UC Davis
San Francisco Estuary and Watershed Science

Title

From Climate-change Spaghetti to Climate-change Distributions for 21st-Century California

Permalink

https://escholarship.org/uc/item/2pg6c039

Journal

San Francisco Estuary and Watershed Science, 3(1)

Author

Dettinger, Michael D.

Publication Date

2005

DOI

https://10.15447/sfews.2005v3iss1art6

Copyright Information

Peer reviewed

From Climate-Change Spaghetti to Climate-Change Distributions for 21st Century California

Michael D. Dettinger
U.S. Geological Survey
mddettin@usgs.gov

ABSTRACT

The uncertainties associated with climate-change projections for California are unlikely to disappear any time soon, and yet important long-term decisions will be needed to accommodate those potential changes. Projection uncertainties have typically been addressed by analysis of a few scenarios, chosen based on availability or to capture the extreme cases among available projections. However, by focusing on more common projections rather than the most extreme projections (using a new resampling method), new insights into current projections emerge: (1) uncertainties associated with future greenhouse-gas emissions are comparable with the differences among climate models, so that neither source of uncertainties should be neglected or underrepresented; (2) twenty-first century temperature projections spread more, overall, than do precipitation scenarios; (3) projections of extremely wet futures for California are true outliers among current projections; and (4) current projections that are warmest tend, overall, to yield a moderately drier California, while the cooler projections yield a somewhat wetter future. The resampling approach applied in this paper also provides a natural opportunity to objectively incorporate measures of model skill and the likelihoods of various emission scenarios into future assessments.

KEYWORDS

California, climate change, temperature, precipitation, streamflow, statistical methods

INTRODUCTION

Projections of climate change due to increasing green-house-gas concentrations in the 21st Century are inevitably uncertain because of the chaotic nature of the global climate system, because of model imperfections, and because of uncertainties regarding what path mankind's emissions of greenhouse gases and other atmospheric contaminants will follow in the future. In the midst of our uncertainties, however, current (climate model) projections exhibit some key commonalities that demand near-term attention from California's resource-management communities: (1) even the most benign of the projected climate-change scenarios are sufficient to significantly alter the California's landscape, hydrology, and land and water resources, and (2) those alterations are likely to become significant within roughly the next 25 years (Barnett et al. 2004; Dettinger et al. 2004; van Rheenen et al. 2004). Thus, California—like the rest of society—is faced with a variety of possible climate changes that are likely to develop within the same time frames as the resource-management decisions necessary to respond to them.

To date, technical responses to this dilemma primarily have involved development and preliminary applications of tools for assessing the potential climate-change impacts and the efficacy of various possible adaptation or accommodation strategies. In part, this response has been motivated by the assumption that projection uncertainties will be reduced sufficiently in the near term to justify postponing more intensive and detailed assessments until later. However, the projected changes include sufficiently important near-term impacts, and the chances that projection uncertainties will decline precipitously in the near term are small enough, so that delays may not be warranted. For example, two highly respected climate modelers, David Randall and Akio Arakawa, recently opined that "a sober assessment suggests that with current approaches the cloud parameter-ization problem [the most vexing aspect of climate and climate-change modeling at present] will not be 'solved' in any of our lifetimes" (Randall et al. 2003). Thus, we should not assume that large reductions of projection uncertainty will arrive in time to allow con-fident planning of responses to climate change. Consequently, new strategies for more completely accommodating projection uncertainties are needed.

The development of the required uncertainty-based strategies will be challenging, but will offer the opportunity to focus more on the likelihoods, rather than just the uncertainties, of climate change. That is, as Myles Allen of Oxford University (2003) has recently commented, "Climate modelers need to start saying what changes can be ruled out as unlikely, rather than simply ruled in as possible." Indeed, it is perhaps time for California analysts to focus on what is more likely rather than on what is just possible. If this distinction can be determined, accommodation strategies and impact assessments will become more focused and practical.

Our view of California's future climate is clouded by uncertainties due to model imperfections and uncer-tainties about how rapidly greenhouse gases will accumulate in the atmosphere, together with the natu-rally unpredictable variations of the climate system. Preliminary depictions of how these uncertainties cloud projections of California's future climate are possible, as demonstrated here using a multiple-model, multiple-emissions collection of currently available climate-change projections. This paper illus-trates new insights provided by characterization of the overall distributions of available climate-change pro-jections, insights that were not forthcoming when our focus was solely on a few extreme projections. Initial insights include recognition that warming by about +5°C is the most common projection for 21st Century California, with relatively little attendant precipitation change. The sign of projected precipitation changes appears to depend on whether one considers one of the warmer or cooler projections, which generally yield modestly drier or modestly wetter outcomes, respectively. However, in order to place even these simple insights into their proper contexts, the entire collection of projections must be presented and sum-marized in terms of objectively derived projection dis-tributions.

PROBLEM

The most common approach for analyzing climate-prediction uncertainties is analysis of ensembles (col-lections) of predictions, wherein each prediction dif-fers from the others due to some prescribed model

condition. Ensembles of climate projections often are used to describe prediction uncertainties associated with model constructions, initial conditions, and future emissions of greenhouse gases into the global atmosphere. In weather- and climate-prediction applications, several studies have argued that ensemble means are better predictors than are any individual members of the contributing ensembles (e.g., Krishnamurti et al. 2000; Richardson 2001; Zhu et al. 2002), and this finding may eventually be found to extend also to climate-change projections. Thus, climate-change ensemble means (or approximations thereof) might reasonably be analyzed, although we have heard of few uses of even this strategy.

Instead, the more common strategy, to date, has been to analyze one or two example scenarios (often determined more by logistics and availability than by their representativeness). More determined efforts are responding to today's limited ensembles of available projections, and to the burdens imposed on some impact studies by each additional ensemble member, by trying to "bookend" the climate-change possibilities by analyzing only the upper and lower bounds of the available projections (e.g., Electrical Power Research Institute 2003; Lund et al. 2003; Miller et al. 2003, as well as the ongoing coordinated efforts by the Joint Department of Water Resources/U.S. Bureau of Reclamation Climate Change Work Team in California). Such approaches ultimately do little to quantify the uncertainties facing decision makers.

Neither the ensemble means, nor the most extreme projections (often outliers), describe the real scatter and uncertainties among current projections. Ensembles of climate-change projections also presumably contain information about the likelihoods of various scenarios and about higher-order statistics of the projection scatter. Ideally, interpretations and applications of climate-change projections in decision making will be informed by the most complete descriptions of the ensembles possible.

