An Integrated Assessment approach to investigate options for mitigation and adaptation to climate change at the farm-scale.

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Abstract

Future climate conditions are just one of a range of drivers of change, such as the economic and policy environment, that will influence strategic planning and decision making at the farm-scale. New management practises will need to achieve a range of multiple-objectives, including green house gas (GHG) emissions mitigation, sustainability and still ensure farm-scale financial viability. Therefore measures to change the land use composition and associated management that make up a farm enterprise will need to address issues beyond just those related to climate change impacts. In order to address this, a holistic Integrated Assessment (IA) approach is required, combining simulation modelling with deliberative processes involving decision makers and other stakeholders. This has the potential to generate credible and relevant assessments of climate change impacts on farming-systems and identify potential adaptation and amelioration strategies. The components that make up the Integrated Modelling Framework (IMF) (LADSS 2005), the primary tool used in the IA, and the overall IA approach (Rivington *et al* in press a), are detailed. Previous studies have shown that the quality of input weather data can have a significant impact on the quality of land use model estimates (Rivington *et al* 2003). Therefore, a first stage in the IA process is to assess and communicate the uncertainty that exists in future climate prediction data, and determine how such uncertainty is propagated through simulation modelling. Without this stage it is argued that interpretation of projected climate change impacts and identification of adaptation strategies becomes infeasible. A simplified method for downscaling Regional Climate Model estimates is described. The intoduced uncertainty in crop model estimates are then highlighted. Within the IMF, grass and cereals are modelled using the CropSyst cropping systems model (Stöckle *et al* 2003), connected to a bespoke livestock system model. An accounting framework permits appraisal of the labour and resources, financial and environmental costs and benefits of changes due to an altered climate. Fundamentally however, it is shown that although this IA and IMF provides a valuable tool for developing adaptation and amelioration strategies, the substantial uncertainty in climate prediction data poses a serious restriction on our ability to make reliable climate change impact assessments.

Introduction

A farm exists as an entity that has many requirements placed on it, in terms of productivity, environmental and ecological functions, as a source of employment and more recently, as a potential tool for climate change mitigation. There are many drivers of change on farms and the land uses within them and how they are managed. It can be argued that the most substantial drivers of change are markets, economic conditions and the policy environment. As such climate change (CC) may be seen as a lesser driver of change, in terms of direct impacts, but policies in particular may develop in the near future in efforts to mitigate CC, which are likely to have a substantial affect on land use management. Decisions at the farm-scale have important consequences for economics, environmental protection and landscape quality that need to be considered at larger spatial scales. A key objective of future policy development will be to ensure that the aims of CC mitigation are achieved whilst maintaining the multiple-objective requirements of land use.

Significant alterations to the biophysical environment due to future changes to the climate may require adaptations to patterns of land use and management. Changes may be required to cope with both an increased incidence of extreme weather events and change in long-term mean conditions. Current management systems may have a certain limit as to how much they can adapt before it is necessary for more radical land use changes involving farm infrastructure alterations. Management systems adaptation to mitigate the impacts of CC is, however, considered the most likely (Easterling 1996). It can be argued that decision-making in terms of change is best studied at the whole-farm scale (Johnston and Chiotti 2000), as it represents the interface between biophysical processes and human intervention through management.

In order to investigate the complex relationships between the on-farm biophysical environment, resource management, and the wider context of market and policy drivers, whilst also considering the multiple-objective requirements placed on farms, it is necessary to take a holistic Integrated Assessment approach. Given the wide range of potential consequences of CC, both at the farm-scale and with a global perspective, it is valuable to explore alternative futures using simulation modelling. Counter-factual experiments can be conducted to better understand the impacts of CC and the possible strategies for amelioration and adaptation. Such analysis enables the assessment of farm system resilience and adaptive capacity (Rivington *et al*, in press a). However, the utility of employing simulation models for future predictions is greatly influenced by the quality of input climate data. This paper argues that issues of introduced uncertainty to model estimates arising from the use of future projected climate data need to be addressed before meaningful conclusions can be drawn on what the biophysical impacts may be, and how adaptation and amelioration strategies can be usefully developed. A key issue is how future projected weather data can be downscaled from Global Circulation Models (GCM) to Regional Climate Models (RCM) and then down to site-specific locations, i.e. a farm. In an extensive study of maximum and minimum air temperature estimates at 185 sites in Europe, Moberg and Jones (2004) found the HADRM3P RCM (50x50km grid cells) produced both good and poor estimates of air temperature for the climate normal period of 1961-90 (hindcast) compared with site-specific observed data. In this paper we detail and provide examples for a simplified approach that enables hindcast and future projected precipitation and air temperature data from the Hadley Centre RCM

(HADRM3) to be adjusted in order to be representative of a particular location. The impacts on land use systems model estimates from using the simplified downscaling method are then investigated. In doing so, we are able to identify and quantify introduced uncertainty and bias to the overall IMF.

