>Household preferences for green space / social amenities</td>
<td>Current artificial surfaces</td>
</tr>
<tr>
<td>Strictness of planning constraints</td>
<td>Distance to coast</td>
</tr>
<tr>
<td>Attractiveness of coast</td>
<td>Remoteness from medium &amp; large cities(^a)</td>
</tr>
<tr>
<td></td>
<td>Unsuitable areas (e.g. lakes, glaciers)(^a)</td>
</tr>
</tbody>
</table>

\(^a\) Rickebusch et al. (in review)

5.2 Model calibration and validation

A calibration of all the input parameters was carried out in the previous version of RUG, which covered East Anglia and North-west England. This was done by running simulations using the baseline data. The parameter values were set, by trial and error, so as to minimise the difference between the simulated and observed maps, bearing in mind the significance of each parameter.

When the RUG model was expanded to 25 European countries, further calibration tests were carried out, particularly for variables such as the strictness of planning constraints, which is less likely to be transferable as different countries apply different planning regimes. Figure 5.1 shows an example of the difference between RUG results using baseline data and the observed proportion of artificial surfaces, for different values of the parameter representing strictness of planning constraints. The value of 0.2 used in the previous version of the model still gave the best results, although it led to slightly too high values (up to an average of +4 %) in densely-urbanised grid cells. Increasing the parameter value to 0.3 or 0.5 increased the differences in densely-urbanised grid cells. On the other hand, decreasing the parameter value to 0.1 led to higher differences at the other end of the scale.

Figure 5.1 also gives an indication of how the model performs generally, given the parameter finally chosen (0.2, red boxes). The differences between the baseline simulation and the observed data are on average around 2-3 %, with most values falling below 7 %. There are also a few outliers with differences of over 30 %. This is probably inevitable with a general model for Europe, as it cannot capture all the diversity within the simulation area.
Figure 5.1: Comparison between RUG baseline simulations and observed CORINE data for four values of the “strictness of planning constraints” parameter. The “bars” (boxes) extend from the 1st to the 3rd quartile (with the median shown by the bold line) and the dashed lines are the whiskers which extend to the most extreme data point.

Figure 5.2 shows the proportion of artificial surfaces given by a RUG simulation with “baseline” parameters (no change in population or GDP per capita, household externalities preference = 2, planning constraints & attractiveness of coast = medium). The results are similar to the artificial surfaces found in the CLC map, though RUG tends to over-estimate the artificial surfaces, as shown in the map of the differences between the two (Figure 5.3, left). These differences are absolute values, which accounts for them being generally greater in heavily built-up grid cells. In relative terms, the differences tend to be larger in cells with low densities of artificial surfaces. For example, an absolute difference of 0.8 in a cell which contains 0.6% artificial surfaces according to CLC is equal to +133.3% relative difference. On the other hand, an absolute difference of 6.0 in a grid cell which is 55.0% built-up according to CLC is only +10.9% in relative terms. However, in both cases CLC and RUG show proportions of artificial surfaces of the same order of magnitude.

There are several causes for the differences between the CLC map and the RUG baseline simulation, aside from the fact that no model can ever represent reality exactly, but at best will show similar patterns. RUG is a growth-only model, i.e. it assumes that no artificial surfaces are removed, even if the population decreases for instance, which accounts for its tendency to over-estimate artificial surfaces. Negative differences are small and can be put down to differences in rounding and aggregation from the 1 km to the 10’ grid. Using the same model parameters, e.g. for planning constraints, throughout Europe has the advantage of allowing the same model set-up to be applied to the whole study area, but the down side is that the baseline parameter values will be more suitable for some countries or regions than
others. Additionally, the regression function linking artificial surfaces with population, despite including factors for country and large city, only explains 72% of the variation, the rest being down to other factors, e.g. industrial development due to the presence of coal.

Figure 5.2: Artificial surfaces derived from the CORINE land-cover map (left) and produced by RUG with baseline parameters (right).

Figure 5.3: Difference in the percentage of artificial surfaces projected by a RUG simulation with baseline parameters and those in the CORINE land-cover map (left). The map on the right shows the same data averaged by NUTS 2 region.
Figure 5.3 (right) shows the mean per NUTS 2 region of the difference in artificial surfaces between the RUG simulation with baseline parameters and CLC. This gives an overview of the regions which are best represented in RUG and those in which the model does not perform as well.

5.3 RUG model outputs and integration with other meta-models

The main variable produced by the RUG model is the proportion of artificial surfaces per 10’ x 10’ grid cell (Figure 5.4), which has a range of 0 to 1 (0-100 %). It is used as a base to calculate other RUG output variables. It is also an input to the SFARMOD land-use model (Section 10).

From the above, RUG calculates the percentage difference in artificial surfaces relative to the baseline value (derived from CLC) for each cell (Figure 5.4). This is used by the WGMM model (Section 9) to calculate the changes in water flow due to surface sealing.

Figure 5.4: Example of the proportion of artificial surfaces (left) and relative change in artificial surfaces (right) for the United Kingdom and Republic of Ireland at 10’ x 10’ resolution for a 2025 scenario.

RUG also calculates the surface of residential (CLC category 1.1) and non-residential areas (CLC categories 1.2 - 1.4), in square kilometres, within each grid cell. This is based on the baseline proportions of residential versus non-residential areas in each cell. For example, if a cell has a baseline value of 1 km$^2$ artificial surfaces of which 75 % (0.75 km$^2$) are residential areas and RUG predicts the artificial surfaces will double, then there will be 1.5 km$^2$ of residential areas. These variables are passed to the CFFlood model (Section 7), to assess damage and risk to people.
Finally, RUG calculates the average percentage difference in artificial surfaces relative to baseline value across all cells. This aggregated indicator is displayed on the IA platform, to give the user a quick indication of the general effect of the settings they have chosen.

5.4 References

6. Development and validation of the metaGOTILWA+ forest meta-model

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6.1 Introduction

MetaGOTILWA+ is used in the IA Platform to simulate the impacts of climate change on forest ecosystems services such as wood production, carbon balance, etc (Table 3.1), and how forest management might play a role to mitigate such impacts on the main forest species that occur over Europe.

MetaGOTILWA+ is based on the GOTILWA+ model. The full GOTILWA+ model requires a lot of computational time to simulate each forest type, in each location (pixel) in Europe under different climates and management regimes. Since the IA platform requires a fast runtime, a new meta-model version has been developed to provide responses in a few seconds. Neural networks have been used to reproduce GOTILWA+ outputs as a function of GOTILWA+ inputs.

6.2 GOTILWA+ model description

The GOTILWA+ model (Growth Of Trees Is Limited by WAter, http://www.creaf.uab.cat/gotilwa+) 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. The input data include: climate (maximum and minimum temperature, precipitation, vapour pressure deficit, wind speed and global radiation); stand characteristics (tree structure and diameter at breast height (DBH) class distribution); tree physiology (photosynthetic and stomatal conductance parameters); and site conditions including soil characteristics and hydrological parameters. The processes are described with different sub-models that interact and integrate the results of simulated growth and evolution of the whole tree stand through time (hourly calculations integrated at a daily time step).

The light extinction coefficient is estimated by Campbell's approach (1986), based on an ellipsoidal leaf angle distribution. The photosynthesis equations are based on Farquhar and co-workers approach (Farquhar & Von Caemmerer, 1982). Stomatal conductance uses Leuning's approach that modifies the Ball, Woodrow and Berry model (Leuning, 1995). Leaf temperature is determined based on the leaf energy balance (Gates, 1962; 1980) and transpiration is estimated according to the Penman-Monteith equation (Monteith, 1965, Jarvis & Mcnaughton, 1986). Autotrophic respiration is separated into maintenance and growth respiration. Maintenance respiration is calculated as a proportion of total respiring biomass (structural and non-structural components distinguished), with rates that depend on temperature according to a Q10 approach. Growth respiration is a fraction of available carbohydrates for growth consumed when transformed into new tissues. A constant efficiency of 0.68 is assumed (g of new tissue / g of carbohydrate). Net primary production (NPP) is allocated first to form new leaves and fine roots to compensate for their turnover. The remaining NPP is allocated to the pool of mobile carbon in leaves and woody tissues. The surplus is invested in new tissues (leaves, fine roots and sapwood) according to the pipe model (Shinozaki et al., 1964). Soil is divided into two layers, organic and inorganic.
horizons. Soil organic matter (OM) is originated by plant litter: leaves, branches, stems and reproductive organs aboveground and coarse and fine roots belowground. OM is decomposed depending on soil temperature (according to a Q10 approach) and soil moisture (optimal at 60% of the maximum soil water-filled porosity). Soil moisture is calculated based on water inputs and outputs and soil traits. Temperature also affects leaf shedding through a Q10 approach. Root mortality is also dependent on temperature (Q10 approach), soil moisture and the length of the growing period.

6.3 GOTILWA+ validation and application

The GOTILWA+ model has been extensively applied in different European projects such as LTEEF-II, ATEAM, SILVISTRAT and ALARM. To check that the model provides realistic results, it has been tested against empirical data from the Forest National Inventories as well as compared with other process based models (see Kramer et al 2002, Morales et al 2005, Keenan et al 2009a). Within the previous projects, GOTILWA+ has been applied Europe-wide (see Schröter et al 2005; Keenan et al 2009b,c; Keenan et al 2010).

6.4 Development of the metaGOTILWA+ meta-model

Artificial neural networks (ANNs) have been developed to emulate the performance of the GOTILWA+ model but provide results in a few seconds. In order to train the ANN, around 900 cells were selected across Europe to explore the response of GOTILWA+ across all ranges of environmental conditions (Figure 6.1). These cells were selected to ensure the representivity of climatic conditions and to include more extreme conditions by selecting cells with higher and lower values for each input variable (Table 6.1). Simulations were run from 1950 until 2100 using climatic data from the HadCM3 global climate model for the A1B emissions scenario. CLIMSAVE is only simulating impacts until the 2050s. However, including a greater range of projections ensures that extrapolation is avoided because the climatic conditions of the 2050s will be well captured within the GOTILWA+ simulations.

Figure 6.1: Sample cells used to train the Artificial Neural Networks. Colors indicate the region to which the cell belongs.
Table 6.1: Input variables for the metaGOTILWA+ meta-model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>Monthly mean temperature</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Monthly mean precipitation</td>
</tr>
<tr>
<td>Effective soil volume</td>
<td>The product of the mean soil depth and the proportion of stones in the soil</td>
</tr>
<tr>
<td>CO₂</td>
<td>Atmospheric CO₂ concentration</td>
</tr>
<tr>
<td>Forest management</td>
<td>Forest management regime (no management, even aged management or uneven aged management)</td>
</tr>
<tr>
<td>Tree species</td>
<td>Dominant tree species in the forest</td>
</tr>
</tbody>
</table>

For each cell simulations were conducted for all characteristic species from the region, all management regimes and with four different levels of effective soil volume to produce the variables listed in Table 6.2.

Table 6.2: Output variables simulated by the metaGOTILWA+ meta-model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Ecosystem Service indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wood yield</td>
<td>Wood yield in managed forests</td>
<td>Wood production</td>
</tr>
<tr>
<td>Net Ecosystem Exchange</td>
<td>Carbon balance of the ecosystem</td>
<td>Carbon balance</td>
</tr>
<tr>
<td>Net Primary Production</td>
<td>Carbon balance of the primary producers</td>
<td>Forest physiological viability</td>
</tr>
<tr>
<td>Gross Primary Production</td>
<td>Total amount of carbon fixed by the trees</td>
<td>Carbon balance</td>
</tr>
<tr>
<td>Biomass stock</td>
<td>Sum of soil organic matter, aboveground biomass and below ground biomass</td>
<td>Carbon stock</td>
</tr>
<tr>
<td>Water stored in soil</td>
<td>Amount of water stored in soil</td>
<td>Water stress indicator</td>
</tr>
<tr>
<td>Length of the growth period</td>
<td>Length of the growth period determined by temperature and water availability</td>
<td></td>
</tr>
</tbody>
</table>

Fast Artificial Neural Networks library (http://leenissen.dk/fann) has been used to build and run the neural networks. An evolving topology training algorithm (Cascade2) was used which dynamically builds and trains the ANN.

6.5 Meta-GOTILWA+ validation and illustrative application

The predictions of the ANN were tested against data from cells which have not been used for training. Although there is inevitable scatter in the example results for Pinus sylvestris (Figure 6.2), there is a strong 1:1 relationship between the outputs of metaGOTILWA+ and GOTILWA+. Figure 6.3 shows example spatial results across the selected climate zones across Europe in which Pinus sylvestris grows for the baseline climate.
Figure 6.2: Comparison of outputs from GOTILWA+ and metaGOTILWA+ for *Pinus sylvestris* with different effective soil depths [GPP - Gross Primary Production; NPP - Net Primary Production; Ws - Water in soil].

6.6 Integration of metaGOTILWA+ with other sectoral meta-models

MetaGOTILWA+ outputs are being used to assess the effects of climate change on European forests and the ecosystem services provided by them. Some outputs such as wood yield are passed according to the climatic conditions, soil depth, management and dominant tree species to the SFARMOD meta-model to include inputs from the forestry sector to optimize land use (see Section 10).
Figure 6.3: Outputs from metaGOTILWA+ for Pinus sylvestris for the boreal, continental and alpine regions using the baseline climate and an effective soil depth of 0.25m (without stones). [GPP - Gross Primary Production; NPP - Net Primary Production; Ws - Water in soil].

6.7 References


7. Development and validation of the fluvial and coastal flood zone meta-models

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7.1 Introduction

The Coastal Fluvial Flood meta-model (CFFlood) aims to provide estimates of the socio-economic and environmental (i.e. flood-plain habitat) impacts of future flooding that are attributed to climate change and sea-level rise in Europe’s coastal and fluvial floodplains. It also accounts for future socio-economic changes by investigating human pressures under a range of socio-economic scenarios. The modelling operates at multiple scales: the impacts at the baseline conditions are estimated using 500 m spatial resolution data sets to establish credible results, while future scenarios are investigated at the 10’ resolution. The baseline data sets are mostly resampled from higher spatial resolution data sets (i.e. 100 m resolution CORINE land use data and 100 m flood maps). The results of the meta-model are communicated to the Integrated Assessment Platform (IAP) at the 10’ resolution and reported to the user in the forms of maps, tables and graphs.