PROVIDING PROJECTION DISTRIBUTION FUNCTIONS (PDFs)

The typical climate-change ensemble, whether numbering tens of members or a very few, offers the analyst

and decision-maker a collection of erratic, often intertwining time series (called "spaghetti" in this paper) of simulated futures, e.g., as in Figure 1. This representation of an ensemble is useful and simple, giving a qualitative sense of scatter, commonalities, and trends. Done correctly, the spaghetti provides a sense of how the trends contrast with shorter term fluctuations in the simulations. However, our eyes are naturally drawn to outliers out of proportion to their significance, and clusters in the morass of curves may receive less consideration than is their due. A more even-handed and quantitative view of the spaghetti of a typical ensemble requires estimation of the probability distribution from which the ensemble was sampled.
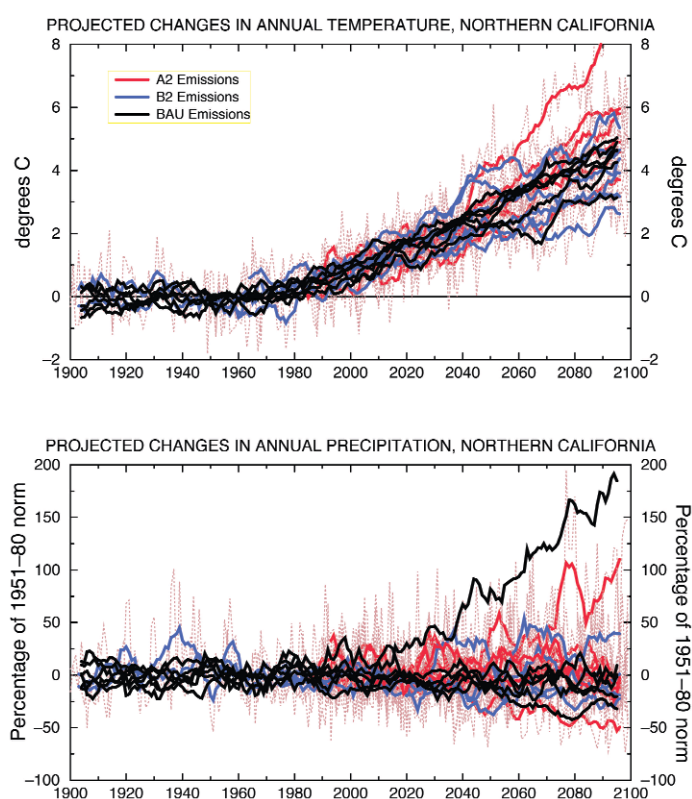

Figure 1. Ensembles of historical and future temperature and precipitation projections from six coupled ocean-atmosphere general-circulation models, each forced by historical scenarios, and then—in the 21st Century—the A2, B2, and IS92a SRES emissions scenarios (Figure 2, Cubasch and Meehl 2001). The dashed background of curves shows annual deviations from the 1951–1980 simulated means; whereas, heavy curves show 7-year moving averages. Projections are for a single model grid cell (ranging from 2.5°C to 5.5°C spatial resolution, depending on model) from each model, centered over northern California.

To be precise about our goals, though, note that we are limited to estimating the probability of obtaining a given simulation of climate change, based on the lessons from the ensemble. Since we are working with imperfect models and forcings, the distribution from which our ensembles are sampled is not the same as the distribution of future real-world climates. The ensemble scatter can only reflect differences between models, specified emission scenarios, and simulated versions of climate variability. If all the models (or emission scenarios) are wrong for some reason, then the probability of obtaining a given simulation could be quite different from the probability of having a particular climatic condition at some specified future time. Thus, we are only able to estimate the distribution of projections of future climates and cannot directly estimate the actual probabilities of various future climates. We can only estimate (what we will refer to as) *projection distribution functions* (PDFs) as the best available approximations of the true climate-change probability distribution functions.

If the ensemble includes many members, then characterizing the ensemble trends and scatter can be as simple as ranking the projections for each time and binning the results to directly form histograms or crude model-scenario PDFs. Even when the PDFs so estimated are crude, they can provide useful measures for comparing projections to observations and can provide a useful basis for comparing different ensembles (e.g., in the weather-prediction sense) (Toth et al. 2003).

When the number of ensemble members is smaller, however, developing even a rough estimate of the PDFs involves assumptions about the character of the projection uncertainties sampled by the ensemble. One approach is to sort and rank the projections, use them as mileposts of the PDF (e.g., the median projection value at a given lead time marks the median in the PDF), and then smooth algebraically to fill in interpolated values. Alternatively, one can attribute error bars of some weight and shape to each ensemble member and then essentially sum the error bars from all the ensemble members to arrive at the overall ensemble PDF (but then important assumptions need to be made regarding the growth rate of the error bars for the individual ensemble members). Both of these approaches have the advantage that they are simple, but have the disadvantage that they require subjective choices or assumptions by the analyst.

In this paper, a third alternative is applied that, in its simplest form, has no subjectively tunable parameters. However, because the particular method used to estimate the PDFs is probably less important than the effect of viewing PDFs (rather than spaghetti), details of this particular alternative are left to an Appendix. The method requires no tunable parameters, because it characterizes the ensemble spread by a data-adaptive decomposition of the projections into (statistically) independent parts and then resamples those independent components as often as necessary to provide a smooth PDF. The resampling method provides an almost unlimited number of new realizations that retain the essential statistical characteristics of the ensemble members, including time variations of average and standard deviation of the ensemble and all the lag and intervariable correlations. The method readily handles ensembles that bifurcate along two or more trajectories and handles the contributions from outlying ensemble members as a matter of course.

CLIMATE-CHANGE DISTRIBUTIONS FOR NORTHERN CALIFORNIA

Experimental design

As an illustration of the difference between describing climate-change ensembles as PDFs and as spaghetti, the resampling procedure described in the Appendix is applied here to an ensemble of climate-change projections of 21st Century (2001–2099) climate. The ensemble considered here was compiled from six climate models, each simulating responses to each of three specified greenhouse-gas-plus-sulfate-aerosols emissions scenarios (Figure 1; see http://ipcc-ddc.cru.uea.ac.uk for access to underlying simulations). The ensemble includes three projections each by the U.S. PCM, Canadian CCCM, German ECHAM4, British HadCM3, Japanese NIES, and Australian CSIRO coupled ocean-atmosphere global climate models; the emissions scenarios are the A2, B2, and IS92a greenhouse-gas-plus-sulfate-aerosol emissions scenarios (Figure 2, Cubasch and Meehl 2001), which represent projections of relatively rapid, moderate, and intermediate rates of 21st Century greenhouse-gas emission increases, respectively (see also Hayhoe et

al. 2004, for discussion of emission scenarios and their consequences for California).