Background

Integrated Assessment modelling tools

This section details the research approach and modelling tools employed within the Integrated Assessment of CC on farm systems.

Integrated Modelling Framework

The core of the modelling framework used in the Integrated Assessment approach is the Land Allocation Decision Support System (LADSS 2005) (Fig. 1), made up of biophysical and management systems models. These are primarily driven by farm-scale bio-physical and management regimen data, though they also reference meso- and macro scale data such as market prices for inputs and sales. The accounting framework defines views on the state variables of the system being simulated. The accounting framework thus presents a coherent and organised view of the state information that may have a particular theme, such as financial (gross/net margins or cash flow) or physical accounting (N balance or net greenhouse gas emissions). Beyond the accounting framework are tools that support particular forms of analysis, these can be simply presentational, more sophisticated as visualisation or more complex such as multi-objective land use planning, cost-benefit analysis or sustainability assessment.

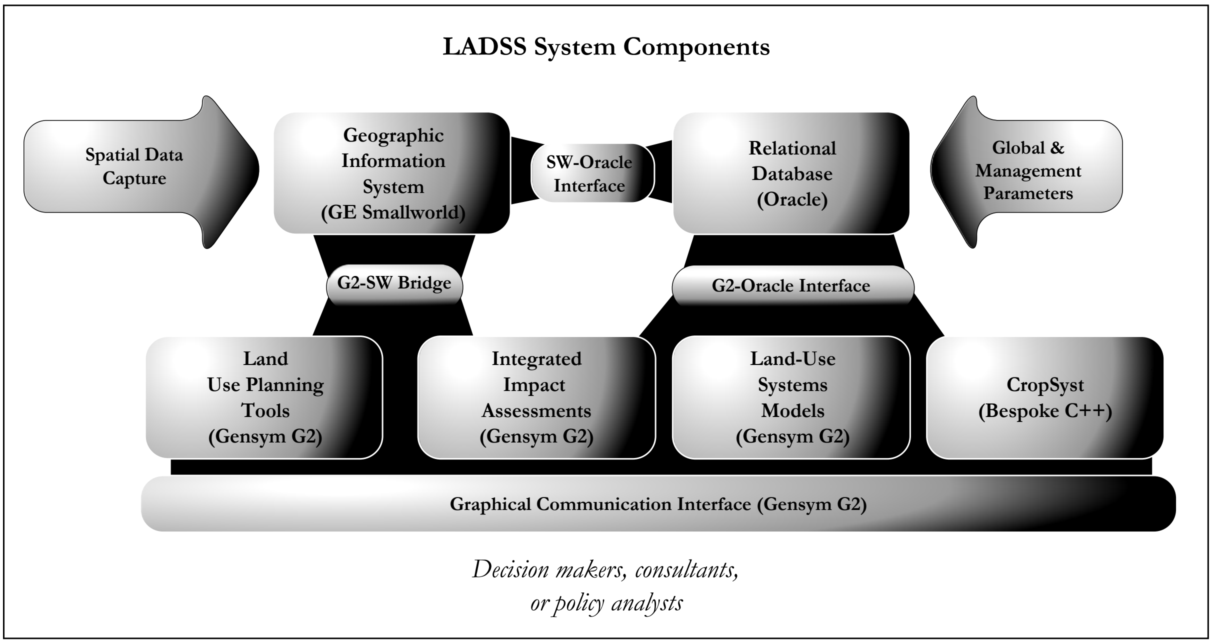

Figure 1. Land Allocation Decision Support System (LADSS) system components

The bio-physical systems models within the framework are CropSyst (Stöckle et al 2003) and a bespoke livestock systems model (LSM). CropSyst is a multi-crop simulation model that estimates production (yield) and environmental parameters (water balance, N and OM status etc.) for a wide range of crops and crop rotations under different management regimen. CropSyst was chosen from a review of alternative crop models since it provides a conceptually unified modelling system for many crops minimising the dangers of structural uncertainty in making cross crop comparisons. Novel crops, i.e. bio-fuels, can be modelled, where parameterisation is possible, permitting exploration of alternative forms of land use.

