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Stratification of climate projections for efficient estimation of uncertainty and variation using weather-driven models

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ABSTRACT: The range of uncertainties inherent in climate models can only be portrayed by provision of multiple climate projections. Unfortunately, such provision poses a challenge to model-based impact studies, since driving the relevant impact models using weather data from large numbers of climate projections may not be computationally feasible. Hence, it is important to investigate how to draw sub-samples of climate projections in a manner that reduces the subsequent computational burden. We describe a stratification-based protocol for sub-sampling climate projections to drive crop models with strata based on changes in mean temperature and changes in relative mean rainfall. As an example of the protocol's utility, simulated weather for each selected climate projection was used to drive 3 contrasting process-based models of plant–environment interactions to predict yields of spring barley, managed grassland, and short-rotation coppice. Many of the questions about potential impact that we wish to answer are related to variation in predicted yields. Variance components analyses of predicted yields for each of 2 time periods (2040s and 2080s) indicated that, after allowing for variability between grid squares, between 16 and 61 % of the remaining variance in annual yields was uncertainty due to climate projections, the corresponding range for mean yields over 9 yr being from 63 to 93 %. We found that our stratification procedure enhanced the precision in the estimate of the variance component due to climate projection, enabling reductions of up to 20 % in the number of climate projections required to achieve equivalent precision compared to simple random sampling.

KEY WORDS: Impact assessments · Stratification · Crop models · Simulated yields · Uncertainty · Variance components

1. INTRODUCTION

The need for mitigation, adaptation, and management of risk in the face of climate change is of national and international importance, challenging researchers and policy makers alike (Smith et al. 2007). Within the UK, the release of the latest UK Climate Projections (UKCP09)[1] in June 2009 represented a major advance, providing improved opportunities for investigating the potential responses of biological, agricultural, and associated social variables to future changes in weather patterns. A key novelty implemented in UKCP09 was the provision of probabilistic projections

[1]See UK Climate Projections website: http://ukclimateprojections.metoffice.gov.uk/ (accessed 3 Feb 2015)

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through large numbers of climate projections per emission scenario rather than the single deterministic projection for each scenario that was available in the previous set of projections (UKCIP02) produced by the UK Climate Impacts Programme. UKCP09 uses a complex methodology to produce the probabilistic projections, which is described in detail by Murphy et al. (2009). In essence, the method uses large ensembles of climate model projections, which are processed using advanced statistical methods to generate thousands of projections which together represent the spread of plausible climate outcomes. Simulated weather data for sequences of years can be generated for each climate projection by the use of the random weather generator tool provided as part of UKCP09 (Jones et al. 2010). The potential benefit of providing this multiplicity of simulated weather data is to enable a more holistic and transparent presentation of the variation and uncertainties that are associated with projected levels of climate change, with immediate application to studies of biological and environmental variables consequent on changes in our climate. A consequence of the way the probabilistic projections have been obtained is that they are not spatially coherent, creating a barrier in their use for making predictions at regional, rather than local, spatial scales and for modelling entities that require spatial contiguity (e.g. water flow in catchments).

The critical difficulties to be overcome in order to realise the potential benefits of probabilistic climate projections are the increased demands placed on computer file space and processing power to store and use the weather data generated from multiple climate projections. The demands on computer processing power are particularly acute when the simulated weather data are used to drive computationally expensive biophysical process models. Aside from the brute force approach of acquiring additional computational resources, the high computational load associated with multiple runs of biophysical process models can be met in 1 of 2 ways. The recently established emulation approach involves approximating each key output from a process model by an empirical statistical model (the emulator) that is computationally cheap and subsequently using the emulator in place of the process model. Whilst emulators have been constructed to reduce the computational burden in assessment of the impact of climate change on crop models (Ramankutty et al. 2013, Ruane et al. 2014) and in other contexts (e.g. Jenkins et al. 2011 and Patidar et al. 2011 to investigate building performance under climate change), some information is unavoidably lost through the use of the emulator in place of the process model. We describe and investigate a different approach to increase efficiency through stratified sampling of the available climate projections; although stratification is standard statistical methodology (Cochran 1953), it appears not to have been used in this context before.

Our approach was developed during an investigation into the benefits of using probabilistic projections of climate to drive 3 different process-based agro-ecological models — DNDC, PALM, and CropSyst — used to simulate yields in response to weather for 3 contrasting crop types: (1) intensively managed semi-permanent grasslands, (2) short-rotation willow coppice and (3) spring barley. See the Supplement (at www.int-res.com/articles/suppl/c066p001_supp.pdf) for a summary of each of these 3 models, and the process by which input parameters describing soil were derived. The key output from each model was annual (or for coppice willow, triennial) yield, and the use of probabilistic climate projections would be considered to be important if it induced substantial additional variation into the simulated yields over and above the variation induced by the UKCP09 weather generator within individual projections. In particular, we wished to know whether a stratification approach to subsampling from the available set of climate projections could reduce the computational burden of the assessment of the consequences of probabilistic climate projections. Thus, the aim was not to compare directly between the models, as they have substantially different modelling approaches, nor were adaptation options to crop management included, as the purpose of the study was not to predict yield responses *per se*. For each model, we assess the importance of using multiple climate projections through the results of a variance components analysis of the simulated yields, and we assess the benefits of stratification by quantifying the additional stability that stratification brings to the variance components analysis. For the CropSyst model of spring barley yields only, we demonstrate an approach to combining yield estimates across spatial units for which the climate projections are not spatially coherent to create estimates of regional mean yields.