By considering this even balancing of models and scenarios, no model or scenario is emphasized over the others. This even-handed treatment of the models and scenarios was valued here sufficiently so that some other models and emissions scenarios were not included in the present analysis either because all three emissions scenarios were not available from a given model (e.g., the British HadCM2 model) or because all six models had not yet run a given emissions scenarios (e.g., A1fi and B1; Figure 2). Ideally, in the absence of known deficiencies in one or another of the ensemble members, the climate-change PDFs should reflect, in an even-handed way, the combination of uncertainties associated with models and the uncertainties associated with future emissions. However, not all models (or scenarios) are equally skillful at reproducing or projecting climate variations. A simple extension of the resampling procedure to allow an uneven treatment of the models (i.e., to weight the most skillful models the most and the least skillful models the least) is outlined at the end of this section. Multiple simulations from a single model and emissions combination can also be included and weighted fairly by the resampling approach applied here.

The 18 ninety-nine-year-long (future) climate projections of Northern California climate change compiled in Figure 1 all share rapid warming tendencies after about 1970 and, by about 2020, temperatures have all warmed beyond most of the background of historical
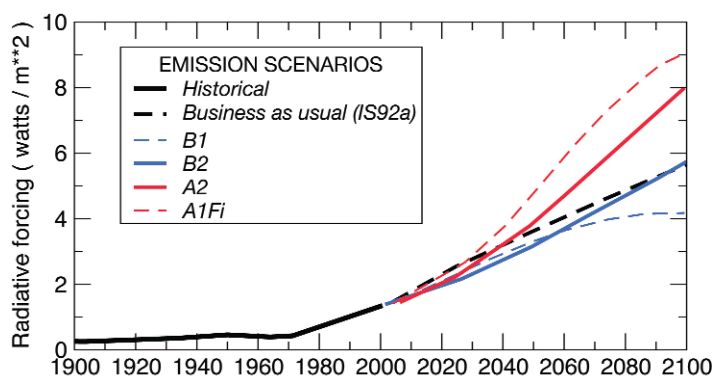

Figure 2. Radiative forcings associated with historical emissions of greenhouse gases and sulfate aerosols and with various projections of 21st Century emissions (modified from Figure 9-13a, Cubasch and Meehl 2001).

temperature variability. The general spread of temperatures by 2100 is from +2.5°C to +9°C. Notably, the scatter among scenarios is not substantially larger or different than the scatter among models considered here. Emission scenarios (e.g., the A1fi and B1 scenarios) that diverge even more than the scenarios analyzed here might be different enough to spread the projections considerably more. Projections of precipitation in the 21st Century are less unanimous, with some projections becoming much wetter (the wettest projections are both from the Canadian model) and some drier. Plotted in this way, the eye naturally focuses on the outliers in the ensemble, and many studies have been constructed to address the bounds of such projection ensembles, rather than exploring the more common results.

To improve visualization, interpretation, and—for some applications—the usefulness of this ensemble, the 18 projections of temperature and precipitation were resampled according to the procedure described in the Appendix. In this application of the resampling procedure, mixing of the ensemble loading patterns was restricted to only allow projections by a single model to be intermixed. This restriction prevents possible inappropriate mixing of incompatible components from the projections by very different climate models. The restriction is easily accomplished by beginning each resampling cycle by choosing one of the models at random, followed by random sampling among only the several amplitude series for that model, to obtain the new realization.

Results

The result of a 20,000-member resampling of the 18-member climate-change projection ensemble is shown in Figure 3. The principal components analysis (PCA) applied in the first step of the procedure was "extended" (Weare and Nasstrom 1982) so that temperature and precipitation changes were analyzed and resampled together. The PDFs shown are thus aspects of the joint PDFs of temperature and precipitation. Consequently, for example, if a particular model has a tendency for excursions of temperature and precipitation to occur simultaneously, the resampled realizations will emulate those linkages.
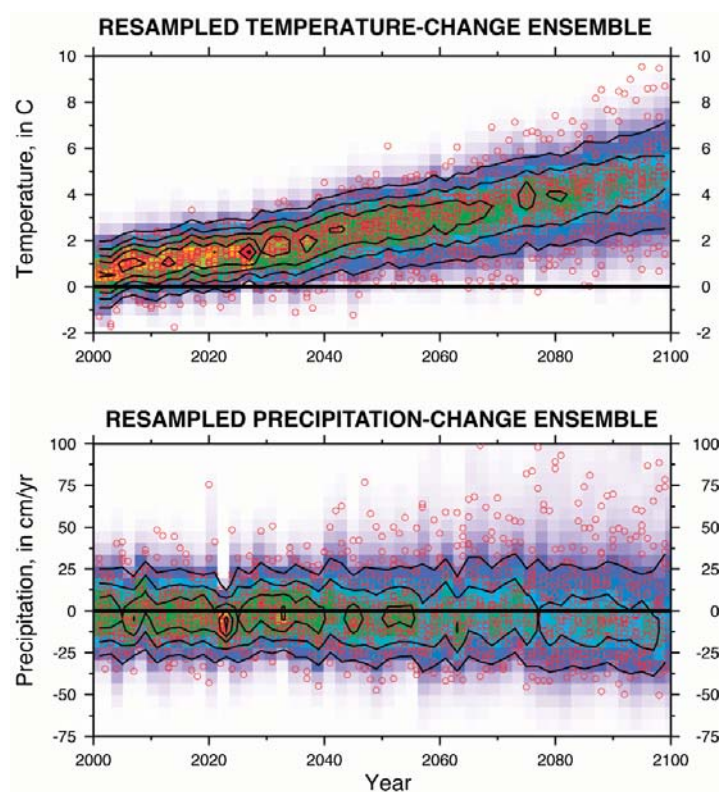
RESAMPLED TEMPERATURE-CHANGE ENSEMBLE

RESAMPLED PRECIPITATION-CHANGE ENSEMBLE

Figure 3. Distributions of original and component-resampled projections of annual 21st Century surface-air temperatures and precipitation changes for a grid cell over Northern California (40°N 120°W), from the ensemble of projections shown in Figure 1. Red circles show the raw ensemble projections; contours and shading show resampled joint temperature-precipitation probabilities, with a contour interval of 0.025.