The LSM is an energetics based livestock growth model that tracks the state of cohorts of ruminants (to date cattle and sheep), as they progress from birth through weaning and growth to finishing for market. The definition of the herds through which cohorts progress, the linkages between herds and the management decisions required, are implemented using a graphical programming toolkit. Intake requirements for specified diet are estimated for each cohort and stocking rates set to be consistent with materials available in the fodder pool, that is made up of on-farm (modelled within CropSyst) and bought in materials. The interactions between grazing stock and pastures are simulated using daily clipping events whose magnitude is set by the LSM.

The quality of analyses will depend on the quality of farm- and meso/macro scale input data, but the biophysical and management systems models have been chosen, if not to minimise data requirements, then to depend on a small number of relatively easily measured parameters. The framework is robust in the face of missing data with the ability to substitute either experiential or standard published figures. This does, however, clearly restrict the range of analyses possible. The models are, where possible, calibrated and validated against onsite data, and if this is not possible then parameterisations based on regional data or similar sites. Un-calibrated or non-validated outputs are flagged and used only as indicative of trends.

The management systems model within the IMF is the resources scheduling tool (RST) (Matthews et al 2003). The RST is a heuristic based scheduler that determines the utilisation of on farm-resources such as labour and machinery, based on tasks generated from patterns of land use and the livestock management regimen. The RST can also assign machinery intensive or specialist tasks to contractors where appropriate. The outputs from the RST are used in determining the fixed costs for patterns of land use and management.

The deliberative support aspects of the IMF are higher-level tools that make use of the functionality provided by the biophysical and management systems models and the accounting framework. These tools support the deliberative process by presenting in a structured way a range of options to decision makers or stakeholders. These serve as *marketing planning* tools, defining a set of alternative states with estimated properties. The options presented may serve as the basis for plans with further customisation by decision makers to reflect their preferences or factors not considered by the tools, or can be used as part of an iterative process of evaluation. The tools developed to date have focused on spatial allocation problems and finding patterns of land use that achieve the best possible balance between multiple objectives. The outputs from these tools are typically a set of Pareto-optimal solutions that define the trade-off between objectives (Matthews et al, 2006).

Within the IMF it is not yet possible to assess animal welfare and consequential labour requirements, crop quality with its implications for market value or feed for livestock, nor the potential impacts on the prevalence of pests and diseases in both plants and animals. Such omissions may, however, be considered qualitatively through the deliberative process with stakeholders and expert review. Structurally the IMF has limitations on the degree of integration between its sub-systems. For example, it is not possible to adaptively adjust stocking rates in response to grazing availability within a single simulation of pasture growth. This can be significant as the grazed pasture's growth is a function both of agro-climatic conditions and the imposed grazing regimen. The grazing regimen determined by the LSM defines one of the management parameters for the CropSyst simulation. Any adjustments to the grazing regimen must be made at the completion of the CropSyst run using the diagnostics provided and a further CropSyst simulation made. A further limitation of the IMF is that while simulations are spatially explicit, in that they are conducted on a field-by-field basis, the component models are not distributed and thus cannot not take account of lateral flows of soil water regimens, or changes in the influences of surrounding land uses (such as shading or shelter) during the course of a simulation.

Resilience and adaptive capacity is a useful conceptual framewowrk within which to organise research and help interpret the outcomes of CC impacts studies. The holistic IA approach described here is able to provide valuable insights into the relationships between biophysical and socio-economic processes. It thus helps to identify the tolerances and thresholds that define the resilience of a farm system and its capacity to adapt. Easterling (1996) contrasts short-term system resilience with long-term adaptive capacity. A system with short-term resilience can adapt its operations to maintain existing functionality, absorbing impacts of varying magnitude. Systems with long-term adaptive capacity are able to manage the process of altering their operations, function and appearance to continue to deliver higher-level goals such as food supply or income for land managers, and landscape value. This adaptive capacity is required when change exceeds the short-term resilience of the system.