2. METHODS

2.1. Generating weather data

For each 5 × 5 km grid square (5 km square), UKCP09 gives probabilistic projections for 7 overlapping 30 yr periods from 2010–2039 to 2070–2099 and for each of 3 different emissions scenarios, High, Medium and Low, which correspond to 3 of the SRES (Nakocenovic & Swart 2000) scenarios: A1FI, A1B and B1 (Murphy et al. 2009). To make the computational burden per grid square as light as possible, we used the minimum size of simulation run recommended for UKCP09 (100 climate projections with 30 yr of weather data per sample, giving 3000 yr), used climate projections for just 2 non-overlapping 30 yr periods (2030–2059, described here as the 2040s, and 2070–2099, described here as the 2080s), and worked with the IPCC A1FI high emissions scenario only. Simulated weather data were also generated for a baseline period (1961–1990). Some assessment of the performance of the UKCP09 weather generator in reproducing observed data is provided by Jones et al. (2010). The methodology underpinning the simulated weather data assumes climate to be at equilibrium within each of the three 30 yr periods, so climate change within each period is not accounted for.

With 9000 simulated years of weather data per grid square, we considered that it would be computationally feasible to run the models for a total of 15 grid squares to investigate the geographical spread of changing patterns of weather. Four of these grid squares were chosen because they contain sites for which considerable meteorological and agricultural information is already available (Craibstone near Aberdeen, Easter Bush near Edinburgh, Auchincruive near Ayr, and Mylnefield near Dundee; see Fig. 1 for these and other locations used). Six additional 5 km squares were selected to give a broad coverage of intensively farmed areas of lowland Scotland. The remaining 4 squares between Aberdeen and Dundee were chosen to allow investigation of variation in spatial mean yields, an important issue hampered by the lack of spatial coherence in climate projections available through UKCP09.

For each grid square, a set of 100 climate projections was selected from the 10 000 available via stratified random sampling. For each 5 km square, projections of change in spring and summer mean temperatures and total precipitation from the baseline to the 2060s were extracted for all 10 000 climate projections available. Spring and summer were combined, thus including the months from March to August and so covering most of the growing season in Scotland. Change to the 2060s was used as a mid-point between the 2040s and 2080s because we wished to use the same climate projections for both periods. These seasonal values are deterministic values associated with each climate projection, hence are quick to derive and straightforward to work with.

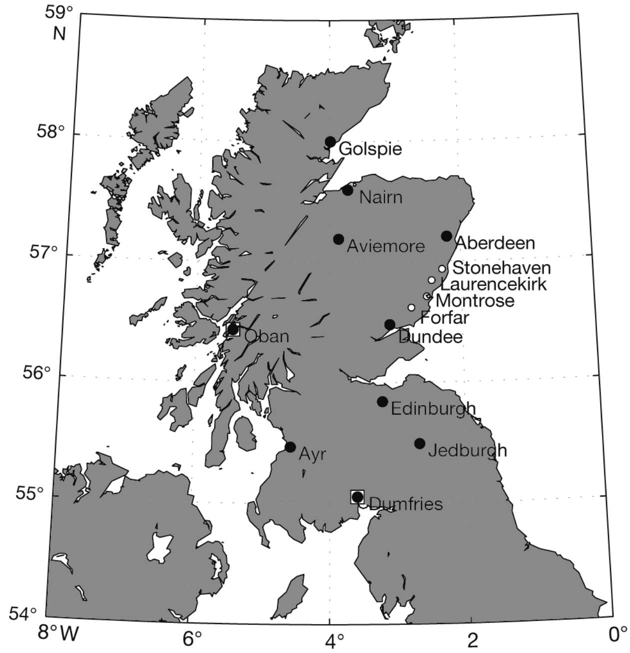

Fig. 1. Location of the 5 km squares used, named according to the principal city/town within each square (filled circles). The 2 grid squares not used for simulating spring barley using Cropsyst are enclosed by squares. Additional grid squares used for assessing local spatial variation are indicated by open circles

Each climate projection in UKCP09 is identified by a unique number (0 to 9999) across future time intervals, so we were able to ensure that those climate projections selected for the 2060s were subsequently used to generate weather data for the 2040s and 2080s. The values for the relative change in precipitation of all 10 000 projections were ranked into numerical order and divided into 5 equal-sized groups on the basis of rank; if the relative change was the same for 2 or more climate projections, then these were ordered randomly. The climate projections within each of these 5 groups were then ranked according to the average change in mean temperature and divided into 5 groups on the basis of these new rankings. This gave 25 strata in all, each containing 400 climate projections. Four climate projections were then selected randomly from each of the 25 strata, giving a total of 100 climate projections, each selected with equal probability, meaning that there was no need for differentially weighting the results derived from the different selected climate projections in future analyses. The same set of climate projections was used to generate 30 yr time series of daily weather for each of the 2040s and 2080s, using different random seeds for the weather generator in each time period.

The stratification procedure for selecting climate projections is demonstrated in Fig. 2 for the 5 km square containing Auchincruive. Note that the sequential nature of stratum construction meant that the temperature strata were nested within rainfall strata, hence the stratum boundaries for temperature change varied between rainfall strata, a feature which became more obvious with larger correlations between the variables defining the stratification. Similarly, both rainfall stratum boundaries and the nested temperature stratum boundaries varied between 5 km squares.