Early in the 21st Century, the projections are closely clustered, somewhat warmer, and somewhat drier on average than the 1951–1980 climatology (because, even by 2000, greenhouse forcings are larger than during that climatology period) (Dai et al. 2001). The ensembles spread over the course of the 21st Century, until by 2099, temperature-change projections range (mostly) from about +2°C to +7°C, and precipitation-change projections range from about –30 to +25 cm/yr, with two outlying exceptions. The probability distributions shown are reflections of the joint variations of temperature and precipitation so that if, for example, the projections that were warmest overall tended also to be the wettest, and vice versa for cooler and drier models, the resampled realizations would maintain these tendencies faithfully.

The smoothing that is provided by the resampling procedure is illustrated by the sequences of time slices through the projection PDFs (in Figure 3) shown in Figure 4. The temperature-change PDFs spread and trend toward warmer conditions as the 21st Century climate evolves. The increasing spread is mostly a result of divergence between the models and divergence of the emissions scenarios, with relatively little contribution by increasing interannual variability within any given model's projections. Notice that, by as early as 2025, realizations that are cooler than normal by 1951–1980 standards are exceedingly rare. Seasonal versions of the temperature-change PDFs (not shown) indicate that summertime (June through August) temperature-change projections scatter most in the ensemble, followed by winter (December through February).
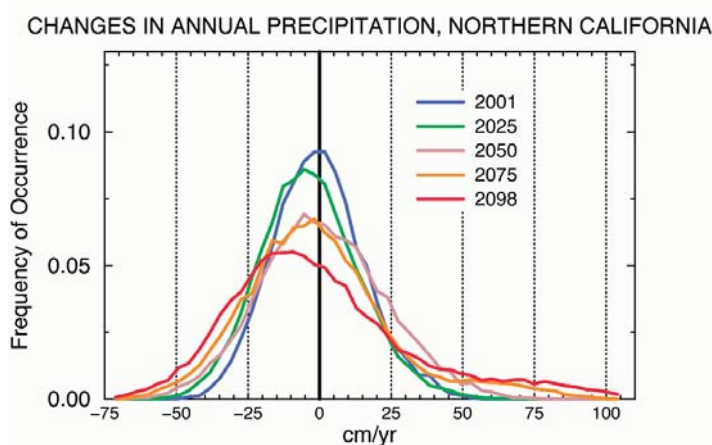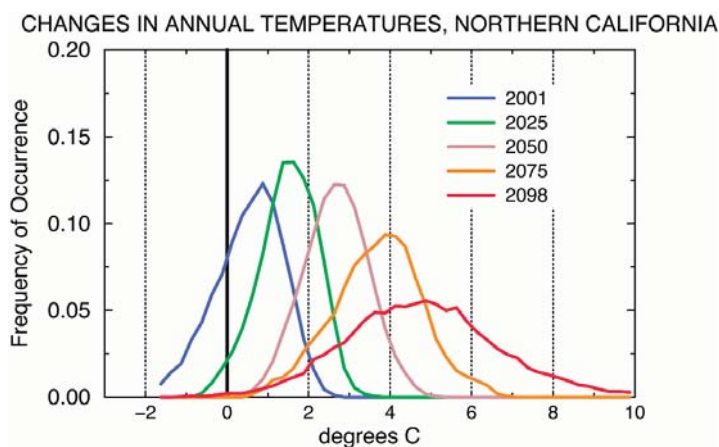
CHANGES IN ANNUAL TEMPERATURES, NORTHERN CALIFORNIA

CHANGES IN ANNUAL PRECIPITATION, NORTHERN CALIFORNIA

Figure 4. Time slices of the distributions of resampled ensemble realizations in Figure 3.

The ensemble-mean summertime temperatures also increase more than the other seasons.

In contrast, the precipitation-change PDFs move and spread much less than do the temperature PDFs (Figure 4). Overall, the resampled realizations (as in the raw projections) most commonly exhibit only modest 21st Century precipitation changes over California. The modes of the smoothed (resampled) PDFs in Figure 4 trend toward drier conditions, which is much more difficult to perceive in the scattered red dots of Figure 3 or in a corresponding "spaghetti" plot overlaying each ensemble member's projected time series. Thus, although no new information is introduced by the resampling procedure, its smoothing can nonetheless be very informative. Seasonal versions of these PDFs (not shown) indicate that the tendency towards drier conditions derives mostly from spring (March to May) precipitation declines, with smaller deficits also developing in winters (December to February).

The general rate of expansion of the ensemble spread around this mean precipitation-change behavior is small, except for a distinct heavy tail spread towards substantially wetter conditions. That heavy tail spread reflects the contributions to the ensemble from the Canadian model's projections, the two outlying much wetter projections in the original 18-member ensemble. That model, under each of the emissions scenarios, evolves towards a much wetter California, as part of its tendency (unique among the models compiled here) to respond to increasing greenhouse forcing with enhanced El Niño conditions. The resulting wetter conditions reflect much wetter winters in that model's projections.

Discussion and extensions

The PDFs illustrate the probability that a random model-emissions combination will yield a given temperature and precipitation deviations, from long-term averages over the 1900-1950 period, by the year shown, in the presence of the simulated natural variability of California's climate. That is, the PDFs reflect uncertainties (surrounding a given year's climate projection) due to the combination of natural variability, model differences, and emission-scenario differences available here. However, when only the

simulations under business-as-usual emissions are resampled, the central tendencies of the PDFs are not substantially different from those shown in Figure 4, although the breadths are reduced. When a single model's (PCM's) simulations of climatic responses to the several emission scenarios are resampled, the spread of the resulting PDFs (not shown) are not much changed, but their central tendencies of temperature change evolve less than in Figure 4. Thus, the PDFs in Figure 4 robustly reflect characteristics of the climate projections, almost regardless of the choice of simulations included (from among the models and emission scenarios considered here).