7.2 CFFlood model description

A conceptual framework of the CFFlood meta-model has been developed to explain the variables and the main steps for implementing the meta-model. The framework consists of three main sub-model components: (1) Coastal flood, (2) Fluvial flood and (3) Habitat change/loss components. These components are coupled and are also integrated to a range of plausible adaptation measures that allow the analysis of plausible responses to climate change and sea-level rise.

7.2.1 Coastal flood sub-model component

The framework of the coastal flood component (Figure 7.1) illustrates the main steps implemented for assessing the impacts of coastal flooding. The method uses the estimated Standard of Protection (SoP) parameter for analysing the change in flood risk due to the effect of relative sea-level rise on extreme sea levels. It assumes that SoP decreases and flood frequency increases with a rise of extreme sea level (Mokrech et al., 2008): baseline extreme sea levels are produced by a combination of astronomical tides and meteorologically-induced storm surges, and future sea levels are increased by sea-level rise.

The flood risk zones are identified by analysing the topography against the regional extreme sea levels, based on present-day extreme sea levels and relative sea-level rise scenarios, as appropriate. Consequently the area at risk of flooding is calculated and an estimate of the people living in the flood risk zones is calculated using population density. A comparison between the extreme water levels and the estimated SoP determines the actual extent of

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1 Note that intra-urban flooding (Evans et al., 2004a; 2004b) which operates at a smaller scale and via different mechanisms (e.g., more intense precipitation and overwhelmed drains) is not considered by the CFFlood meta-model.
flooding within these flood risk zones. Hence, the number of people who experience flooding is determined (based on the population within the flooded areas). The flood damages for residential properties (both contents and structure) are also calculated based on flood water depths following the damage curves provided by Linham et al. (2010).

**Figure 7.1: Coastal flooding component in the CFFlood meta-model.**

### 7.2.2 Fluvial flood sub-model component

The fluvial flood component follows a similar approach to the coastal flood component (Figure 7.2). For data, it uses flood maps for the rivers in Europe produced by the JRC Institute using LISFLOOD simulations at 100 m resolution (Feyen et al., 2011). These simulations provide flood maps for fluvial catchments (both extent and water depth) with return periods of 2, 5, 10, 20, 50, 100, 250 and 500 years, assuming no flood defences. These maps have been used as indicative maps of the flood risk zones in the CLIMSAVE project. The fluvial flood model is implemented as illustrated in Figure 7.2 to estimate the outputs of land area in flood hazard zones, people living in flood hazard zones, people affected and flood damages. The flood maps are analysed in conjunction with the CORINE land use data and the results are gridded at the 10’ resolution. The estimated Standard of Protection (SoP) parameter is used to analyse the change in flood risk due to changing run-off values (Mokrech et al., 2008). The changes in the peak river flow are derived from the WaterGAP model (Section 8).
7.2.3 Wetland change/loss sub-model component

In addition to flood constraints on agricultural production and damages on people and property, the CFFlood model assesses possible changes in the area of flood plain habitats comprising ‘saltmarsh’, ‘intertidal flats’ and what we term here ‘coastal grazing marsh’ in coastal flood plains, and ‘fluvial grazing marsh’ in river valleys. Changes to these areas are of interest under the Habitats Directive. Saltmarsh and intertidal flats exist seaward of defences and are subjected to tides, while coastal grazing marshes are largely artificial habitats that exist landward of defences in areas that would otherwise be intertidal habitats. The direct impact of sea-level rise on coastal wetlands is assessed following the broad scale model of McFadden et al. (2007) (see also Richards et al., 2008). The wetland change/loss component accounts for both habitat loss and habitat change, where the three influencing factors of accommodation space, sediment supply and rate of relative sea-level rise are considered. Consequently, habitats such as saltmarsh, coastal grazing marsh and intertidal flat can be either lost under high forcing conditions or can experience transition under the low to moderate forcing conditions (as shown in Figure 7.3). The model is being calibrated at the regional scale to determine the proportions of change. The direct effects of sea-level rise and the effects of defence abandonment due to managed (or unmanaged) realignment are also included. In river valleys, loss of areas is a function of human management of the floodplain and this will be one output from the agriculture model. Policy can also decide to conserve and enhance these habitats. The model of fluvial wetlands is based on identifying land areas within the fluvial flood plain that can be candidates for inland marshes. These are linked to the environmental emphasis of the explored futures.
The CORINE land cover data is used to establish the baseline of the intertidal habitats: saltmarsh and intertidal flat. However, the designated habitats landward of coastal flood defences are not defined in the CORINE land cover dataset. There is not a standard European nomenclature for these areas and they are variously termed ‘coastal grazing marsh’ (in the UK), or ‘summer polders’ (in the Netherlands/Germany) to give two examples. Therefore, to develop a generic methodology, pasture areas located within the coastal flood plain are assumed to be ‘coastal grazing marsh’ and this term is used for all such habitats in CLIMSAVE. This assumption is being tested against European sites and data, including designation. There may be issues in the Mediterranean and Baltic due to their low tidal range (see Rupp-Armstrong & Nicholls, 2007). If defences are abandoned or realigned, the new intertidal land experiences a transition to saltmarsh and intertidal flats. Similarly, pasture areas in the fluvial flood plain are assumed to be ‘fluvial grazing marsh’.

Figure 7.3: Example of modelling wetlands loss/change for coastal areas (adapted from McFadden et al., 2007).

7.2.4 Pre-processing and indicators

Estimating the indicative flood protection level across Europe

There is no European dataset on existing flood protection levels for coastal and river areas. Hence, as a first step, standard of protection values are assigned according to the land use/cover classes in the impact zones. Hence, indicative standards for flood defences for Europe (coastal and fluvial) have been estimated following the UK DEFRA methodology (MAFF, 1999) linked with the CORINE land use/cover data. The resulting dataset is being calibrated using published data about flood protection in individual regions/nations in the European Union – for example, the Netherlands has built an extensive coastal defence system that provides protection up to the 1 in 10,000 year flood event, while the Thames Barrier provides the city of London with protection against a 1 in 1000 year flood event, and we have the national flood defence data for England and Wales. This method provides a consistent
approach for establishing a European dataset on flood protection without representing any entitlement or obligation for achieving these protection levels. The calibration process is expected to continue until the IAP is finalised to allow the integration of all published information about levels of flood protection in Europe, as well as assessments within this project and assessment of other unpublished sources, wherever possible. Table 7.1 shows the indicative standards of protection for five land use bands in fluvial and coastal flood zones considering an indicative range of land use – the average ranges of fluvial and coastal indicative standard of protection is adopted for the European region. If better local data can be acquired, this data will be used.

Table 7.1: Indicative standards of protection and land use (from CORINE) (after MAFF, 1999).

<table>
<thead>
<tr>
<th>Land use band</th>
<th>Description</th>
<th>Land Use (CORINE classes – third level)</th>
<th>Indicative standard of protection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fluvial</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Return period (years)</td>
</tr>
<tr>
<td>A</td>
<td>Intensively developed urban areas.</td>
<td>111</td>
<td>50-200</td>
</tr>
<tr>
<td>B</td>
<td>Less intensive urban areas with some high grade agricultural land and/or environmental assets.</td>
<td>112, 121, 122, 123, 124, 131, 141, 142, 211, 212, 213, 221, 222, 223</td>
<td>25-100</td>
</tr>
<tr>
<td>C</td>
<td>Large areas of high-grade agricultural land and/or environmental assets with some properties.</td>
<td>132, 133</td>
<td>5-50</td>
</tr>
<tr>
<td>D</td>
<td>Mixed agricultural land with occasional properties at risk of flooding.</td>
<td>241, 242, 243, 244,</td>
<td>1.25-10</td>
</tr>
<tr>
<td>E</td>
<td>Low-grade agricultural land (often grass) or seasonally occupied properties at risk.</td>
<td>31, 311, 312, 313, 321, 322, 323, 324, 333</td>
<td>0-2.5</td>
</tr>
<tr>
<td>F</td>
<td>All other classes</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Topographical data

The SRTM data at 3 arc second (i.e. almost 90 m) spatial resolution and the Gtopo30 data at 30 arc second (i.e. almost 1 km) spatial resolution have been processed to produce a DTM with full European coverage. The DTM is classified into bands at 0.25 m elevation intervals along the coastline, covering the maximum range of combined sea-level rise, land subsidence and the extreme storm surge of a 1000 year event. This data set is then grided at the 10’ spatial resolution.

Extreme sea-level data

Four extreme sea-level events (i.e. the 1 in 1, 1 in 10, 1 in 100 and 1 in 1000 return period events) and associated land uplift/subsidence (the local geological component of sea-level
change) have been gridded at the 10’ resolution. These data are derived from the DIVA database (Vafeidis et al., 2008).

Socio-economic indicators

The socio-economic scenarios are used to develop a series of socio-economic indicators relevant to flooding as follows:

- Change in GDP is used to reflect the change in economic conditions and how these will influence the flood damages of properties’ contents.
- Average household size: this indicator allows the number of properties to be estimated as a function of population. The NUTS3 data set provides the average household size for the baseline - this data is gridded at 10’ spatial resolution.
- Population density: the population density is used to estimate the number of people in flood risk areas. The NUTS3 data set provides this variable for the baseline - this data is gridded at the 10 arc-minute spatial resolution.

7.2.5 Adaptation strategies within the CFFlood meta-model

The adaptation strategies investigated within the CFFlood meta-model are designed to focus on human safety and/or an environmental emphasis (to sustain or enhance habitats) (see Table 7.2).

Table 7.2: Adaptation measures for the CFFlood meta-model.

<table>
<thead>
<tr>
<th>Policies</th>
<th>Emphasis on Human Safety</th>
<th>Emphasis on Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Improved flood protection</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td>2. Retreat</td>
<td></td>
<td>√</td>
</tr>
<tr>
<td>3. Flood resilience</td>
<td>√</td>
<td></td>
</tr>
<tr>
<td>4. Mixed response</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>

Emphasis on Human Safety

These adaptation measures aim to reduce flood risks (for people and properties) through the following three categories:

a) Increase flood protection by 50%, 100%, 500% and 1000%: this will be applied directly to the baseline protection levels and applied uniformly for all Europe.

b) Resilience measures: considering that new properties will not be affected by flooding (e.g., by raising them above ground levels) up to a predefined threshold of flood event (e.g., 100 year event), while the old properties will suffer from flood damage but at a reduced rate depending on the types of resilience measures applied (e.g., using flood gates).

c) Mixed response: four mixed responses that are consistent with the four socio-economic scenarios are applied in a portfolio of adaptation measures (cf. Evans et al., 2004b; Thorne et al., 2007), where a number of plausible scenarios that combine flood protection improvement, retreat, and flood resilience measures are investigated. The link with the socio-economic scenarios considers the storylines of each scenario for designing these responses and will be defined with WP3.
In order to develop the four mixed response adaptation strategies and to determine when to defend, retreat and/or apply resilience measures, population density (and possibly land use/cover data) will be used to determine ranges and thresholds of population density (for both the baseline and the future time slices of the 2020s and the 2050s). For example, highly urbanized areas will be protected, retreats will be applied in undeveloped areas, and resilience measures will be applied in areas with low to high urban developments. The thresholds for determining and applying these measures can be linked with the socio-economic scenarios.

**Emphasis on Environment**

This includes the possibility of either maintaining wetland habitat areas at the baseline level or doubling the area of these habitats. Habitat area losses will be determined from the habitat model by comparing with the baseline stocks, while the rules for determining candidate sites for habitat creation (via retreat) may include the following:

**Retreat rules:**
- Retreat will take place in areas inside the floodplains (coastal and fluvial).
- Non-urbanized areas will be considered first.
- If non-urbanized areas are not sufficient for maintaining or doubling habitat stocks, then very low urbanized areas can be considered – this will require establishing a threshold of population density by analysing the population density for the baseline and the future time slices of the 2020s and 2050s within the floodplains (e.g., 1 in 1000 year event for the coastal floodplain and 1 in 500 year event for the fluvial floodplain). The highly urbanized areas (i.e., 111 urban class) will be definitely excluded.

**Rules at habitat levels:**
- Saltmarsh and intertidal flat: the coastal grazing marsh areas that will be changed to saltmarsh due to a change in salinity in the habitat model will be considered to be suitable for saltmarsh. Any other areas within the coastal floodplain will be considered candidate for saltmarsh. We will assume that areas that are not at the correct height are raised or lowered to an optimum height. The available areas can be split between candidate areas for creating saltmarsh and candidate areas for intertidal flat (e.g., 50% for each).
- Coastal grazing marsh: assumes all pasture can be considered as candidates for coastal grazing marsh. Fluvial (inland) marsh is also treated similarly within fluvial floodplains.

### 7.3 CFFlood meta-model calibration and validation

The input parameters into the CFFlood meta-model have been calibrated using available published data and studies. Figure 7.4a shows an example of the coastal flood protection levels used to calibrate the data set produced from the classification of the CORINE land use/cover data. This process will continue for the flood protection data set until the IAP is finalised as more data become available for various regions in Europe. The flood maps are also verified using available flood maps, e.g. Figure 7.4b shows good agreement between the flood map of the 250 year return period and the 200 year indicative flood map (2003) in the Norfolk region (in England).
The outputs of the CFFlood meta-model are being validated using existing studies and results – for example, by comparing against regional results from the RegIS2 model outputs for the East Anglia region in the UK.

(a) Coastal flood protection in the Netherlands.  
(b) Screenshot of the 250 year flood map and the 200 year indicative flood map for an area in eastern England (part of Norfolk).

Figure 7.4: Calibrating/validating the input parameters into the CFFlood meta-model.

7.4 Integration of CFFlood with the other sectoral meta-models

Input data on the square kilometres of residential (CLC category 1.1) and non-residential areas (CLC categories 1.2 - 1.4) within each grid cell is provided from the RUG meta-model (Section 5) and used to assess damage and risk to people. Changes in peak river flows are derived from the WaterGAP model (Section 8) to use in the analysis of fluvial flood risk.

The coastal and fluvial flood analysis is used as an input to the SFARMOD agricultural land use model (Section 10) – it constrains arable farming which is assumed to be not possible for areas flooded more often than once every 10 years, while any types of agricultural land use is assumed to be not possible for areas flooded more often than once every year (Mokrech et al., 2008).