2.2. Implementation of the models

2.2.1. General

Simulation runs were conducted differently for the 3 models because they are non-comparable in terms of concept, execution, and entity modelled. Given the aim of investigating the consequences of climate projection stratification, rather than conducting a full climate change impacts study, model simulations were kept as simple as possible to enable meaningful statistical analysis of the model estimates. Hence, modelling issues around which there is still considerable uncertainty, particularly the responses of crops to different temperature, water, and atmospheric CO_2 concentration combinations, for which a simple CO_2 fertilization value is not appropriate for modelling future crop productivity under varying environmental conditions (Bishop et al. 2014), were not included in the simulations. Specific details of the implementation of the use of the simulated weather data in model runs are given below. The diversity of models and implementations reflects the range of possible model constructions and the ways such dynamic process models can use simulated weather data. We did not include management adaptations under future estimated climates because the aim was to demonstrate the variability in model estimates due to weather data input, not responses to different potential management adaptations. However, the crop responses under the different stratifications could be used to better understand the range and variability of adaptations needed. Crop responses to elevated CO_2 levels were not included, again because the main aim was to illustrate the climate data stratification method and consequences on model estimates: hence, by not including CO_2 responses, the comparison between current and future climates has fewer other introduced sources of uncertainty.

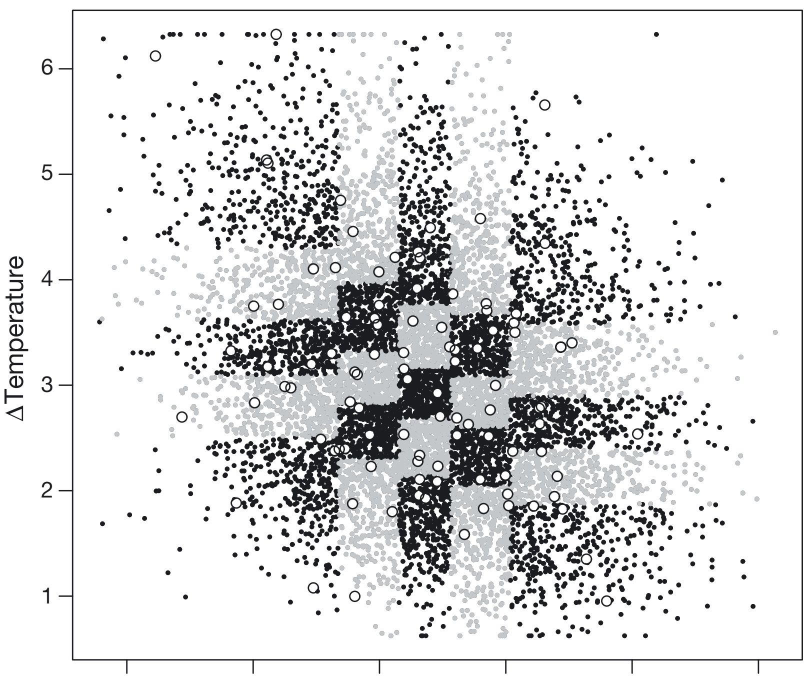

Fig. 2. Demonstration of the definition of the strata used for selection of climate projections for the 5 km square containing Auchincruive near Ayr. The strata were defined firstly by division of the 10 000 climate projections into 5 equally sized groups according to relative change in precipitation during spring and summer, from the baseline period to the 2060s. Each rainfall group was then subdivided into 5 equally sized groups according to change in mean temperature from the baseline period to the 2060s. This process gave 25 strata of size 400 (closed symbols shaded to enable differentiation between adjacent strata), and 4 climate samples (open symbols) were drawn at random from each stratum for further use

2.2.2. DNDC

For each grid square and each 30 yr period, the model was set to run for each of the 100 selected climate projections for a continuous period of 60 yr with a carry-over of soil and water processes from one year to the next. The first 30 yr, using the full sequence of daily values of precipitation and maximum and minimum temperature, were used to reach an approximate equilibrium point of key soil parameters including soil carbon and nitrogen pools, as trial runs indicated substantial trends following initialization. After the 30 yr spin-up, the carbon and nitrogen pools were stable, and therefore, any effect on the yields over the subsequent 30 yr period was not directly caused by the initialisation of the carbon and nitrogen pools. Consequently, results from the first 30 yr were discarded, whereas results from continuing the run with simulated weather from each of the 30 yr again were used in subsequent analyses. At the end of each of these 60 yr runs, the model was re-initialised for the next climate projection.

2.2.3. PALM

For each grid square and each 30 yr period, the model was driven by daily values of precipitation, solar radiation and maximum and minimum temperatures, for each of the 100 selected climate projections for a continuous period of 30 yr with soil and water processes continuing from one year to the next. At the end of each of these 30 yr simulations, the model was re-initialised for the next climate projection. No fertilizer or irrigation was applied throughout each simulation period. For each simulation, during the winter in the first year, stooling (or cut back) was carried out to initiate multiple sprouts in the following spring. Successive wood harvests (or coppicing) were taken at 3 yr intervals. We ignored the first 2 such harvests as part of the establishment phase of the crop because yields then are considerably less than for later harvests. Subsequent triennial harvest values were divided by 3 to represent equivalent annual yields.

