

Changing Human Landscapes Under a Changing Climate: Considerations for Climate Assessments

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Abstract Climate change is a fundamental aspect of the Anthropocene. Climate assessments are frequently undertaken to evaluate climate change impacts, vulnerability, and adaptive capacity. Assessments are complex endeavors with numerous challenges. Five aspects of a climate assessment that can be particularly challenging are highlighted: choice of assessment strategy, incorporation of spatial linkages and interactions, the constraints of climate observations, interpretation of a climate projection ensemble, uncertainty associated with weather/climate dependency models, and consideration of landscape–climate influences. In addition, a climate assessment strategy that incorporates both traditional “top-down” and “bottom-up” methods is proposed for assessments of adaptation options at the local/regional scale. Uncertainties associated with climate observations and projections and with weather/climate dependency (i.e., response) models are incorporated into the assessment through the “top-down” component, and stakeholder knowledge and experience are included through the “bottom-up” component. Considerable further research is required to improve assessment strategies and the usefulness and usability of assessment findings. In particular, new methods are needed which better incorporate spatial linkages and interactions, yet maintain the fine grain detail needed for decision making at the local and regional scales. Also, new methods

are needed which go beyond sensitivity analyses of the relative contribution of land use and land cover changes on local/regional climate to more explicitly consider landscape–climate interactions in the context of uncertain future climates. Assessment teams must clearly communicate the choices made when designing an assessment and recognize the implications of these choices on the interpretation and application of the assessment findings.

Keywords Climate assessments · Uncertainties · Land use land cover change · Climate change adaptation

Introduction

Landscapes in the Anthropocene, a National Science Foundation-funded workshop held in March 2010, focused on the grand challenge of understanding human–landscape systems during the “Anthropocene,” defined as a possible new geological era dominated by human activity (see Chin and others 2010 for a summary of the workshop). The workshop highlighted the need for improved frameworks and methods to characterize, understand, and project human–landscape interactions.

Climate change is an important facet of the Anthropocene. The effects of climate change on natural processes and human activities are anticipated to substantially alter human–landscape systems. Climate assessments frequently are undertaken to evaluate climate change impacts, vulnerability, and adaptive capacity, although the definition of “assessment” varies among users. For example, the US Global Change Research Program (2013) defines climate assessments as “essential tools for linking science and decision making,” and elaborates that assessments

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“survey, integrate, and synthesize science, within and between scientific disciplines and across sectors and regions.” As defined by the Intergovernmental Panel on Climate Change, however, an assessment is not merely a tool, but rather a framework characterized by multiple approaches that can accommodate a variety of methods to “inform decision-making in an environment of uncertainty” (Carter and others 2007, p. 135).

Our goal is to highlight approaches, challenges, and limitations for investigating the potential influences of climate change on human–landscape systems within the framework of a climate assessment. We focus on several important decision points and challenges for a climate assessment, namely, the choice of assessment strategy, incorporation of spatial linkages and interactions, constraints of climate observations, interpretation of a climate projection ensemble, uncertainty associated with weather/climate dependency models, and consideration of landscape–climate influences. In addition, we present a modified assessment strategy for local/regional climate assessments that have evaluation of adaptation options as their goal and utilize the modified strategy to highlight limitations in this and other assessment strategies. Climate assessments are complex, and a number of different decision points and/or potential challenges could have been emphasized. Those that we elected to highlight have been recurring issues and concerns for the assessments in which we have been participants. We hope that the discussion presented here will help assessment teams address these issues and concerns early in the assessment-planning process and recognize the implications of their choices on the interpretation and application of the assessment output and findings.

We draw on examples from agriculture to illustrate the challenges of climate assessments. Agriculture is a particularly appropriate example as approximately 45 % of the total land area in the USA (USDA Economic Research Service 2012), and 40–50 % of the global land area (Smith and others 2007) is devoted to agriculture (e.g., cropland, grassland pasture, and rangeland). Thus, agriculture is a defining component of the landscape for many areas worldwide. The potential impacts of climate change on agriculture are expected to be substantial and complex (e.g., Easterling and others 2007), and will extend well beyond this sector given agriculture’s contribution to social, economic, and political systems at local-to-global scales, including food supply and security (Hatfield and others 2013). A number of the examples provided in this article focus on the perennial crop subsector, specifically the sour (tart) cherry industry. This industry is particularly sensitive to future changes in the frequency of damaging freeze events following early spring warm spells. For example, in March 2012, the eastern and central USA experienced record-breaking warm temperatures