Climate Change Impacts Assessment

Numerous studies have identified potential CC impacts for a range of farm system components, e.g. individual crops at the regional (Southworth et al 2002) and national scale (Holden et al 2003), site-specific cropping systems (Tubiello et al 2000), milk yield and dairy herds (Topp and Doyle 1996), crops and management (Ghaffari et al 2002) and crop yields and ecosystem processes (Izaurralde et al 2003). These studies, and others, provide a range of contrasting interpretations as to potential crop responses under future climate scenarios. Higher temperatures may result in a reduction in yield due to reduced growth period duration, but elevated CO_2 concentrations could counter this (i.e. Wheeler et al 2000). It is certain that there will be consequential impacts on livestock systems associated with changes in primary production of feed resources. The form and magnitude of crop responses to CC will not be determined simply by the altered climate and CO_2 concentration, but by localised biophysical conditions as managed by individual farmers.

It is important to understand the complexities of inter-relationships within a farm system; particularly as weather events are often the prime driver for the timing and nature of management operations. Bellocchi et al (2004) highlighted the need to apply characterisation metrics to future CC scenario weather data in order to estimate impacts on soil access and workability. The resources available within a farm and their spatial configuration may also impose particular constraints on the feasibility of adaptation and amelioration strategies. To draw conclusion about the impacts of CC on farming systems, it is necessary to integrate the analysis of the biophysical processes and their influence on land use productivity, with socio economic drivers and assess down stream effects. In order to do this satisfactorily, it is first necessary to quantify the uncertainty that can be introduced to crop model estimates through the use of input data derived from climate models.

Meteorological data as a source of uncertainty

Heinemann *et al* (2002) showed that the accuracy of rainfall observations is critical for the simulation of yield and that the variability of simulated estimates is directly correlated to the accuracy of model inputs. This emphasizes the importance of data quality (accuracy of measurement), as well as site-specific representation. Rivington et al (2003) found there could be substantial levels of uncertainty introduced to crop model estimates when using neighbouring station data, illustrating the spatial variability of the weather variables. Aggarwal (1995) tested the relationships between the uncertainty in crop, soil and meteorological inputs with the resulting uncertainties in estimates of yield, evapotranspiration and crop nitrogen uptake, within a deterministic crop growth model. It was then possible to identify the 'uncertainty importance' of an input for a given scenario. The non-linear response of models representing biophysical process has been demonstrated by Nonhebel (1994a), who showed that average weather data produced different simulation results than daily data (an over-estimation in potential production of 5-15% and up to 50% in water limited production in dry conditions). This was due to i). the response of non-linear relationships within the model used, where average input did not give average output, and ii). the large variability in daily weather data being different from the average value. Similarly, Nonhebel (1994b) found that inaccuracies in solar radiation of 10% and temperature of 1°C resulted in yield estimation errors of up to 1 t ha^{-1}, and up to 10 days difference in vegetative period between emergence and flowering. These, and other findings (Rivington et al, in press) indicate that considerable care has to be given to the process of selecting sources of input weather data for crop models.

Materials and Methods

Climate data assessment

The Hadley Centre RCM, HADRM3, produces daily climate variables data for 50x50km grid cells, covering the North Atlantic, North Africa, Europe and Western Russia. Simulations are run for the climate normal period of 1960-90 (here refered to as 'hindcast data'), as well as future time periods (i.e. 2070-2100). Precipitation, maximum and minimum air temperature and solar radiation data produced by the HADRM3 model were supplied by the British Atmospheric Data Centre (for grid cell 4695), along with observed data for Carnwath meteorological station (55.7 degrees N, 3.63 degrees W) in Scotland. Comparisons were made between site-specific observed data variables and the hindcast estimates for Carnwath. The basis for this is that if the hindcast data show systematic errors, then the future projected weather data will contain the same errors. The hindcast data do not attempt to recreate the data for each specific year, instead the means for each variable are to be representative of the 50x50 km grid cell. To overcome the non-temporal relationship between observed and hindcast air temperature and solar radiation data, the mean daily values were calculated. Observed solar radiation data was only available for seven years, restricting analysis to graphical observations. For precipitation, the propability of excedence (Weibull 1961) was calculated. These approaches allowed differences between the observed and estimated to be identified for each variable. From this a simple set of adjustment methods were developed and applied to the hindcast and future projection data. For temperature, optimised values were derived to either add or subtract from the daily temperature data, constrained by minimising the difference between observed and estimated mean daily values for the growing season, so as to achieve a zero value for the sum of mean daily differences. For precipitation a two stage approach was taken, firstly to correct the number of rain days and secondly to optimise against the mean annual total. The data derived from these adjustment methods were then used within the CropSyst model to determine the response of yield estimates for spring barley and a grass silage system.

