Scaling Methods in Regional Integrated Assessments: From Points Upward and from Global Models Downwards

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ABSTRACT

Scaling methods in regional integrated assessments are often adopted as givens, when in fact there are a range of methods that each have their strengths and weaknesses. Methods such as a site within a polygon, spatially uniform grids, grids with relational data on polygons, interpolation and stochastic spatial models are reviewed for crop-climate modeling of climate change impacts developed in the European Union's Clivara project. A similar suite of methods for downscaling from global climate models to local conditions exists, and is reviewed. Up- and down-scaling issues relate to availability of data, the level of technical expertise in the project team, validation, uncertainty and risk, stakeholder participation, and modeling of actor-agents. Given the many aims of integrated assessments, no one approach is best.

Keywords: scaling, integrated assessment, climate change, CLIVARA.

1. INTRODUCTION

All models contain a simplification of the spatial or temporal scale of the real system, either by averaging or aggregating small scale elements or by treating large scale changes as a constant [1–3]. Three examples illustrate the importance of scale in climate change impact assessment.

First, understanding of crop-climate modelling at the site scale is far more profound than is readily captured in spatial, regional models. Yet, spatial shifts in agricultural potential, demand for water, use of fertiliser and competitiveness are more profound for agricultural systems than point estimates of changes in potential yield.

Second, climate change captured in low resolution global climate models may not relate to the sensitivity of local climate impacts. Changes in extreme events, such as ground frost, persistent drought, and ocean-atmosphere anomalies, are poorly represented in existing models. Yet, such changes are likely to be more significant than gradual changes in means.

Third, understanding adaptation requires a new breed of climate change impact assessment – one that portrays realistic decision making, environmental, economic and social signals, and thresholds for action [4]. Scaling between the cognition of decision agents and their broader environments will be a considerable challenge.

This paper primarily focuses on methodologies required to address the first of these demands for understanding scale in integrated assessment – scaling up impacts. We also provide an entrée into the literature on downscaling climate. The discussion introduces issues in scaling agents – a critical aspect of agent-based simulation.

In many respects, these issues are part of the arcane toolkit of impacts modeling. However, resolving the scale issue can make a difference (see, for example, Easterling et al. [5], Mearns et al. [6, 7]). The CLIVARA project undertook a European-scale assessment of climate change

and potential crop production, using high resolution, multi-scale crop-climate models. On two occasions we have (subjectively) compared our results with the results from single-scale spatial models used in global assessments. We have the diverging results – the global models predict major adverse impacts of climate change whereas our process-oriented understanding shows widespread benefits and few adverse impacts on potential crop production. However, these comparisons are simply visual – further comparison of impacts models remains an urgent agenda for research.

2. SCALING UP IMPACTS

This section provides examples of different approaches to scaling up, drawn from the experience of the Climate Change, Climatic Variability and Agriculture in Europe (CLIVARA) project [8].

The choice of scale is part of the process of formulating a model [9]. For some physical models strong spatial interactions between the principal model variables, such as air movement between neighbouring grid cells, guide the choice of an appropriate spatial scale. Such spatial interactions are limited in agriculture (e.g., competition between plants for water, pests), although scaling is still present in crop models, for example, by modelling the average conditions over a small area and by using average daily weather rather than trying to reproduce the changes throughout the day.

The techniques described here apply to common methods in climate change impact assessment, specifically crop-climate modelling. The focus is on crop phenology and yield. We assume nutrients will be applied and pests controlled. Scaling up all of the factors affecting crop production (e.g., agronomic management) and agricultural systems (e.g., costs and prices) is more difficult.

Methods for bridging scales range from using available climate stations to forcing all data, processes and output to a uniform gridscale and multi-level approaches that embed reduced form or emulation models (e.g., Polsky and Easterling [10]).
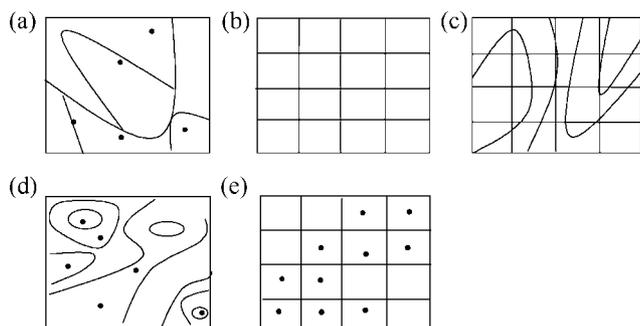

Fig. 1. Approaches for representing spatial variability in models: (a) site driven (site/polygon and multiple sites in a polygon); (b) spatial uniform grids; (c) uniform grids with relational soils (spatially combined); (d) spatial interpolation; and (e) stochastic space.

One aspect of the scaling-up has been to determine the optimum amount of input data and model runs that are needed to represent the responses to environmental change in a 'region.' Several studies have discussed this issue, in particular the regional study on Central England [11] and the Danish country study [12].

Five approaches for representing variability across space are illustrated schematically in Figure 1 (see Downing et al. [2]). Site-driven approaches (Fig. 1(a)) begin with station data. In contrast, raster grids for the basis for most spatial modeling [Fig. 1(b)], although much data is held in polygons rather than grids [Fig. 1(d)]. The two forms can be combined in various ways [Fig. 1(c–e)].

2.1. Site-Driven Approaches

A common approach in determining regional yields is to identify sites and soils that can 'represent' that region. Such an approach is generally based on soil polygons for natural resource data. If soil units cover a large geographic region, they may be intersected with an agroclimatic index, such as aridity or agroecological zone, topography (often a proxy for temperature), or agronomic management regions e.g., known land use or irrigated areas.

Each resulting polygon is associated with representative climate data. Ideally, this would be a station within the boundaries of the polygon. If this is not available, the climate data may need to be interpolated from stations outside the polygon. Or, more simply, the nearest station is used. In either case, a single site represents the entire polygon. This is the site/polygon approach.

A slightly more complex approach is the multiple site/region method. This assumes that several sites can be used to represent the spatial variability within a region. Brooks and Semenov [11] investigated how many sites were required to capture the variability in climatic and soils parameters for modelling climate change effects on winter wheat in central England. Analysis of data at numerous sites in the region indicated that it could be considered as a single climatic region with three main soil types. Empirical relationships were then derived between site predictions from a process-oriented wheat model (Sirius) and observed regional yield statistics for climate change.

A different interpretation of the multiple site/region method is illustrated in Davies et al. [13] in a study on the economic response of potatoes to climate change in England and Wales. Here, site-based crop and economic models were applied to 93 meteorological stations in the region for current conditions and several climate change scenarios. Model output variables (e.g., yield, gross margins) were then spatially interpolated from the 93 sites to a 10 km grid across England and Wales.

In a case study in Denmark [12], correlations using summer precipitation with 650 precipitation stations identified regions of Denmark, represented by 6 climate stations.

Using the maximum correlation scheme the areas that were best correlated to each site were identified.

This approach has the benefit of retaining complex soils data and can readily utilise detailed climate data (e.g., 30-year daily time series of temperature, solar radiation, wind, humidity and rainfall) that would be difficult to grid for a study region. Soils are acknowledged as more important for crop suitability than local differences in climate. If soil units are large, then one climate station may not be representative and the soil units may need to be subdivided by climatic regions. A site-polygon approach was also adopted in the regional studies in Hungary [14].

The main technical drawback to site-driven approaches is the relative complexity of the modelling environment. Creating and accessing databases in different formats requires special facilities not generally provided in a Geographic Information System (GIS) or crop-climate programmes. Even with generic shells, such as AEGIS [15], considerable investment is required to set up a study area and carry out simulations. Even creating a spatial map of the length of growing period requires fully processing the crop model for each soil-climate polygon, summarising the model output, and presenting the resulting statistics for the soil-climate thematic layer in the GIS. However, the approach does preserve the original data formats and integrity.

The conceptual limitations concern notions of space as an inherent variable. The model only has to be run once for each soil type and crop management group within each climate polygon. There is no a priori test for choosing the number of soil-climate spaces and the number of climate stations required to represent each polygon. To the extent that long term change alters present environmental relationships, choosing ideal polygons for the present situation does not guarantee an adequate representation of the future.

The estimation of the variance of modelled regional yield requires the spatial correlation of simulated yields to be assessed. This can be done for current conditions by running a model for each database grid using observed weather data for a given period. However, climate change scenarios downscaled to sites generally are not spatially correlated and so cannot be used to investigate the future yield covariance structure. This is true for scenarios constructed using a weather generator to produce independent time series of synthetic weather data for each site (but see the spatial weather generator in Semenov and Brooks [16]). Regional climate models are another approach gaining popularity, but at some expense in terms of data handling.

2.1.1. Central England Case Study

A study has been conducted using the soil/polygon approach in Central England [11]. The methodology involves predicting regional yield under future climate by scaling-up output from a site-based wheat model. Limited site information is assumed to be available so that the method is applicable in most circumstances; only soil data for the region and detailed weather data at a few sites are required. The predictions of yield assume good management and the absence of pests and diseases with spatial variations in modelled yield therefore being due to differences in weather and soil conditions throughout the region.

The first step was to investigate the relationships between the input and output variables of the Sirius wheat model by conducting a comprehensive sensitivity assessment. Next, a simpler model was constructed based on an analysis of the inherent relationships within the Sirius model and results from the sensitivity assessment. The model was able to reproduce the Sirius yields closely for a variety of UK conditions. Test data sets with a wide range of yields produced root mean square errors of around $800\,kg\,ha^{-1}$, compared to standard deviations in the Sirius model of some $2000\,kg\,ha^{-1}$. Correlations were above 0.90.