The resampling procedure applied here generates realizations of temperature and precipitation change that are jointly distributed. Thus, it is also possible to evaluate tendencies for correlated temperature and precipitation changes. The joint probabilities of precipitation and temperature change among the 20,000 resampled realizations are mapped in Figure 5 for several years during the 21st Century. Notice that, as indicated previously, temperatures generally warm and precipitation changes little overall. However, the joint probability distribution is also somewhat bimodal in ways not obvious from either the unvariate PDFs or the spaghetti plots. The joint probabilities indicate that the warmest climate-change projections tend to also bring drier conditions; the cooler projections tend to be slightly wetter, most obviously by 2050. By 2100, when all the scenarios have warmed considerably, the same tendency still persists, but the warmer-drier scenarios dominate overall.

The resampled realizations of the projections also provide a ready supply of examples of coordinated temperature and precipitation changes for use in evaluating climate-change impacts. As a simple example, the 20,000 temperature-and-precipitation-change realizations generated for Figures 3 and 4 were introduced to the streamflow amount and timing response surfaces mapped by Jeton et al. (1996) for the North Fork American River in the central Sierra Nevada. Those response surfaces (Figs. 16b and 17c in Jeton et al. 1996) show the mean simulated changes in annual streamflow amounts and in the median-flow dates (days of year by which half the year's flow is past), in response to 100-year-long synthetic climate series with
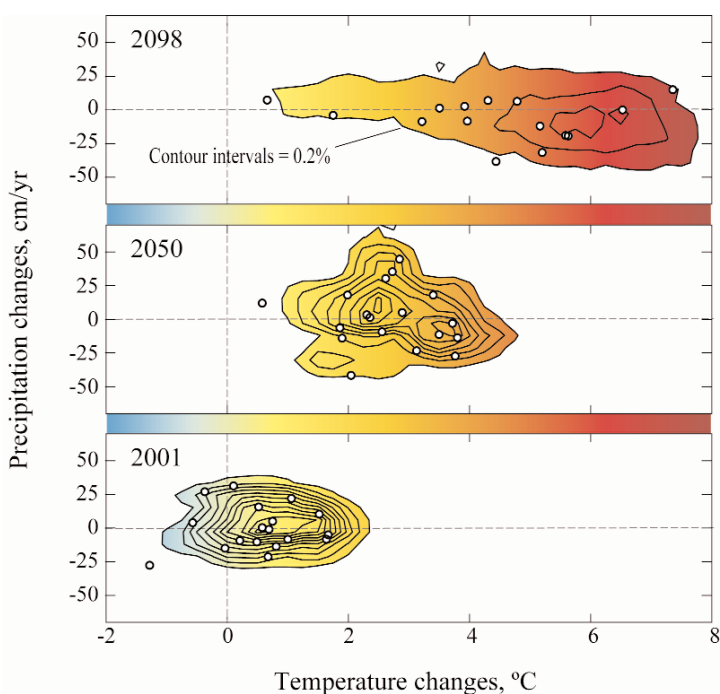
Figure 5. Time slices of the joint temperature-precipitation distributions of resampled ensemble realizations from Figure 3. Circles indicate values in the original 18-member ensemble of projections (Figure 1).

arbitrarily specified mean-climate changes ranging from cooler to warmer, and from drier to wetter. The mean streamflow changes mapped by Jeton et al. (1996) — corresponding to the temperature and precipitation changes in each of the 20,000 resampled ensemble realizations (from each of the time slices in Figure 4) — were accumulated, and the resulting PDFs of streamflow amount and timing are shown in Figure 6.

The PDFs of annual streamflow changes in Figure 6 are similar to the PDFs of precipitation change in Figure 4, reflecting the strong control that precipitation change exerts on total streamflow amount, as well as the nearly complete buffering of streamflow amounts against responses to temperature changes, discussed at length by Jeton et al. (1996). By the end of the 21st Century, streamflow amounts are outlying biased towards a drier mean and mode, although the much wetter Canadian climate models ensures a heavy tail of significantly wetter streamflow-amount realizations.

The corresponding projections of streamflow timing (Figure 6, bottom panel) mostly reflect the warmer temperatures projected by all the models, although

concurrent precipitation changes in the realizations couple nonlinearly with the temperature effects in the Jeton et al. (1996) response surfaces to yield much broader and more multimodal timing distributions. Some of the multimodal character of the timing PDFs presumably derives from the bimodal character of the joint temperature-precipitation distributions (Figure 5). By 2025, years with earlier than normal median-flow dates (1951–1980) are all but eliminated among the resampling-driven realizations. By the end of the 21st Century, the most common median-flow date projections are over a month earlier than the 1951–1980 norms; see Stewart et al. (2004) for a more comprehensive and geographically far-reaching discussion of this phenomenon.

Now, consider the differences between the messages and information content of Figure 1 and Figure 4 (or 6). How attractive does the bookending strategy look, once the PDFs have been examined? From the spaghetti of Figure 1, we surmised mostly that projected temperature changes are more unanimous than are
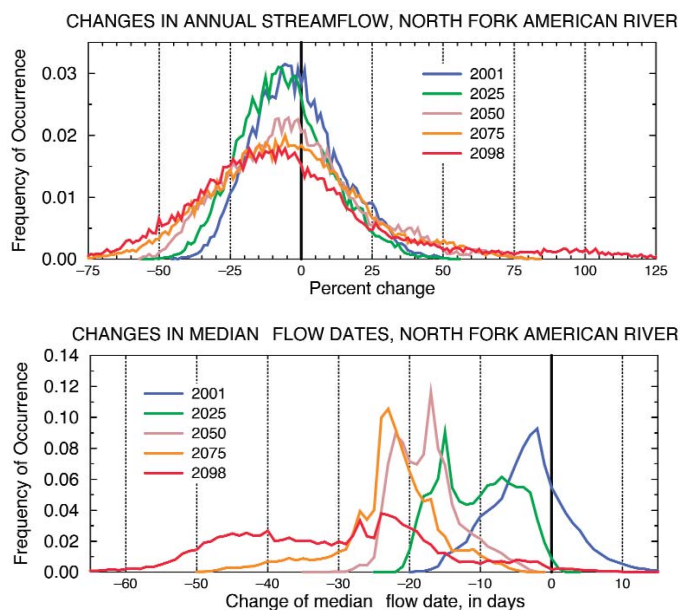

Figure 6. Distributions of annual streamflow amounts and median-flow dates (i.e., date by which half of a year's flow is past) in the North Fork American River, in response to 20,000 resampled climate-change realizations (illustrated in Figure 4). Streamflow responses were estimated from response surfaces mapped in Jeton et al. (1996, figures 16b and 17c).

the projections of precipitation change, and that very wet projections are a significant threat (or opportunity). The PDFs, in contrast, suggest that the envelope of (most likely) temperature projections spreads more through time than does the envelope of precipitation changes. The less-than-obvious tendency for the mode of precipitation changes to drift towards drier conditions is also much clearer in the PDFs. In fact, no new information has been added to the ensemble by the resampling procedure, but our understanding of the potentialities that the ensemble represents is arguably much clearer. In addition to this clarification, the users of such an ensemble have much more freedom to select their own levels of risk aversion when ensemble results are quantified by PDFs rather than by spaghetti. That freedom is needed, because risk is not simply the likelihood of an adverse impact; rather, risk is essentially a product of likelihood and cost of that impact. Consequently, in applications, each newly discovered potential impact brings with it its own unique requirements from the projection ensembles. A more PDF-centric approach is the more proactive approach.