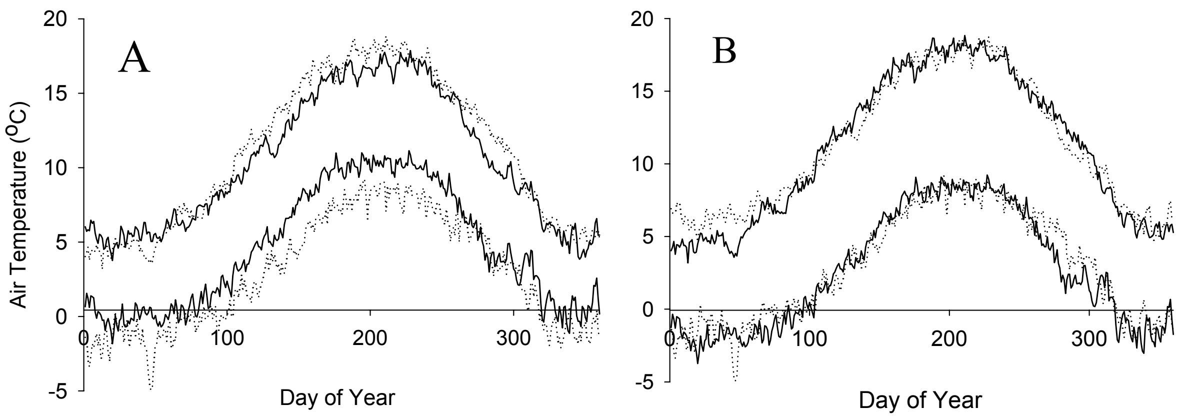

Figure 2. Observed (dotted line) and HADRM3 estimated (solid line) mean daily maximum and minimum air temperature for Carnwath, Scotland 1960-90, before (A) and after (B) application of adjustment factors.

Results

Climate data analysis

Comparison of hindcast with observed data showed that the maximum air temperature was on average 1^{o}C too low and the minimum air temperature 1.8^{o}C too high. Thus the RCM estimates appear to have too narrow a range between maximum and minimum air temperature (Fig. 2). For precipitation, analysis showed that there were too many days when a rain event occured, mostly made up of small events (<1 mm). For the study site, there were on average

132 observed days per year with no rain in the period 1960-90, whereas the HADRM3 model estimated 50 no rain days. The model also produced annual totals that were too high. The modelled mean annual total was 1036 mm whereas the observed mean annual total was 817 mm. Application of the adjustment factors reduced the difference in no rain days to 4, and a mean annual total difference to 1.4 mm. However, this resulted in a shift in the probability of excedence (Fig. 3), such that rain events in the low to mid-range of magnitude (i.e. 0 – 30 mm) have a more similar probability of occuring. However, there was a reduction in the number and magnitude of large rain events.