The methodology consists of identifying the areas within the given region that have similar soil-weather characteristics. Unless the region is very large, contains major topographical features or a vast diversity of soil types, there will only be a few such soil-weather combinations. Predictions of regional yield are then made by combining site-scale Sirius predictions for each soil-weather combination with predictions of the inter-site correlation pattern. The mean regional yield is simply defined as the weighted sum of the mean site yields. When data from only a few sites are available the yields across the region must be inferred using this data. In particular, areas that are considered to have similar weather and soil conditions are likely to show a similar change in yield and can be considered as one large site.

It was necessary to assess the relationships between the site weather data and the site soils data. A sensitivity analysis on the full mechanistic winter wheat model and resulting simpler model showed that the single important soil variable, under non-nitrogen limiting conditions is the total available water capacity. Different soils can therefore be grouped together if their water capacities are similar.

Those areas identified as having similar climates and soils are considered as a single large site in the estimation of the mean and variance of regional yield. This overcomes the need to simulate each individual farm within the region. The mean regional yield is calculated for present and future climatic conditions for each different soil-climate combination. This is undertaken using the Sirius model with synthetic weather data produced by the LARS-WG stochastic weather generator (see Barrow et al. [17]). The estimation of the variance of regional yield requires the spatial correlation of the simulated yields to be assessed.

The close correspondence of the weather characteristics of the sites means that they can be grouped together. Since the topography of the region is fairly homogeneous, the whole region's weather can be represented by just one site. There is a slight temperature gradient from north to south and a

precipitation gradient from west to east for the three sites. Hence, a centrally situated site would be the most representative. However, the weather database does not contain such a site with observed weather data for 1960–1990 and so, instead, the site of Oxford was chosen as it has a complete record and site climate change scenarios are available.

The input parameters used for the three sites were the same and so the differences in synthetic yield are entirely due to the different weather data at the three sites. The analysis of the weather data indicated that the systematic differences were small and so the region could be considered as experiencing a single climate. Furthermore, the random differences were not sufficiently great that they needed to be modelled explicitly. The comparison of yields supports this conclusion with small differences between the sites. The sensitivity analysis showed that small random differences in weather could produce significant differences in yield and, thus, the differences in yield observed here are consistent with small random differences between the sites.

The recorded regional yield data only covers the period 1974–1979 and 1983–1995 and will be influenced by a number of factors that are not included in this study, particularly the effects of pests and diseases and changes in management practices and technology. This prevents a meaningful comparison with the mean and standard deviation of yields modelled for central England.

However, a limited validation can be made by examining the yield pattern across the region. Actual yields should contain a climate signal and a comparison of regional yields across Britain shows that there are strong correlations between yields of nearby regions. This is consistent with the model analysis in that yield is related to cumulative values of the climate variables and that many of the relationships are approximately linear so that the relationship of yield to climate should not have large discontinuities. The similarity of the climate across Britain means that there should not be large differences in the climate related effects on yield.

The methodology produces the most accurate prediction of the regional yield variance by combining the weather generated climate scenarios and the observed climate data. However, this prevents an analysis of the distribution of regional yields or of the statistical significance of the results. An indication of the likely shape of the distribution of regional yield can be obtained from the observed data by multiplying the predicted yields for each year for the three soil types by the soil relative area values to give a simulated regional yield. The lack of data (only 30 values) and the fact that the climate change scenario does not include changes in variability limits the value of such results. The simulated regional yield distributions for the observed data and for the observed data adjusted for the two scenarios of climate change are slightly negatively skewed. The skewness probably results from several of the years being at or close to potential yield so that variations in water deficit between those years have no effect on yield.

2.2. Uniform Grid Approach

The most common approach to linking GIS and crop models is to convert all of the input data into raster grid databases with uniform pixel size and geographical co-ordinates. The original data need to be interpolated to the raster grid. Data with irregular boundaries such as soil data are forced to match the grid. The site-based crop model (or a simplified version) is then applied consecutively to each grid cell in the region.

The resolution is generally chosen based on the availability of data, resulting size of database and computing resources. Ideally the resolution would reflect the sensitivity of model results to spatial variation and discontinuities as well as corresponding to the accuracy of the input data.

Recent examples of this method are studies that have applied complex site crop models to relatively fine grids at national scales. Carter et al. [18] applied the CERES-Wheat and POTATOS site-based crop models to data held in a network of 3827 grid boxes at a 10×10 km resolution across Finland. The application of simplified and complex site models to gridded input data has been deomonstrated by Rounsevell et al. [19].

The European study in CLIVARA also used this approach by applying a simplified crop model to gridded climatological and soil data [20].

Gridded models generally require converting site models to a regional scale model and using aggregated regional inputs. Model parameters and inputs need to be scaled, by running the model throughout the region either by using interpolated inputs or by dividing the region into sub-regions with the same characteristics.

At the site level, detailed crop-climate models simulate plant responses to a wide variety of environmental and management changes. These results are used to calibrate parameters in more generic, reduced-form models that run on the spatial data (e.g., EuroWheat at the European scale [20].

Brisson et al. [21] studied large scale spatial variations in maize suitability in France. The main aim was to build a crop model (GOA-Maize) with the minimum of biological detail needed to produce useful information for decision making and which is able to use readily available input data. The model was applied to climatic data on a ten-day time step at a gridded resolution of 20 km^2.

Brignall and Rounsevell [22] developed a simple model to assess the effects of climate change on winter wheat potential in England and Wales. This classified crop performance into well-suited, moderate, marginal or unsuited based on calculations of machinery work days and drought stress.

Two reduced-form models were developed by Wolf [23, 24] and compared with output from complex site-based models under current and future climatic conditions. The

POTATOS reduced-form potato model was compared with the NPOTATO site model, whilst the SOYBEANW reduced-form soya bean model was compared with the SOYGRO site model. Results were highly variable showing that the models produced similar responses at some sites and under some climate change scenarios, but quite different results at others.

The main advantage of the gridded methods is that it is relatively simple once data have been converted to the grid. The principal disadvantage is the lost connection between the input data and model processes. The original data is simplified and generalised to fit the grid. For example, daily rainfall is reduced to monthly time series and crop-climate models are simplified to work at this scale. If a very high resolution is chosen, the required computer resources (data storage and processing time) generally limit the number of simulations attempted. Since the original data are not available to the model, testing of model sensitivity and uncertainty may be reduced, especially if each run requires significant computing resources.

The disadvantages are especially important in treating soil information. In Figure 1(b), soil types do not correspond to the imposed grid – some grid cells have more than one soil. Refining the grid to correspond more closely to the soil boundaries is possible, but would dramatically increase the size of the database, as the same information is duplicated for many pixels – there are fewer soils than there are grid cells.

Where more than one soil is present in a pixel, often the dominant soil type is gridded and other soils in the grid or associated soil types are not included in further modelling. Alternatively, the best soil is gridded, although the definition of best would vary by crop and season. Another approach is for soil properties (such as water holding capacity) to be averaged, based on their prevalence in each pixel. However, this may result in quite unrealistic input data if the soil types are quite distinct. Some soils will be unsuited for agriculture and can be masked from the database. Input soil databases for each soil can be prepared and models run for every soil type. The output would still have to be aggregated to the pixel level, generally using a weighted average or stochastic dominance criteria.

2.2.1. European Case Study

Simplified crop simulation models for wheat, potato and grapevine have been either developed or adapted for application at the continental scale [20]. These reduced-form models approximate the behaviour of complex site-based models, but require less demanding input and calibration data. The models were combined with the use of statistical functions to temporally downscale climatic input variables from the monthly to daily resolution. A GIS was used to run each model across spatial data sets interpolated to a regular 0.5° latitude/longitude grid. Each 0.5° grid cell was assumed to represent a homogeneous

region and the model was applied independently to each cell.

Results from these models provide a continental overview of the effects of climate change on crop suitability and productivity. The performance of the continental scale models in simulating current regional variations in crop productivity was evaluated against observed agricultural statistics. Ratios for calculating actual yields from simulated water-limited yields were available for wheat and potato [25]. This allowed a comparison of the range of simulated yields in all grids in any country with the observed yields and gave a satisfactory validation of the models.

The effects of climate change on wheat, potato and grapevine production across Europe was investigated using two climate change scenarios from global climate models (GCMs) for the year 2050. Spatial uncertainties in crop responses, which are attributable to uncertainties in GCM projections of future climate, were also quantified for wheat.

The scaling-up method involved the application of reduced-form mechanistic crop models to spatially gridded input datasets. Various statistical functions were explored for temporally downscaling the relevant climatic input variables (minimum and maximum temperatures and solar radiation) from the monthly to daily resolution (Fig. 2).

A GIS was used to run each model across the spatial data sets interpolated to a regular 0.5° latitude/longitude grid. Results were aggregated to the country level, providing estimates of the impact of climate change on agroclimatic environments across Europe and a statistical test of significant differences from the present to the scenarios of future yields (Fig. 3).

2.3. Spatially Combined: Uniform Grids with Relational Soils

An alternative to uniform grids is to hold soil data as a relational database. Each grid cell points to a database of soils to look up all the soils that are found in that grid cell. This can provide access to richer soils data. Connections to representative soil profiles for each soil unit can add information for soil layers.

Conversely soil data can be gridded and climate overlaid as polygons (as in Olesen et al. [12]).

This approach improves upon uniform grids by facilitating access to complex soils data and eliminating redundant soil data for each pixel. Linking the raster (gridded climate) and vector (soil polygon) data requires some programming and may not be easy to do within standard GIS packages.