(NOAA-NCDC 2012). The timing of critical growth stages of perennial vegetation was accelerated because of the warm temperatures, leaving many perennial plants vulnerable to subsequent cold temperatures. The sour cherry industry in the northwestern Lower Peninsula of Michigan experienced an estimated 70–80 % crop loss because of sub-freezing temperatures that occurred after the temperature-sensitive “waterbud” growth stage had been reached (Rothwell personal communication). This crop loss follows a number of recent damaging freeze events, including the catastrophic loss in 2002 of the entire sour cherry crop in the region, which habitually accounts for over 50 % of the USA production of sour cherries (NASS 2010). These recent damaging freeze events have prompted industry leaders to seek assistance in evaluating the historical variability and potential future changes in these events and consequent crop productivity, to better assess the climate-related vulnerability of their industry.

Challenges of Climate Change Assessments

Selection of an Assessment Strategy

An initial decision of a climate assessment lies in the selection of an assessment approach and strategy. Three commonly defined approaches for climate assessments are impact assessments, adaptation assessments, and vulnerability assessments, where an assessment approach is simply “the overall scope and direction of an assessment” (Carter and others 2007, p. 135).

Assessment strategies (i.e., methods) typically vary by approach. Impact assessments often employ a “top-down” strategy, in contrast to adaptation and vulnerability assessments which more often employ a “bottom-up” strategy. An understanding of the potential risks of climate change and the need for adaptation are considered the primary goals of a top-down strategy, whereas an understanding of the processes and actions influencing vulnerability and/or adaptive capacity are the goals of a bottom-up strategy (Carter and others 2007). In general, a top-down strategy treats climate information as an external forcing that influences a system or component of a system (e.g., yield) for a particular location or region over a certain period (Pielke and others 2007b). The typical starting point of a top-down assessment is global-scale climate projections, usually obtained from simulations of global climate models (GCMs) (Carter and others 2007). These projections are usually “downscaled,” using one or more of a multitude of available techniques, to a local and/or regional spatial resolution. The downscaled climate variables serve as input to “weather/climate dependency models” that simulate the response of the activity or system to climate fluctuations.

In contrast, a “bottom-up” strategy begins with an assessment of location-specific thresholds and responses to change (Carter and others 2007; Pielke and others 2007b), or what Brown and Wilby (2012) refer to as a “stress test,” often with extensive stakeholder input. Applications of “bottom-up” approaches differ in terms of their use of climate projections and weather/climate dependency models. For some assessment teams, identification of the vulnerability or hazard is the final assessment outcome, whereas others employ climate projections (either derived from GCMs or stochastically generated scenarios) fed into dependency models to further evaluate climate risk (e.g., Prudhomme and others 2010).

A majority of climate assessments have employed top-down strategies (Carter and others 2007), although recently several authors have advocated for the increased use of bottom-up strategies (e.g., Brown and Wilby 2012; Pielke and Wilby 2012). Proponents of bottom-up approaches argue that these strategies are more appropriate than top-down approaches, as the former are not as dependent on highly uncertain climate projections that often either ignore or incompletely represent important factors contributing to a perturbed climate such as land cover change (e.g., Pielke and others 2007a; Pielke and Wilby 2012) and instead more heavily rely on stakeholder input. However, arguments also can be made for the efficacy of top-down approaches. For example, potential “surprises” that fall outside stakeholder experience often are better illuminated with top-down strategies that start first with climate projections and then evaluate sensitivity to the projected changes.

Top-down and bottom-up strategies are, in our opinion, complementary rather than competing methods, and distinctions between the two strategies often are blurred. Both strategies frequently share component models (e.g., weather/climate dependency models). In addition, stakeholder input cannot be considered the purview of only bottom-up strategies. Rather, stakeholders often are extensively engaged in top-down strategies as well, especially in the selection, development, and modification of weather/climate dependency models, or in the definition of climate parameters for which climate projections are prepared. Whatever the choice of assessment approach, this decision point in a climate assessment has implications for data needs, including climate observations and projections; model development, modification and/or application; the nature and extent of stakeholder involvement; and the constraints when utilizing the assessment outputs and findings in decision making.