2.2.4. CropSyst

For each grid square, each 30 yr period, and each of the 100 selected climate runs, the CropSyst model was driven by daily values of precipitation, solar radiation and maximum and minimum temperature. Simulations were re-initialised at the start of each simulation year to field capacity, with organic matter and nitrogen content so that with the addition of mineral fertilisers, the crop would not be N-limited. Whilst this means there is no carry-over effect from one year to the next, after initial testing of continuous and re-initialisation approaches, re-initialisation was found to be necessary to avoid unstable cumulative changes in estimated soil, nitrogen, and water conditions that on some occasions gave unrealistic values in long runs. Year-on-year spring barley is also an unrealistic cropping system under UK conditions, but the incorporation of other crops to capture rotations would make disentangling the variation due to weather from variation due to rotation effects more difficult. Hence, a very simple simulation was constructed to illustrate the stratification consequences more clearly. Simulations were not performed for 2 of the additional grid squares as these did not lie in barley growing areas.

2.3. Statistical analysis

Model-generated yields (predicted yields) were analysed by fitting linear mixed models to the predicted yield data for each crop and each time period, assuming random effects follow Gaussian distributions with mean zero. These statistical models all contained a categorical fixed effect for year, to remove any trend over time. Categorical random effects were included for grid square, the grid square by year interaction, climate stratum within grid square, and climate projection within climate stratum within square. Different sets of climate projections were used for different grid squares, hence the nesting of climate projections within grid square. A full model with all of these terms for any time period can be defined as follows:

$$z_{ijkl} = y_l + g_i + (gy)_{ij} + s_{ij} + c_{ijk} + e_{ikjl} \qquad (1)$$

where z_{ijkl} is the simulated yield for year l using climate projection k of climate stratum j of grid square i, y_l is the mean yield over grid squares and climate projections in year l, g_i is the grid square effect with variance σ^2_g, $(gy)_{ij}$ is the interaction between grid square and year with variance σ^2_{gy}, s_{ij} is the effect of climate stratum j of grid square i with variance σ^2_s, c_{ijk} is the effect of climate projection k of climate stratum j of grid square i with variance σ^2_c, and e_{ikjl} is the residual term with variance σ^2_e, the residual being synonymous with the effect of year within combinations of grid square, climate stratum, and climate projection within stratum. Along with presentations of the results from this full model, we also present the results from the 2 submodels that either omitted climate stratum within grid square (effectively setting $\sigma^2_s = 0$) or omitted climate projection (effectively setting $\sigma^2_s = \sigma^2_c = 0$). We do not present the results corresponding to including a climate stratum main effect, because the stratum boundaries were defined independently for each grid square, although we do discuss the consequences of including such an effect.

In the framework of the linear mixed model described above, the question of evidence for additional variation in the predicted yields due to allowing for multiple climate projections comes down to a comparison between the model that ignores climate projection ($\sigma^2_s = \sigma^2_c = 0$) and the model that allows for an unstructured effect of climate projection ($\sigma^2_s = 0$, $\sigma^2_c \neq 0$). Similarly, the question of evidence for an effect of the strata on the predicted yields comes down to a comparison between the model that treats climate projections as independent ($\sigma^2_s = 0$, $\sigma^2_c \neq 0$) and the model that allows for an effect of climate stratum within grid square ($\sigma^2_s \neq 0$, $\sigma^2_c \neq 0$). We made the associated statistical tests for significance by comparing the changes in residual log likelihoods (RLL) on adding variance parameters to the random effects model. In addition to these formal tests, we also wished to establish the practical impact that the added uncertainty due to climate projection was having on the spread of predicted yields. To do this, we noted that, assuming independence between successive predicted yields, the variance of the mean of n predicted annual yields for any given climate projection would be σ^2_e/n, whereas the variance of n predicted annual yields for a random climate projection would be $\sigma^2_s + \sigma^2_c + \sigma^2_e/n$. Thus, the percentage of variation in mean yield that is attributable to climate uncertainty could be calculated as $100\% \times (\sigma^2_s + \sigma^2_c) / (\sigma^2_s + \sigma^2_c + \sigma^2_e/n)$.

To assess the benefit of stratification, we estimated the relative stability with which the estimate of the climate projection variance component ($\sigma^2_s + \sigma^2_c$, or equivalently σ^2_c with σ^2_s set to 0) could be obtained in the absence and presence of stratification. This cannot be done by inspecting the residual likelihoods of the linear mixed models fitted to the predicted yields because the data sets of predicted yields were derived in the presence of stratification. Instead, we took a simulation approach, creating new data sets of simulated yields according to Eq. (1), using the estimated variance components. These new data sets of simulated yields were produced in pairs, both members of each pair using the same simulated random effects, but with one crucial difference: creation of one of each pair respected the stratification, using each of the 25 simulated values for climate stratum within grid square in a balanced way by allocating each to 4 climate projections to make up the requisite 100 climate projections; creation of the other of each pair ignored the stratification by selecting independently and at random from the same 25 values for climate stratum within grid square when constructing each of the mean values for the requisite 100 climate projections. The same linear mixed model (1) was fitted to each simulated data set, resulting in 1 set of estimates of $\sigma^2_s + \sigma^2_c$ obtained using the stratification and 1 set without. The ratio of variances of the 2 sets of estimates of $\sigma^2_s + \sigma^2_c$ provided a quantitative measure of the benefit of stratification in estimation of the climate $\sigma^2_s + \sigma^2_c$, this ratio indicating the relative number of climate projections required with and without stratification to achieve the same precision. Statistical significance of these ratios of variances was assessed by a randomisation test (Manly 2008) under the assumption that, if the stratification were having no effect, variance estimates should be exchangeable within pairs. Some exploration indicated that the creation of 2000 pairs of variance estimates, followed by 1000 randomisations, gave a reasonable balance between computational burden and statistical power.