A variation of the grid approaches is to sample the grid. The baseline conditions can be modelled on a uniform grid with a high resolution (provided the underlying data are of sufficient quality). Scenarios of climate (or other) change can then be modelled on the basis of a sample of the baseline grid. Some a priori tests of the model response surfaces
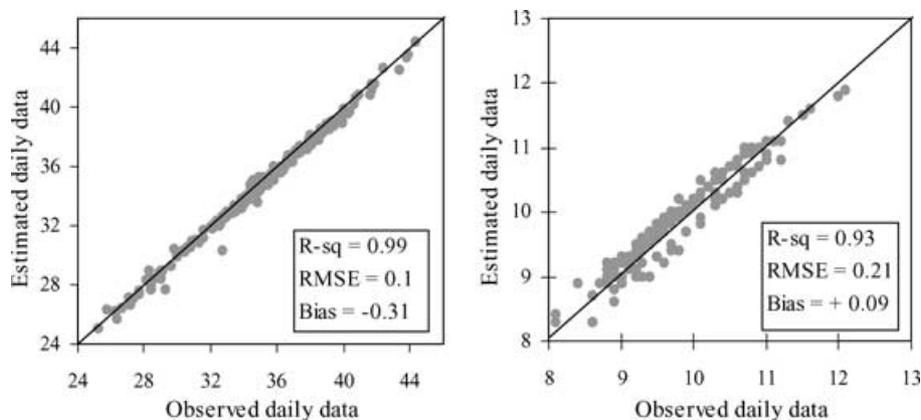
Fig. 2. Comparison of the mean duration of (a) the grain filling period (in days) and (b) mean grain yield (in t ha^{-1}) calculated using observed daily data and daily data estimated using a sine curve interpolation routine at 175 sites.

should illuminate an optimal grid for sampling. For instance, the slope of the model response (yield) can be mapped and related to the model input data (to-pography, mean climate, soils). Agroecological regions can be defined based on the model response surface, rather than on the input data.

It is likely that the change in model responses (e.g., the difference between baseline yield and yields with climate change) are easier to model and require fewer sample points than actual yields.

The results need to be interpolated to the original grid. Two approaches are:

1. Distance interpolations: The actual values for the sample results are interpolated based on distance-weighted distributions.
2. Mean anomalies: As is often done for climate time series, the sampled results are expressed as deviations from the baseline average. The anomalies are interpolated to the study area grid, then converted back to actual units.

Butterfield et al. [26] compared the spatially gridded inputs and spatially combined inputs approaches for modelling climate change impacts on wheat in Great Britain. Climatic data and data for the dominant soil type was initially interpolated to a 10 by 10 km grid. The Sirius wheat model was then applied to the 2,840 grid cells in the region. The model was then rerun using the spatially combined inputs approach for 12,924 unique soil/climate polygons in the region. The comparison showed that model output from the two approaches was not statistically different for current climatic conditions. Hence, the authors recommended the gridded input approach for their study as this was more computationally efficient.

Brklacich et al. [27] used a similar approach in a study of agricultural land rating in the Mackenzie Basin in northwest Canada. Climate data were gridded at a 10 km resolution and soils data were held in polygons at the 1:1 million scale. To reduce the number of calculations the climate associated with the 10 by 10 km grid cell closest to the centroid of each soil polygon was used.

The AEGIS (Agricultural and Environmental Geographic Information System) approach [28] is comparable to that of Brklacich et al. [27], except that a representative meteorological station within each soil polygon is utilised. If a meteorological station is not available within the boundaries of the polygon then the nearest station is used. AEGIS contains the DSSAT suite of site crop models in a PC GIS-based environment and is designed as a regional decision support system for policy making in agriculture.

Van Lanen et al. [25] combined three types of data held in polygons to study crop growth potential in the European Union. Here, the authors defined 4,200 Land Evaluation Units (LEUs). Each LEU was a unique combination of a soil unit, a representative meteorological station for each of 109 agro-climatic zones and administrative regions. Qualitative (based on expert knowledge) and quantitative (based on crop simulation models) land evaluation methods were then applied to each LEU to determine the current potential suitability and productivity of wheat.

This approach is a compromise between running everything at a high resolution and formal hierarchical model designs. The sample frame may vary depending on the modelled process. For instance, crop phenology requires fewer sample points than soil water processes (e.g., infiltration, runoff, erosion), while changes in yield are somewhere between these two extremes. The sample frame is likely to reflect soil and agroecological spaces, as noted in creating soil-climate polygons. Denser sample networks are required where model responses are more variable. Statistical methods for sample design and validation are well developed and can measure the errors associated with various sample designs.

2.3.1. Great Britain Case Study
The example for Great Britain [26] used soil polygons overlaid on a 10 by 10 km monthly climate grid (Fig. 4). To determine the necessary spatial resolution, yields were calculated as averages for each grid and as the yield of the dominant soil in each grid. The effect on yields of using a
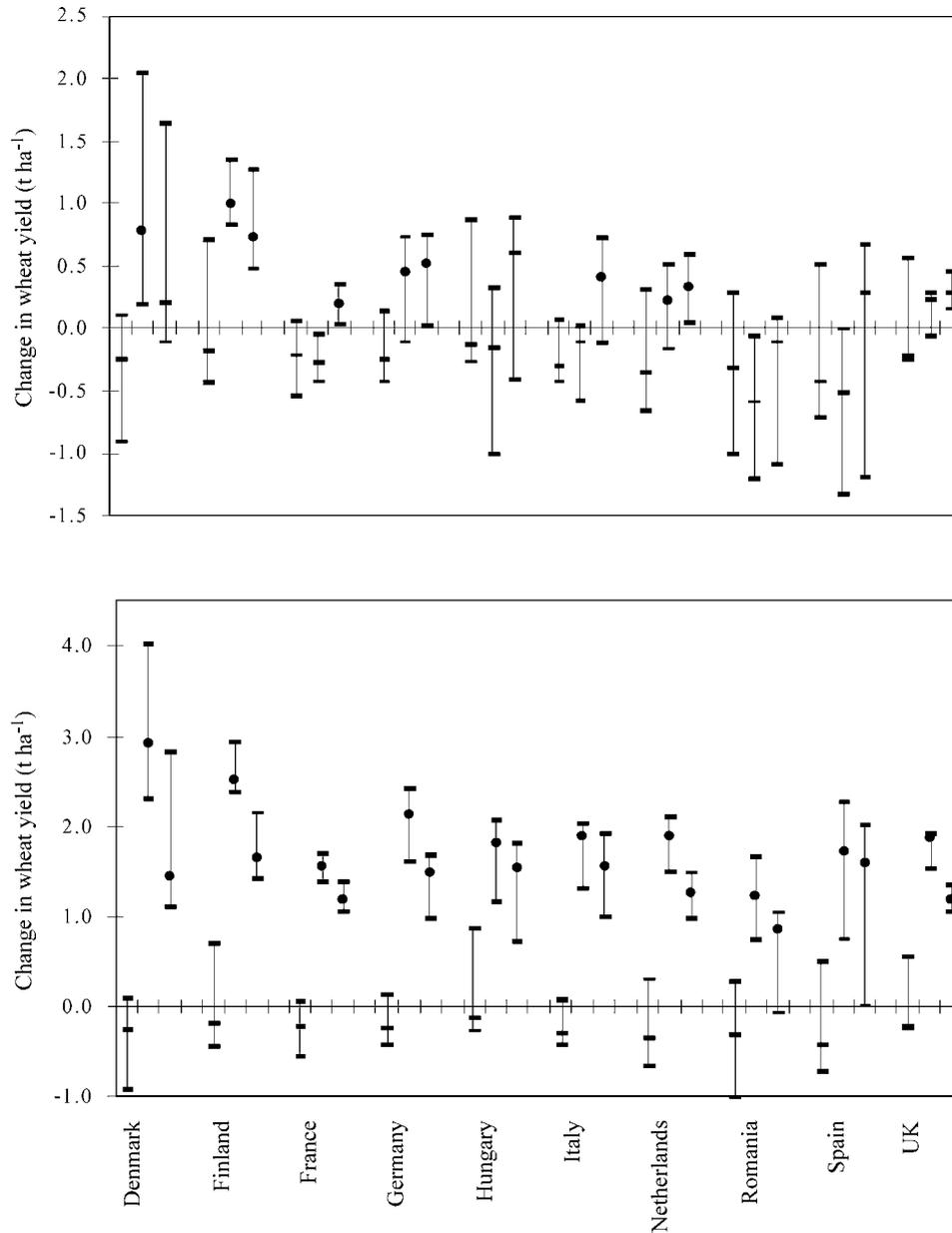
Fig. 3. Change in mean water-limited wheat yield (from the 1961–1990 baseline) for ten European countries due to natural climatic variability (noise; left bar; n = 7) and due to climate change by 2050 under the IS92a emissions scenario (REF; middle bar; n = 4) and the IS92d emissions scenario (IS92d; right bar; n = 4). Atmospheric CO_2 concentration is: (top) held constant at 334 ppmv; and (bottom) increased to 515 ppmv for the REF scenarios and to 435 ppmv for the IS92d scenarios. Horizontal lines show the maximum, minimum and median estimates for each scenario. Countries where climate change causes a significant (95 percent significance from a two-tailed t-test) change in yield are marked with a black dot for the median estimate (Source: Harrison et al. [20]).

dominant soil per climate grid rather than all soil polygons in a grid was not significant. The spatial patterns were compared using a polynomial equation to relate the pattern to the x, y grid using generalised least squares. Using a cubic polynomial to describe the spatial pattern of the dominant yield per grid and the average yield per grid showed that the intercept (an x, y coordinate) and other coefficients of the models, relating to the x and y coordinates, were not significantly different at the 5% level. There is, therefore, a

very high probability that the spatial patterns were not different.