Incorporating Spatial Linkages and Interactions

Most applications of traditional top-down and bottom-up assessment strategies focus on a single location or a

modest-sized region. While the fine spatial resolution is often considered to be a strength of these assessments, the small spatial extent can be a limitation. For example, an agricultural commodity is produced at many locations worldwide, which are likely to be differentially impacted by climate variability and change. Consequently, relative changes in the productivity of one region in comparison with other production regions have implications for the viability of the agricultural activity at a particular location, as the worldwide supply (along with demand) of a commodity influences profitability for individual growing regions. The sour cherry industry illustrates stakeholder interest in spatial variations in climate risk. Before 2002, the USA imported only a small portion of domestic sour cherry consumption (Aguilar 2006). The unprecedented damaging freeze event in spring 2002 (Winkler and others 2012a) opened the door to imports from Europe to sustain market supply and stabilize price (Thornsbury and Woods 2005). Imports were primarily from Poland, where sour cherry production has been rapidly expanding. In listening sessions as part of the Pileus Project, an assessment effort to develop climate change decision support tools for the Michigan sour cherry industry (see Zavalloni and others 2006; Winkler and others 2012b; <http://pileus.msu.edu/> for more information), growers in Michigan emphasized that a climate assessment for their industry required that the potential impacts of climate change on the Polish industry (now considered a major competitor) also be considered. Furthermore, similar listening sessions in Poland as part of the follow-up Climate and International Markets (CLIMARKS) Project (see <http://cherry.cse.msu.edu/>) revealed that Polish cherry growers are concerned about new production regions in Europe and elsewhere, especially those that do not have as large a current or projected risk of damaging freeze events.

One option for expanding the spatial extent of assessments is to employ global-scale integrated assessment models (e.g., van Asselt and Rotmans 2002) that allow for feedbacks across regions. However, outputs from these models often do not have the fine-scale spatial, temporal, and sub-sectoral resolution needed to assist stakeholders with industry- and location-specific decision making. Also, current integrated assessment models are not fully integrative across all aspects of a system and have relatively simple characterizations for some, if not all, of the system components. Recently, Winkler and others (2010) proposed an expanded top-down strategy for climate assessments of international market systems, such as agricultural subsectors, whereby detailed evaluations of productivity for multiple locations are integrated through international trade. A goal of the expanded strategy is to preserve the granularity in assessment outcomes that is needed for decision making at the local, or even individual, level

while incorporating spatial interactions. This strategy has not yet been fully implemented and evaluated, and, furthermore, application to other human–landscape systems requires replacing international trade as the integration mechanism with a mechanism appropriate to the system being studied. The incorporation of important spatial linkages and interactions in a climate assessment remains a challenge.

Constraints Imposed by Availability and Limitations of Climate Observations

Climate observations are, in many ways, the “backbone” of a climate assessment. They are used for model development and evaluation, as input to many of the assessment components, for detection of historical trends and fluctuations, and as a reference for comparing potential future conditions. While, at first glance, climate observations may appear to be abundant, the availability and quality of historical climate information is an impediment to many, if not most, climate assessments. The distribution of climate stations is highly uneven in space, with generally fewer observations over less populated areas. Furthermore, the density of observations varies by climate variable. For example, in the USA, the Cooperative Observer Program (COOP), with approximately 10,000 stations, records only temperature and precipitation, whereas humidity and wind, the two variables used in the estimation of evapotranspiration, are recorded at airport locations within the sparser Automated Surface Observing System network. As an extreme example, daily solar radiation, which is an essential variable of many climate assessments for agriculture, is regularly measured by only the 114 stations of the Climate Reference Network, most of which are located outside of primary agricultural regions and have a short period of record (Leduc and others 2009).

Time-dependent biases also complicate the use of climate observations in assessments. These biases are introduced by changes in time of observation, station moves, instrumentation changes, and changes in the surrounding environment (Winkler 2004). Adjustments for several time-dependent biases have been proposed (e.g., Peterson and others 1998), although adjusted series need to be interpreted cautiously. For example, temporal trends calculated from adjusted observations can vary substantially from those calculated from unadjusted observations (Balling and Idso 2002). In addition, missing observations are common, and efforts to “fill in” missing values with values from neighboring stations (e.g., Pielke and others 2002), mean values (e.g., Nonhebel 1994), or stochastically generated values (e.g., Luo and others 2009; Meza and Silva 2009) can introduce inhomogeneities in the time series. Datasets with adjustments for time-dependent biases,

missing values, and other inhomogeneities exist, but these datasets tend to have more limited spatial coverage as seen in Fig. 1. The first map in Fig. 1 displays the location of COOP stations across the Upper Great Lakes region (Minnesota, Wisconsin, and Michigan), whereas the COOP stations that have been judged of sufficient quality to be included in the United States Historical Climate Network (USHCN) are shown in the second map. USHCN stations were selected based on length of period of record, percent missing data, number of station moves, and spatial coverage (Menne and others 2009). The change in station density between the two maps is marked with large regional gaps in USHCN coverage.