Outputs on the areas of flood plain habitats are used as inputs to the SPECIES model (Section 13) to mask the potentially suitable climate space for individual species associated with saltmarsh and coastal grazing marsh habitats.
7.5 References


Linham, M., Green, C. & Nicholls, R. J. (2010). Costs of adaptation to the effects of climate change in the world’s large port cities. AVOID - Avoiding dangerous climate change report AV/WS1/D1/02. London, UK; Department of Energy and Climate Change (DECC) and Department for Environment Food and Rural Affairs (DEFRA).


8. Development and validation of the WaterGAP water resources and water use meta-models

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8.1 WGMM model description

The WaterGAP meta-model (WGMM) is used in the IAP to assess the impacts of global change on water resources and water use in Europe. WGMM is designed to be a surrogate for the global hydrology and water use model WaterGAP (Water - Global Assessment and Prognosis), which has been developed at the Center for Environmental Systems Research (CESR) aiming at an integrated perspective of the impacts of global change on the water sector (Alcamo et al., 2003; Döll et al., 2003). It consists of two main components: a global hydrology model and a global water use model.

In order to achieve a very short runtime, the spatial detail of WGMM is reduced from more than 180,000 grid cells of WaterGAP3 for Europe to about 100 spatial units larger than 10,000 km². Those spatial units, hereafter referred to as river basins, are made up either by single large river basins or clusters of smaller, neighbouring river basins with similar hydro-geographic properties. For each river basin, the meta-model simulates the output parameters given in Table 8.1, which are long-term statistics of the corresponding WaterGAP3 results for 30-year time periods.

Table 8.1: WGMM output parameters.

<table>
<thead>
<tr>
<th>Model output parameter</th>
<th>Description</th>
<th>Spatial level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q_{avg} (m³/s)</td>
<td>Long-term average river discharge</td>
<td>Grid cell</td>
</tr>
<tr>
<td>Q_{95} (m³/s)</td>
<td>Low flow river discharge (exceeded in 95% of the days)</td>
<td>Grid cell</td>
</tr>
<tr>
<td>Q_{5} (m³/s)</td>
<td>High flow river discharge (exceeded in 5% of all days)</td>
<td>Grid cell</td>
</tr>
<tr>
<td>Q_{med} (m³/s)</td>
<td>Flood flow, median of the annual maximum daily discharge</td>
<td>Grid cell</td>
</tr>
<tr>
<td>Ecosystem service indicator (ESI) for flow regulation</td>
<td>Difference of Q_5 and Q_{95} normalized by Q_{avg}</td>
<td>Grid cell</td>
</tr>
<tr>
<td>Water availability (mil. m³ / y)</td>
<td>Annual renewable water resources</td>
<td>River basin</td>
</tr>
<tr>
<td>Water available for agriculture (mil.m³/y)</td>
<td>Water availability minus water consumption in other sectors</td>
<td>River basin</td>
</tr>
<tr>
<td>Water availability per capita (m³/cap/year)</td>
<td>Ratio of water availability and number of people</td>
<td>River basin</td>
</tr>
<tr>
<td>Total water use (mil. m³/y)</td>
<td>Total water use (withdrawals and consumption)</td>
<td>River basin</td>
</tr>
<tr>
<td>Water stress indicator (-)</td>
<td>Water withdrawals-to-availability ratio</td>
<td>River basin</td>
</tr>
<tr>
<td>ESI for drinking water provision</td>
<td>Satisfaction of water demand (withdrawals) in domestic sector</td>
<td>River basin</td>
</tr>
<tr>
<td>ESI cooling water</td>
<td>Satisfaction of water demand (withdrawals) in thermal electricity production</td>
<td>River basin</td>
</tr>
</tbody>
</table>
Moreover, WGMM output parameters related to river flow, i.e. $Q_{95}$, $Q_{\text{avg}}$, $Q_5$, and $Q_{\text{med}}$, are downscaled to the 10’ x 10’ grid cells. Here, each grid cell belongs entirely to exactly one river basin. For each parameter, the downscaling is achieved by multiplying the grid cell values for baseline conditions by the changes in the matching river basin relative to baseline conditions.

8.1.1 The WGMM hydrology model

The aim of the hydrological model WaterGAP is to simulate the characteristic macro-scale behaviour of the terrestrial water cycle in order to estimate water availability. Based on the time series of climatic data, the hydrological model calculates the daily water balance for each grid cell, taking into account physiographic characteristics like soil type, vegetation, slope and aquifer type. Runoff generated on the grid cells is routed to the catchment outlet according to a global drainage direction map (Lehner et al., 2008) taking into account the extent and hydrological effects of lakes, reservoirs, dams and wetlands. The model is calibrated by adjusting one free parameter, which controls the fraction of total runoff from effective precipitation in order to minimize the error in simulated long-term annual discharge.

For the current version, WaterGAP3, the spatial resolution of the model raster has been increased from 30’ x 30’ to 5’ x 5’. Partly enabled by this finer spatial resolution, the process representations of runoff formation and runoff concentration in the hydrological model have been substantially improved, including:

- Revision of the snow dynamics on the sub-grid scale (Verzano & Menzel, 2009);
- Representation of permafrost occurrence directly affecting groundwater recharge (aus der Beek & Teichert, 2008);
- Implementation of a variable flow velocity algorithm (Schulze & Döll, 2004);
- Introduction of a meandering factor to improve the representation of river length (Lehner et al., 2008);
- Estimation of potential evapotranspiration and ground water recharge taking into account Köppen’s climatic regions (Weiß, 2009);
- Implementation of dams from the Global Reservoir and Dam Database (GRanD) and the European Lakes and Reservoir Database (ELDRED2) in order to consider anthropogenic flow regulation (Döll & Fiedler, 2009).

These model revisions are a prerequisite for the application of WaterGAP3 to analyse the hydrological extremes in addition to long-term water availability. The model’s general ability to simulate flood discharges has been evaluated by Verzano (2009).

The meta-model makes use of a look-up table populated with the results of 273 pre-run WaterGAP3 simulations, aggregated for river basins, driven by monthly CRU climate input (Mitchell & Jones, 2005) with simultaneously modified mean temperature and precipitation. A constant offset was added to all values in the input time series of temperature leading to a shift in mean annual temperature while the dynamics are not changed. The manipulation of precipitation was done in a similar manner except by multiplying the values by a factor instead of adding an offset. The applied temperature variations range from 0.0 to +6.0°C in steps of 0.5°C while precipitation variations range from -0.5 (-50%) to 1.5 (+50%) in steps of 0.05.
During the runtime, the WGMM derives the change in temperature and precipitation for the individual river basins from the 10’ climate input provided by the IAP as compared to the baseline. According to these changes, the corresponding river basin-level changes of $Q_{\text{avg}}$, $Q_{95}$, $Q_5$, and $Q_{\text{med}}$ are taken from the look-up table and are subsequently downscaled to the IAP grid as mentioned above.

8.1.2 The WGMM water use model

WGMM provides simplified estimates of water withdrawals and water consumption in the domestic sector, in manufacturing, and in thermal electricity production.

In WaterGAP3, the domestic sector includes household use, small businesses and other municipal uses. The basic approach of the domestic water use model is to first compute the domestic water use intensity (m³/cap-year) and then to multiply this by the population of water users. Changes in water use intensity are expressed by structural changes and technological changes (Alcamo et al., 2003; Flörke & Alcamo, 2004). The concept of structural change is based on the observation that as average income increases, water consumers tend at first towards a more water-intensive lifestyle. Finally, a maximum level is reached after which the per capita water use is either stable or declines. In this way, human behaviour is covered. The relationship between water use intensity and income (GDP) is derived for each country by a fit to historical data. Water use is then downscaled to river basins according to the spatial distribution of population across Europe.

WaterGAP simulates water withdrawals in the manufacturing sector on a country scale based on the specific structural water use intensity, i.e., the ratio of water use to the manufacturing gross value added (GVA), which is derived from the base year (Flörke & Alcamo, 2004). The product of country-specific water use intensity and the scenario values for GVA yields the country wide water withdrawals, which are re-scaled to river basins according to sub-national statistics and the spatial distribution of urban population.

The amount of freshwater abstracted for cooling purposes in thermal electricity production is computed for each power plant as the product of the annual thermal electricity production (TEP in MWh) and the water use intensity of the power station (m³/MWh). The total annual cooling water needs in a river basin are then calculated as the sum of the withdrawals of all power plants located within the region (Vassolo and Döll, 2005; Flörke et al., 2011).

Water use modelling in the meta-model WGMM 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 GDP, population, GVA, TEP and technological change. In a second step, the country-level changes are applied to water uses at the river basin scale. For this purpose, WGMM uses a static relationship between the relative change in a river basin and the relative change in European countries. The latter is derived from WaterGAP3 results for the base year on a 5’ x 5’ resolution.

The concept of technological change is used in all sectors to account for the important effect that improving technology tends to improve water use efficiency by a certain percentage per year. In addition, changes in water use due to changes in people’s commitment to saving water is taken into account by applying a structural change factor.
8.2 WGMM model calibration and validation

The modelling approach for hydrological parameters in WGMM is mainly a reproduction of WaterGAP3 results. WaterGAP3 is a state-of-the-art hydrological model for the continental to global scale with a focus on the reliable estimation of long-term water resources and water use. Information on the calibration and validation of WaterGAP3 itself can be found in the literature listed above. In the following paragraphs, it is demonstrated that the additional model uncertainty caused by the major simplifications of the meta-model is still acceptable for the purpose of the IAP.

The daily WaterGAP3 simulations of river discharge that are used to derive $Q_{\text{med}}$, $Q_{95}$ and $Q_5$ (see Table 8.1) are based on monthly precipitation input, i.e., only total monthly precipitation and the number of rain days per month are known. The model disaggregates this kind of precipitation input to daily values using a statistical approach that leads to a considerable reduction in the day-to-day variability in the resulting ‘pseudo-daily’ precipitation time series as compared to observations. However, a comparison of simulated versus observed discharges for European gauging stations where daily time series for the period 1971-2000 are available shows fairly good agreement for $Q_{\text{med}}$, $Q_{95}$ and $Q_5$ (Figures 8.1, 8.2 and 8.3).

Another simplification of the meta-model approach is related to the technique to transfer river basin changes of river discharge to the 10’ minute grid of the IAP. This downscaling is done by multiplying gridded baseline values by the relative changes at the river basin outlet. Implicitly, this method assumes a uniform relative change in discharge for all segments of a river network although runoff generation and river routing is actually a non-linear process. Hence, there is in general a difference between WGMM results and corresponding aggregated WaterGAP3 output on the grid cell-level as soon as climate input differs from the baseline. Note, that the baseline grids are derived by spatial aggregation of WaterGAP3 output (5’) to the IAP grid (10’) using the same aggregation routine. The maps in Figure 8.4 show the relative deviation of $Q_{\text{avg}}$ simulated by WGMM from aggregated WaterGAP3 output for $Q_{\text{avg}}$. The maps indicate that: (i) in major parts of Europe the deviation is between ±5%, (ii) WGMM tends to overestimate $Q_{\text{avg}}$, and (iii) the overestimation of $Q_{\text{avg}}$ increases with increasing precipitation.

![Figure 8.1: Simulated vs. observed flood parameter $Q_{\text{med}}$ for 25 gauging stations across Europe, dashed line = 1:1 line, red (solid) line = linear fit.](image1)

![Figure 8.2: Simulated vs. observed high flow parameter $Q_5$ for 25 gauging stations across Europe, dashed line = 1:1 line, red (solid) line = linear fit.](image2)
8.3 Integrating WGMM with the other sectoral meta-models

Water use in the agricultural sector is not covered in the WGMM since it is calculated by the agricultural land use meta-model SFARMOD (Section 10). Nevertheless, SFARMOD takes into account an estimate of WGMM regarding the available water for agricultural use, i.e. mainly irrigation, as the maximum allowed water withdrawals for irrigation.

In order to estimate the amount of water available for agriculture on the river basin scale, WGMM balances the water availability and a “first guess” of total water consumption. The
latter is the sum of the projected non-agricultural water consumption plus the agricultural water consumption in the base year. If this demand can be satisfied, water availability for agriculture in the river basin is calculated as water availability reduced by non-agricultural water consumption. In the case of a water shortage, a ‘water sharing rule’ is applied uniformly across all affected river basins to distribute the available water resources to different sectors. The share of water resources falling upon agriculture is passed to SFARMOD. The default rule is to split water resources proportional to the base year conditions. However, the user of the IAP will be able to choose between several rules, which are currently implemented. Finally, SFARMOD returns the amount of water actually used in agriculture, which is taken into account by WGMM to correct the “first guess” water use estimates if necessary.

WGMM is also linked to the meta-models SPECIES (biodiversity; Section 13) and CFFlood (flood damages; Section 7). In these cases WGMM provides input for SPECIES (Q\text{avg}, Q_95, Q_5) and CFFlood (Q_\text{med}) but no feedback to WGMM is taken into account. For further information on how WGMM output is used by these meta-models see Sections 7 and 13.

8.4 References


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9. Development and validation of the crop yield meta-models

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9.1 Development of the crop meta-models

The development of the crop meta-models for the IAP was affected by the following considerations:

1. A relatively demanding time scale for the crop meta-models to be available and integrated into the IAP;
2. Pan-European coverage for all major crops was required;
3. Several yield levels (e.g. potential as well as water and nitrogen limited yields) were required;
4. The meta-models should include the CO$_2$ fertilization effect.

As a result of the above requirements, the CLIMSAVE team opted to use the full agricultural model ROIMPEL that has been validated in previous studies (e.g. Mayr, 1996; Rounsevell et al., 2003; Audsley et al., 2006; Alexandrov, 2006) and used in similar though smaller scale studies (e.g. Audsley et al., 2008; Henseler et al., 2009). In addition ROIMPEL was applied as the principal crop model in earlier FP5 projects e.g. ACCELERATES and ACELCEEC and its outputs used in a number of others (e.g. CECILIA, AGRIDEMA, ADAGIO).