Another methodological issue is how climate data should be downscaled from the monthly to the daily time scale. Downscaling from monthly to daily climate data using the Brooks sine curve interpolations on monthly temperature and radiation data have been successfully tested for Sirius using Great Britain sites (reported above, see Harrison et al. [20]).
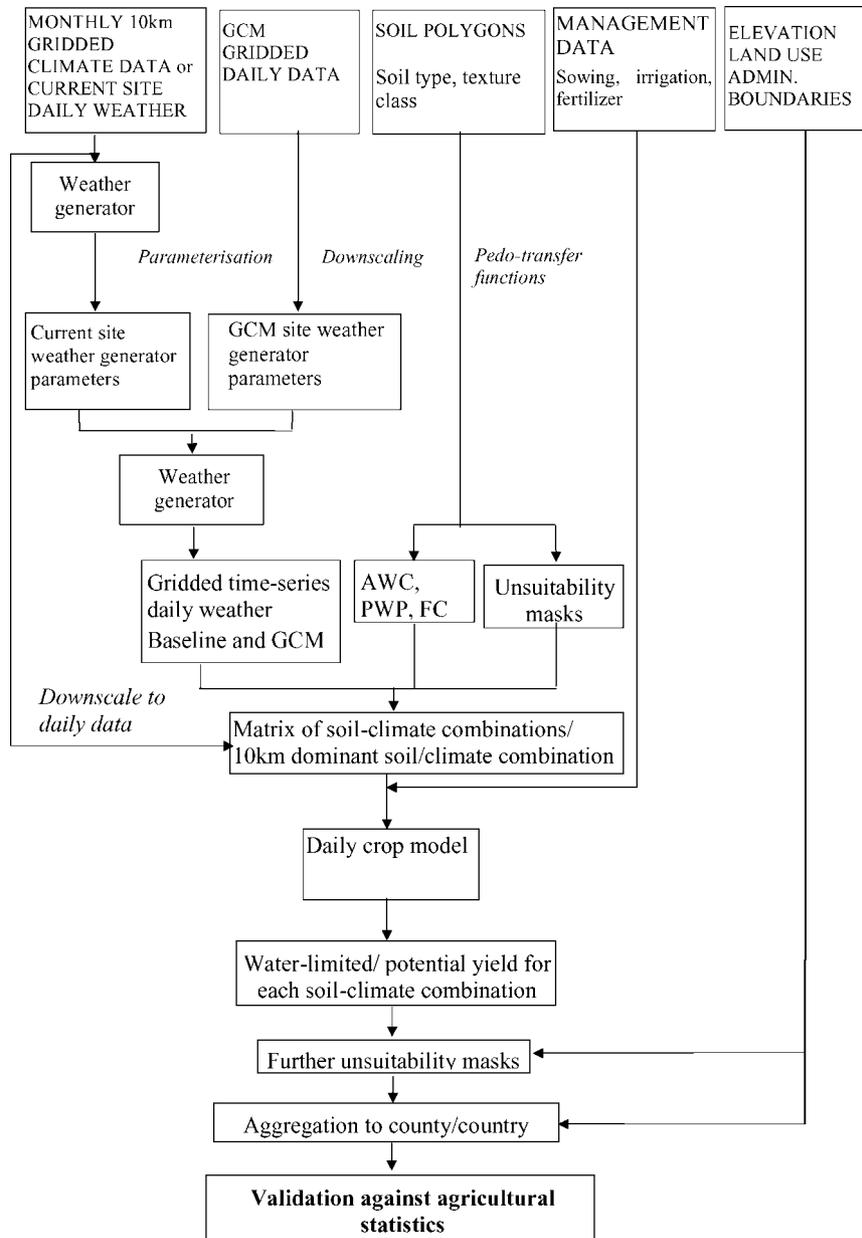
Fig. 4. Schema showing the approaches for the spatial application of crops models in Great Britain (Source: Butterfield et al. [29]).

Other methods of downscaling including use of weather generators were also tested. Daily precipitation was derived in the Great Britain study from monthly totals and mean number of rain days. Mean rain per rainy day was distributed randomly to days in the month. Observed daily site climate data were used with polygon soil data to test the downscaling method. This involved running the model on the 26-year observed precipitation data then averaging the data to give monthly values and using the downscaling approach to derived daily values and rerun the model. The combined effect of down-scaling temperature and radiation (using the sine curve) as well as downscaling precipitation as described was also tested using the observed daily data at the six sites.

The results across the six sites indicate that although the maximum difference in any year may be up to $2.9\,\text{t ha}^{-1}$ the mean is always less than $0.6\,\text{t ha}^{-1}$ (Table 1). As our monthly database is a 1961–1990 average, the error due to downscaling the monthly data is equivalent to this mean. The same approach for downscaling data was applied for the POTATOS model and errors were found to be insignificant.

For the grapevine model differences between using observed and estimated daily data of temperature and radiation were calculated using data from the five test vineyards to check that large errors would not be introduced into the grapevine model output by using downscaled climatic data. Errors were found to be highly insignificant, with all R^2 values greater than 0.95.

Table 1. Modelled mean, maximum and minimum yields calculated for MAFF's Government Office Region. Survey data for county average collated into regions and adjusted to 1990 levels. Observed 1997 and 1998 survey yields and average of 10 highest farm yields in the survey for 1997.

	SIRIUS Model results				MAFF statistics			
	Model mean	Regional max	Regional min	Average county standard deviation	Average survey yields adjusted to 1990	1997 survey yields	1998 survey yields	Max survey yield 1997
North East	9.99	13.07	7.06	1.27	6.23	6.47	6.81	8.64
Yorkshire and the Humber	10.53	12.76	5.94	1.13	6.09	6.81	6.51	10.29
East Midlands	9.99	12.20	5.65	1.31	5.90	6.73	7.61	10.5
Eastern	10.69	12.57	5.92	1.12	6.11	7.18	7.71	10.28
South East and London	9.97	13.05	5.92	1.34	5.93	6.79	7.14	11.25
South West	10.16	13.61	5.34	1.23	5.78	5.53	8.16	9.37
West Midlands	10.33	12.53	5.74	1.30	5.90	6.53	7.34	12.05
North West and Merseyside	10.01	13.52	5.72	1.50	6.15	3.87	6.59	8.64

Variation across regional modelled yields seems conservative when looking at regional averages, but the maximum and minimum figures indicate the wide range being predicted across these large regions. For the purposes of validation the correlation coefficient for modelled yields against observed yields adjusted to 1990 levels for all English and Welsh counties was calculated and found to be close to zero. This occurred because the higher than expected modelled yields in the west and lower than expected modelled yields in the east that are skewing the data. In general the model is giving reasonable estimates of water-limited yield in most areas considering that the model does not take into account the effect of pests, diseases or weeds. As with all model estimates there is a difference between 'potential' (maximum possible yield) and 'actual' yield (those seen in the field). Comparing the 1990 baseline yields with the Sirius model results actual yield can be estimated as 0.6 of the potential yield. Although the range in mean yield across the regions is close in magnitude for the modelled and survey yields ($0.7\,t\,ha^{-1}$ compared with $0.45\,t\,ha^{-1}$), the range in modelled and survey yields when looking at the county scale is larger ($3.3\,t\,ha^{-1}$ compared with $1.3\,t\,ha^{-1}$). This is important in terms of our confidence in predicting 'regional' yields and also may contribute to improving the application of mechanistic models at these scales.

Validation of the results is limited because of the temporally averaged climate data (it was not possible to simulate results for individual years which could be compared with yearly crop statistics). The Ministry of Agriculture, Fisheries and Food (MAFF) survey data are very limited at the county level and only five years of survey data were available for county validation. The high sensitivity of the Sirius model to available soil water causes winter wheat yields to be lower than expected in some areas of East Anglia although when the mean of the Eastern region was calculated it gave the highest mean of all regions. Very high modelled yields in areas close to those marginal to

production due to excess winter precipitation and difficulties in working the land also gave cause for concern. These problems could be overcome if some allowance for excess water or impact of high summer rainfall on lodging were included in the model.

Aggregation of the results to the regional level gives confidence in this approach (Table 1). The range in mean yield over all the English regions (for the 1961-90 mean climatology) is small as is that seen in the MAFF survey yields (average of five years). In recent years yields are also becoming comparable with the model yields and observed farm maximum yields are comparable to model maximums. Such an assessment at the county and regional scales would not be feasible using a traditional site-based approach to crop modelling. The spatial aspects of the approach gives knowledge on possible new areas of expansion for production of specific crops (e.g., grapevine) and shifts in the optimal locations for production of traditional crops in the future. This information is difficult to gain using a site-based approach.

The method described limits the model output to long term period means. When all climate variables in the gridded climatology are available as a time series it will be possible to conduct a time-series analysis for comparison of yields year-by-year. Not only will this improve the model validation, it will also allow assessment of the year-to-year variability in yields, which is of particular benefit in the assessment of risk when considering production of novel crops.

2.4. Spatial Interpolation Approach

Spatial interpolation techniques (e.g., kriging, neural network) can be used to estimate model outputs at unsampled sites. Spatial interpolation is also used for preparing irregularly scattered data to construct contour maps or contour surfaces. Both create a regular grid of interpolated points. The selected spatial interpolation methods differ in

their assumptions, local or global perspective, and deterministic or stochastic nature.

Using crop models developed for simulating point responses to predict regional yields has raised the question of whether to spatially interpolate inputs and run the model for every interpolated point or run the model for points where there are inputs and then spatially interpolate model outputs variables. The quality of the results obtained using these two approaches is mainly due to the degree of non-linearity of the model, as well as the spatial structure of the inputs. Unfortunately, the process of extending point model estimates on the land surface is often complex and nearly impossible in very irregular terrain.