To overcome some of the limitations described above, a number of gridded historical climate datasets have been developed, primarily for temperature and precipitation (see Winkler and others 2011a for a listing and description of widely used gridded datasets). In general, these datasets are developed either by averaging station values within a grid cell (e.g., Peterson and Vose 1997) or by spatial interpolation (often with consideration of topography) of station observations to a regular grid (e.g., Daly and others 2002; Hijmans and others 2005). Although the gridded datasets provide more uniform coverage and are not as highly impacted by missing observations, they suffer from similar time-dependent biases as the original station observations (Guentchev and others 2010). Also, the often fine resolution of gridded datasets can provide an appearance of realism that is not consistent with the initial observations (Daly 2006); or, in other words, a gridded dataset can be

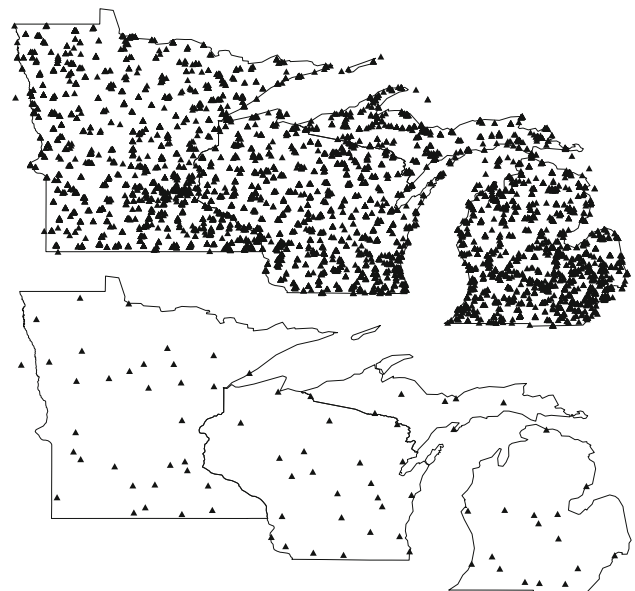


Fig. 1 Spatial distribution of climate stations in the COOP (*above*) and the USHCN (*below*) networks in the Upper Great Lakes region of the USA

mistakenly interpreted as conveying more information than what exists in the underlying observed data. Another source of gridded climate information for retrospective analyses and model evaluations is “reanalysis” datasets that blend output from atmospheric models with observations and satellite measurements. Although extremely useful, reanalysis fields also suffer from inhomogeneities because of changes in data volumes and biases introduced by error in the underlying atmospheric model (see Winkler and others 2011a for a listing and description of common reanalysis datasets).

The limitations of climate observations are well illustrated with our example agricultural commodity, sour cherry production in the northwestern Lower Peninsula of Michigan. Cherry orchards are located on hill slopes and hilltops, whereas most COOP stations are located at lower elevations and consequently are colder than orchard locations. Furthermore, this production area falls within a noticeable gap in the USHCN coverage (Fig. 1), indicating a lack of high-quality COOP stations with long-term records. Also, our experience with gridded datasets for the region indicates that known biases at individual stations are reflected in the gridded fields. Consequently, it is difficult to provide, with a high level of confidence, the information on historical variations in springtime warm spells and damaging freezing temperatures that sour cherry growers need for risk and vulnerability assessment.

Another issue surrounding climate observations is that the limitations of a climate dataset may violate underlying assumptions of models, particularly empirical models, employed within the assessment and/or for decision making. While developers of climate datasets have been pressed to consider not only the “usefulness” of climate information but also its “usability” for decision making (see Lemos and others 2012 for a review), much less attention has been placed on the responsibility of users (including stakeholders) of climate datasets to recognize the limitations of these datasets in the context of their application. Auffhammer and others (2013) provide an initial effort, highlighting potential pitfalls when gridded climate observations are used as explanatory variables in the development of econometric models. They point to the possibility that spatial averaging, the correlation among climate variables, spatial correlation introduced by interpolation algorithms, and temporal breakpoints in time series violate the assumptions of econometric models. Similar concerns are relevant for other applications as well and need to be addressed by an assessment team and/or stakeholders.