The models described above were initially fitted by the method of residual maximum likelihood (Patterson & Thompson 1971) using the REML and associated commands in GenStat Release 12.2 (VSN International). Evidence for including each additional variance component in the model was assessed by comparison of maximised residual likelihoods, with twice the difference in residual log likelihood (−2RLL) assessed against a χ^2_1 distribution. The REML method involves iterative estimation of non-linear parameters (the variance components) and so is ill-suited for use with large numbers of simulations. Since the yield data generated by the process models and also the subsequent simulation from the fitted linear mixed models created balanced data sets, identical estimates of variance components could be derived from an analysis of variance treating each random effect as defining an error stratum and equating residual mean squares in each stratum to their expectations (Searle et al. 2006). This approach based on analysis of variance was much faster than the REML-based approach since it avoids the need for iterative numerical optimisation: consequently, this faster approach was adopted during the formal assessment of the benefits of stratification.

For the predicted yields of spring barley produced by CropSyst, we created regional mean yields by treating the predicted yields for the relevant subset of 5 km squares as defining distributions of values, from which we needed to select 1 from each square in a manner that makes up for the lack of spatial coherence in the weather data. We did this by assuming the yields from the different 5 km squares in any year should be transformable to a multivariate normal distribution with correlation matrix having elements c_{ij} defined by a function $C(\alpha, d_{ij})$ whose value depends on parameters in the vector $\boldsymbol{\alpha}$ and the distance d_{ij} between squares i and j. Using the 1-parameter exponential model with correlations given by $c_{ij} = \exp(-\alpha . d_{ij})$, we simulated sets of 10 000 random vectors, each with 1 value per 5 km square, for a range of values of α. For each vector in a set, we replaced each element of the vector by the correspondingly ranked values from the predicted yields for each square (e.g. 3rd highest out of 3000 for the element according to square 1, 5th highest out of 3000 for the element according to square 2, etc.). The corresponding rank value was identified by taking the cumulative lower probability of the normal distribution, multiplying by 3000 and rounding to a whole number. For comparison, we also combined equally ranked predicted yields from each square. The means of the vectors of yields created in this way are derived from the distributions of predicted yields, but with an imposed spatial correlation to make up for the lack of spatial coherence in the weather data.

3. RESULTS

Overall, the model runs suggested that, given the simulated daily weather data for future climate projections under the A1FI high emissions scenario, we might expect to see increases in mean yield from silage and woody coppice crops, but to see decreases in mean yield from spring barley (Table 1), with changes from the baseline growing between the 2040s and 2080s. The dependencies of mean predicted yields on temperature and rainfall class present were as follows: mean silage yield responded positively to increasing rainfall and temperature; mean barley yield responded negatively to increasing temperature but positively to increasing rainfall in the lower temperature classes; and mean wood yield displayed small positive responses to increasing temperature and decreasing rainfall.

Fitting linear mixed models to the predicted yields provided strong evidence for contributions to the variance in yields due to climate projection within grid square and climate stratum within grid square. For all 3 models and both future time periods, the differences in values of −2RLL were >3000 ($p \ll 0.001$) upon including a random effect with an associated variance component for climate projection in the model and >50 ($p \ll 0.001$) for then including a random effect for climate stratum in the model (Table 2, final row for each of 2040s and 2080s). The residual variance (σ^2_e, measuring variation between years within combinations of grid square, climate projection, and climate stratum) decreased by between

Table 1. The mean annual yields for each process based model using 2040s and 2080s weather, according to the stratum into which the climate projections were divided (presented as 2040s mean/2080s mean). For silage yield, this is the total of the 2 annual cuts; for wood yield, it is the mean triennial cut divided by 3 after ignoring the 2 cuts during the establishment period. Mean annual yields for the baseline period were 1.76 t C ha^{-1}, 9.72 t ha^{-1}, and 9.86 t ha^{-1} for silage, spring barley, and short-rotation coppice respectively

Rainfall class	Temperature class									
	Lowest		Low		Medium		High		Highest	
	2040s	2080s	2040s	2080s	2040s	2080s	2040s	2080s	2040s	2080s
Silage yield (t C ha^{-1})										
Lowest	1.95	2.09	1.98	2.14	1.96	2.14	2.06	2.29	2.11	2.34
Low	1.97	2.10	2.02	2.19	2.00	2.20	2.05	2.22	2.15	2.34
Medium	1.96	2.07	1.99	2.13	2.05	2.21	2.07	2.27	2.15	2.37
High	2.00	2.14	2.03	2.22	2.09	2.26	2.10	2.31	2.16	2.40
Highest	2.05	2.17	2.07	2.20	2.09	2.27	2.12	2.31	2.18	2.38
Barley yield (t ha^{-1})										
Lowest	7.91	6.92	7.92	6.79	7.71	6.65	7.52	6.30	7.10	5.85
Low	8.25	7.30	7.90	6.80	7.64	6.51	7.45	6.33	7.15	5.84
Medium	8.21	7.35	7.98	6.92	7.80	6.84	7.65	6.55	7.26	6.05
High	8.21	7.16	7.92	7.05	7.68	6.51	7.68	6.41	7.13	5.81
Highest	8.31	7.26	8.10	7.11	7.95	6.82	7.51	6.06	7.22	5.98
Wood yield (t ha^{-1})										
Lowest	10.63	11.46	10.81	11.59	10.89	11.75	11.02	11.70	11.28	11.36
Low	10.57	11.44	10.73	11.52	10.84	11.65	10.96	11.62	11.21	11.58
Medium	10.48	11.12	10.61	11.38	10.76	11.65	10.96	11.65	11.19	11.57
High	10.53	11.17	10.64	11.33	10.85	11.59	10.96	11.69	11.02	11.29
Highest	10.50	11.19	10.54	11.17	10.69	11.34	10.99	11.68	11.18	11.58