The major advantage of using ROIMPEL is the considerable amount of results available from past EU projects. The data available for the development of meta-models included outputs of the full ROIMPEL model for EU-15 and most of the Central and Eastern European countries for the baseline climate and 2050 Low, Medium and High climate scenarios. Runs for the period centered around 2080 were also available for more than 50% of the territory. The available outputs of ROIMPEL are actual, potential and irrigated crop yields and crop sowing and maturity dates. Strengths of ROIMPEL are its modularity, the fact that it was developed specifically for GIS-based regional and sub-regional land-use evaluation projects (unlike most detailed crop models) and that initial detailed screening of soil/climate conditions for land suitability for a given crop is performed. The daily dynamics of development stages and of water-, temperature-, and nitrogen stresses are the main crop processes simulated in ROIMPEL which determine the land suitable for a given crop. The accumulation of biomass is based on radiation use efficiency and net photosynthetically active radiation, which is sensitive to CO$_2$ concentration. The radiation-potential daily biomass increase is corrected according to the temperature, water and nitrogen stresses. Additional penalties on crop yields are included through alarm criteria (for example, for unfavorable weather parameters during the most sensitive development stages) based on crop specific physiology.

Meta-models have been developed for the following crops:

- Winter wheat and spring wheat;
- Winter barley and spring barley;
- Winter oil seed rape;
- Potatoes;
- Grain maize;
- Sunflower;
- Soybean;
- Cotton;
- Grass; and
- Olives.

Sets of soil and climate predictors for the meta-models were selected based on available databases to emulate the full crop model results. The soil data were characterized by:

- The available water content in the rooting depth (1 parameter);
- The proportion of this water available between five suction levels between Wilting Point and Field Capacity (4 parameters);
- Surface soil texture index, estimated using the formula \[\text{Int}\left[\frac{4c+2z+d-78}{22.2}\right]\) where c, z, and d are the percentage clay, silt and sand respectively and \(\text{Int}[x]\) is the integer part of x. The index increases as the soil becomes heavier – more clayey than sandy (1 parameter); and
- Rooting depth, surface horizon hydraulic conductivity and wilting point soil moisture water content (3 parameters).

The climate data used by the full crop model consists of daily air temperature (maximum and minimum), precipitation, potential evapo-transpiration and solar radiation. These daily data are generated from monthly means and the climate data were therefore characterized by:

- Mean annual potential evapotranspiration (PET);
- Mean sum of PET from April to June;
- Mean sum of PET from July to September;
- Mean annual sum of precipitation;
- Proportion of precipitation from April to June;
- Proportion of precipitation from July to September;
- Mean annual temperature;
- Mean temperature from April to June;
- Mean temperature from July to September;
- Mean temperature from December to February;
- Mean maximum temperature from June to August;
- Mean minimum temperature from December to February;
- Mean annual sum of global radiation;
- Proportion of global radiation from April to June;
- Proportion of global radiation from July to September; and
- Ambient concentration of carbon dioxide in the centre of the particular time-slice.

The preparation of the crop meta-models was a two-step procedure. The first versions of the crop meta-models were based on step-wise regression models. These produced outputs in the expected range, allowing the identification of the best set of predictors, but lacked precision and reliability. The second version which go into the IAP are based on artificial neural networks (ANN) combined with temperature thresholds to prevent crops growing in unsuitable territories.
9.2 Calibration and validation of the crop meta-models

The crop meta-models were calibrated on a training set of data from the results of the original ROIMPEL runs mostly carried out under the ACCELCEEC and ACCELERATES projects. Calibration datasets were always sampled to adequately cover the whole range of both predictors and the predicted variables, e.g. sowing date or actual yield. The sampling of the calibration dataset took into account values outside ± 1 standard deviation from the mean of each parameter (both input and output). From the interval between 1 and 2 standard deviations, two-thirds of the data were used for model calibration and of those data points above/below 3 standard deviations 90% were used for model calibration. After calibration, each meta-model was independently tested on a complementary validation set in order to assess performance accuracy.

As the training and validation datasets include over 150,000 data points, a custom-made software application for the development and training of the ANNs for the 60 meta-models (12 crops x 5 output variables) was developed. The procedure for the meta-model development is summarised in Figure 9.1. This application aids the effective selection of the most suitable ANN design (e.g. input parameter selection, number of layers and hidden layers) and, based on 100 iterations of the best design, selects the top five ANNs based on the R$^2$, RMSE and MBE to prepare an ensemble of ANNs. As the run-time of the meta-models increases considerably with the number of ANNs in the ensemble, five was selected as an acceptable balance between model performance and runtime. The outputs from each of these five ANNs are then combined together in order to generate a final composite projection. There is a large body of statistical theory and practical work showing the superiority of ensembles over the use of any single model (Naftaly et al., 1997; Sharkey, 1999; Granitto et al., 2005). When needed, the ANNs are combined with temperature thresholds that are designed to “prevent” a given crop growing at sites which are not considered suitable (but in which the limiting factors are not covered by the input parameters, e.g. in the case of winter wheat, the mean annual temperature must be over 4.3°C and mean temperature from April to June above 8.25°C. Using these criteria, the number of locations at which the meta-models wrongly predicted possible cropping decreased by 60-75%.

The results of the 60 meta-models (for mean water and nutrient limited yield, mean water limited yield, mean water and nutrient unlimited yield, sowing date and harvesting date for each of 12 crops) are summarised in the Table 9.1. The meta-models show excellent performance in predicting sowing and harvest dates, with usually more than 90% of the variability explained. The meta-models were less successful in reproducing crop yields (nutrient and water limited, water limited and unlimited) but in all cases the results are considered acceptable. Overall the RMSE for the yield estimates is in most cases below 0.5 t/ha and the MBE that is close to 0 indicating that there is low/no systematic bias.
Figure 9.1. Overview of the ANN development for the crop metamodels

9.3 Crop meta-model illustrative results

Figures 9.2 to 9.6 show complete results of the meta-models for winter wheat in comparison to the outputs of ROIMPEL. Figure 9.7 shows results from each of the best five ANNs and the ANN ensemble mean in comparison to the outputs of ROIMPEL. Given the complexity and variability of conditions across Europe, it was not possible to achieve the level of accuracy reported by Audsley et al. (2008) for the much smaller area of eastern England. However, the validation statistics shown in Table 9.1 are acceptable and it is likely that the uncertainty arising from using ANNs instead of ROIMPEL will be smaller than that reported, as the final IAP will use a clustering approach such that aggregation will likely lead to higher accuracy of the meta-models.
Table 9.1. Meta-model validation performance statistics for the 1980-1990 period of the ensemble mean of the five best performing artificial neural networks (ANN) for mean water and nutrient limited yield (Yield\_Av), mean water limited yield (Yield\_POT) and mean water and nutrient unlimited yield (YieldPOTI), sowing date (Sowing) and harvest date (Harvesting).

<table>
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<tr>
<th>Metric</th>
<th>Meta-model output</th>
<th>Winter wheat</th>
<th>Spring wheat</th>
<th>Winter barley</th>
<th>Spring barley</th>
<th>Winter oil seed rape</th>
<th>Potatoes</th>
<th>Grain maize</th>
<th>Sunflower</th>
<th>Cotton</th>
<th>Soybean</th>
<th>Grass</th>
<th>Olives</th>
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<td>0.82</td>
<td>0.75</td>
<td>0.86</td>
<td>0.93</td>
<td>0.86</td>
<td>0.85</td>
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<td>0.86</td>
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Figure 9.2: Comparison of sowing date (Julian Day – 1st Jan = Day 1) for winter wheat as predicted by (left) the mean of the meta-model ANN ensemble and (right) ROIMPEL.

Figure 9.3: Comparison of harvest date for winter wheat as predicted by (left) the mean of the meta-model ANN ensemble and (right) ROIMPEL.
Figure 9.4: 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.

Figure 9.5: Comparison of yields limited by nutrient availability for winter wheat as predicted by (left) the mean of the meta-model ANN ensemble and (right) ROIMPEL.
Figure 9.6: Comparison of water and nutrient-limited yield for winter wheat as predicted by (left) the mean of the meta-model ANN ensemble and (right) ROIMPEL.

9.4 Integrating the crop meta-models with the other sectoral meta-models

In the IAP design the crop meta-model outputs are not used directly but only in association with the agricultural land use or farm model (SFARMOD; Section 10). Only after evaluation of the farm model gross margins which, given the crop yields, can be calculated from the crop prices, subsidies and variable costs is it possible to estimate the crop production in a particular area. Interaction between individual sectors and the crop meta-models is therefore provided by the SFARMOD meta-model and discussed in Section 10.
Figure 9.7: Comparison of winter wheat yields limited by the nutrient and water availability as predicted by ROIMPEL and by the five best ANNs and their mean used in the final meta-model.
9.5 References


10. Development and validation of the SFARMOD rural land use allocation meta-model

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10.1 Introduction

SFARMOD is the generic name given within CLIMSAVE to the routine for selecting rural (non-urban) land use. The concept is that the profitability of the competing uses for land is estimated using a general linear programming model and it is assumed that in the long-term the use that is most profitable will be the one selected. This procedure was used in Audsley et al. (2006), and example outputs are shown in Figure 10.1. There are basically three land uses: agriculture, forestry or unused. Agriculture can be either arable cropping, intensive or extensive grassland or long-term “fruit tree” cropping. Unused is often described as abandoned but could equally be simply unused for agriculture such as bare rock.

Figure 10.1: Modelled proportions of baseline arable agriculture predicted by the SFARMOD-LP model (from Audsley et al., 2006).

The full model used to develop the SFARMOD meta-model within CLIMSAVE is the SFARMOD optimising linear programme (hereafter referred to as the SFARMOD-LP) of whole farm planning, based on profit maximisation subject to the constraints of soil, precipitation and sound agronomic practice. This calculates the profitability of arable and intensive grass cropping on the land. Further details of the SFARMOD-LP can be found in Audsley (1981), Holman et al. (2005) and Annetts & Audsley (2002).
There are two converging strands to the work. The first is the software engineering challenge of the delivery of a module to run on the web-based Integrated Assessment Platform (IAP). The second is the creation of the meta-model of SFARMOD which can deliver the functionality of the module.

10.2 Description of the SFARMOD-LP – Silsoe Whole Farm Model

SFARMOD-LP (also known as the Silsoe Whole Farm Model) is a mechanistic farm-based optimising linear programming model of long-term strategic agricultural land use. Crops are defined by their gross margin, the amount and timing of the labour and machinery they require, restrictions on crop rotations, and their sowing and harvest dates, plus in some cases the amount of irrigation required. Gross margins are determined from the yield, which is a function of soil and climate, and given by the yield meta-model (Section 9) which also provides sowing and harvest dates and yield at different irrigation levels. Soil workability is a function of soil and climate. In addition farmers have uncertain future knowledge of actual prices and yields, and this is simulated in the full model by ten combinations of yields and prices from which the average cropping represents the expected land use. Price of crops is affected by supply and demand considerations as is the price of water for irrigation and is modified iteratively. The decision variables are crop areas, crop rotations, amount of labour and machinery, and operational timing within its feasible period.

The inputs to the full SFARMOD-LP model are:

- Soil type as an index reflecting the trafficability and available water capacity ranging from 2.5 on heavy land to 0.5 on sand.
- >30 year mean annual precipitation and evapotranspiration.
- Gross margins determined by:
  - Prices and support regime rules.
  - Yields: provided by the crop yield meta-models described in Section 9. Crops may be irrigated or not or both may be considered as options.
  - Input costs.
- Harvest and sowing date - these are used to determine where it is feasible to grow the crop in terms of it being able to reach maturity. The model decides whether it is economic to grow the crop.

The outputs produced are:

- Net profit, at the farm level, but also each crop’s gross margin including outputs and variable costs and the running and capital costs of the machinery fleet and associated labour.
- Crop outputs (yields) after timeliness, rotational and storage penalties and losses.
- Environmental burdens: nitrate leaching, nitrogen use.
- Measures for biodiversity indicators required by the SPECIES model in Section 13, such as over-winter stubble and use of pesticides.
The SFARMOD-LP model enables the simulation of a number of adaptation and policy interventions. These include:

- **Coercion:** Prescriptions and prohibitions can be modelled as constraints on the amount of crops or operations, e.g. banning mid-winter ploughing or compulsory set-aside.
- **Exchange:** Taxes and subsidies are readily modelled, such as a nitrogen or irrigation tax or subsidised crops.
- **Persuasion:** It is more difficult for a LP model to simulate the effects of shifting behaviour, e.g. through providing free education and campaigning for eco-friendly farmer behaviour. Decision-making behaviour can be modelled as multiple objective optimisation rather than profit maximisation and represent the effects of persuasions as small shifts in weight from profit to an ecological outcome.
- **Technology set change:** One important indirect source of intervention and adaptation that can be modelled is changing technologies, such as salt tolerant crops and improvements to irrigation to use less water for the same effect.

### 10.3 Development of the SFARMOD meta-model

The objective of the SFARMOD meta-model is to simulate the behaviour of the full SFARMOD-LP model described above, as applied to all soil-climate combinations. The procedure must estimate the profitability of the land for agriculture in each 10’ x 10’ CLIMSAVE grid, allocate it to categories of land use and calculate the total expected production of each type of crop output for each scenario.

#### 10.3.1 Data pre-processing

To enable the rapid calculations which are needed for the IAP, a significant amount of pre-processing has been carried out on the spatial input data to the model. The pre-processing analysis has proceeded as follows:

1. In the soil data file derived from an inter-section of the European soil map with the CLIMSAVE 10’ grid, there are 143,955 soil type-grid combinations within the 23,871 grid squares, and with up to 47 different soil types (officially known as Soil Typological Units) within each grid square, and a total of 5,107 different soil types. This needed to be simplified to facilitate efficient application of the meta-model:
   a. Firstly, the soil attribute database for each soil type was limited to those parameters required by the meta-models for crop yield, forestry and SFARMOD such as Available Water Capacity at four suctions from Saturation to Permanent Wilting Point, stoniness, and soil texture. On this basis many soil types are identical and the total is reduced to 582 soils.
   b. Secondly, a clustering procedure was applied to the soil data (Figure 10.2) to produce 137 similar soil types, with the procedure aiming to not cluster soil types of over 5,000,000 ha unless they are very similar. This is the Akaike Information Criteria (AIC) optimum for loss of information.
2. A similar clustering procedure was also applied to the baseline climate data for the 23,871 grid squares, which are assumed to be uniform over a grid, which produced 233 clusters (Figure 10.3). The clustering was based on grouping grid cells with similar average summer and average winter temperature, potential evapotranspiration and precipitation, and days (from 1st January) until average temperature > 0°C and 6°C.