Different spatial interpolation techniques can be used for eco-climatic classification (e.g., fuzzy classification of remotely sensed imageries, kriging, splining, etc.) [30, 31]. Accordingly, it is possible to hypothesise that these techniques can provide information on the spatial distribution of outputs from crop simulation models. The extent to which these approaches can be used to estimate crop productivity, derived from crop simulation models, in complex terrain is, however, mostly unknown. In particular, there is a lack of methods that use satellite images and ancillary data (elevation, distance from the sea, latitude, etc.) for spatially extending model parameters computed at ground stations (i.e., the duration of phenological stages, yield etc., see Bindi et al. [32]).

Following these considerations different sources of information (remotely sensed imageries, morphological and geographical data) have been used to link site crop simulation model outputs to their spatial regional distribution. Specifically, crop model parameters are extended between meteorological sites over a region using three spatial interpolation techniques (fuzzy classification, kriging, neural network). This method assumes that estimated parameters are spatially autocorrelated, and also that they are mainly determined by eco-climatic factors which also drive global vegetative development. Kriging and neural network approaches are used to find the spatial correlation of model output variables; whilst Normalised Difference Vegetation Index (NDVI) profiles provide information for the eco-climatic factors. Climate data are available from stations evenly distributed over a specified region and environmental data on altitude, latitude and slope are also required. Digital terrain model (DTM) data is required to provide information on the surface conditions.

One technique to interpolate over space is to use a spatial production function. Site model results can be used to derive regional statistical predictor functions of the relationships between yield, technology and climate. An emulator can derive the response surface from multiple runs of the site model, using statistical techniques (e.g., Buck et al. [33]). A reduced form model based on the results of the Sirius winter wheat model was developed in the Central England study [11]. Specific needs arise when the available data resolution is too coarse for input into models (e.g., daily climate data

being derived from monthly means); insufficient data are available at the required resolution or when historic data records are insufficient (weather generators, also used to apply scenario changes).

Statistical predictor functions can be derived between sample site results and gridded data. The statistical formula is used to interpolate the model results to the original grid. For example in a study on wheat and soya bean in Spain [34] statistical analyses were used to derive yield response functions from the results of temperature, precipitation and CO_2 sensitivity runs conducted at seven sites which were chosen to represent the agro-climatic regions of Spain. Agricultural response functions were then developed from these site-specific results and applied to monthly climatic input data on a 10 by 10 km grid across Spain for current conditions and several climate change scenarios.

The advantages of the spatial interpolation approach are that spatial relationships are taken into account as well as eco-climatic factors. The disadvantages are the requirement of satellite NDVI data and DTM data. Advanced processing methods are also required.

2.4.1. Tuscany, Italy Case Study

Most studies on the impacts of climate change on natural vegetation and agricultural crops have been undertaken at two spatial scales. First, experiments on the effects of elevated atmospheric CO_2 concentration and higher temperatures on plant growth and yield have been performed at the plant level using different system facilities (e.g., growth chambers, open top chambers, plastic tunnels, FACE) (see Van de Geijn et al. [35]). Considerable work has also been done at this site level using growth simulation models. Models use the knowledge gained from experimental studies to systematically investigate the effects of future climate predictions from global climate models (GCMs) on crops, including appropriate response strategies. Second, a few studies have been conducted on the impact of climate change at the regional scale by linking crop simulation models to spatial interpolation techniques. Thus, in order to investigate the effects of climate change and climatic variability on crop productivity at the regional scale a method is needed to estimate crop model parameters in the area between ground-based meteorological stations.

To address these issues a methodology has been developed and tested for extending the output from a grapevine model over a spatially complex region in central Italy (Tuscany) [32]. The method has been used to evaluate the regional response of grapevines to climate change.

The grapevine model was calibrated using field and climatic data for three experimental stations located in Tuscany. It was then applied at 67 sites for both current and future climatic conditions. Present and future climate datasets for 31 years were produced using the LARS stochastic weather generator [36] calibrated on observed historical weather data and output from GCMs, respectively.
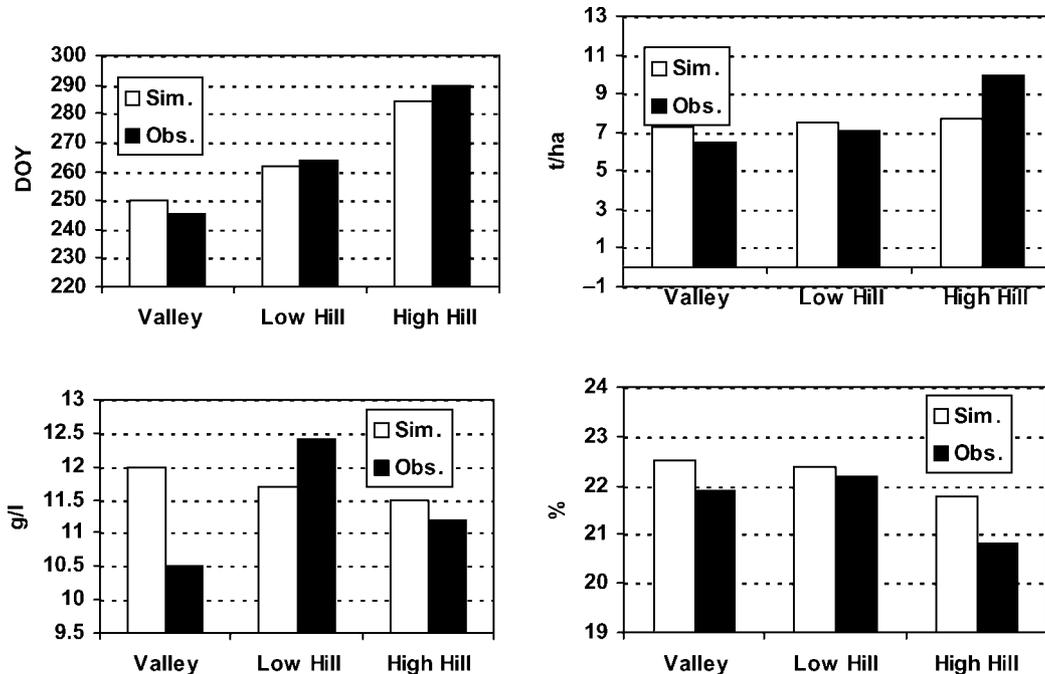
Fig. 5. Comparison between simulated model output variables (Sim) and the observed statistical data (Obs) for the three major viticultural landscapes in Tuscany: (a) date of maturity, (b) fruit dry matter, (c) acid content, and (d) sugar content (Source: Bindi et al. [32]).

Different methods for spatialising the site model output variables were evaluated and used to investigate the effects of climate change on viticultural production at the regional scale. Three methods were tested for spatialising the means and coefficients of variation (CV) of model output variables computed for 31 years at the 67 sites. Specifically, a fuzzy classification approach was utilised for processing the remotely sensed data and a kriging approach was used to explore the spatial variation of model parameters and their extension over the land surface. A method for statistically combining the results of the fuzzy classification and kriging procedures was also investigated in order to optimise the estimation process. The third method examined the possibility of using neural networks for spatialising the means and coefficients of variation (CV) of output variables from the grapevine model.

Errors associated with the different methods have been quantified and indicate that all three methods provide satisfactory and similar estimates of mean model output variables. Alternatively, only the neural network approach was able to accurately estimate the CV of model variables.

The regional grapevine model was validated in two steps. Firstly, by comparison with model outputs from the original site-based simulation study (see Bindi et al. [32] for details) and, secondly, by comparison with observed data obtained from the Agrometeorological Service of Tuscany, Institutes of Agricultural Ministry and private consortia of the most important viticultural areas of Tuscany. The date of physiological maturity is predicted to occur from the middle of August in the valleys to the middle of October on the upper hills of Tuscany. These estimates are in reasonable agreement with the observed data, although the estimates show a lower spatial variability (Fig. 5).

The model is also able to reproduce the correct spatial pattern of yield and acid and sugar concentration, although simulated values tend to be slightly lower and have a lower spatial variability. This lower spatial variability of the model outputs is due essentially to the methodologies used to extend the site model output parameters (i.e., neural networks) and to generate the synthetic weather data (LARS-WG). Both these methodologies tend to smooth extreme values resulting in lower variability.

Two climate change scenarios were used from the Hadley Centre's HadCM2 GCM. These were mean climatic changes from the greenhouse gas only experiment (HCGG) and the greenhouse gas and sulphate aerosol experiment (HCGS). The model was run using a CO_2 concentration of 353 ppmv for the baseline and 515 ppmv for the climate change scenarios. Model parameters were adjusted to account for the direct effects of elevated CO_2, using results from free air carbon dioxide enrichment (FACE) experiments. Results are available for mean and variance of phenology, yield and quality characteristics of the grapevine.

2.5. Stochastic Space Approach

In this approach the variability over geographic space is estimated using remote sensing (see Delécolle [37]). This method is achieved by estimating the current variability of crop conditions over a region by remote sensing. A

stochastic parameterisation of a crop model is then derived. The advantages of this method are the possibility of quick estimation of regional field-by-field variability of crop conditions. The method assumes no explicit soil variability, a single sowing date and equal climate across the region. Daily weather data are required at the regional scale. The advantages are that a quick estimation of regional field-by-field variability of crop conditions is possible. This source of variability, which can be considered as a buffer to climate change, is not possible to identify with any other method. The disadvantage is that high resolution infra red remote sensing data is expensive and processing is time consuming.

