Climate Modeling for Decision-Makers and Stakeholders in Alaska

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Alaska's statewide annual average temperature has increased by 3.4°F since the mid-20th century, and the increase is much greater (6.3°F) in winter. The higher temperatures of the recent decades have been associated with an earlier smowmelt in spring, a reduction of summer sea ice coverage, a retreat of many glaciers, and a warming of permafrost. These surface changes, as well as their associated climate drivers, have two characteristics that require advances in modeling if projections of change are to meet the needs of decision-makers and planners. First, feedbacks between ice, snow and the atmosphere exert potentially strong leverage on high-latitude climate change, and these feedbacks introduce large uncertainties into simulations by existing climate models. For example, the recent retreat of summer sea ice is occurring at a faster rate than projected by any of the models in the recent Fourth Assessment (2007) of the Intergovernmental Panel on Climate Change (Stroeve et al., 2007). There are also indications that feedbacks may already be occurring between the earlier spring snowmelt and the surface energy budget, resulting in an increase of vegetative greenness (photosynthetic activity) in parts of Alaska (Euskirchen et al., 2007). Second, the surface changes are highly variable over small spatial scales, largely as a result of complex topography and coastal configurations around the region. The figure below illustrates the fine resolution required to capture the spatial variations in Alaskan climate.

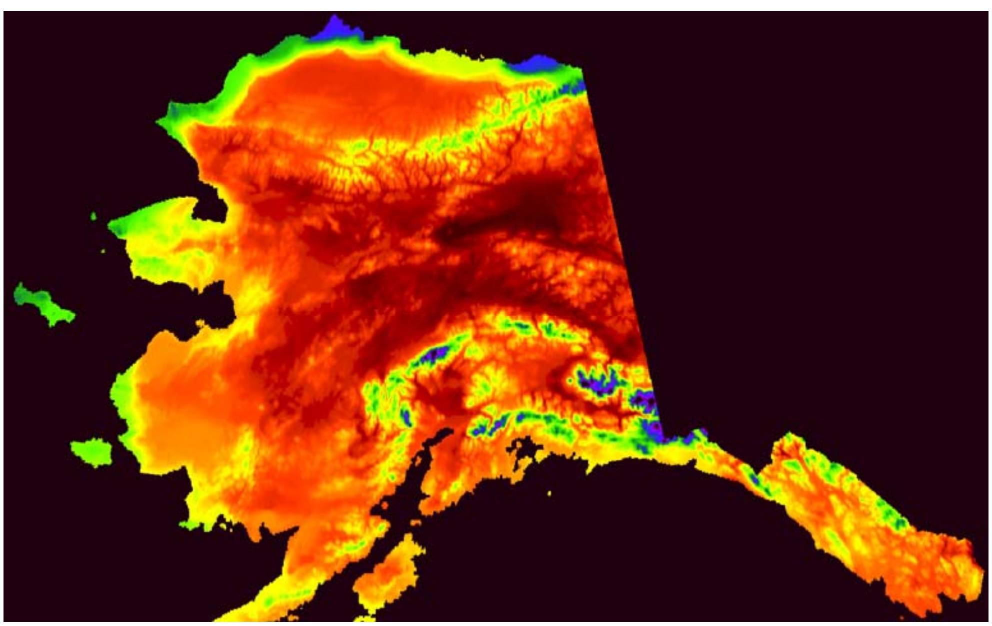

Figure 1. Average July daily high temperatures in Alaska for 1961-1990. Color ranges are 40-45°F (blue), 45-50°F (green), 50-55°F (yellow), 55-65°F (orange), and 65-75°F (darker red). Image is from the PRISM database (Daly et. al., 2008).

In contrast to the 2 km resolution in figure above, the grid cell dimensions (spatial resolution) of global climate models are typically 100-200 km. Figure 2 below shows the smoothness of projected temperature changes obtained from the global models for Alaska. The mis-match of scales is even greater for precipitation, which is a variable that is of great interest to users of climate information pertaining to water supplies, inland transportation, forestry, and terrestrial ecology.