3. Combined, there are 6754 climate-soil clusters, a factor of 20 reduction, since not all soils occur in all climate regions. Due to the diversity of soil types within a single grid square, there are often multiple climate-soil clusters within a grid square (but representing only a single climate). It should be noted that this approach has required the crop yield meta-models (Section 9) and forestry model (Section 6) to produce data on the same soil-climate clustering (not per grid).

10.3.2 Calibration of the SFARMOD meta-model

The SFARMOD meta-model estimates the potential profit of each climate-soil cluster for agricultural land use, so that land can be classified as intensive agriculture, extensive, forestry or not suitable. Considering the problem of replacing the linear programme model with a meta-model to provide a rapid approximation to the complex LP-based model, the main
factors considered are the comparative gross margins of the crops, the workability of the soil and the timing of sowing and harvesting. It can be shown for example that given a cropping solution of the model for wheat, rape and potatoes on a particular soil type, then if a heavier soil type with its reduced workability is chosen, which reduces the area of potatoes which is profitable, there exists an increased potato gross margin at which the model will select the original cropping.

The approach taken to develop the meta-model is to use the full SFARMOD-LP to systematically model the input parameter space and then to create a meta-model that relates the input parameters to the SFARMOD-LP outputs. In order to fully cover the parameter input space, SFARMOD-LP was run with 20,000 randomly selected sets of gross margins for each crop, the net precipitation used in the SFARMOD-LP workability formula and a summer temperature which modifies the harvest and sowing dates for each crop. In order to simulate the uncertainty the gross margins were adjusted in the same way as in the full SFARMOD-LP to provide ten uncertain gross margins for each set. These results were then used to create the meta-model.

A meta-model was derived for each crop to predict the proportion of the potential agricultural area of the climate-soil cluster allocated to the crop. In order to provide some mechanistic understanding to the meta-model, a range of combined input parameters were created. The input parameters to the meta-models were:

1. The gross margin of the target crop and the square of the gross margin (in €1000).
2. The effective precipitation measure used by the LP to calculate workability and the value squared.
3. The distance of the sowing date from the start of the year (fortnights) and the inverse.
4. The distance of the harvest date from fortnight 21 and the inverse.
5. The soil type on a scale of 1 (sand) to 9 (heavy clay).
6. If the latitude is greater than 4 degrees = 1 else 0.
7. A measure of summer temperature on a scale of 0 to 1.
8. The ratio of the gross margin of every other crop to the target crop omitting spring versions of wheat, barley and rape which are very strongly correlated to their winter version) plus the square of the winter wheat ratio.
9. The ratio of the target crop to winter barley and of winter wheat to winter barley. The product of the latter with the target crop.

This results in 23 or 24 input values for each crop.

A number of approaches were taken for the meta-modelling but the most reliably successful proved to be a neural network approach. A 23_15G_10_5_1 network, where G indicates the use of a Gaussian transfer function, was used. Of the 20,000 randomly selected gross margins, 4000 were randomly selected for training and 6000 for testing.

10.3.3 Validation of the SFARMOD meta-model

Examples of three fits are shown for crop areas for wheat, sugar beet and potatoes in Figure 10.4. Where points are a very bad fit, these were examined and found to be cases where extreme gross margins existed and limits had been set on the ratios of the gross margins.
Training correlation 0.978
Test correlation 0.967

Training correlation 0.986
Test correlation 0.969

Training correlation 0.988
Test correlation 0.984

Figure 10.4: Comparison of the performance of the SFARMOD meta-model with the results for the full SFARMOD-LP for the percentage of the cluster allocated to (top) wheat, (middle) sugarbeet and (bottom) potatoes.

Given the crop areas and using the gross margins and workability, a separate neural network calculates the farm profit (Figure 10.5). The capital and labour costs are higher where the land is heavier and precipitation is high due to fewer workable hours, which is exacerbated where the crop is harvested later in the year. Naturally where the capital costs are too high
the crop will not be grown, but this is a function of the price of the commodity and the input costs such as labour costs which are lower in some regions of Europe than others.

![Figure 10.5: Comparison of the performance of the SFARMOD meta-model with the results for the full SFARMOD-LP for profit (1000€/100 ha).](image)

Other output parameters are determined from the cropping, in particular irrigation requirement. Thus we have a rapid approximation to the linear programming model. For the future, the socio-economic scenarios define the crop demand and hence the crop price, and also modify the costs and level of inputs including irrigation, and the costs of labour and machinery. Given a new socio-economic and climate scenario this speed will also enable prices to be iteratively adjusted in future scenarios to meet a demand based on population. For example if an increased area is able to grow cotton, then it is likely the price will need to be reduced to prevent oversupply and vice-versa if climate reduces the area that can produce good yield due to drought, the prices will need to rise to ensure low yielding areas still produce to meet demand.

10.4 Application of the SFARMOD meta-model within the IAP and integration with the other sectoral meta-models

There are four stages to the running of the SFARMOD meta-model:

1. Calculation of the gross margin of each crop within the soil-climate cluster from the modelled yields and scenario data;
2. Application of the SFARMOD meta-model neural networks to calculate the potential percentage of the agricultural area under each crop within the cluster;
3. Application of the SFARMOD meta-model neural network to calculate the profit within the soil-climate cluster; and
4. Comparison of the potential profit to profitability thresholds to determine land use and resultant crop allocation (if relevant).

These steps are described in greater detail below.

The gross margins of each crop is calculated as:

\[ G = (P*Y*F) - (C*M) - (I*E*W) \]
where

- \( P \) is the price of the commodity, e.g. cereal;
- \( Y \) is the yield given by the yield meta-model (Section 9);
- \( F \) is a scaling factor to relate the modelled yield to the current actual yield levels based on NUTS2 Eurostat data;
- \( C \) is the input costs of the crop which varies with yield (low yields require low nitrogen input);
- \( M \) is the scenario factor for input costs (e.g. fossil fuel prices give higher fertilizer prices) (crop invariant);
- \( I \) is the amount of irrigation required by the crop (determined as the optimum);
- \( E \) is the scenario factor for efficiency of irrigation (crop invariant); and
- \( W \) is the price of irrigation water.

Thus given \( Y \) for each cluster by the yield meta-models, \( I \) is selected which maximises profit, \( C \) is modified based on the modelled yield versus the base yield and hence \( G \) is determined for each crop. This then enables the meta-models to calculate the cropping areas and profit by:

1. Determine the profitability of each climate-soil cluster for forestry using output from metaGOTILWA+ (Section 6).
2. It is assumed that each soil within each grid will be used for the most profitable option. The land use of each climate-soil cluster is based on lower thresholds of €350/ha for intensive agriculture and €150/ha for extensive agriculture. If forestry is more profitable than agriculture, then the cluster is allocated to forestry.
3. Apply the cluster results to the grids. Note that each grid contains \( N \) cells which are the soils belonging to different clusters:
   a. The cells are reduced in area pro-rata by the proportion of the urbanisation in the grid given by the RUG meta-model (Section 5).
   b. The cells with the worst soils (defined as those with the lowest Available Water Capacity) are assumed to be the protected areas of natural and semi-natural habitats and these are allocated progressively starting with the worst soils until the required area has been satisfied.
   c. Land which is flooded (input from the CFFlood meta-model; Section 7) has two categories: land which is flooded frequently and unusable for agriculture and which is removed pro-rata from each cell, and land which is flooded infrequently and is only suitable for grassland, which is removed pro-rata and is allocated to extensive grassland.
   d. The remaining area of each cell is assumed to have the land use of its cluster.
   e. Data is then summed over the grid as required, giving the area of each crop type in the grid, the average yield of the crop grown in the grid, and the water used for irrigation in the grid.
   f. For future scenarios, the supply of crops is then compared with the demand and irrigation required is compared with availability (summed by catchment) provided by the WGMM meta-model (Section 8).
10.5 References


11. Development and validation of the pest meta-models

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11.1 Pest occurrence model description

The pest meta-models were designed based on the outputs of the climate-matching software program CLIMEX that estimates the geographical distribution of a species based on the climate conditions of a given location. CLIMEX is based on the assumption that the climate suitability for a given species can be derived from knowing its present area of occurrence. In other words, CLIMEX attempts to mimic the mechanisms that limit species’ geographical distributions and determine their seasonal phenology. CLIMEX is a climate-rather than weather-driven modelling program that is designed to provide insights into species’ requirements for climate, as expressed by their geographical distribution, seasonal phenology and relative abundance. This approach suits the aim of showing climate induced and robust shifts in pest species’ distributions under future climate(s). CLIMEX is based on the premise that it is possible to define climates that are conducive to the generation of particular weather patterns, which directly affect populations on a short time-scale (Sutherst et al., 2000). The software has been used extensively in the fields of biological control, climate change and pest risk assessment with positive results in many countries.

Knowing the climatological requirements of a given species allows assessment of the suitability of a particular area for population growth and to determine the stress induced by unsuitable climate conditions. These are expressed in terms of the ecoclimatic index (EI), which describes the overall suitability of climate conditions for the establishment and long-term presence of a pest population at a given location:

\[ EI = GIA \times SI \times SX, \]

where GIA is the annual growth index describing population growth under favourable conditions, SI is the annual stress index describing survival during unfavourable periods, and SX represents stress interactions. The calculation of GIA and the stress indices are based on the ranges of threshold parameters for species development adjusted by the user. Temperature parameters include the lower and upper thresholds and optimal range of air temperature for development, and similar parameters are used for soil moisture. In addition to temperature and moisture limitations, CLIMEX also takes into account the process of diapause, which is driven by temperature (initiation and termination temperature) and day-length thresholds. The number of generations is calculated based on the number of degree-days above the lower temperature threshold per generation.

Generally EI ranges from 0 to 100, where EI = 0 indicates climate conditions unfavorable for long-term species occurrence and EI > 30 represents very suitable climate conditions for species occurrence (Sutherst & Myawald, 1985; Sutherst et al., 2001). Hoddle (2003) considers locations with EI > 25 as very favorable for species occurrence, 10 < EI < 25 as favorable and EI < 10 as limiting for species survival and occurrence. CLIMEX models use monthly input data of minimum and maximum temperature, relative humidity at 9 am and 3 pm and precipitation. In the CLIMSAVE project mean daily relative humidity is used to
approximate required inputs as sensitivity analysis showed a negligible effect on the model outputs when observed or estimated relative humidity values are used to calculate EI.

11.2 Pest occurrence model validation

In the first stage of assessing meta-model performance, the results from CLIMEX were compared with reports in the CAB International database and Fauna Europea. Figure 11.1 shows the evaluation of the presence/absence of seven species according to these databases. The figure shows the number of countries in which the results from CLIMEX and the observed databases agree (both present – light green; both absent – dark green) or disagree (orange and red). However, these data are only provided at the national level and hence have limited value for direct model validation and cannot be used to derive validation statistics, such as Kappa.

![Bar chart showing the number of European countries with presence or absence of seven pests according to CLIMEX vs. records available in databases of the observed pests' occurrences (CABI and Fauna Europea)]:

- Light green: CLIMEX and databases agree on presence.
- Dark green: CLIMEX and database agree on absence.
- Red and orange: CLIMEX and databases disagree on presence and absence.

Figure 11.1: Number of European countries with presence or absence of seven pests according to CLIMEX vs. records available in databases of the observed pests’ occurrences (CABI and Fauna Europea): light green – CLIMEX and databases agree on presence; dark green - CLIMEX and database agree on absence; red and orange - CLIMEX and databases disagree on presence and absence.

The performance of CLIMEX was therefore compared against a range of available data originating from published studies and the results are summarized in the following sections.

11.2.1 Ostrinia Nubilalis

The European corn borer (O. Nubilalis) is the most important native pest of grain maize and is widespread in Europe. Under current climate conditions, O. nubilalis has between one and three generations per year, depending on latitude and temperature conditions. In northern areas it has one or a partial generation. In central Europe, it has one generation in north-
western Hungary and two in the southern part of the country (Keszthelyi, Lengyel, 2002). In warmer areas the pest can complete two or three generations (south-west of France, Italy).

To provide increased confidence in CLIMEX, the performance of CLIMEX was compared with that of the process-based ECAMON model (Trnka et al., 2007) using the reported distribution of the European corn borer (ECB) in the Czech Republic. The database, consisting of almost 900 reports of *O. nubilalis* occurrence from more than 200 sites spanning the entire Czech Republic, was derived through personal contacts with individual research stations and from farmers for the period 1961 to 2003. Figure 11.2 shows that both CLIMEX and ECAMON show very good agreement with observations during two different model periods (1961-1990 and 1991-2000). Both models also properly recorded the pest expansion based on the higher temperatures of the last decade of the 20th century, which seems to support the hypothesis that this expansion was at least partly climate driven. The slight superiority of ECAMON over CLIMEX is due to the very detailed developmental module and the use of a daily time step compared to the simpler climatology used in CLIMEX. However, CLIMEX yields reliable results whilst having far lower input data requirements, and so demonstrates its applicability for incorporation within the IAP.

Figure 11.2: Validation of ECB (*Ostrinia nubilalis*) occurrence in the Czech Republic according to the detailed model ECAMON (a,b) and CLIMEX (c,d) that has been used to develop the meta-models for the IAP. Figures a) and c) correspond to the estimated range for the 1961-1990 climate whilst b) and d) correspond to the estimated range for the 1991 - 2000 climate.
Validation of the CLIMEX model for *O. nubilalis* was carried out coupled with the model of *L. decemlineata* in the domain of central Europe (Kocmánková *et al.*, 2001), where the predicted number of generations was in accordance with observed records. Across the whole of Europe the model correctly simulated the higher number of generations in Italy and France, and a single generation of *O. nubilalis* in northern countries such as Norway, Sweden, Finland, Denmark, United Kingdom and Ireland (Figure 11.3), where it is long-established.

![Image of CLIMEX simulation](image)

**Figure 11.3:** CLIMEX simulation of the Ecoclimatic index representing the climate conditions favourable for the establishment of one (green), two (yellow), three (orange), and four (red) generations of (left) *O. nubilalis* and (right) *L. decemlineata*. The yellow line constitutes the northern range limit from CLIMEX. Red circles mark observed occurrences of the pest available in the Global Biodiversity Information Facility database (http://data.gbif.org/).

### 11.2.2 *Leptinotarsa Decemlineata*

The Colorado Potato Beetle (*L. decemlineata* (Say)) is one of the most destructive potato pests. The beetle is present throughout Europe except for Britain, Ireland and Scandinavia, having its northern range limit in Russia (60°N) (EPPO, 2006). The number of Colorado beetle generations is largely a function of temperature, varying between about four in the hottest areas to one full and one partial generation near the colder extremes (Hiiesaar *et al.*, 2006).