2.5.1. Paris Basin, France Case Study

Mechanistic crop models are, in general, adapted to the field scale. There are numerous examples of applications of crop models at this scale. In this study, a field is considered to be a homogeneous entity (without spatial variability) and is described by the type of crop planted (species, variety) and a collection of practices and events (sowing date and density, dates and amounts of fertiliser applications, etc.). A region
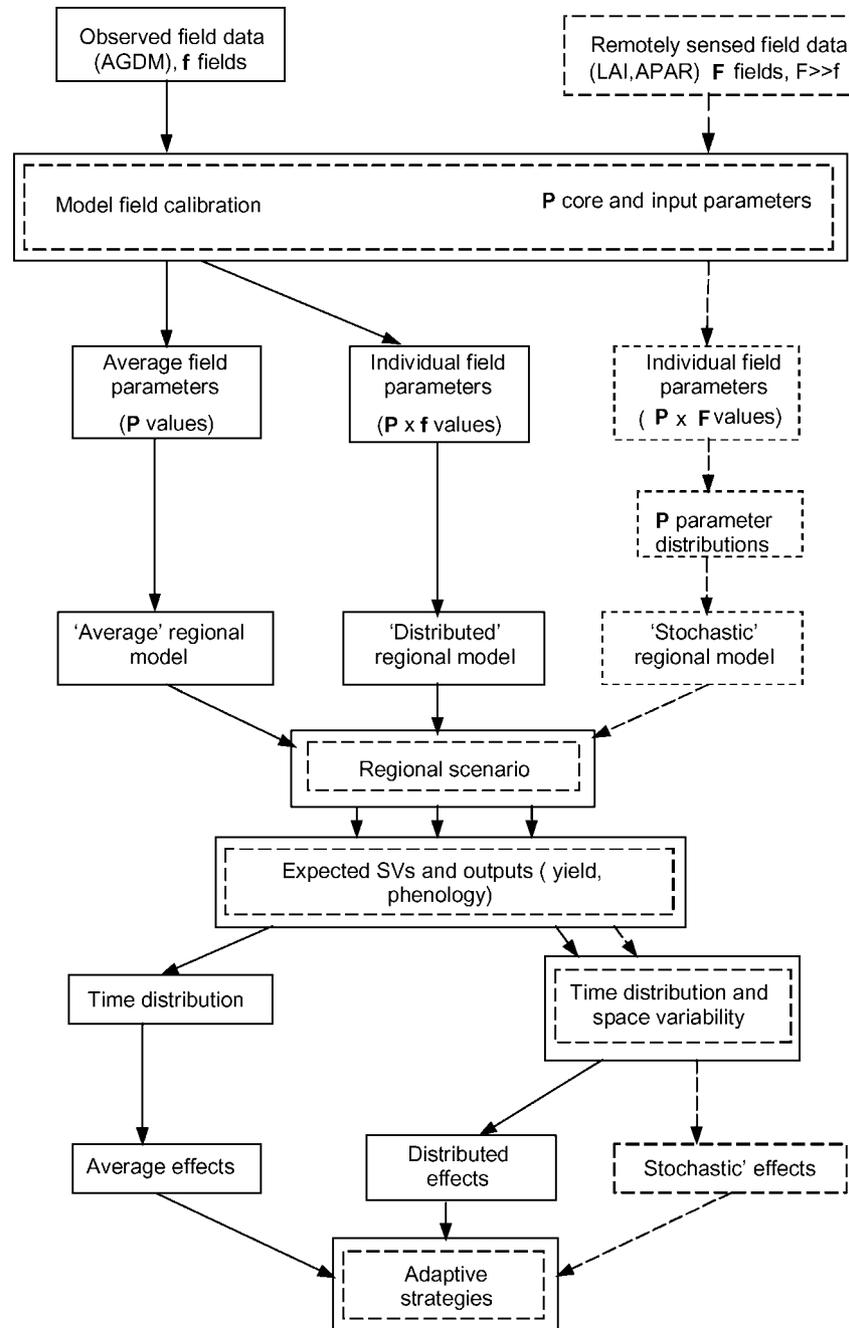

Fig. 6. Flow chart showing the three types of calibration undertaken for STICS-Wheat and their application (Source: Delécolle [37]).

can be represented as a mosaic of individual fields. Hence, mechanistic crop models can be used to simulate regional production by running a model for each field within a region. However, this assumes that the information required to calibrate the model is available for every field, which is generally not the case. Thus, regional studies often assume that a region is a large field and define equivalent regional crop state variables and parameters before directly applying a site crop model. Such equivalent values cannot be measured, only calibrated, and are generally meaningless.

An alternative method, adopted in the Paris Basin study [37], is to introduce the spatial variability of crop conditions within a region as distributions of related crop parameters into the site process model (Fig. 6). Scaling-up from the site to the regional scale therefore involves estimating joint probability laws (including correlations) for all model parameters. Distributions of crop state variables or final production is then established by generating sets of parameters through a Monte-Carlo scheme [38], and running the model for each of these parameter sets and regional values of the input (climate) variables. The shape of the distribution of model outputs indicates the variability and

stability of yields within the region. It is thus possible to determine whether the spatial diversity within a region represents a source of resilience to changing climatic conditions or whether it is likely to amplify the impacts of climate change.

The principle of this method is that regional models can be stochastic versions of standard site crop models. Stochasticity is provided by treating some of the model parameters as random variables rather than fixed values. Each field planted with a given crop species in a region is associated with a single set of conditions (genotype, management, soil) which can be translated into values of related parameters in a crop model. Calibrating the model for all fields therefore provides a collection of values for these parameters, which can be used to construct empirical distributions. Such a detailed model calibration is made possible by using scenes of the region provided by high resolution satellites, giving access to field-by-field information at certain times over the whole region.

The impacts of climate change are simulated at the regional scale by taking P values of model parameters at random from the estimated empirical distributions
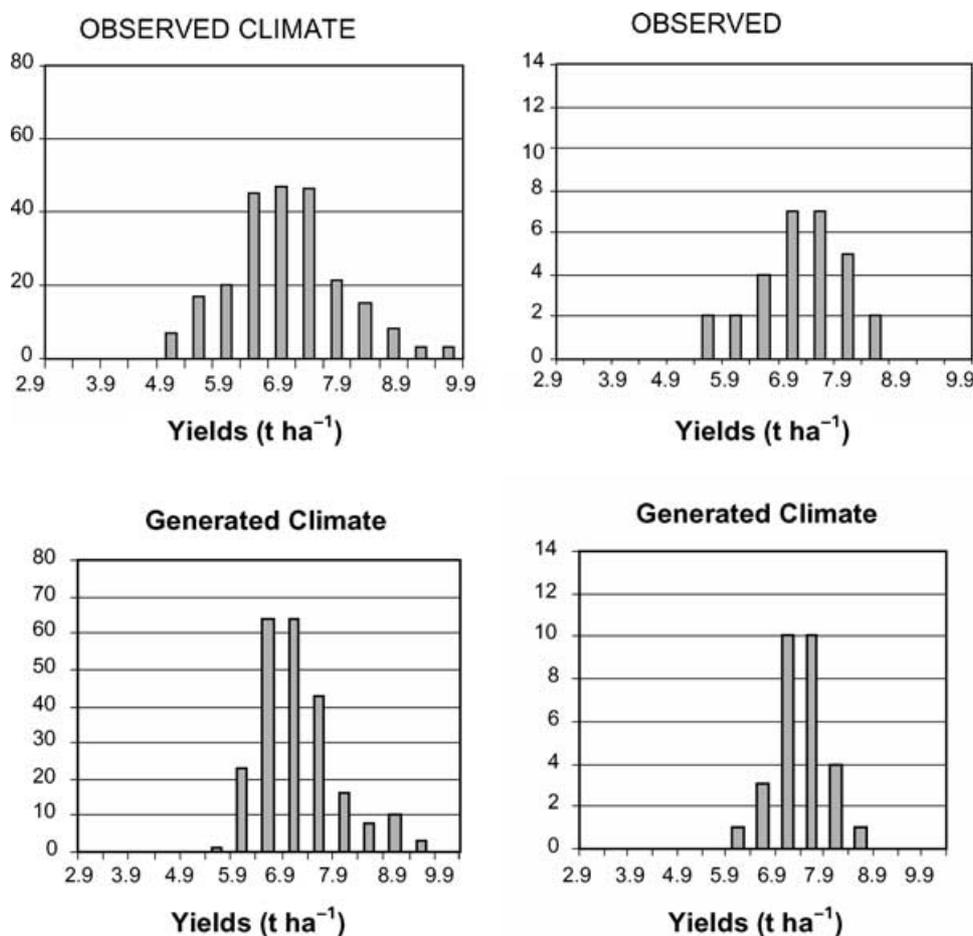

Fig. 7. Simulated distributions of yield for the observed climate (first row) and the generated baseline climate (second row), using the distributed calibration method (first column) and the average calibration method (second column) (Source: Delécolle [37]).

(representing spatial variability). Each model configuration is then fed with N years of climate data generated from a scenario of climate change (representing temporal variability). The result is a distribution of N × P yield values, which illustrate the yield response of the region to the change in climate, assuming management conditions remain the same.

Four steps were undertaken to develop the method:

1. Automatic segmentation of the region into individual fields.
2. Selection of an appropriate site crop model for winter wheat.
3. Construction of the regional model, calibrated on present conditions.
4. Application of the regional model to climate change scenarios.