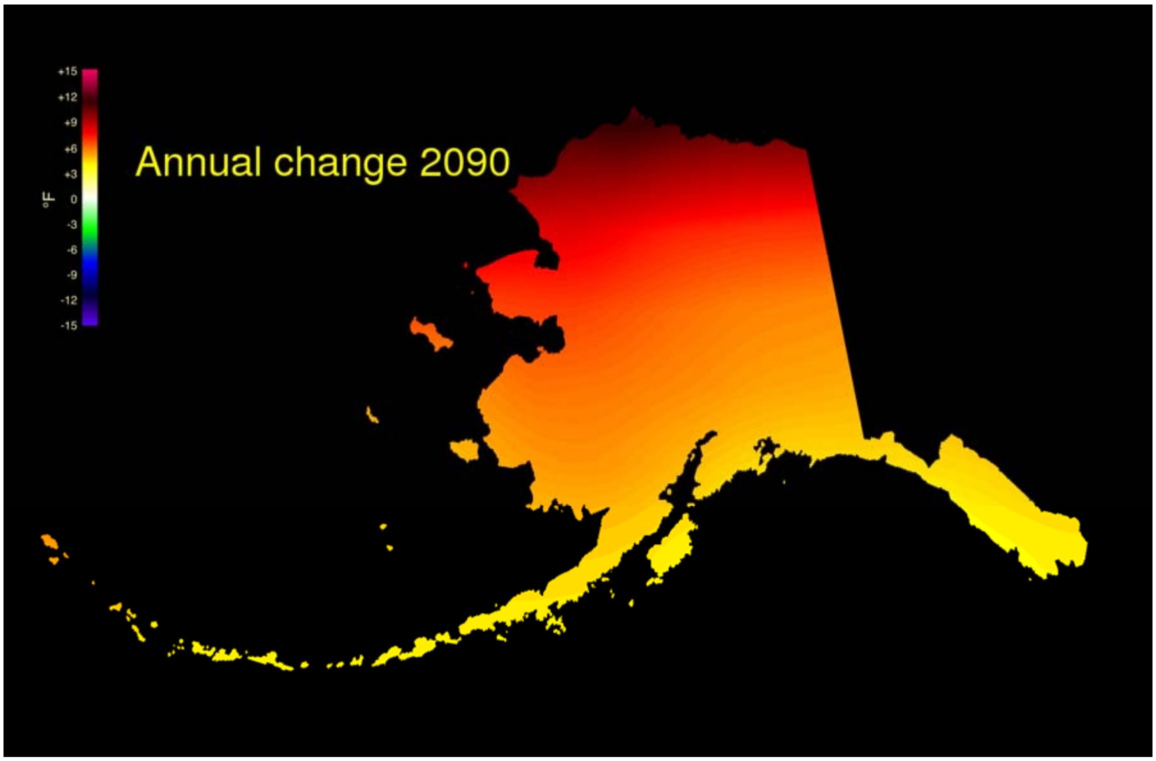

Figure 2. Projected changes of annual mean temperature (°F) over Alaska for the late 21st century (2090), based on the B1 simulations by the models used in the IPCC's (2007) Fourth Assessment. Yellow denotes a warming of 3-5°F, deep red a warming of 8-10°F.

How can the utility of climate projections be made more useful to decision-makers and stakeholders in Alaska? Based on the experience of the Alaska Center for Climate Assessment and Prediction (a NOAA Regional Integrated Sciences and Assessment Center), the greatest needs are (1) downscaling of the coarse-resolution model output, (2) reduction of the uncertainty inherent in the model-derived projections, and (3) tailoring of model output to include variables and information more directly relevant to the needs of planners and stakeholders. In the remainder of this testimony, we address these needs and approaches to meeting these needs.

The mis-match of scales between Figures 1 and 2 can be addressed by two types of downscaling: dynamical and statistical. Dynamical downscaling consists of the nesting of a high-resolution regional model inside a coarser-resolution global model. This approach has been tested in various regions of the world, and its effectiveness is highly dependent on the validity of the input supplied at the lateral boundaries by the global model. For Alaska, the approach is being applied to simulations of the mass balance of glaciers in southeastern Alaska. The nesting of finer grids inside coarse grids achieves 1 km resolution over the glaciers. Applications to other surface features (e.g., permafrost, ecosystem changes) are being developed. The second approach to downscaling is statistical in its nature. In this case, statistical algorithms (e.g., multiple regression equations) are developed to relate model-computed quantities and observational data for which sufficiently long records exist. The predictors can be either pre-selected or screened. This approach, which generally requires *a priori* knowledge of a system's behavior in order to select candidate predictors, has been used successfully in weather prediction, where the term "Model Output Statistics (MOS)" describes the products.. The predictor fields can be model counterparts of the desired quantity (i.e., a model's grid-cell temperature can be used as a predictor of temperature at a specific location, e.g., a weather station), or the predictors can include other model variables such as wind, humidity and cloud cover from the target location's grid cell and/or from upstream grid cells. This approach has significant potential to meet user needs for site-specific scenario information, but it has not been applied extensively in Alaska.

The reduction of the uncertainty in climate projections from global models is essential for the validity of applications such as downscaling, whether dynamical or statistical. While global models are improving over time (Reichler and Kim, 2008), a promising area for advancement is the selection of subsets of models that are most credible for the application at hand. In the case of Alaskan climate simulations, several global climate models used in the IPCC Fourth Assessment capture the present climate (including its seasonal cycle) more successfully than other models. Preliminary studies indicate that a composite over a subset of the best 5-7 models (out of the total of 20-25 available models) provides the greatest skill in simulations of Alaska, the Arctic and the Northern Hemisphere. These models tend to project larger changes of temperature and precipitation over Alaska for the remainder of the 21^{st} century. In this respect, selection of models based on quantitative metrics of performance can reduce the uncertainty of future climate projections. Such activity should be a high priority for user services provided by the climate modeling community.

A high priority in climate research is the tailoring of model output to include variables and information most relevant to the needs of planners and stakeholders. The variables carried by climate models are not always the ones that correspond to user needs, which can include (for example) the firmness of the ground for overland transportation; snow cover characteristics; vegetative dryness during fire season, etc. A recent illustration of such needs is the attempt by P. Larsen (Nature Conservancy) to estimate the economic risks to public infrastructure in Alaska as a result of climate change in the coming decades. While global model uncertainties limit the robustness of such estimates, an even greater limitation is the availability of variables beyond temperature and precipitation. Infrastructure such as roads and buildings will clearly be affected by changes freeze-thaw cycles, snow loads, temperature extremes, peak-wind events and occurrences of flooding. There has been little effort to translate model output for Alaska into these quantities that are most relevant to infrastructure risks as well as to other concerns of users. The bridging of models and user needs is an emerging area of activity, and it is intertwined with the need for site-specific (downscaled) climate projections and for reduced uncertainty in climate model output.

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