Interpretation of Climate Projection Ensembles

Climate projections frequently are an integral part of a climate assessment, especially for traditional top-down

assessments. A challenging aspect of the use of climate projections is the development and interpretation of a climate projection ensemble.

Most often climate projections are derived from output from GCM simulations. Usually simulations from different modeling groups that are driven with varying greenhouse gas (GHG) concentrations are used in an assessment. Assessments infrequently have included multiple simulations from the same GCM, where selected physical parameterizations are perturbed or where initial conditions are slightly modified. However, a recent analysis by Harding and others (2012) found that “within-GCM” ensembles can vary as much as “between-GCM” ensembles, suggesting that this contribution to the uncertainty surrounding climate projections and scenarios also needs to be included in an assessment.

Another source of uncertainty is the downscaling and debiasing procedures used to infer a finer spatial resolution or to account for error in the GCM simulations. Often downscaling and debiasing are performed simultaneously (e.g., Maurer and others 2007), although debiasing also can be a post-processing step (e.g., Themeßl and others 2011). Downscaling often is classified as dynamic or empirical, although alternative classifications have been proposed (see Winkler and others 2011b for a review). Dynamic downscaling involves the use of numerical models, such as regional climate models (RCMs) driven by coarse-scale GCM output, to simulate climate fields with a relatively fine spatial resolution, whereas empirical downscaling encompasses a large variety of statistical approaches to deriving fine-resolution climate scenarios.

Ideally, a climate assessment would employ a sufficient number of climate projections such that the relative uncertainty introduced by the choice of GHG concentrations, GCM models, GCM parameterizations and initial conditions, and downscaling and debiasing methods can be evaluated and compared. This is generally not the case, however. Although most assessments employ simulations from multiple GCMs, Harding and others (2012) point out that some climate assessments continue to rely on a single GCM simulation, particularly those that employ time-intensive dynamic downscaling. They argue that these assessments are “unacceptably influenced” by the choice of GCM simulation. Furthermore, most assessments employ a single downscaling method, thus ignoring this aspect of the uncertainty surrounding climate projections.

Even when a large suite of climate projections is available, interpreting the ensemble is challenging. Most often, an ensemble of climate projections is considered to provide a lower bound for the maximum range of uncertainty (Stainforth and others 2007). In part, the rationale for this interpretation is that a particular suite of projections represents an “ensemble of opportunity” that is limited by

existing available climate models (Tebaldi and Knutti 2007), and, we would add, limited by existing downscaling and debiasing procedures. Adding an additional projection to an ensemble may not provide an improved estimate of the overall uncertainty if the errors associated with the GCM model and downscaling procedure used to develop the projection are similar to those of projections already included in the ensemble. Also, the degree to which consensus among projections can be interpreted as increased confidence in a future change is unclear (Parker 2013). Therefore, although multiple climate projections must be considered, cautious interpretation of the ensemble is necessary.

Uncertainty Surrounding Weather/Climate Dependency Models

Weather/climate dependency models simulate the responses of a system to climate fluctuations. Although sometimes referred to as “response models” or “impact models,” we prefer the “weather/climate dependency model” nomenclature as it more clearly indicates that climate observations are the key input variables, and that these models translate climate information into management-related variables (e.g., crop yield). In a top-down strategy, weather/climate dependency models often are part of a sequentially linked (feed forward) series of models, where climate observations/projections are fed into the weather/climate dependency models and the output of these are models is in turn fed to “downstream” models such as decision making models and policy frameworks. In a bottom-up strategy, weather/climate dependency models are often used to help one evaluate the sensitivity of a system to change.