Although the resampling procedure used in this section added no real information to the ensembles, the procedure can readily be extended to add crucial information in clear and helpful ways. For example, the resampling procedure used above treated each model's projections as equally likely and each emissions scenario as equally likely. However, the procedure can be modified to reflect any *a priori* preferences for, or beliefs in, the various models and scenarios. For example, if the accuracies of each model were quantitatively indexed by a measure of the likelihood that its projections were the most accurate (among all the models considered), then that index could be used to weight the fraction of samples that each model would contribute to the resampling procedure. This would mean that the most accurate models would contribute the most to the resampled distributions, and the least accurate models would contribute the least. Similarly, if the likelihood of emissions scenarios could likewise be ranked quantitatively, then the resampling probabilities could be adjusted to reflect those outcomes as well.

To illustrate an outcome from such an experiment, consider that three (PCM, HadCM3, and ECHAM) of the six models used in the present analysis are generally recognized as the more realistic climatic representations in that these models require no special corrections to their air-sea connections. In contrast, in the other models (Canadian, Australian, and Japanese), the modelers must insert extra heat exchanges between ocean and atmosphere preemptively or else the models drift into unrealistic climatological conditions when simulations last many years. Figure 7 shows the result of resampling the temperature and precipitation projections in Figure 1 while choosing the projections from the "preferred" models twice as often as those from the other models. This version of the resampled distributions of temperature and precipitation changes is not much changed from Figure 4 by this weighting: Temperature projections still spread roughly as much as in Figure 4 and the central tendencies of the warming remain the same. Precipitation projections remain centered on "no change" and spread slightly less over the course of the 21st Century. This calculation illustrates a more general conclusion—reached independently by both Philip Duffy (Lawrence Livermore National Laboratory, oral communication, 2004) and Thomas Wigley (National Center for Atmospheric Research, written communication, 2004)—that the averages and scattering of projections from ensembles of all current models are not significantly different from the corresponding averages and scatter when only those models that seem to be most skillful at reproducing the present-day climate are included. It seems that the differences among models that lead us, at present, to trust one more than another are not the differences that yield the most important climate-change differences for California. Some other, more pertinent way of choosing which models to trust will be needed if we are to reduce uncertainties in projections of California's 21st Century climate change.

SUMMARY

In current climate-change applications, the availability of ensembles of projections that contain very large numbers of members and ensembles that evenly mix model uncertainties with emissions uncertainties are rare. The availability of such ensembles would substantially ease statistical analyses and interpretations, and could be used to judge simulation skill. This study describes and demonstrates the clarifications that are possible when

CHANGES IN ANNUAL TEMPERATURE, NORTHERN CALIFORNIA
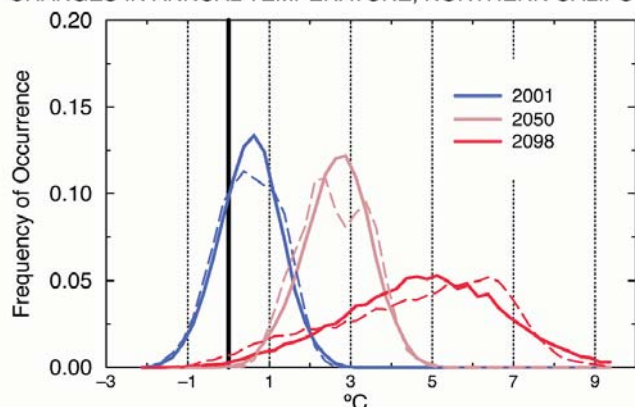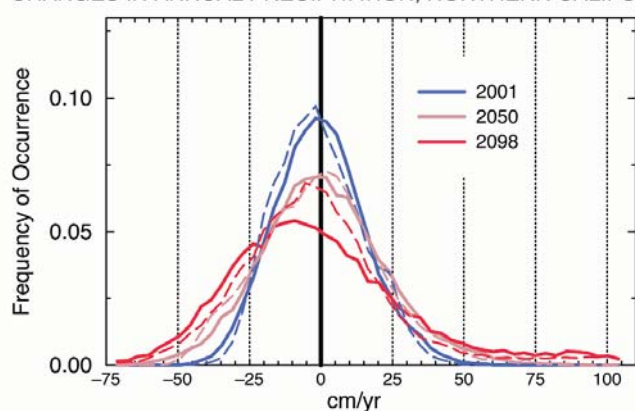
CHANGES IN ANNUAL PRECIPITATION, NORTHERN CALIFORNIA

Figure 7. Same as Figure 4, except that the dashed curves are generated with climate projections from the PCM, HadCM3, and ECHAM models selected for resampling twice as often as projections from the Canadian, Australian, and Japanese models.

projection-distribution functions can be estimated quantitatively by resampling much smaller ensembles.

A PDF, of the simple form used here, simply provides more information of direct relevance to resource managers, engineers, utilities, farmers, and others, and a clearer depiction of central tendencies and the risks at the extremes than does the typical spaghetti plot. Although little or no actual new information was introduced by the resampling procedure in the example shown here, it already provides an objective method for developing reproducible estimates of detailed distribution functions from small ensembles that clarifies the implications of an available climate-change ensemble considerably. Information describing

the historical skills of contributing models, and probabilities of various forcing scenarios, can readily be added to improve the uncertainty estimates. The result is a bridge between subjective interpretations of spaghetti plots of small ensembles and the kinds of visualizations and calculations that could be accomplished with much larger ensembles. Thus, the methods and ensemble explored here suggest that:

Depicting climate-change ensembles in terms of the density distributions in the projection ensembles can provide new insights into the projections that are not obvious or directly measured in the more common spaghetti diagrams/listings—even when no new information is added in the process of estimating those distributions. In the example presented in this paper, spaghetti diagrams had fueled the idea that precipitation projections were more scattered than temperatures, and that a very wet California was a strong possibility. An objective depiction of the distribution of projections indicated instead that the ensemble distribution of temperature projections spreads more (in relative terms) than does the corresponding precipitation distribution, and that the wet projections are true outliers with much smaller changes in precipitation being much more common (likely) among current projections.