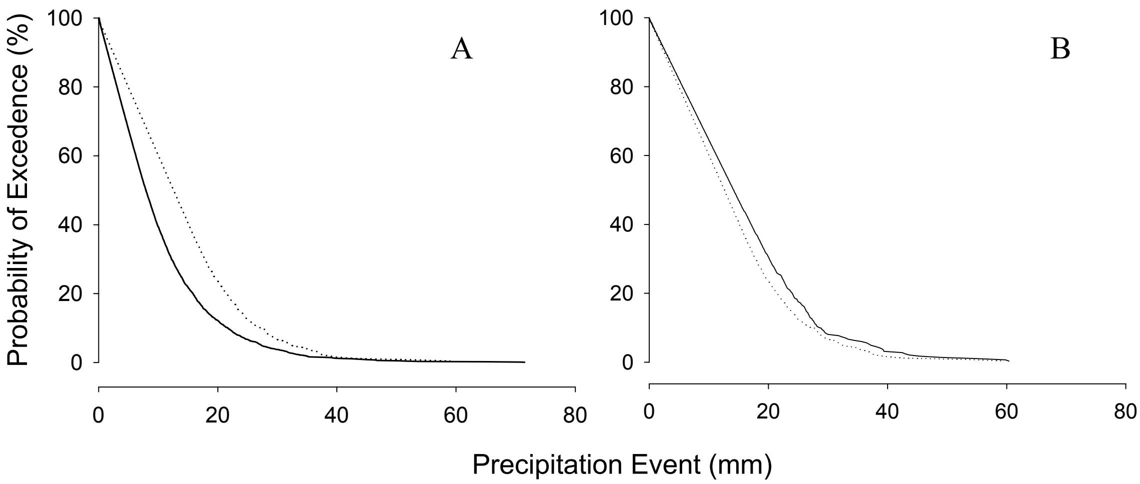

Figure 3. Observed (dotted line) and HADRM3 estimated (solid line) Probability of Excedence for precipitation (mm) for Carnwath, Scotland 1960-90, before (A) and after (B) application of adjustment factors.

Impacts on crop model estimates

The use of the adjusted hindcast data greatly improved the match between spring barley yield estimates derived from observed weather data (Fig. 4). The mean harvest dates (day of year) were: observed data = 250; original hindcast data = 242; adjusted hindcast data = 251. The small difference in harvest date indicates that the larger yield estimates derived from the original hindcast data can be attributed to higher temperatures and precipitation giving higher potential evapotranspiration rates, resulting in more biomass accumulation, which is not moderated by the earleir harvest date (less time to accumulate biomass).

Whilst the use of the adjusted data appear to produce favourable spring barley yield estimates, large differences still occur within a grass silage production system (Fig. 5). This is partially due to the increased evapotranspiration rates accumulating biomass, which in turn means after a silage cut (at a set % removal), there is a larger amount of biomass from which re-growth can occur.

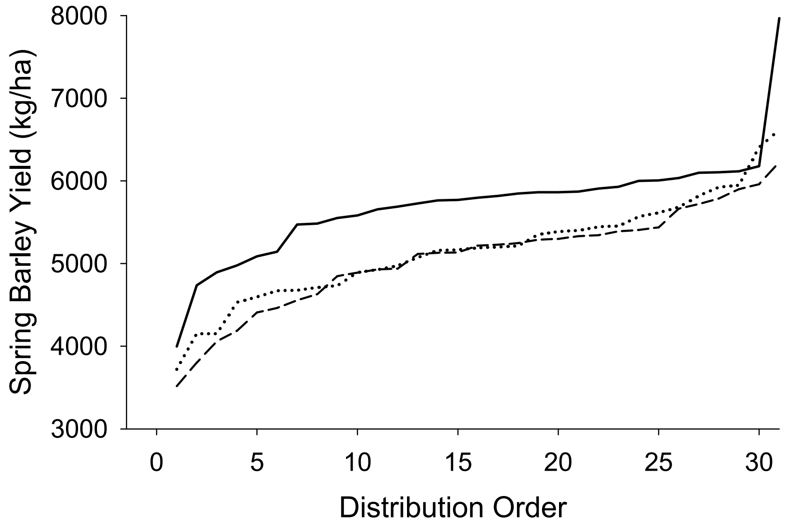

Figure 4. CropSyst estimates of Spring Barely yield (kg/ha), using observed weather (dotted), original hindcast (solid) and adjusted hindcast (dashed) data.