The CLIMEX model for *L. decemlineata* has been validated in previous studies, with the spatial distribution of the number of generations corresponding with observations across central Europe (Kocmánková *et al.*, 2001). Within the wider spatial extent of CLIMSAVE, CLIMEX correctly indicates that the climate of southern and south-eastern England and the southern border of Sweden as potentially suitable for the establishment of the *L. decemlineata* (Figure 11.3). It is only pest management in these countries that has successfully avoided the long-term survival of the pest to date.
11.2.3 *Cydia Pomonella*

Codling moth (*Cydia pomonella*) is the oldest known and the most widely distributed pest of deciduous pome fruit (Ferro and Harwood, 1973). The native home of the codling moth is considered to be south-eastern Europe from where it has spread to wherever the climate is suitable for commercial production of apple and pear trees. The present distribution of codling moth is related to climatic factors as well as to food conditions (Wearing *et al.*, 2001), with temperature considered to be the determining factor of the life-cycle length and consequently of the number of completed generations.

Records regarding the number of generations of the moth across the European area were used for validation. Codling moth develops one generation in the coldest regions, four or five generations in the hottest regions, generally three generations are present in Spain (Gonzales, 2007), two generations in Romania (Neamtu *et al.*, 2008), three generations in Italy (Reggiany *et al.*, 2006), and a maximum of two generations in the Czech Republic (SRS, 2007). The number of generations predicted by the CLIMEX simulation are in agreement with these records (Figure 11.4), and the simulated northern boundary of the pest occurrence area corresponds with the Global Biodiversity Information Facility (http://data.gbif.org/occurrences/).

![Figure 11.4: CLIMEX results of the Ecoclimatic index representing climate conditions favourable for the establishment of one (green), two (yellow) and three (orange) generations of (left) *C. pomonella* and (right) *L. botrana*. Red circles mark observed occurrences of the pest available in the database of the Global Biodiversity Information Facility (*C. pomonella*) and Fauna Europea/Suffolk Moth Group (*L. botrana*). The yellow line constitutes the CLIMEX estimate of the potential northern range limit.](image)

11.2.4 *Lobesia Botrana*

The European grapevine moth (*L. botrana*) is a significant pest of berries and berry-like fruits in Europe and the Mediterranean. *L. botrana* is native to southern Italy but is now distributed in vineyards throughout Europe (CABI Distribution Maps of Plant Pests, [www.cabi.org](http://www.cabi.org)).
The number of generations is determined by several factors including photoperiod, temperature, humidity, latitude, food quality, and the effects of predators and diseases (Deso et al., 1981). In response to differences in climate, the number of generations completed by L. botrana differs geographically. In general, more generations are completed in southern latitudes than in northern latitudes - up to four generations can be completed in warmer regions such as Greece (Moschos et al., 1998), whilst two or three generations are present in Germany (Lous et al., 2002).

CLIMEX simulations have successfully estimated the climate conditions which are favourable for completing the number of generations in the relevant European countries mentioned above (Figure 11.4). The CLIMEX results for Poland are consistent with Fauna Europea (www.faunaeur.org), which indicates the moth as surviving in this area. Although CLIMEX indicates that Denmark and the southern coastal areas of Sweden and Finland as the northern limit for L. botrana occurrence, in disagreement with both CABI and Fauna Europea, CLIMEX correctly indicates the climate suitability in Gotland (where the moth presence is recorded by Fauna Europea). L. botrana is a rare immigrant to Suffolk in the United Kingdom (www.suffolkmoths.org.uk), which CLIMEX has assessed as suitable.

11.2.5 Oulema Melanopus

The Cereal leaf beetle (O. Melanopus) is an invasive pest of small grain cereal crops, particularly of wheat, oats, and barley (CAB International, 2002). This species is now present throughout Europe. O. melanopus typically has one generation per year, but occasionally two years are necessary to complete the development of a single generation in more northern climates (NCSU, 2003).

The climate suitability for the establishment of O. melanopus was, due to the obligate univoltinism of the pest, evaluated at three levels: unsuitable, suitable and very suitable climate. The model correctly predicts pest presence in northern areas such as in Norway, Sweden, Finland and Denmark, and in the United Kingdom and Ireland where it is widespread. The moisture requirements of the pest in southern countries like Greece and Italy were also fulfilled (Figure 11.5).

11.2.6 Rhopalosiphum Padi and Sitobion Avenae

The Bird cherry-oat aphid (R. Padi) and the English grain aphid (S. avenae) which are both cereal pests, are important vectors of plant viruses that may cause considerable damage, the most important among them being BYDV (Barley yellow dwarf virus). The distribution of cereal aphids is generally affected by climatic conditions and some biotic factors such as the quality of host plants, dispersal efficacy and natural enemies (Elliot and Kieckhefer, 2000).

The geographical distribution of both species is almost pan-European, including Scandinavia, UK, Ireland and also southern locations such as Italy or Sicily. However, the CABI and Fauna Europea databases do not provide more detailed specification of the pests’ occurrence. The CLIMEX model matches the occurrence of infested areas such as in Norway where CLIMEX estimated suitable climate conditions for both species on the south-eastern coast only and for S. avenae on the southern coast of Finland (Figure 11.6). The verification of the number of generations is also rather problematic due to the complicated and variable reproduction cycle of aphids, but there are records in England where S. avenae can develop eighteen generations, in agreement with CLIMEX.
Figure 11.5: CLIMEX results of the Ecoclimatic Index representing Suitable (yellow) and Very Suitable (green) climate conditions for the establishment of *O. melanopus*. Red circles mark observed occurrences of the pest available in the Global Biodiversity Information Facility (http://data.gbif.org/) database. Yellow line constitutes potential northern range as was estimated based on the CLIMEX results.

Figure 11.6: CLIMEX simulation of the Ecoclimatic index representing climate conditions favourable for the establishment of eight (green), twelve (yellow), and sixteen (orange) generations of (left) *R. padi* and (right) *S. avenae*. Red circles mark observed occurrences of the pest available in the Global Biodiversity Information Facility database. Yellow line constitutes the potential northern range as estimated by CLIMEX.
11.3 Development and validation of the pest meta-model

Overall the CLIMEX model reproduces well the regional, as well as the local, presence/absence suitability for the seven pest species, and therefore has been used as the basis for the development of the pest meta-models. Preliminary pest meta-models based on step-wise regression models lacked precision and reliability, and so meta-models using artificial neural networks (ANNs) were developed to reproduce the behaviour of the CLIMEX model.

The procedure for developing the pest meta-models is summarised in Figure 11.7. In the first stage, the best performing ANN design (e.g. input parameter selection, number of layers and hidden layers) was determined, by training the ANN on a calibration dataset and then validating it on an independent validation subset. The best design was then initiated using 100 different random seeds and the top five ANNs were selected based on their R², RMSE and MBE. The training and validation dataset included the whole CLIMSAVE 10° European domain (1961-1990). For the five top ANNs, a higher number of iterations were used in order to obtain the best final meta-model ensemble. The run-time of the meta-models increases considerably with the number of ANNs in the ensemble and therefore it was decided to keep the number low (five) whilst maintaining good model performance.

![Figure 11.7: Overview of the development of the pest meta-models based on ANNs.](image)

The results of 13 meta-models are summarised in Table 11.1, showing the ensemble mean performance and the range across the five constituent meta-models. It shows very good performance for the meta-models for all pest species for both the Ecoclimatic Index and the number of generations with at least 91% of the variability explained. Figure 11.8 also shows, as examples, the excellent spatial comparison between the results of CLIMEX and that of the
mean of the five constituent ANN meta-models for the Ecoclimatic Index for three species for the period 1961-2000.

**Table 11.1:** Results of the meta-model validation for the period 1980-1990 for the ensemble mean (range across the five best performing ANNs in parentheses).

<table>
<thead>
<tr>
<th>Pest species</th>
<th>Ecoclimatic Index</th>
<th>Number of Generations</th>
<th>RMSE</th>
<th>Number of Generations</th>
<th>MBE</th>
<th>Number of Generations</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Cydia pomonella</em></td>
<td>0.99</td>
<td>0.99</td>
<td>1.77</td>
<td>0.09</td>
<td>0.03</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.98-0.98)</td>
<td>(0.99-0.99)</td>
<td>(1.81-1.89)</td>
<td>(0.09-0.1)</td>
<td>(-0.08-0.05)</td>
<td>(-0.005-0.001)</td>
</tr>
<tr>
<td>*Leptinotarsa</td>
<td>0.98</td>
<td>0.99</td>
<td>1.67</td>
<td>0.06</td>
<td>-0.011</td>
<td>0.0004</td>
</tr>
<tr>
<td>decemlineata</td>
<td>(0.98-0.98)</td>
<td>(0.99-0.99)</td>
<td>(1.67-1.68)</td>
<td>(0.06-0.06)</td>
<td>(-0.089-0.002)</td>
<td>(-0.002-0.004)</td>
</tr>
<tr>
<td><em>Lobesia botrana</em></td>
<td>0.98</td>
<td>0.99</td>
<td>1.41</td>
<td>0.05</td>
<td>-0.012</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.98-0.98)</td>
<td>(0.99-0.99)</td>
<td>(1.45-1.49)</td>
<td>(0.04-0.11)</td>
<td>(-0.055-0.03)</td>
<td>(-0.003-0.004)</td>
</tr>
<tr>
<td><em>Ostrinia nubilalis</em></td>
<td>0.98</td>
<td>0.99</td>
<td>1.54</td>
<td>0.04</td>
<td>-0.012</td>
<td>0.0007</td>
</tr>
<tr>
<td></td>
<td>(0.98-0.98)</td>
<td>(0.99-0.99)</td>
<td>(1.56-1.60)</td>
<td>(0.04-0.04)</td>
<td>(-0.055-0.03)</td>
<td>(-0.0005-0.002)</td>
</tr>
<tr>
<td><em>Oulema melanopus</em></td>
<td>0.99</td>
<td>-</td>
<td>1.54</td>
<td>-</td>
<td>-0.03</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.98-0.98)</td>
<td></td>
<td>(1.64-1.72)</td>
<td></td>
<td>(-0.06-0.001)</td>
<td></td>
</tr>
<tr>
<td>*Rophalosiphum</td>
<td>0.95</td>
<td>0.99</td>
<td>2.47</td>
<td>0.317</td>
<td>-0.015</td>
<td>0.003</td>
</tr>
<tr>
<td>padi</td>
<td>(0.94-0.94)</td>
<td>(0.99-0.99)</td>
<td>(2.58-2.71)</td>
<td>(0.367-0.49)</td>
<td>(-0.05-0.11)</td>
<td>(-0.028-0.03)</td>
</tr>
<tr>
<td><em>Sitobion avenae</em></td>
<td>0.92</td>
<td>0.99</td>
<td>2.74</td>
<td>0.34</td>
<td>0.092</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.91-0.91)</td>
<td>(0.99-0.99)</td>
<td>(2.87-2.96)</td>
<td>(0.45-0.47)</td>
<td>(-0.047-0.24)</td>
<td>(-0.04-0.05)</td>
</tr>
</tbody>
</table>

**Figure 11.8:** Comparison of the Ecoclimatic Index for three species (*Cydia Pomonella*, *Oulema melanopus* and *Rophalosiphum padi*) according to (a) CLIMEX and (b) the mean of the five meta-models.
11.4 Pest meta-model illustrative results

Figure 11.9 shows the results of the meta-models for *Ostrinia nubilalis* across the CLIMSAVE 10° European domain, including the sensitivity of EI and the number of generations to temperature changes across the range from -2°C to +6°C. This shows, for example, the increasing northward shift in the number of generations with increasing temperature.

![Illustrative results for the value of (a) Ecoclimatic index (EI) and (b) number of generations per season for *Ostrinia nubilalis* during the period 1961-1990 with the meta-model being tested for sensitivity to temperature change from -2°C to +6°C.]

11.5 Integrating the pest meta-models with the other sectoral meta-models

The pest meta-models will interact with the SFARMOD agricultural land use model (Section 10). However, the exact form of interaction is yet to be determined. In addition, outputs on the occurrence of pests may be integrated with outputs from the SPECIES model (Section 13) on the occurrence of natural predators/parasites of the pests but this depends on the availability of observed European distributions for the natural predators.

11.6 References


12. Development and validation of the LPJ-GUESS biodiversity meta-model

Dorte Lehsten and Florian Sallaba
Department of Earth and Ecosystems Sciences, University of Lund, Sweden

12.1 LPJ-GUESS model description

LPJ-GUESS, a complex dynamic global vegetation model, is a process-orientated ecosystem modelling framework (Smith et al., 2001). It simulates successional vegetation dynamics on different scales (Schurgers et al., 2009, Wania et al., 2009) 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). The model input parameters are climate variables on a daily or monthly basis, atmospheric CO₂ concentration on an annual basis, soil parameters as static values, and plant specific traits to distinguish between species. The vegetation is modelled on a so-called stand. Within a stand, input parameters are equal. Establishment, growth, mortality, as well as disturbance events are simulated for a number of replicate patches within a stand to reduce stochasticity.

12.2 LPJ-GUESS model calibration and validation

LPJ-GUESS has been applied successfully in studies of different ecosystems and their responses to changing climatic drivers (Hickler et al., 2004, Schröter et al., 2005, Gritti et al., 2006, Morales et al., 2007, Thomas et al., 2008). In these studies LPJ-GUESS was tested and further developed through extensive calibration and validation work. However, ecosystem models tend to over-estimate low- to mid-range net primary production at boreal and temperate sites (Cramer et al., 1999). Given this extensive previous validation of the underlying model, the LPJ-GUESS meta-model was not further calibrated or validated.

12.3 Development of the LPJ-GUESS meta-model

To build a meta-model for LPJ-GUESS, which runs within a few seconds, it is impracticable to let LPJ-GUESS run on a reduced functionality. Therefore, it was decided to produce look-up tables of LPJ-GUESS model outputs for each time slice and scenario, which the user can select on the IAP.