The process of estimating projection distributions from the ensemble spaghetti offers a natural opportunity for actually adding information to the interpretation of ensembles. In the resampling procedure used here, skill scores for the models and any outside information about the relative likelihoods of various emissions scenarios can easily be used to condition the resampling probabilities, so that the resulting estimates of projection probabilities more nearly reflect the strengths and weaknesses of each contributing ensemble member. Such weighting is not an option unless the step from a spaghetti plot to a projection distribution is taken.

Uncertainties from both model differences and emissions scenarios cloud our view of the future climate. The even-handed mixture of projections from both different models and different forcings is an ideal that should be pursued as much as possible, and that should be brought to California applications at the earliest feasible date.

For the future, besides working to develop and use more relevant model skill scores in the resampling procedure, it is worth noting that the procedure demonstrated here is currently only suited for use with a handful of projected variables. Estimating the joint PDFs of simultaneous projections of many variables or many locations will require modifications and extensions of the procedure. However, the benefits of replacing ensemble spaghetti plots with quantitative estimates of the likelihood of various projections make that extension a worthwhile goal.

ACKNOWLEDGMENTS

REFERENCES

Allen MR. 2003. Possible or probable? Nature 425:242.

Allen MR, Ingram WJ. 2002. Constraints on future changes in climate and the hydrologic cycle. Nature 419:224–232.

Barnett T, Malone R, Pennell W, Stammer D, Semtner B, Washington W. 2004. The effects of climate change on water resources in the West: introduction and overview. Climatic Change 62:1–11.

Cubasch U, Meehl GA. 2001. Projections of future climate change. In: Houghton and others editors. Climate Change 2001: the scientific basis. Cambridge University Press. p 525-582.

Dai AT, Wigley ML, Boville BA, Kiehl JT, Buja LE. 2001. Climates of the twentieth and twenty-first centuries simulated by the NCAR climate system model. Journal of Climate 14:485–519.

Dettinger MD. In review. A component-resampling approach for estimating probability distributions from small forecast ensembles. Climatic change.

Dettinger MD, Cayan DR, Meyer MK, Jeton AE. 2004. Simulated hydrologic responses to climate variations and change in the Merced, Carson, and American River basins, Sierra Nevada, California, 1900–2099. Climatic change 62:283–317.

[EPRI] Electrical Power Research Institute. 2003. Global climate change and California: potential implications for ecosystems, health, and the economy. California Energy Commission Report 500-03-058CF. Available at: http://www.energy.ca.gov/reports/2003-10-31_500-03-058CF.PDF.

Hayhoe K, Cayan D, Field C, Frumhoff P, Maurer E, Miller N, Moser S, Schneider S, Cahill K, Cleland E, Dale L, Drapek R, Hanneman RM, Kalkstein L, Lenihan L, Lunch C, Neilson R, Sheridan S, Verville J. 2004. Emissions pathways, climate change, and impacts on California. Proceedings of the National Academy of Sciences 101:12422-12427.

Jeton AE, Dettinger MD, Smith JL. 1996. Potential effects of climate change on streamflow, eastern and western slopes of the Sierra Nevada, California and Nevada. U.S. Geological Survey Water Resources Investigations Report 95–4260. 44 p.

Krishnamurti TN, Kishtawal CM, LaRow T, Bachiochi D, Zhang Z, Williford CE, Gadgil S, Surendran S. 2000. Multimodel superensemble forecasts for weather and seasonal climate. Journal of Climate 13:4196–4216.

Lund JR, Howitt RE, Jenkins MW, Zhu T, Tanaka SK, Pulido M, Tauber M, Ritzema R, Ferriera I. 2003. Climate warming and California's water future. UC Davis Center for Environmental and Water Resource Engineering Report 03-1. Available at: http://cee.engr.ucdavis.edu/ faculty/lund/CALVIN/ReportCEC/CECReport2003.PDF

Miller NL, Bashford KE, Strem E. 2003. Potential impacts of climate change on California hydrology. Journal of the American Water Resources Association 39: 771–784.

Randall D, Khairoutdinov M, Arakawa A, Grabowski W. 2003. Breaking the cloud parameterization deadlock. Bulletin of the American Meteorological Society. 1547–1564.

Richardson DS. 2001. Measures of skill and value of ensemble prediction systems, their interrelationship and the effect of ensemble size. Q. J. R. Meteorological Society. 127:2473–2489.

Stewart I, Cayan DR, Dettinger MD. 2004. Changes in snowmelt runoff timing in western North America under a "business as usual" climate change scenario. Climate Change. 62:217-232

Toth Z, Talagrand O, Candille G, Zhu Y. 2003. Probability and ensemble forecasts. In: Jolliffe IT, Stephenson DB, editors. Forecast verification: a practitioner's guide in atmospheric science. San Francisco (CA): John Wiley & Sons. p 137–164.

Van Rheenen NT, Wood AW, Palmer RN, Lettenmaier DP. 2004. Potential implications of PCM climate change scenarios for Sacramento-San Joaquin River basin hydrology and water resources. Climate Change 62:257–281.

Weare BC, Nasstrom JS. 1982. Examples of extended empirical orthogonal function analyses. Monthly Weather Review 110:481-485.

Wigley TML, Raper SCB. 2001. Interpretation of high projections for global-mean warming. Science 293:451–454.

Zhu Y, Toth Z, Wobus R, Richardson D, Mylne K. 2002. The economic value of ensemble-based weather forecasts. Bulletin of the American Meteorological Society. 83:73–83.