The structure of weather/climate dependency models can vary widely. Again using agriculture as an example, both empirical and process-based weather/climate dependency models are frequently employed in climate assessments. Each model type has its specific strengths and weaknesses, and substantial differences in the simulated output (e.g., yield) are expected. Empirical models are developed based on statistical relationships between climate variables and crop parameters such as crop yield (e.g., Chen and others 2004; Isik and Devadoss 2006; Schlenker and Roberts 2009). These models can be expanded by including other variables such as economic determinants to investigate the joint influence of climate and nonclimate variables (e.g., Vera-Diaz and others 2008). Critical drawbacks of empirical models are that the statistical relationships are specific for a particular location or region and may not be stable with time (Yin and Struik 2010). In addition, the models are often developed using aggregated climate data such as monthly means of precipitation and

temperature which may not be adequate to capture the impacts of extreme weather events, such as damaging spring freezes, on crop growth and development (Challinor and Wheeler 2008). Empirical models also have limited ability to explain plant responses to climate exposures (Challinor and others 2009a), as nonlinear relationships between environmental conditions and crops are often simplified (Soussana and others 2010).

On the other hand, process models, such as the crop models employed in the Decision Support System for Agrotechnology Transfer (Jones and others 2003) or Agricultural Production Systems Simulator (Keating and others 2003), simulate growth, development, and yield of a crop along with temporal changes during the cropping period of soil water, carbon, and nitrogen. Process models conceptually offer an advantage in climate assessments as they can be applied to a wide range of environmental (including climate) conditions and farm management practices (Meinke and others 2001; Hoogenboom and others 2004). However, current process crop models either omit or poorly simulate the effects of agricultural limiting factors such as weed, pest, and disease infestation on crop growth and development (Soussana and others 2010). This is a concern as climate variability and change can be expected to change the intensity and frequency of pest and disease infestations (Diffenbaugh and others 2008; Luck and others 2011). Other concerns include the failure of current process models to adequately simulate the effects of carbon dioxide fluctuations (DaMatta and others 2010) and the implicit rather than explicit consideration of economic determinants (e.g., fertilizer and irrigation costs) (Vera-Diaz and others 2008). In addition, these models have large data requirements, and data availability varies regionally. Furthermore, process crop models do not currently exist for all agricultural commodities. For example, the availability of biophysical models for perennial crops such as sour cherries is limited.

Differences in the structure of weather/climate dependency models have only recently been recognized as an important source of uncertainty for climate assessments. This is in spite of the considerable interest by stakeholders in the model outputs, which often are viewed as more relevant for management and decision making than climate observations and projections alone (Tribbia and Moser 2008; Prudhomme and others 2010). A nonagricultural example of the uncertainty introduced into assessments by the structure of weather/climate dependency models is the influence of the choice of hydrological model on projections of lake levels for the North American Great Lakes. Smaller drops in lake levels are projected when evapotranspiration is directly estimated using an energy budget approach (Lofgren and others 2011) compared with the case when air temperature is used as a proxy for estimating

evapotranspiration (Croley 2003). One of the most comprehensive attempts to estimate the uncertainty introduced by the structure of weather/climate dependency models is provided by Buisson and others (2010) who were concerned with the potential impacts of climate change on French stream fish species and assemblages. Using a top-down approach and a factorial design, climate projections from three GCMs with four GHG emissions scenarios were fed into empirical weather/climate dependency models (i.e., species distribution models) developed using seven different statistical techniques, each of which was built using 100 randomly selected subsets from observed climate and environmental variables. Based on the over 8,000 future projections of fish species/assemblages, the structure of the species distribution models was found to contribute the most to the variation in the future projections. For agriculture, the choice of crop model has long been known to have a large impact on yield estimates (e.g., Toure and others 1995; Mearns and others 1999), and currently is being investigated in a climate change context as part of the Agriculture Model Intercomparison and Improvement Project (AgMIP; http://www.agmip.org/?page_id=1064). Recent findings of AgMIP indicate that simulated climate change impacts on wheat yield vary across the available wheat process models because of differences in model structures and parameter values, and that, similar to the findings of Buisson and others (2010), a greater proportion of the uncertainty in yield projections is due to the differences between crop models than the differences between downscaled climate projections (Asseng and others 2013).

In sum, the three examples summarized above for lake levels, species assemblages, and crop yield point to the necessity of considering the uncertainty introduced by the structure of weather/climate dependency models in a climate assessment. The inclusion of multiple weather/climate dependency models with differing structures needs to become a standard practice in assessment studies, similar to the inclusion of multiple climate projections.