Not including the baseline and its sliders on the IAP, the input parameters for the DLL of the LPJ-GUESS meta-model are the emissions scenario (A1, A2, B1, B2), time slice (2020s, 2050s), and GCM (HadCM3 and PCM have been used for model development as output from these climate models was already available, but the specific GCMs included in the IAP may be different once the analysis of GCM data in WP3 has been completed), coming directly from the user’s selection. A fourth input parameter is the land use type with four categories. The percentages of each land use type for each grid cell will be provided by the SFARMMOD meta-model (Section 10). This means that 64 different outputs from LPJ-GUESS have to be produced. The outputs are stores in 16 look-up tables, representing each combination of user choice. Therefore, 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- LAI, timber) (already cover ratio could be included instead of LAI). An extra file will be
stored of the dimensions of the grid cell times the number of land use types times three (for the soil water content, transpiration rate, and scenic potential).

The information on the user choice will be provided by the Running Module to the DLL. Within the DLL the appropriate look-up table will be called to provide the relevant indicators to the IAP. Species will be grouped into plant functional types (PFT) (such as coniferous trees) and the DLL will send back only those species/PFTs that the user has requested. Within the Running Module the matrix will be multiplied by the land use type percentages. Timber will be calculated according to a percentage of biomass, cover ratio will be calculated according to LAI, and productivity is given by the net primary production. Scenic potential is a measure for landscape diversity, in this case biodiversity. Scenic potential will be calculated by the sum of the squared quotients of \( \text{LAI}_{\text{species}} \) to \( \text{LAI}_{\text{total}} \). For each land use type the scenic potential will be calculated and multiplied with the ratio of this land use type. Finally, the Simpson’s diversity index (Simpson, 1949) will be calculated, using leaf area index as a measure for species abundance, as an aggregate indicator of climate change impacts on biodiversity.

When the baseline climate is selected in the IAP, the user can change a number of sliders related to annual temperature change, summer and winter precipitation change and \( \text{CO}_2 \) concentration. The number of combinations of slider changes 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 altered climatologies and the outputs of LPJ-GUESS.

12.4 LPJ-GUESS sensitivity analysis

The sensitivity analysis of LPJ-GUESS has been undertaken for 63 grid cells situated along two transects that cover several bio-geographical zones as shown in Figure 12.1.

The sensitivity of vegetation to climate parameters (annual temperature, winter and summer precipitation) and atmospheric \( \text{CO}_2 \) concentration was analysed in order to estimate their influence on net primary production, biomass accumulation and leaf area index across the Arctic, Boreal, Continental, Atlantic, Alpine, Mediterranean and Pannonian climatic and bio-geographical zones.

The LPJ-GUESS simulations were performed using CRU data from 1900 – 2006 (University of East Anglia Climate Research Unit, 2008) as the baseline climate data. The sensitivity analysis is divided into two parts: (i) independent changes; and (ii) dependent changes of the climatic drivers.

12.4.1 Independent changes of climatic drivers

This part of the sensitivity analysis involves the adjustment of one climatic driver in a LPJ-GUESS simulation. Table 12.1 shows the agreed minimum and maximum values for each climatic driver and atmospheric \( \text{CO}_2 \) concentration which were adjusted during the independent sensitivity analyses by the stated increments. The climatic driver values were added to the CRU data (Mitchell & Jones, 2005) in each of the 43 simulations.
Figure 12.1: Cross European transects capturing North to South-West and North-West to South-East climatic transitions. The area of a cell is 1° and is based on the 10’ CLIMSAVE grids. The extent of a grid is ~60km - ~100km depending on its location – since Lambertian equal area projection is not isogonic or isometric it leads to distortion towards the edges.

Table 12.1: Minimum and maximum values of each climatic drivers and their individual increments.

<table>
<thead>
<tr>
<th>Climatic Driver</th>
<th>Temperature [°C]</th>
<th>Winter Precipitation [%]</th>
<th>Summer Precipitation [%]</th>
<th>Atmospheric [ppm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min. Value</td>
<td>0</td>
<td>50</td>
<td>50</td>
<td>350</td>
</tr>
<tr>
<td>Max. Value</td>
<td>6</td>
<td>150</td>
<td>150</td>
<td>700</td>
</tr>
<tr>
<td>Increment Value</td>
<td>0.5</td>
<td>10</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td>Sum of Steps</td>
<td>13</td>
<td>11</td>
<td>11</td>
<td>8</td>
</tr>
</tbody>
</table>
12.4.2 Dependent changes of climatic drivers

The second part of the analysis is based on dependent changes in which changes in multiple climatic drivers influence the vegetation dynamics in different dimensions. The climatic driver adjustments are constrained to the climatic driver values as stated in Table 12.2. The constrained climatic driver values are added to the CRU data (Mitchell & Jones, 2005) and led to 500 different simulations.

Table 12.2: Definition of the climatic drivers used within the multivariate sensitivity analysis.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>50</td>
<td>50</td>
<td>350</td>
</tr>
<tr>
<td>2</td>
<td>75</td>
<td>75</td>
<td>437.5</td>
</tr>
<tr>
<td>4</td>
<td>100</td>
<td>100</td>
<td>525</td>
</tr>
<tr>
<td>6</td>
<td>125</td>
<td>125</td>
<td>612.5</td>
</tr>
<tr>
<td>-</td>
<td>150</td>
<td>150</td>
<td>700</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

12.4.3 Results of the sensitivity analysis

The independent changes of climatic drivers along the transects lead to a wide range of effects on NPP. Figure 12.2 visualizes the range of NPP values (maximum minus minimum NPP) for each grid cell along the transects. Considering the difference between the minimum and maximum NPP values, the first transect (red line - Figure 12.2) has small NPP variations in the Norwegian Alpine and Boreal bio-geographical zones (0.1 – 0.2 kgC*m⁻²). Increasing NPP variations up to ~0.3 kgC*m⁻² occur from southern Sweden to southern Germany in the Continental bio-geographical zone. In the Alpine zone the NPP variations are less elevated at ~ 0.2 kgC*m⁻². High NPP variations (up to 0.4 kgC*m⁻²) are modelled in the Mediterranean zone of France and northern Spain. In central Spain NPP variations are stable on an elevated level and increase strongly (0.4 kgC*m⁻²) towards the Atlantic coast.

The second transect (blue line in Figure 12.2) shows a slight increase in NPP variations from Scotland (~0.2 kgC*m⁻²) through England (~0.25 kgC*m⁻²) and northern France (0.3 kgC*m⁻²) in the Atlantic bio-geographical zone. In the Continental zone the variations are stable at ~0.3 kgC*m⁻² NPP towards the Alpine zone. The model results show a decline of ~0.2 kgC*m⁻² NPP variations in the Alpine zone. From the eastern Alpine to the Pannonian zone NPP variations increase up to ~0.35 kgC*m⁻². In the Romanian Alpine (Carpathian Mountains) zone the variations show a dip. Then the NPP variations increase to ~0.35 kgC*m⁻² in the Continental bio-geographical zone. Towards Bulgaria and the Mediterranean, NPP variations decrease down to ~0.25 kgC*m⁻².

The effect of independently changing climatic drivers leads to elevated NPP variations in the Continental and Mediterranean bio-geographical zones. The Alpine and Boreal zones as well as areas of higher altitude seem to be less sensitive towards the independent changes.
Figure 12.2: Independent changes of climatic drivers that cause minimum and maximum values of NPP in each cell. Showing the range of minimum and maximum annual total NPP for each grid cell along the two transects: [upper] north to south-west transect; [lower] north-west to south-east transect.

The main driver of maximum total NPP values is high atmospheric CO₂ concentrations (600 to 700 ppm) in 89% of the grid cells. This is due to the effects of CO₂ fertilization as a main driver of NPP as reported by Cramer et al. (2001). In the Norwegian Alpine zone elevated temperature (2 - 3.5°C) leads to maximum total NPP values in ~10% of the grid cells.

Minimum NPP values are caused by rising temperature (5 - 6°C) in 55% of the grid cells—mostly in the Mediterranean and Continental bio-geographic zone due to water limitation caused by high temperatures. Elevated summer (110 – 150%) and winter precipitation (140 – 150%) lead to minimum NPP values in 12% of the grid cells – mostly in the Alpine zone.

The dependent changes of climatic drivers along the transect lead to higher dynamics of NPP compared to the independent changes. Figure 12.3 illustrates the range of NPP values (maximum minus minimum NPP) for each grid cell. The first transect (red line - Figure 12.3) has small NPP variations in the Norwegian Alpine bio-geographical zones (~0.2 kgC*m⁻²). From the Boreal zone in northern Sweden to the Continental zone in southern Germany, NPP variations increase from ~0.2 kgC*m⁻² to ~0.5 kgC*m⁻². In the Alpine zone, NPP variations decline to ~0.3 kgC*m⁻². High NPP variations (up to ~ 0.6 kgC*m⁻²) are modelled in the Mediterranean zone of France and northern Spain. In central Spain NPP values vary at an elevated level of ~0.35 kgC*m⁻² and increase strongly (0.4 kgC*m⁻²) towards the Atlantic coast.
The second transect (blue line in Figure 12.3) shows fluctuating NPP variations from Scotland (~0.3 kgC*m⁻²) through England and northern France (~0.4 kgC*m⁻²) in the Atlantic bio-geographical zone. However, there might be a slightly increase of NPP to the East. In the Continental zone the variations show a fluctuation of NPP values at a low level along the transect (~0.45 kgC*m⁻²). The NPP variations decrease in the Alpine zone to ~0.3 kgC*m⁻². From the eastern Alpine to the Pannonian zone, NPP variations increase by up to ~0.5 kgC*m⁻². In the Romanian Alpine (Carpathian Mountains) zone, the variations show a dip followed by a strong increase (~0.6 kgC*m⁻²). Towards Bulgaria and the Mediterranean, NPP variations decrease slightly to ~0.5 kgC*m⁻². In southern Greece NPP variations fall to ~0.35 kgC*m⁻².

![Figure 12.3](image)

**Figure 12.3:** Dependent changes of climatic drivers. Climatic driver combinations that cause minimum and maximum NPP. Showing the range of maximum and minimum annual total NPP for each grid cell along the two transects: [upper] north to south-west transect; [lower] north-west to south-east transect.

The climatic driver combinations of high atmospheric CO₂ concentrations (612.5-700 ppm) and increased summer (125 - 150%) and winter (125 – 150%) precipitation lead to maximum NPP values in 52 % of the grid cells. In the Alpine zones increased temperature (+2-4°C), high atmospheric CO₂ concentrations (612.5-700 ppm) and elevated summer precipitation lead to maximum NPP. Minimum NPP is caused mainly by high temperature (+6°C) and decreased summer precipitation (50%) in 71% of the grid cells. The effect of changes in winter precipitation vary, but it generally has less influence on minimum NPP compared to the other drivers.
In the Norwegian Alpine zone, minimum NPP is caused by increased summer and winter precipitation. Temperature does not limit NPP production. The other European Alpine zones are sensitive to increased temperature (+6°C) and decreased precipitation patterns, resulting in minimum NPP values.

Figure 12.4 illustrates the changes of annual temperature and annual summer and winter precipitation of the dependent sensitivity analysis over all grid cells. NPP increases with rising temperature until it reaches an optimum between 10 and 16°C. Further increases of temperature reduce NPP values again. The influence of precipitation on NPP shows NPP increasing with rising precipitation up to an optimum. The optimum depends directly on annual temperature. Optimal annual temperature and maximum precipitation leads to maximum NPP.

Figure 12.4: Three-dimensional scatter plot of the dependent sensitivity analysis in all 63 grid cells, considering all changes of temperature and combined summer and winter precipitation. It represents NPP as a function of temperature and precipitation.

The sensitivity analysis of NPP to independent and dependent changes of atmospheric CO₂, temperature, summer and winter precipitation considers total NPP. Therefore, it does not reflect PFTs or species so far. However, we are looking for relationships that describe NPP, LAI and Cmass as a function of atmospheric CO₂, temperature, summer and winter.
precipitation for natural European vegetation (species) in the literature. Thus the relationships will be integrated into the LPJ-DLL meta-model as a simplified “LPJ-GUESS model” in order to calculate NPP, LAI and Cmass according to the given sensitivity sliders.

12.5 References


13. Development and validation of the SPECIES biodiversity meta-model

Paula A Harrison, Robert Dunford and Pam M Berry

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13.1 SPECIES model description

The SPECIES model (Spatial Estimator of the Climate Impacts on the Envelope of Species; Pearson et al., 2002) is used in the IA Platform to simulate the impacts of climate change on the suitable climate space of over 100 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; see Section 14, Table 14.1).

SPECIES is based on ensembles of artificial neural networks (ANN), which integrate bioclimatic variables for projecting the distribution of species through the characterisation of bioclimatic envelopes. Integrated algorithms, including a soil water balance model, are used to pre-process climate (temperature, precipitation, solar radiation and wind speed) and soils (AWC – available water holding capacity) data to derive relevant bioclimatic variables for input into the ANN. Those variables found to be most successful for projecting the distributions of birds (Harrison *et al.*, 2003) and other taxa (Berry *et al.*, 2003) are given in Table 13.1.

**Table 13.1: Bioclimatic input variables used for birds and other taxa in the SPECIES model (from Harrison *et al.*, 2006).**

<table>
<thead>
<tr>
<th>Birds</th>
<th>Other taxa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growing degree days &gt; 5°C</td>
<td>Growing degree days &gt; 5°C</td>
</tr>
<tr>
<td>Absolute minimum temperature expected over a 20-year period</td>
<td>Absolute minimum temperature expected over a 20-year period</td>
</tr>
<tr>
<td>Mean summer temperature (MJJ)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Annual maximum temperature</td>
</tr>
<tr>
<td>Mean summer precipitation (MJJ)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Accumulated annual soil water deficit</td>
</tr>
<tr>
<td>Mean winter precipitation (DJF)&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Accumulated annual soil water surplus</td>
</tr>
<tr>
<td>Mean summer water availability (MJJ)&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
</tr>
</tbody>
</table>

<sup>a</sup> May, June, July  
<sup>b</sup> December, January, February

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. To improve performance, these variables, which can vary by several orders of magnitude, are first normalised to the range 0 to 1 using the minimum and maximum values for the European and North African region (Tarassenko, 1998) before proceeding with model training.
13.2 SPECIES model calibration and validation

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, 2007; 2009). The outputs from each of these models are then combined together in order to generate a final composite projection. There is a large body of statistical theory and practical work showing the superiority of ensembles over the use of any single model (Naftaly et al., 1997; Sharkey, 1999; Granitto et al., 2005).