APPENDIX

Component-resampling method

Consider an ensemble of n climate-change projections of, say, temperature at a given model grid cell, each m time steps long, and each containing elements $\{x_{ij}, i=1, m\}$ where j indicates the ensemble member. A PCA of the n projections vectors, with all expectations calculated across the ensemble members, as described in detail by Dettinger (in review), will decompose the original ensemble into m loading patterns $\{e_i, i=1, m\}$ and m corresponding sets of amplitudes $\{p_{ij}, j=1, n\}$. By construction, the loading patterns (like empirical orthogonal functions) and the amplitudes (like principal component series) both form orthogonal bases for describing the original ensemble. The amplitudes measure the part of the original ensemble member that parallels each loading pattern. The orthogonality of amplitudes means the amplitudes of one of the ensemble members projected onto a particular loading pattern is statistically independent of its amplitude with respect to any of the other patterns. The k-th original (properly standardized) ensemble member can be recovered completely by:

$$x_{ik} = \sum_{j=1}^{j=m} e_{ij}\ p_{jk}$$

Another new projection vector with statistics that are indistinguishable from those of the original ensemble elements, to second order, can be obtained by scrambling the amplitudes (picking the k indices in equation (1) at random, with replacement, from $k=1, n$, at each step in the summation). Because the amplitudes are independent from loading pattern to loading pattern, the first- and second-order statistics do not depend on which one is chosen at each step.

The procedure is as follows:

1. Calculate the ensemble mean values m_i of x_{ij} at each time i, with expectation taken across the ensemble:

$$m_i = \sum_{j} x_{ij}\ /n$$

and subtract these means from the climate-change projection vectors to obtain centered (zero-mean at each lead time) projection vectors. Any mean or trend shared by all the ensemble members is removed by this step. When the ensemble is resampled later, this temporally varying ensemble mean can readily be added again.

2. Calculate the ensemble standard deviations s_i of the centered projections at each time i, again with expectation taken across the ensemble, and divide the centered projection vectors at each lead time by the corresponding standard deviation to obtain a standardized projection ensemble (zero mean and unit variance at each lead time). This ensures that any temporal evolution of the spread of the ensemble is captured and can be reintroduced after resampling. Removing the temporally varying standard deviation at this point in the analysis ensures that inter-ensemble variations in the early part of the projections (when the ensemble typically has not spread much) are treated in the same detail as those later in the projections.

3. Compute the cross correlations of the standardized projections at each time and lag, with expectations taken across the ensemble. The resulting cross-correlation matrix is m x m, and summarizes the covariations of the projections at a given time in each ensemble member with the projection one time step later, two time steps later (and so on) in the same and other ensemble members. In some applications of the method, the number of ensemble members may be much smaller than m, in which case the principal components may not all be well estimated; however, unlike most other applications of PCA, all m loading patterns are recombined (below) in each newly formed ensemble member. As a result, this limitation does not affect the results (Dettinger, in review).

4. This cross-correlation matrix is decomposed into loading patterns and their attendant amplitude series by PCA. The loading patterns describe the temporal evolution of the ensemble members in the most economical form. For example, perhaps most ensemble members trend throughout from warmer towards cooler, while a few might increase for a while and then decrease like the others. The two behaviors would tend to be captured by two distinct loading patterns, and

those ensemble members in the former category would be weighted more heavily in the former loading pattern; whereas, the latter ensemble members would be weighted more heavily on the latter pattern. These weights are measured by the respective amplitude series. For a given loading pattern, the amplitude series measures the weight (similarity) of time series of each ensemble member in turn to that pattern, and a given ensemble member's amplitude for any of the loading patterns is statistically independent of its weight on any other loading pattern.

5. Randomly resample the PCA results to generate as many additional "projection" realizations as described in the first equation. Because the amplitudes for the various loading patterns are, independent of each other, by construction it does not matter which ensemble member's amplitude for a given loading pattern is mixed with which other ensemble member's amplitude for another loading pattern. With m loading patterns, each of which can take on any of the n amplitudes, the number of distinct resampled realizations that can be constructed is m^n; e.g., in a 10-member ensemble of 20-year projections, 20^{10} resampled realizations can be generated. If, as in many PCA, only about 20% of the amplitude series contributed much variance to the realizations, the effective candidates for independent samples would drop to perhaps 4^{10} or about 1,000,000 possible independent samples, which is still a useful expansion of the apparent size of the ensemble.

6. Having reconstructed a "new" member of the standardized ensemble of climate-change projections by resampling (in Step 5), rescale the result by the time-varying ensemble standard deviations and then add the time-varying ensemble means. By this rescaling, the stationary and shared variability are restored, and the large numbers of results can be ranked and summarized in detailed histograms to obtain PDFs as fine as desired.

The method ensures that features shared by all members are shared by the component-resampled ensemble members, that variations shared by subsets of the ensemble members are reproduced realistically and in proportion to their occurrence in the original ensemble, and even that the noisy (unshared) variations are faithfully captured and reproduced in the component-

resampled ensemble. Because the method is based on PCA, the component-resampled ensemble is described mostly in terms of its first and second statistical moments, so that the resulting smoothed PDFs tend toward Gaussian shapes; however, that tendency is relatively weak. When present, bifurcations in the ensemble of projections should be captured in the PCA loading patterns and weighted appropriately (in both amplitude and numbers of participating ensemble members) by the corresponding amplitude series. Then, when the amplitude series are resampled randomly, both the shapes and relative frequencies of the bifurcations are naturally reproduced in a satisfying way.

One way to picture the method is to imagine that the original ensemble has been filtered into a large number of narrow and non-overlapping frequency bands. The result is that an ensemble member might have power A at low frequencies, power B at medium frequencies, and so on. Another ensemble member would have a different set of powers in each frequency bin. Now, assuming that an ensemble's power in the first frequency bin has little bearing on its power in the second, and so on, one can imagine generating new ensemble surrogates with the same statistical properties as the original ensemble, by taking the filtrate from one ensemble member (at random) from the first frequency bin, adding to it the filtrate from an ensemble member (at random) the second bin, and so on, until samples from all the frequency bins have been incorporated. The sum of the frequency components constitutes a new time series with statistical properties that are derived strictly from the ensemble's overall power spectrum. For example, if the 10-year periodicities in the ensemble members were most powerful and 8-year periodicities notably lacking, the resampling would still yield members with powerful 10-year periodicities and weak 8-year periodicities, because the resampling only uses observed values from each frequency bin. The present method improves on such a hypothetical frequency-binned resampling by (1) guaranteeing—by the construction of the PCA decomposition of the ensemble members—that the various elements resampled (the loading patterns, which would correspond to sine waves of given frequency in the hypothetical) are always independent of each other, and (2) allowing more flexibility of loading-pattern shape than is offered by a simple frequency-domain approach.