The average and distributed model calibrations produce comparable results for the Paris Basin region under both current and future climatic conditions (Fig. 7). This means that, in general, results are similar if the model parameters are averaged or if the model output from the ten individual fields is averaged (implying some linearity in processes). The first solution of averaging model parameters is much less expensive in terms of run time. A different conclusion may have been reached if other model parameters had been selected for calibration. Data from ten surveyed fields were available to produce the distributed calibration. A different number of sample fields may also cause different results, as might a denser time profile of observed dry matter.

Different results are produced by the average and distributed calibrations for extreme yield values. However, the probability of yields being greater than 8 t ha^{-1} under the observed climate is 5% for the distributed calibration and 0% for the average calibration. For the generated baseline climate, the respective scores are 9 and 5%. This must be put together with the changes in yield distribution according to the climatic input (as expected from Semenov and Porter [39]). As no real change in distribution tails is induced by the scenario-generated climates, the distributed calibration allows more indepth analysis of extreme values.

The stochastic calibration method produces different values for model parameters than the average and distributed calibration methods for all climatic datasets (i.e., observed, generated baseline and climate change scenarios). This is because different crop state variables are used in the calibration procedures, satellite-estimated LAIs for the stochastic calibration and measured above-ground dry matter for the average and distributed calibrations. The number of time replications available for each variable also differs between the calibration methods.

This method could be used in alternative applications to climate change impact assessment, such as simulating the time evolution of agricultural landscapes. Its tractability nevertheless relies on the frequent availability of high-resolution satellite images during the crop-growing season. When the frequency of images is insufficient they must be supplemented by low resolution more frequent scenes, but transfers between different resolutions are still uncertain.

3. DOWNSCALING

Downscaling involves the translation of coarse resolution model outputs to finer resolutions corresponding to real space and time. The business of downscaling blossomed with the use of General Circulation Model (GCM) scenarios to chart the impacts of climate change. Thus it is usually with respect to GCM output that downscaling is applied; however, the term can apply equally to other attempts to re-express large-scale information in a form more relevant at the small (temporal and/or spatial) scale.

The first generation of GCMs had resolutions on the order of 5 degrees latitude and longitude, clearly too broad-scale to instil much confidence in local or even regional changes. While newer models have higher resolutions, approaching 2 degrees or 200 km, these scales are still orders of magnitude larger than the typical impact unit and issues of downscaling are still relevant.

This section provides a brief review of the main methods.

3.1. Overview of Methods

Downscaling techniques can be classified into three types according to complexity and computational demands (other typologies are possible – see for example Wilby and Wigley [40], Xu [41]): simple downscaling, statistical downscaling (and sub-types) and dynamical downscaling. These categories are summarised in Table 2.

3.1.1. Simple Downscaling
The crudest approach to downscaling is to apply the large-scale GCM climate change outputs to observed climate at the scale of interest. In a typical approach, GCM data for some period in the future are first expressed as ''change fields'' relative to the GCM climatology over a period in the recent past (e.g., 1961–1990.) This removes many biases in the GCM climatology from the scenario.

The GCM change fields are then used to adjust an observed ''baseline'' climate dataset, representative of the same climatological period (e.g., 1961–1990), usually in a simple additive manner. At a single site, the baseline is likely to be a meteorological record. Where spatial scenarios are required, GCM change fields are usually added to a gridded data set of surface climate variables. GCM data are either used as is, or can be interpolated to appropriate grid resolution (or the location of interest) and then applied.

To date, simple downscaling has primarily been applied using changes in meant monthly or seasonal climate, but changes in variance of monthly climate can also be incorporated (e.g., Hulme and Jenkins [42]). Similarly, with

Table 2. Approaches to downscaling.

Approach	Description	Examples
SIMPLE	Apply the GCM grid box change fields to the local climate time series	[42, 62, 63, 64, 65]
	⊞ Easy to do for numerous models	
	⊞ Provides first-order indications	
	⊟ Fails to capture local effects	
	⊟ Difficult to provide information on extremes	
Statistical	Relate large-scale predictors in GCM to parameters of interest in local time series.	[51, 61, 66, 67, 68]
	⊞ Gives site-specific information	
	⊞ Non-trivial model development	
	⊞ Potential for multiple GCM downscaling	
	⊟ Requires accurate local data	
	⊟ Mismatches between current and future predictors	
Circulation Indexing	Reconstruct circulation indices (or weather types) and relate local conditions to changes in frequency of indices	[57, 69, 70, 71]
	⊞ Has meteorological basis	
	⊟ Identification of indices can be difficult	
	⊟ Problems in areas where convection is prominent	
Weather generator	Force a numerical weather generator with changes derived from GCMs	[60, 72, 73, 74]
	⊞ Weather generators are relatively common	
	⊞ Flexibility in constructing time series – can have multiple series.	
	⊟ Difficult to scale up to regional changes	
Dynamical (regional model; high-resolution GCM)	Use a high resolution model with boundary conditions forced from GCM	[44, 45, 49, 75, 76, 77, 78, 79, 80]
	⊞ Matches resolution of weather forecast models.	
	⊞ Provides large range of weather parameters.	
	⊞ Preserves spatial covariance of weather.	
	⊟ Requires advanced computing.	
	⊟ Relatively few scenarios available.	
	⊟ Unable to provide site-specific data.	

more daily data from GCMs becoming available, changes in the variance of daily climate can also be incorporated.

Simple downscaling has several advantages, the main one being that it is quick and easy, enabling rapid comparison of data from more than one GCM simulation – either GCMs from different modelling centres and/or ensemble members from the same modelling centre [43].

There are several potential disadvantages to simple downscaling. Data that are readily available are typically only at monthly resolution, therefore provide no information about changes in the structure of daily climate, especially rainfall; even if daily data are available from GCM simulations, their probability distribution functions frequently bear little relation to the real world, raising the question of whether the method is appropriate at daily resolutions. The approach clearly cannot capture sub-GCM grid-scale changes in meteorology. This is particularly so with rainfall, where sub-grid precipitation and cloud processes are a major source of error and/or uncertainty.

3.1.2. Dynamical Downscaling

Dynamical downscaling attempts to overcome some of the spatial limitations of simple downscaling by explicitly modelling the climate at higher resolution than standard GCMs. This permits the inclusion of realistic topography and land-sea configurations, and in some cases, improved dynamical processes. Currently, these approaches have a maximum spatial resolution of 20–50 km, so there remains a scale mismatch where local-scale climate information is required. These scale mismatches will reduce with time, as the spatial scale of regional models continue to improve with increases in computing power.

There are two main approaches to dynamical downscaling: GCM time-slice or variable resolution experiments and nested regional modelling.

3.1.2.1. Time Slice/Variable Resolution

This approach makes use of a high resolution GCM ($> $T100 or $1-0.5°$ lat/lon) or a variable resolution GCM (one that has a "standard" resolution over most of globe, but fine resolution over the region of interest) to provide high resolution output at a future "time slice" [44–46]. These simulations are typically forced with coarse resolution GCM SST and sea ice fields, as well as GHG forcings.

Results to date are equivocal: patterns of regional changes can be more dependent on the AGCM than the SST forcings used. The approach does produce improvements in the large-scale meteorology, but in some cases the biases in course

resolution GCMs are overcorrected, producing biases of opposite sign. This is because (in part at least) the model physics and parameterisations are scale dependent (and many course resolution GCMs are non-hydrostatic, so don't work as well at higher resolutions where topography requires hydrostatic physics).

Reliance on single model is also potentially problematic as results would then be highly model-dependent (as with standard GCMs).

3.1.2.2. Regional Modelling

In these approaches, a higher resolution atmospheric climate model (RCM), usually with scale-appropriate physics, is forced over a limited domain (e.g., Europe [7, 47–49]) by the surface and lateral boundary conditions derived from a GCM.

The choice of the regional domain is important. If the domain size is too small "edge effects" from the adjacent boundary conditions can affect the region of interest. However, if too large a domain is used the regional climate can become decoupled and produce meteorology that is independent of the global forcings. Domain boundaries should also be defined so that they do not coincide with regions of steep or complex topography.

Recent developments include the coupling of RCMs to other models of climate system components, most importantly land, biosphere and/or hydrology models, and also multiple nesting (RCMs within RCMs).

There is good evidence that regional models provide added value, particularly for precipitation, which remains a key driver of many impact systems. Nonetheless, RCMs remain reliant on good quality GCM forcing fields. To date RCM experiments have been very goal-specific, and the ideal of multiple RCMs forced by multiple GCMs (ensembles) to obtain information about the spread of predictions (uncertainty) has not yet been achieved.

Despite the improved spatial resolution of RCMs, they still fail to deliver site-specific information. In such cases, some form of additional downscaling is required. This can be achieved by simple downscaling (described above), or using statistical methods (see below). In both cases the coarser scale information derived from a RCM is likely to be superior to that derived from a GCM.

A key advantage of RCMs that their ability to simulate multi-site (albeit on a model grid) climate where the spatial covariance of the climate is preserved. This remains a methodologically difficult task for the statistical methods described below.

3.1.3. Statistical Downscaling

Statistical downscaling techniques aim to obtain "added value" over and above the grid-scale surface climate information provided by GCMs. The underlying rationale is that although GCMs reproduce the larger-scale atmospheric circulation reasonably well, grid point realisations of surface climate are less well simulated, and are fundamen-

tally limited because of the resolution limitations of GCMs. For example, GCMs are unable to resolve local topographic controls on climate, small-scale land-sea interactions, mesoscale landsurface forcings and convectional precipitation processes. Three main types of statistical downscaling are regression, weather typing and stochastic methods. Although convenient, this tripartite division masks the fact that many techniques are combinations of two or more of these end members.

3.1.3.1. Regression and Weather Typing

At the heart of regression and weather typing techniques lies the belief that local climate processes which are not resolved at the GCM grid scale, are nonetheless dependent on larger scale atmospheric and surface climate output from GCMs.