Table 2. Estimated variance components (t ha^{-1})^2 for random effect terms in the linear mixed models fitted to simulated annual yield data. Fitted models varied in whether they contained a random effect for climate projections ('Ignored' if not), and if so, whether they did ('Structure used') or did not ('Structure ignored') include a random effect for climate projection stratum. The changes in −2RLL are all highly significant ($p \ll 0.001$) when referenced against the χ^2_1 distribution

Variance component	Silage			Barley			Wood		
	Ignored	Structure ignored	Structure used	Ignored	Structure ignored	Structure used	Ignored	Structure ignored	Structure used
2040s									
Grid square	0.614	0.614	0.614	0.628	0.623	0.621	3.339	3.338	3.338
Square by year	0.001	0.001	0.001	0.028	0.034	0.034	0.226	0.228	0.228
Square by climate stratum			0.007			0.192			0.065
Climate projection within square		0.018	0.012		0.557	0.371		0.166	0.104
Residual	0.115	0.096	0.096	1.382	0.825	0.825	0.235	0.069	0.069
Change in −2RLL		3337	103		9834	98		6770	152
2080s									
Grid square	0.638	0.638	0.638	0.388	0.379	0.377	3.352	3.348	3.347
Square by year	0.000	0.001	0.001	0.000	0.010	0.010	0.238	0.242	0.242
Square by climate stratum			0.012			0.330			0.079
Climate projection within square		0.040	0.029		0.934	0.615		0.357	0.281
Residual	0.150	0.110	0.110	1.528	0.593	0.593	0.489	0.132	0.132
Change in −2RLL		6844	89		19406	107		7272	53

16% (0.115 vs. 0.096 for 2040s silage yield) and 73% (0.489 vs. 0.132 for 2080s wood yield) on inclusion of the random effect for climate projection. The variance component for climate projection (σ^2_c) in turn was reduced by inclusion of the random effect for climate stratum, the magnitude of this reduction varying from 21% (0.357 vs. 0.281 for 2080s wood yield) to 37% (0.166 vs. 0.104 for 2040s wood yield).

For each crop type, the relative contributions of the climate projection variance component (σ^2_c) and the residual variance (σ^2_e) to the variance of predicted yields depends on their relative magnitudes and on whether the aim is to predict yields of individual years or mean yields across a number of years (Table 3). For individual years, the percentage of the variance of simulated yields attributable to climate projection ($100\% \times \sigma^2_c / [\sigma^2_c + \sigma^2_e]$) was lower for silage ($100\% \times 0.018 / [0.018 + 0.096]) = 16$ and 27% for 2040s and 2080s, respectively) than for barley ($100\% \times 0.557 / [0.557 + 0.825]) = 40$ and 61% for 2040s and 2080s, respectively. All these percentages increase as the number of years over which the average is calculated increases whilst maintaining their initial ranking; considering mean yields across 9 yr, they range from $100\% \times 0.018 / [0.018 + 0.096/9] = 63\%$ for silage in the 2040s to $100\% \times 0.934 / [0.934 + 0.593/9] = 93\%$ for barley in the 2080s. The equivalent percentages for wood yield, which are only available in multiples of 3 yr, lie between the percentages for 2040s barley and 2080s barley, reaching nearly 90% for mean yields across 9 yr.

For all combinations of yield type and time period, the variance of the estimate of $\sigma^2_s + \sigma^2_c$, the combined climate projection variance component, was higher if stratification was ignored in simulating the yields than if stratification was used (Table 4). This happened because the variance between climate strata within grid squares was >30% of the combined cli-

Table 3. Summary of variance components from fitting linear mixed models to simulated annual yields, and the percentages of the variance of simulated mean yields that were attributable to the variance component for climate projection within square (% variance, calculated over periods of different lengths)

Time period	Variance component (t ha^{-1})^2		% variance			
	Projection within square	Residual	Period length			
			1 yr	3 yr	9 yr	30 yr
Silage						
2040s	0.018	0.096	16	37	63	85
2080s	0.040	0.110	27	52	77	92
Barley						
2040s	0.557	0.825	40	67	86	95
2080s	0.934	0.593	61	83	93	98
Wood						
2040s	0.166	0.069		71	88	96
2080s	0.357	0.132		73	89	96

Table 4. Assessment of benefits of stratification, in terms of ratios of the estimated variances of $\sigma^2_s + \sigma^2_c$, the combined climate projection component of variance. Estimates of $\sigma^2_s + \sigma^2_c$ were derived from data simulated either in a balanced fashion with respect to the 25 strata for each 5 km square (using stratification) or randomly with respect to the strata (ignoring stratification). Statistical significances of the ratios of the variances of the estimates of $\sigma^2_s + \sigma^2_c$ were derived using 1-sided randomisation tests