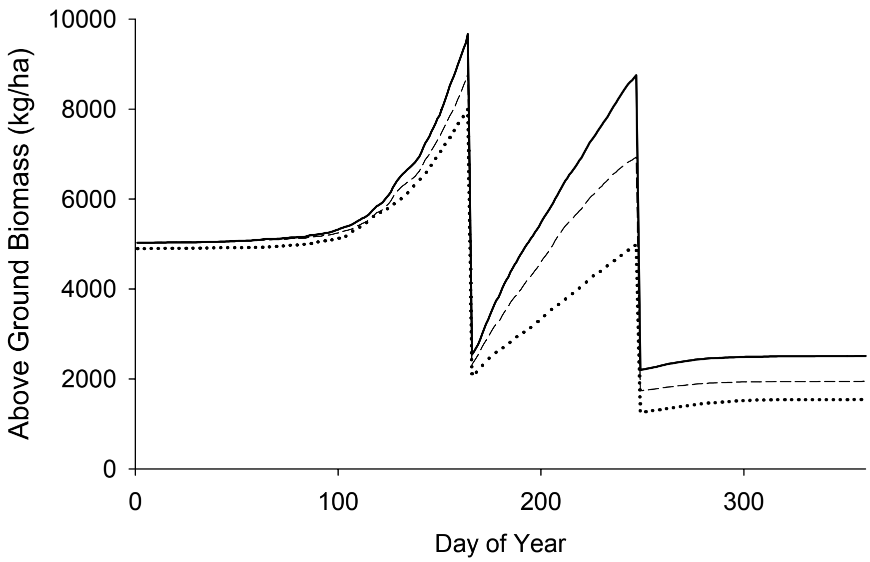

Figure 5. Grass above ground biomass (kg/ha) estimates from CropSyst in a 2-cut silage system using observed weather (dotted), original hindcast (solid) and adjusted hindcast data (dashed).

Discussion

The IA approach described here is able to contribute to our understanding of the impacts of climate change by combining both biophysical and socio-economic considerations. Biophysical impacts cannot be looked at in isolation from other drivers of change and the need to achieve multiple-objectives from land use. The use of simulations models within the IA enables researchers to explorer options for CC mitigation and adaptation for a wide range of possible scenarios. The ability to incorporate novel forms of land use within the IMF permits options for diverse new farming systems to be appraised, not just in terms of their financial viability, but also their ability to acheive CC mitigation and perform environmental functions. However, there are restictive issues concerning how impacts and corresponding mitigation and adaption strategies developed for a specific location can be generalised to larger spatial scales.

Whilst there will always be uncertainty in future climate predictions, this research has demonstrated a need to be able to quantify what errors may be introduced to CC impacts modelling studies. The introduced uncertainty in model estimates demonstrated here will have significant effects within the overall IMF and AI approach. If such errors go undetected, they will be propogated throughout the entire modelling system, increasing the probability that inappropriate adaptation and amelioration strategies may be developed. Using the two examples given here, it can be seen that the magnitude of errors introduced to a spring barley crop are substantially lower than those for a grass system, with such introduced bias making comparisons between the two land use systems infeasible. This can be expanded to livestock systems, which utilise the crops produced on the farm. Use of the HADRM3 hindcast data over-estimates the yield of a second silage cut by c. 2 t/ha. This in turn informs the LSM that more feed is available, hence fewer supplements are required to be bought in. One of the key issues for livestock farms is whether they will have sufficient fodder for over-wintering, as it determines the number of animals they will keep and how much additional fodder has to be bought in. Therefore errors introduced to estimates of primary production (crops and biophysical processes) also distort subsequent estimates of secondary production (livestock), the associated financial and environmental accounting, and ultimately the overall management of the farm.

By demonstrating an awareness of how errors are introduced to primary production models, and their approximate magnitude, it is possible to interpret other model estimates accordingly. The application of the adjustement factors to future climate projection data gives us more confidence in the quality of estimates made by the crop model. The use of the model estimates within the IA can also be assessed as part of the deliberative process, where stakeholders are informed of the quantified errors.

Conclusions

This paper has demonstrated that studies of the implications of climate change at the farm scale, combining biophysical with economic, social and policy considerations, requires a holistic, integrated assessment appraoch. However, where such an approach employs models representing the biophysical processes, an understanding is required of how weather data, when used within the models, can introduce substantial amounts of uncertainty to the range of estimates they produce, i.e. productivity. These errors are then propogated through the overall IA. It is therefore necessary to be able to quantify the introduced uncertainty in order to best utilise the outputs from the IA in order to develop appropriate mitigation and adaptation strategies. The estimation and application of simple adjustment factors to allow site-specific representaion by RCM estimated weather variables greatly improves the quality of crop model estimates. However, errors are still introduced which manifest themselves differently depending on the type of land use modelled. Assessment of these errors can be seen as a vital step in understanding, quantifying and communicating the uncertainty that future projected weather data introduces to CC impacts studies.

Acknowledgements

The authors gratefully acknowledge the funding support of the Scottish Executive Environment and Rural Affairs Department.

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