Regression methods make use of linear (e.g., multiple regression) or non-linear (e.g., artificial neural networks) statistical relationships between large-scale GCM variables and/or derived fields and the local climate data – either station data or high resolution gridded products [40, 41, 50–56]. The models are usually trained/calibrated on GCM model data, usually some combination of temperature, upper and lower level pressure fields, wind and atmospheric moisture content. They are then run in a similar manner to RCMs, in that they are forced with GCM predictors for the future and changes in the surface climate variables of interest are determined.

Weather-typing (or analogue downscaling) relates particular modes of mesocscale (synoptic) weather features to the observed surface climate. These modes can either be defined empirically (e.g., Conway and Jones [57]) or statistically, for example through principal component analysis [58]. The defined weather types are then related to the observed surface climate, usually through some linear or non-linear regression process similar to those described above.

3.1.3.2. Weather Generators

Weather generators (WGs) are statistical models of observed sequences of weather variables (see Wilks and Wilby [59] for a recent review). Most of these simulate daily weather phenomena, usually with "secondary" climate variables predicted as a function of precipitation occurrence and amount. The weather generator model is calibrated against observed station data, either a single site or multiple sites. In the latter case, the model must be extended to incorporate the spatial covariance structure of precipitation [60]. Once the WG has been conditioned, long runs of synthetic climate with the same statistical structure to the observed climate can be generated.

To use in a "climate change" mode, the parameters of the WG model must be perturbed in an appropriate manner, as some function of the GCM output; these may be conditioned on some large-scale atmospheric state, or on the grid point output of the model (e.g., if GCM precipitation rainday frequency changes, then alter the probability of rainday occurrence in the WG proportionally). Clearly, the trick is to

be able to perturb the WG parameters in a meaningful manner.

Many WG models underestimate the variance of daily weather variables, especially rainfall. This need to be corrected for using, for example, inflation [56] or by adding white noise, possibly conditioned on synoptic state.

3.1.3.3. Some Problems in Statistical Downscaling A rarely addressed shortcoming of statistical downscaling is that the downscaling model is calibrated and run in predictive mode using different GCM output. Most approaches calibrate the downscaling model against re-analysis data – this is necessary to relate "observed" large scale parameters to observed station data – but then use GCM to simulate climate change. The GCM and re-analysis typically have different resolutions and different climatologies (e.g., low pressure zones occurring at different latitudes, or with differing intensity). Thus the conditioned model may not operate appropriately when forced with GCM data. A further problem is that, in some instances, different variables mean different things in different climate models: using (nominally) the same predictor variables from reanalysis and GCMs may not be strictly valid and may make the outcomes unstable when used in predictive mode.

Choice of predictor variables is important. In the case of rainfall, some measure of atmospheric humidity is critical (Wilby, personal communication), but these are often not very well simulated in re-analysis and very few evaluations of this variable in GCMs have been undertaken.

Statistical downscaling will only be able to predict climate change as a function of the GCM predictor variables. If other processes lead to changes in local climate, then these changes will not be reflected in the downscaled climate. For example, Schubert [61] showed that changes in temperature extremes over Australia were forced by radiative properties of the atmosphere and not circulation changes, and could therefore not be predicted by his statistical downscaling methodology.

3.1.3.4. Advantages Statistical methods remain the only way to generate site-specific climate data, and in many instances have been demonstrated to provide "added value" to simple downscaling. They are computationally cheap, relative to dynamical methods, and are eminently suitable for multiple simulations (using multiple integrations with the same GCM, or multiple GCM runs, or both). Finally, they are appropriate for a "bottom-up" approach to impact assessment, where the local-scale climate variables important for an impact study can be identified at the outset, and included in the downscaling model.

4. ISSUES IN SCALING METHODS

Methodologies for up and down scaling vary considerably in their requirements for data and technical expertise, potential for validation, and their contribution to the quality of the overall research effort. Issues of stakeholder participation in (and representation in) integrated assessment are also relevant.

4.1. Input Data

A reduced-form modelling approach may not be appropriate if a study requires very detailed information, which is only provided by complex site-based models. In such cases, the fundamental problem is how to relate the detailed model to geographic regions.

4.2. Technical Expertise

Expertise already present at an institute will largely determine the amount of time required to develop a methodology. Using datasets from earlier projects or by other accessible groups may reduce the financial and time costs.

4.3. Validation

Models may be validated in many different ways, reflecting the different scales involved in crop modelling. At the process level model results may be compared with the results from controlled experiments where only a few external conditions have been manipulated, such as soil water content [81]. Crop simulation models differ in their description of physiological processes, but are in general able to describe reasonably well the response of crop production (especially yield) to changes in temperature and precipitation.

At the site level models may be compared with observed yields, if the models include management data (e.g., Landau et al. [82]).

Comparison of observed aggregated regional and national yields with simulated yields, adds extra uncertainties to the validation process. The scaling-up method may itself be a source of error. This includes uncertainties in the model inputs, both regarding soils and climate data, but also regarding management data.

Often data on average or "normal" management have to be used for simulating regional yields. Results of comparing simulated county and national yields with observed ones have shown that the model can explain 20 to 30% of the interannual variability in observed yields in Denmark [12]. Similar results have been found for the application of the Sirius model for the Brandenburg region in Germany (Jamieson, personal communication, 1999) and for the Canterbury region in New Zealand (Olesen, personal communication, 1999). In contrast the crop models have been shown to explain a much larger part of the variation in yields in Finland [18].

These results suggest that at the margin of a crop's growing area (such as Finland and probably some Mediterranean countries for wheat) there will be a good

correspondence between simulated and observed yields, because it is the main climatic factors that constrains yields. In the core of the wheat growing area in Europe, wheat yields are generally not directly determined by climate, but by management, some of which may also be climate related, but not currently described in our models.

In the validation of scaling-up methodologies, it is important to consider the variability of simulated and measured yields in both time and space and the possible interaction between time and space. There are a number of options available to perform this validation.

4.4. Uncertainty and Risk

Given the large range of uncertainties in climate change [83–88], what should have priority?

Up- and down-scaling introduce additional uncertainties into climate change impact assessment, and integrated assessment. Is the additional effort justified? Do the benefits override the required effort and uncertainty? There appears to be little guidance for these strategic questions. In most cases, the sophistication of multi-scale methodologies is driven by disciplinary research teams rather than a priori consideration of what users need.

Handling extremes and extreme events is perhaps the most difficult, and yet most important, issue. How can useful information, especially on changes in joint probabilities of phenomenon – e.g., dry spells, consecutive hot summers, dry spells and increased wind – be extracted from global climate models? The recent ECLAT workshop [89], concluded that downscaling of extremes had not been addressed to any great extent, but probably represented an order of magnitude increase in methodological difficulty, most especially because the large scale forcing is less well resolved at the GCM scale.

From a 'bottom up' perspective, sensitivity to extreme events is often poorly captured in impact models. In such cases, one might wish to map 'impacts scenarios' before investing scarce resources in defining extreme event scenarios that are not likely to be robust.

4.5. Stakeholder Participation

Really useful modelling requires stakeholder participation. Given the common constraints of time, how can stakeholders understand the complex issues of scale?

Some will be overly convinced that high resolution maps equate with robust predictions. Others will look at the list of caveats and conclude that the uncertainties overwhelm the insight. Modellers themselves tend to anchor their expertise on their own models – but have difficulty in translating their insight for new users.

We suggest that an agent-based approach may provide stakeholders with easier access to model participation and interpretation.

4.6. Scaling Agents

The translation of climate change research from impacts ("if climate change, what are the impacts") to adaptation ("how can we cope with climate change?") requires novel methodologies and techniques (see Downing et al. [4]).

One promising approach is the use of software agents to represent decision makers (variously called actors or stakeholders). The idea is to capture the cognitive processes, decision algorithms and layers to decision making in software agents. The paradigm has its roots in computer science, where software robots search the web looking for particular kinds of information for example. A community of decision theorists, sociologists and psychologists has extended the approach, in what may be termed agent-based social simulation (see AgentLink as an example of efforts underway: www.AgentLink.org).

An important feature of such models is that they capture representations of changing social relations. These relations encompass the social embedding of an individual and the complexity of an individual's exchange with the environment. Such changing relations include institutional changes in exchange, changing organisational structures, the development of new mental models by agents and how these affect policy assessments.

A key issue is the scale of the agents. Are they individuals? Aggregations of individuals? Communities, for example, defined by geography or class? Corporate actors with recognised structures? Or do we need models of agent cognition – the psychology of decision making (in which the agents might be the ego and id, as one example)?

5. CONCLUSIONS

No easy conclusions can be drawn from this comparison of up and down scaling methodologies. Data, expertise, time and financial resources are limited, and may drive the choice of method more strongly than the technical merits of different schemes.

Based on the model testing in the CLIVARA project, however, it is possible to make some general statements. The simplest, site-driven approach may be justified in some homogeneous environments (Denmark) for some parameters (mean and variability of yield). For spatial grids a subset of the complete grid is adequate for many purposes. A baseline can be estimated on the whole grid and a series of sensitivity tests run on a stratified sample.

Conversely, in complex terrain, a regional approach can expose key non-linearities that may not be apparent from site-based analyses. Including remote sensing techniques in impact studies allows full representation of landscape dynamics while not necessarily making the analysis overly complex.

Similarly, sophisticated methods of downscaling climate change scenarios may be warranted where local variability in the terrain or in impacts are of great concern. However, where the coarse grain scenario varies significantly (e.g., different GCMs report significant increases or decreases in precipitation), simple downscaling methods may be sufficient to capture a sense of the risks.

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