Time period	Estimated variance component (t ha^{-1})^2				Variance of estimated combined climate projection variance component (t ha^{-1})^2		Ratio of variances (C/D)	Statistical significance of randomisation test
	Climate stratum within grid square (A)	Climate projection within stratum within square (B)	Combined climate projection (A+B)	Residual	Ignoring stratification (C)	Using stratification (D)		
Silage								
2040s	0.0062	0.0122	0.0184	0.0960	1.00×10^{-6}	0.91×10^{-6}	1.10	$p = 0.018$
2080s	0.0120	0.0285	0.0404	0.1098	4.10×10^{-6}	3.81×10^{-6}	1.08	$p = 0.047$
Barley								
2040s	0.192	0.371	0.557	0.825	9.23×10^{-4}	7.44×10^{-4}	1.24	$p < 0.001$
2080s	0.319	0.615	0.934	0.593	24.7×10^{-4}	19.6×10^{-4}	1.26	$p < 0.001$
Wood								
2040s	0.062	0.104	0.166	0.069	0.63×10^{-4}	0.55×10^{-4}	1.14	$p = 0.002$
2080s	0.076	0.281	0.357	0.132	2.86×10^{-4}	2.74×10^{-4}	1.04	$p = 0.16$

mate projection variance component (e.g. 100% × 0.0062/0.0184 = 34% for 2040s silage) except for 2080s wood yield, for which the corresponding value was 21%. The ratios of the 2 estimates of $\sigma^2_s + \sigma^2_c$ ranged between 1.04 (= $2.86 \times 10^{-4}/2.74 \times 10^{-4}$) and 1.26 (= $24.7 \times 10^{-4}/19.6 \times 10^{-4}$), with the largest values (1.24 and 1.26 for 2040s and 2080s, respectively), and hence the greatest benefits of stratification, occurring for barley yield. The ratios of variances for silage yield (1.10 and 1.08 for 2040s and 2080s respectively) were lower than for barley yield due to the small size of the signal to be detected, as measured by the ratio of the combined climate projection variance component to the residual variance. The smallest ratio of variances, 1.04, occurred for 2080s wood yield, this being due to the small proportion (21%) of the combined climate projection variance component that was attributable to the stratification. Since the statistical significance level for the 2080s wood yield was so low, a further run of 10000 pairs of simulated data sets were constructed. For these, the ratio of variances again was rounded to 1.04, but the 1-sided significance test gave $p = 0.02$.

Distributions of mean spring barley yields over the 6 squares between Aberdeen and Dundee are given in Fig. 3, for values of α corresponding to a correla-

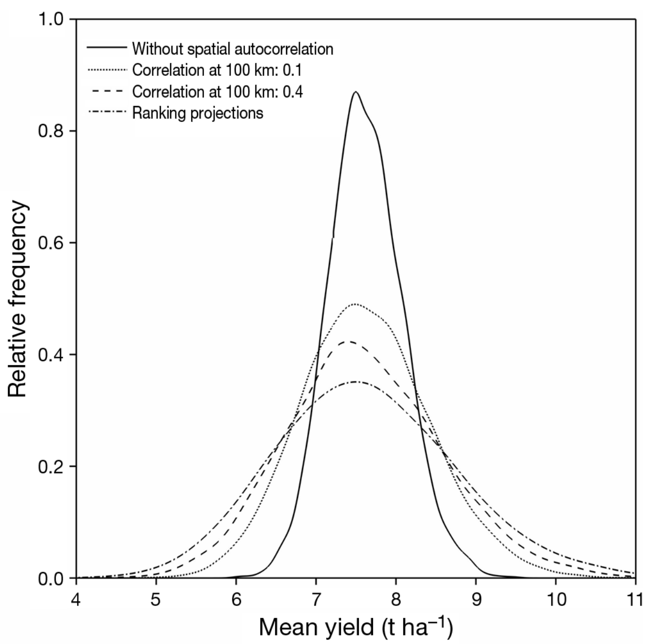

Fig. 3. Distribution of projected mean spring barley yields over the 6 selected squares between Aberdeen and Dundee for differing levels of assumed spatial autocorrelation, along with the most extreme forms of correlation obtained by ranking simulated yields for each square and considering all yields of equal rank to occur simultaneously

tion at a distance of 100 km ranging from 0 to 0.4. The distribution is also shown for the maximum correlation given the number of model runs, which is obtained by combining equally ranked yields from each square.

4. DISCUSSION

The principal purpose of the work described here was to quantify the additional uncertainty in predicted crop yields introduced by using the multiple climate projections made available in UKCP09. This has been done using simulated daily weather data to drive 3 contrasting crop-environment process models and estimating the contribution to the variance of predicted yields that can be attributed to variation between climate projections: this variation due to climate projection can be thought of as uncertainty because we do not know which climate trajectory will be followed in future. Exclusion of uncertainty in future yield projections arising from other sources (e.g. crop responses to elevated CO_2, water, and temperature combinations, adaptive management and technological innovation), has enabled a more direct quantification of the additional uncertainty from the multiple climate projections than would have been possible had these additional effects and their associated uncertainties been included. Thus, our work is complementary to other studies, notably Asseng et al. (2013) and Martre et al. (2015), which make more comprehensive assessments of climate change impacts on crops but using limited ranges of potential future climates.