Landscape–Climate Interactions

Landscape–climate interactions also complicate climate assessments. Land use and land cover change (LULCC) arising from human activities can influence climate, and, in turn, climate change can influence LULCC. LULCC contributes to climate change through biogeochemical and biogeophysical feedbacks with the climate system (Pielke and others 2011), although biogeophysical effects are believed to have the largest influences (Forster and others 2007; Pielke and others 2011). Biogeochemical feedbacks refer to changes in GHG composition and concentrations, either directly through human activity associated with land utilization (e.g., nitrous oxide emitted to the atmosphere

from fertilizer use) or through land conversion (e.g., carbon dioxide release as a result of deforestation) (Fig. 2). On the other hand, biogeophysical feedbacks refer to changes in albedo, surface roughness, evaporation/transpiration, and other physical properties resulting from LULCC (Skinner and Majorowicz 1999; Pielke and others 2007a). Both biogeochemical and biogeophysical changes influence global-scale climate processes and systems, which in turn can impact regional climate. In addition, landscape changes can directly influence mesoscale atmospheric processes and circulations, and hence local and regional climates, provided that the areal coverage of the LULCC changes is sufficiently large that changes in surface heat flux are not entirely compensated for by changes in convection and/or local airflow (Pielke and others 2011).

The magnitude and direction of LULCC contributions to climate change remain highly uncertain. At the global scale, LULCC changes (primarily deforestation) since 1750 are estimated to have had a negative radiative forcing. This global estimate of LULCC impact likely masks regional variations. In general, deforestation is believed to have contributed to warming at low latitudes because of changes in the partition of latent and sensible heat fluxes and to cooling at mid- and high-latitudes because of increased surface albedo and enhanced snow–albedo feedbacks (Pitman and others 2011). Atmospheric teleconnections between areas with substantial LULCC changes and remote areas could enhance the global impact of a regional change, but have not yet been conclusively demonstrated (Pielke and others 2011).

The relative contribution of LULCC in conjunction with other radiative forcing factors (e.g., enhanced GHG concentrations) is even more uncertain. As cogently stated by Pielke and others (2011, pp. 841–842), “the magnitude of

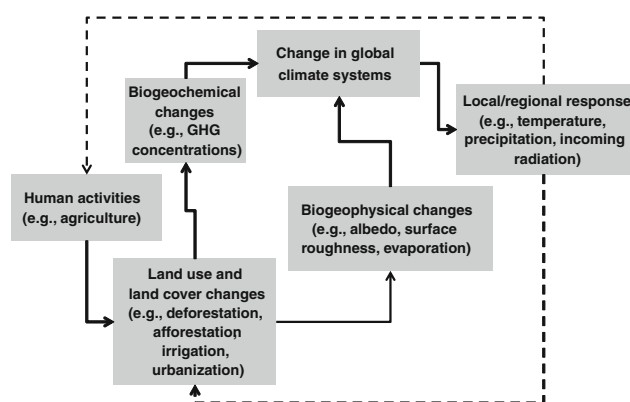


Fig. 2 Illustration of the interactions between land use and land cover change (LULCC) and global and local/regional climate. Thin, solid lines represent the contribution of human activities through LULCC to regional/local climate, whereas dashed lines represent the interactions where regional/local climate can influence human activities and LULCC

used to illustrate the distribution of ensemble outcomes (e.g., Schmidhuber and Tubiello 2007; Carter and others 2007; CCSP 2009), although, as noted above, these representations must be interpreted cautiously as ensemble members should not be considered independent of one another (Knutti 2010). Local knowledge and experience can be incorporated into the proposed strategy through interviews, surveys, or discussions with stakeholders (Salter and others 2010). Adaptation to varying climate conditions is not a new paradigm for farmers or other stakeholders (Adams and others 1998; Smit and Skinner 2002; Panel on Adapting to the Impacts of Climate Change National Research Council 2010; Reidsma and others 2010); thus, it is essential to incorporate this local knowledge in a climate assessment.

The lower portion of the diagram represents components of the assessment that are informed by both top-down and bottom-up approaches. Potential conflicts (i.e., negative externalities) of a selected adaptation option must be considered in the decision-making process. As pointed out by Hallegatte (2009), implementation of an adaptation option may benefit a particular sector but have marginal effects on other sectors due to potential negative externalities. For example, irrigation as an adaptation option may contribute to enhanced crop production but increased demand for irrigation water may threaten water supplies for human consumption and industrial needs. High economic costs for a particular adaptation option can also be considered a negative externality in this context, as farmers may not have adequate resources to implement the adaptation option and/or may require government support to implement. Acceptable externalities are those options that are considered to have a smaller negative impact (or even a positive impact) on other sectors, contributing to the plausibility of the adaptation option. Unacceptable externalities lead to the adaptation option no longer being considered as plausible, and alternative options need to be considered. Local knowledge and experience is essential for this evaluation.