Ensemble forecasting in SPECIES has been carried out using an aggregate k-fold cross-validation. This involves randomly subdividing the available data into training (70%) and validation (30%) sets k times in order to construct k different ANN sub-models. Each sub-model is calibrated on one of the training sets and then independently tested on the complementary validation set in order to calculate statistics indicating its performance accuracy. Each training and validation set is constructed so that it contains the same presence-to-absence ratio as seen in the full dataset, thus eliminating any representational bias in the datasets between presence and absence points. Bootstrapping is then used to construct training and validation sets which are the same size as the full dataset and containing equal numbers of presence and absence points. This ensures that the datasets have a 50/50 prevalence between presence and absence points, thereby reducing any sensitivity bias in the trained models towards projections of overly high or low suitability values.

A value of ten for k was chosen based on preliminary tests showing this value as giving a good trade-off between greater model stability / reduced spatial variance and longer model running times. An ensemble model output is then formed by combining the simulations from the ten ANN sub-models based on whether presence or absence is most commonly projected for a grid cell.

The performance of each ANN sub-model is statistically evaluated using Cohen’s Kappa statistic of similarity (K) and the Area Under the Receiver Operating Characteristic Curve (AUC). Kappa is a commonly used statistic that provides a measure of similarity between spatial patterns, adjusted for chance agreement (Cohen, 1960). Kappa values vary from 0, indicating no agreement between observed and projected distributions, to 1 for perfect agreement and are dependent on the particular classification threshold being applied for determining whether simulated results are treated as presence or absence points. Maximum agreement for Kappa is calculated by iteratively adjusting this threshold from 0 to 1 in increments of 1x10⁻⁴. AUC is calculated from plots of the Receiver Operating Characteristic (ROC) curve. ROC curves measure the trade-off between a model’s sensitivity (the proportion of true presences to the actual number of projected presences) and its false positive fraction (the proportion of false presences to the actual number of projected absences) as a function of all possible classification thresholds. This index is an unbiased measure of a model’s predictive accuracy and is independent of both species prevalence in the validation dataset and classification threshold (Fielding & Bell, 1997). AUC ranges from 0.5 for models with no discrimination ability, to 1 for models with perfect discrimination.

The accuracy of the ensemble model, as measured by AUC and Kappa, is approximated by the average performance of the ten individual sub-models. This provides a conservative estimate of the ensemble’s accuracy as its performance is usually at least as good as this and usually even better (Bishop, 1995). There are several rules-of-thumb available to help interpret measures of agreement between observed and simulated distributions. For example,
Monserud and Leemans (1992) suggest the following ranges of agreement for Kappa: excellent $K>0.85$; very good $0.7<K<0.85$; good $0.55<K<0.7$; fair $0.4<K<0.55$; and poor $K<0.4$. For AUC, Swets (1988) recommends interpreting values using the ranges: excellent $\text{AUC}>0.90$; good $0.80<\text{AUC}<0.90$; fair $0.70<\text{AUC}<0.80$; poor $0.60<\text{AUC}<0.70$; fail $\text{AUC}<0.60$.

Models have been trained and validated for all species and all show AUC statistics greater than 0.8, indicating good discrimination ability and 84% has AUC statistics greater than 0.9, 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 47% of species indicating very good agreement between observed and simulated distributions, and between 0.4 and 0.7 for 35% of species indicating reasonable agreement. Further visual comparison between observed and simulated distributions is being undertaken and any models that are unable to capture the core observed distribution will be removed from the IA Platform.

13.3 SPECIES model illustrative results

13.3.1 Species suitable climate space

Once a network is trained and validated for the European and North African region, it is then applied across the CLIMSAVE 10° European grid to produce a climate suitability surface. This is converted into a presence/absence distribution (see Figure 13.1) by applying the decision threshold which maximises agreement between observed and simulated distributions derived from the ROC curve. Further details concerning the definition of decision thresholds are provided in Pearson et al. (2002).

Figure 13.1: Illustrative results for Silene gallica (small-flowered catchfly) for Europe: (left) simulated climate suitability surface; (right) presence/absence distribution. Presence/absence ROC threshold is 0.22, AUC = 0.943, maximum Kappa = 0.64.

13.3.2 Species vulnerability

Two species vulnerability indices are calculated from the outputs of the SPECIES model for the European region as a whole and for individual EU countries: vulnerability assuming no use of new climate space and vulnerability assuming full use of new climate space (Berry et
Each index is a function of the amount of change in suitable climate space, which is measured in terms of four species’ indicators: new climate space; lost climate space; overlap between present and future climate space; and size of the future distribution. Lost climate space indicates the sensitivity or degree of change. In reality, it is more likely that losses will be realised, as the species becomes stressed, less competitive and ultimately exhibits a mortality response. Gained or new climate space indicates the degree of opportunity for species to disperse and increase its range and thereby decrease its vulnerability. Overlap between present and future climate space indicates the continuity of suitable climate space. This measure also indicates the degree of threat to a species, as where there is little overlap between a species’ current and potential future climate space, there could be a small population remaining *in situ* and the species will be forced to disperse if it is to realise much of its future climate space. Dispersal for some species is difficult and slow, thus they will become vulnerable. The size of the future distribution indicates the future rarity of species, as rarity is one factor thought to confer vulnerability to climate change (Berry, 2004).

The Vulnerability Index with no use of new climate space assumes that autonomous adaptation is restricted to within the boundaries of the 10’ grid cells which the species currently occupies, due to limited dispersal and there is no new planned adaptation. The Vulnerability Index with full use of new climate space assumes that autonomous and planned adaptation will take place to help species disperse into new areas. The degree to which planned adaptation can be implemented is assumed to be a function of the extent of new climate space, as this indicates the limit of the species’ potential future distribution. Both indices range from 0 for no vulnerability to 20 for high vulnerability to climate change (Figure 13.2).

![Figure 13.2: Illustrative output for the SPECIES vulnerability indices for Europe.](image-url)
13.4 Integrating the SPECIES model with the other sectoral meta-models

13.4.1 Agricultural and forest meta-models

Predictions of potential climate space from the SPECIES model are combined with output on the area of arable and forest land, nitrogen and pesticide inputs and overwinter stubble from the SFARMOD land use model (Section 10) to simulate the impacts of climate and socio-economic changes on species’ suitability in agricultural and forest habitats. The area of arable and forest land is used to create a habitat mask, which can optionally be applied to the species suitability maps. This habitat mask therefore alters with the climate and socio-economic scenarios depending on the spatial distribution of arable agriculture and forestry within the land use model.

The effects of nitrogen inputs on plant species are simulated by applying thresholds based on an individual species’ sensitivity to nitrogen derived from the Ellenberg indicator values for Europe (Ellenberg, 1974; Ellenberg et al., 1991). The various values were divided into classes indicating low, medium or high tolerance to nitrogen increases, as the Ellenberg values are on an arbitrary scale and species’ ecological requirements may vary in different parts of their range and according to local conditions, thus a broad classification was appropriate. The species’ nitrogen tolerances were linked to data on nitrogen inputs from the agricultural land use model based on results from Audsley et al. (2008) which attributed thresholds to the plant tolerance classes. These thresholds may require recalibrating once the meta-models are fully linked within the first prototype of the IA Platform. Illustrative output on combining the effects of nitrogen inputs with the SPECIES climate space outputs for the region of East Anglia in the UK is shown in Figure 13.3.

![Illustrative output](image)

**Figure 13.3:** Sensitivity of *Scandix pecten-veneris* (shepard’s needle) in East Anglia, UK derived from combining results from the SPECIES model with nitrogen fertilizer values from the SFARMOD agricultural land use model. Source: Audsley et al. (2008).

The effects of pesticide inputs on plants and pollinators are simulated by applying thresholds based on an individual species’ sensitivity to pesticide derived from a literature review. The various values were divided into classes indicating low, medium or high tolerance to pesticides, as the species’ tolerance may vary according to the pesticide type and thus a broad classification was appropriate. In each case, evidence for the highest level of sensitivity was used.
Overwinter stubble provides important habitat for ground nesting birds and can be an important food source during the winter. The effects of overwinter stubble on birds are simulated by applying thresholds based on an individual species’ sensitivity to percentage changes from base in the amount of overwinter stubble per 10’ grid cell from the agricultural land use model.

13.4.2 Water meta-model

Predictions of potential climate space from the SPECIES model are combined with output on low and high river flows (Q95 and Q5 values, respectively) from the water model (WGMM-Section 8) and habitat data on wetlands from the flooding model (CFFLOOD- Section 7) to simulate the impacts of climate and socio-economic changes on species’ suitability in wetland habitats. The area of inland wetlands is used to create a habitat mask, which can optionally be applied to the species suitability maps. This habitat mask therefore alters with the climate and socio-economic scenarios depending on the spatial distribution of wetlands within the CFFLOOD model.

The effects of low and high river flows on wetland species are simulated by applying thresholds based on an individual species’ sensitivity to drought and waterlogging derived from Ellenberg indicator values (Ellenberg, 1974; Ellenberg et al., 1991). The various values were divided into classes indicating low, medium or high drought or flooding tolerance, as the indicator values are on an arbitrary scale and species’ ecological requirements may vary in different parts of their range and according to local conditions and thus a broad classification was appropriate. The species’ water level requirements were linked to the outputs from the water model based on results from Harrison et al. (2008) which attributed thresholds to the plant tolerance classes. Similar to the nitrogen thresholds, these drought and waterlogging thresholds may require recalibrating once the meta-models are fully linked within the first prototype of the IA Platform. Illustrative output on combining the effects of water stress with the SPECIES climate space outputs for north-west England is shown in Figure 13.4.

Figure 13.4: Sensitivity of *Sphagnum cuspidatum* in northwest England derived from combining results from the SPECIES model with Q95 values from a hydrological model. Source: Harrison et al. (2008).
13.4.3 Coastal flooding meta-model

Predictions of potential climate space from the SPECIES model are combined with output on the area of salt marsh and coastal and floodplain grazing marsh from the coastal model (CFFLOOD – Section 7) to simulate the impacts of climate and socio-economic changes on species’ suitability. Changes in the area of salt marsh and coastal and floodplain grazing marsh simulated by the coastal model are directly overlaid onto the climate space simulations to create a habitat mask, which can optionally be applied to the suitability maps. This habitat mask therefore alters with the climate and socio-economic scenarios depending on the spatial distribution of these habitats within the coastal model.

13.4.4 Habitat re-creation

A habitat re-creation slider on the adaptation screen of the IA Platform will allow the user to increase the percentage of protected areas (Natura 2000 sites). This will affect the outputs from the other sectoral meta-models, particularly the SFARMOD land use model, and thus the habitat available for different species. Two sets of rules for allocating the percentage increase in protected areas (PAs) have been developed, one which focuses on increasing existing protected areas (“buffering strategy”) and one which focuses on improving connectivity within the Natura 2000 network (“connectivity strategy”). For the buffering strategy grid cells to the northeast (the direction in which most species’ suitable climate space are likely to move) of existing protected areas are prioritized for habitat re-creation.

13.5 References


14. Concluding remarks

Work Package 2 has made good progress to date. Table 14.1 summarises the range of stakeholder-relevant impact indicators and indicators which translate the outputs from the integrated sectoral models into ecosystem services indicators which the meta-models each simulate. The impact and ecosystem service indicators listed in Table 14.1 may be subject to change, depending on the feedback received from stakeholders within the WP1 workshops.

The focus of activity within the next phase is to complete the implementation of the meta-models within the Platform (D2.3), ready for testing of the prototype Platform in the summer of 2011 (M2.2).
Table 14.1: Summary of current sectoral output and potential ecosystem service indicators produced by the meta-model DLLs.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Meta-model DLL</th>
<th>Sectoral output indicators</th>
<th>Ecosystem Service indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>RUG</td>
<td>● Artificial surfaces (area and % change)</td>
<td>N/A</td>
</tr>
<tr>
<td>Snow</td>
<td>SnowCover</td>
<td>● Days with &gt; 1 cm and &gt; 10 cm snow</td>
<td>● Recreation (C)</td>
</tr>
<tr>
<td>Cropping</td>
<td>metaROIMPEL</td>
<td>● Crop yields (unlimited by nutrients and water availability; unlimited by nutrients availability; and limited by nutrients and water availability)</td>
<td>N/A</td>
</tr>
<tr>
<td>Forestry</td>
<td>metaGOTILWA+</td>
<td>● Wood yield in managed forests</td>
<td>● Timber production (P)</td>
</tr>
<tr>
<td>Rural land use</td>
<td>metaSFARMOD</td>
<td>● Total crop production</td>
<td>● Food production (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Biomass energy</td>
<td>● Animal production (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Food energy</td>
<td>● Bioenergy production (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Irrigation water demand</td>
<td>● Fibre production (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Intensively farmed, Forested and Abandoned land</td>
<td>● Irrigation use (P)</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>● Attractiveness of agricultural landscapes (C)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>● Naturalness (C)</td>
</tr>
<tr>
<td>Water</td>
<td>WGMM</td>
<td>● Naturalised high &amp; average monthly river flow</td>
<td>● Drinking water (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Water availability</td>
<td>● Cooling water (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Water availability per capita</td>
<td>● Water storage (R)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Real low, average and high flows</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>● Water stress</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Total water use</td>
<td></td>
</tr>
<tr>
<td>Flooding</td>
<td>CFFlood</td>
<td>● Area at risk of flooding</td>
<td>● Flood protection (R)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Damages caused by flooding</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>● People affected by flooding</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>● People in flood risk zones</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>● Areas of coastal grazing marsh, salt marsh, intertidal flats and inland marshes</td>
<td></td>
</tr>
<tr>
<td>Pests</td>
<td>Pestmm</td>
<td>● Number of generations per season (6 species)</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Ecoclimatic index (quality of the ecoclimatic niche for 6 species)</td>
<td></td>
</tr>
<tr>
<td>Biodiversity</td>
<td>SPECIES</td>
<td>● Species Presence/Absence</td>
<td>● Wild food plants (P)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Species Vulnerability Indices</td>
<td>● Pollination (R)</td>
</tr>
<tr>
<td></td>
<td>metaLPJ-GUESS</td>
<td>● Net Primary Production (by Plant Functional Type, species and grid square)</td>
<td>● Charismatic or iconic wildlife (C)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>● Biomass (by Plant Functional Type, species and grid square)</td>
<td>● Species for hunting (C)</td>
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