In our study, we illustrated the stratification approach using 3 models representing 3 very different cropping systems, but using fine-resolution weather data derived from a sequence from GCM to regional climate model to weather generator (5 km grid cells) chain (Murphy et al. 2009). Many climate-impact studies are based on coarse-scale GCM projections, whereas crop model accuracy and data quality are often better at local to regional scales (Challinor et al. 2014). Variation between climate projections is, however, only one aspect of uncertainty, as we have not considered uncertainty in the crop models, data for calibration, etc. Some authors (e.g. Palosuo et al. 2011, Rötter et al. 2012, Asseng et al. 2013) have considered the uncertainty derived from multiple models for the same crop, such as wheat or barley. Asseng et al. (2013) concluded that a greater proportion of the uncertainty in climate change impact projections was due to variations among crop models than to variations among downscaled GCMs. Over and above the limitations posed by using single models to estimate yields for each of the 3 crops considered, there are many reasons why it would be wrong for us to claim we are now in a position to make accurate predictions about future yields for any of the crops we have modelled, as there are many adaptive steps that we have not attempted to incorporate. These adaptations range from tactical farm-level decisions involving local land allocation and agronomic management (Lal et al. 2011, Del Prado et al. 2013) through to wide-scale strategic activities such as the development of new varieties (Matthews et al. 1997, Smith et al. 2007).

What our study clearly demonstrates is that the magnitude of the contribution of variance in predicted yields from single models that is due to climate projection is dependent on whether we are interested in single or multiple years: for single years, interannual variation due to weather was the dominant term for silage yields, whereas for barley yields, the contributions of climate projection and annual weather were of roughly equal magnitude (Table 3, column labelled '1 yr'). When considering mean yields over increasing numbers of years (Table 3, subsequent columns), climate projection always became the dominant component, with dominance achieved when averaging over 3 yr for 5 of the 6 combinations of crop and time period we considered. Thus, variation between climate projections is an important contributor to variation in predicted yields, all the more so when considering mean yields across years.

To derive a computationally efficient estimate of the contribution of variance in yield that is due to climate projection, we had to decide how to select from amongst the 10 000 climate projections available for each grid square. Selection by means of a stratified sampling scheme was a natural candidate for investigation, since the process of stratification is widely used to control known sources of variation in statistical sampling. Thus the focus of this study was our novel method of stratified climate-projection sampling and our approach in assessing this method. Our method for performing the stratification used the mean values for spring and summer temperature and total rainfall for each climate projection, which are quick to obtain and relevant to the crops for which the process models were being run. This method can easily be used in combination with the UKP09 User Interface, which is the standard means of accessing the probabilistic climate projections — the use of stratification simply means that a set of climate projection reference numbers need to be provided manually when prompted to provide 'Sampling method'. We estimated that the proportion of the variance attributable to climate projection that was controlled by stratification varied between 21 % (2080s wood yield) and 34 % (2040s barley): the direct benefit of the balanced sampling of the strata is to crystalise out the variation between strata, leaving only the variation between climate projections within strata uncontrolled and hence subject to the vagaries of random sampling. Whilst the proportion of variance that could be allocated to strata could be increased by having more tightly defined strata, the proportion of variance attributable to the variables underlying the stratification is fixed, and so the benefits of increasing the number of levels in the stratification are likely to be small.

Our measure of the benefit of stratification was the ratio of variances of the estimates of $\sigma^2_s + \sigma^2_c$—the combined climate projection variance component—obtained either ignoring or capitalising on the benefits of using the stratification scheme to control variation. This measure was calculated by simulating data from the linear mixed models fitted to the predicted yields from the crop-environment process models, with calculated ratios ranging from 1.04 to 1.26. The formulae relating such ratios of variances to equivalent ratios of sample sizes are complex and difficult to generalise since the formulae involve the true values of other variance components as well as structure of the analysis of variance (Searle et al. 2006, their Appendix F). However, some additional simulations indicated that the 6 ratios of variances in Table 4 are very similar to the ratios of the number of climate projections required without and with stratification to achieve the same level of precision in the estimate of $\sigma^2_s + \sigma^2_c$.

We have also demonstrated that regional distributions of mean yields can be calculated, despite the lack of spatial coherence in the climate projections. These distributions of regional yields are much wider when spatial correlation is allowed for than when spatial correlation is ignored (the standard deviations ranged between 0.465 t ha^{-1}, ignoring spatial correlation, and 1.138 t ha^{-1}, when combining equally ranked predicted yields). The difficulty of obtaining sufficient geographically referenced yield data meant that we were unable to make satisfactory estimates of the parameter relating geographical separation to correlations in yield. However, Fig. 3 demonstrates that the distribution of mean yields is actually fairly similar over quite a wide range of values of this parameter.

In conclusion, the results reported in this paper provide evidence that substantial computational gains can be achieved by stratified sampling from amongst an ensemble of climate projections. There is an inherent limitation on the gains that can be achieved, since stratification was based on climate values (means across years), whereas the equivalent annual means of simulated weather data showed considerable variation about these climate values. Further efficiency gains could have been achieved by deriving a stratification scheme based on the mean values of the simulated weather variables subsequently used to drive the process models, or summarised in a manner that more completely captured the relationship between climate projection and mean yield. Some judicious use of pilot runs of the process models may also be beneficial, but further work is required to establish how best to balance the benefits of establishing enhanced stratification schemes against the time costs of establishing such schemes.

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