There are two limitations of the proposed assessment strategy that need to be addressed in the context of the assessment challenges raised above. The first is the local/regional focus and the consequent lack of consideration of the potential influence of climate change impacts and adaptation decisions from outside of the assessment region, or what was referred to earlier as spatial linkages and interactions. To some extent, this can be overcome by applying the proposed strategy to perform local/regional climate assessments at other relevant locations (e.g., other production areas) and linking the individual assessments through an appropriate mechanism (e.g., international trade), although identifying such a mechanism can be challenging. The second limitation is the lack of explicit interactions between human-induced and climate-

influenced LULCC, although the proposed strategy provides an outline for a sensitivity analysis of LULCC and climate. LULCC scenarios developed based on local knowledge and experience can be used to modify local/regional climate projections and/or incorporated into weather/climate dependency models. The two limitations highlighted here are not unique to the proposed strategy but represent weaknesses of current assessment strategies in general. These limitations also reflect what we consider to be two major research questions regarding assessment strategies, which must be addressed to make assessment outcomes more useful in decision making: (1) how can local/regional climate assessments incorporate spatial linkages and interactions yet maintain the spatial, temporal and sub-sectoral detail needed for decision making by industry stakeholders? and (2) how can the complex interrelationships between LULCC, human activities, and climate be introduced into an assessment such that the uncertainty surrounding the future background climate is also considered?

Summary

Climate change is an important component of the Anthropocene, and future human–landscape interactions are likely to be profoundly influenced by climate change. As noted in the *Landscapes in the Anthropocene* workshop report, new and modified frameworks are, and will be, needed to characterize, understand, and project human–landscape interactions. Climate assessments are the primary framework that has been employed to evaluate climate risk, vulnerability, and adaptive capacity. These are extremely challenging endeavors and are complicated by the numerous interactions within human–landscape systems. We highlighted in this article several challenges that in our experience have been particularly problematic when designing and conducting climate assessments and which many assessment teams may not be sufficiently aware. These include the choice of assessment strategy, incorporation of spatial linkages and interactions, the constraints of climate observations, interpretation of a climate projection ensemble, uncertainty associated with weather/climate dependency models, and consideration of landscape–climate influences in the context of uncertain future background climates. Hopefully, this review will help assessment teams to address these challenges early in the assessment-planning process and to recognize the implications of their choices on the interpretation and application of the assessment findings.

In addition, we presented a modified assessment strategy for local/regional climate assessments that combines traditional top-down and bottom-up methods. The underlying

premise is that top-down and bottom-up approaches are complimentary rather than competing methods, and that an assessment can benefit from the strengths of, and insights gleaned from, both methods. A number of the assessment challenges are considered in the modified assessment strategy such as consideration of the influence of the structure of weather/climate dependency models (also referred to as response models) on the output and findings of an assessment. Nonetheless, several limitations remain. The proposed assessment does not easily incorporate relevant spatial linkages and interactions between the regions for which the assessment is conducted and other locations worldwide, and further work is needed to develop assessment strategies that have the fine grain resolution needed for local/regional decision making but also contain the spatial interactions that improve the usefulness/usability of the assessment output and findings. Also, the proposed strategy does not sufficiently capture the many and extremely complex landscape–climate interactions, especially under an uncertain background climate, although it does provide a guideline for the needed sensitivity analyses of the potential influences of LULCC scenarios on local/regional climate. Both these limitations also are limitations of more traditional assessment approaches and represent areas within climate change science that require substantial additional attention.

An assessment team faces a number of “decision points” when designing and conducting a climate assessment. Resources often constrain the decisions that are made, including the choice of assessment strategy. Consequently, assessment teams must interpret their output and findings within the restrictions imposed by the choices and assumptions that were made. Acknowledgment of these constraints must be front and center of any application and reporting of assessment findings, and there is a great need for the thoughtful integration of the output and findings from assessments employing different strategies and assumptions to better anticipate the potential consequences of climate change.

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