Uncertainty in Socioeconomic Modeling Systems: Assessment and Recommendations

FINAL REPORT

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Uncertainty in Socioeconomic Modeling Systems: State of the Practice and Implementation Guidelines

Introduction

Understanding uncertainty of MAG's three-tier modeling process is part of its current Socioeconomic Enhancement Project. Tier I uses a demographic model developed by the Arizona Department of Commerce (DOC) that provides regional (Maricopa County) demographic forecasts. Based on these forecasts, MAG creates regional forecasts for housing, employment, and other socioeconomic variables. Tiers II and II allocate the County forecasts first to Regional Analysis Zones (RAZ) and then to the smaller Socioeconomic Analysis Zones (SAZ). A spatial interaction model, known as DRAM/EMPAL, along with SAM-IM previously provided the subregional forecasts. Going forward, UrbanSim (with key elements from SAM-IM) will be used for these forecasts.

A review of MAG's current and proposed socioeconomic modeling system (SEMS) has been completed. Sources of uncertainty were identified for the County and subregional forecasts and recommendations were offered to enhance MAG's forecasting process and models. This information is contained in a white paper entitled, *Uncertainty in the Maricopa Association of Governments' Socioeconomic Modeling System: Assessment and Recommendations*.

This second and final white paper focuses on methods and procedures for building additional uncertainty assessment into the land use and socioeconomic modeling process at MAG. It examines the current state-of-the-practice for representing uncertainty in forecasts based on a literature review and a survey of regional planning and state agencies that produce "official" forecasts. The last section of the paper provides guidelines and options for enhancing the assessment of uncertainty of MAG's forecasts.

The General State-of-the-Practice[1]

Forecasting is an uncertain business and many factors can influence the future course of events including technological and medical advances, norms toward childbearing, immigration policy, the increased ability to work away from the office, alterations in travel behavior, and changes in land use, transportation, and economic policies at all levels of government. The evolution of local land use and transportation policies will play an especially crucial role in how the MAG region and its cities, communities, and neighborhoods will change. Having a better understanding of uncertainty can enhance the usefulness of forecasts and make the work of forecasting agencies an even more valuable product for planners, policy makers, and the public.

[1] The section contains adaptations from pages 331-340 in S. Smith, J. Tayman, and D. Swanson. 2001. S*tate and Local Population Projections: Methodology and Analysis*. New York: Kluwer Academic/Plenum Publishers; Chapter. 7 in J. Bongaarts and R. Bulatao, Editors. 2000. Beyond Six Billion: Forecasting the Worlds Population. Washington, DC: National Academies Press; and W. Lutz and J. Goldstein. 2004. Introduction: How to Deal with Uncertainty in Population Forecasting. *International Statistical Review*, 72: 1-4.

How can this uncertainty be accounted for? Two basic approaches have been used in the past. One is to produce several alternative scenarios based on different sets of assumptions. The other is to develop statistical probability intervals based on historical data. Also discussed are the potential roles of experts in defining forecast uncertainty.

Alternative Scenarios

To assess and communicate uncertainty, forecasters often construct alternative scenarios by varying key assumptions. The use of a most likely scenario provides a basis against which to compare the alternative viewpoints. These alternatives are not intended to be a forecast of what will occur, but they convey the potential for different trajectories going forward, especially if the alternatives are based on plausible and realistic assumptions. Scenario evaluation has been widely used by state and local forecasters and among producers of "official" population projections it is the most common way to deal with uncertainty.

For counties and other larger geographic areas, the traditional approach for dealing with uncertainty has been to construct a range of future predictions. For population forecasts a range can be developed using various combinations of mortality, fertility, and migration assumptions. Ranges around households and housing units, for example, can be developed by varying assumptions about household headship and vacancy rates. Two interpretations can be given to the individual series in a range. One is that each series gives a reasonable view of the future change and that no particular series is any better than any other. The second interpretation is that although each series provides a reasonable view of the future, one particular series is preferred to all the others. There are also several interpretations of the range itself. One is that the high and low series provide a "reasonable" range, and it is expected that the range will contain the future activity observed in the target year; although, no specific probability statements are made. Another is that the series making up the range simply provide several alternative views of the future. Under this interpretation there are no stated expectations that the range will contain the future population.

For subcounty areas, explicit ranges to connote forecast uncertainty have been used. Forecast uncertainty has also been evaluated based on a comparison of more general and broad-based scenarios such as different land use and transportation policies (e.g., smart growth, urban limit lines, transit emphasis, and highway emphasis). These scenarios are often conducted in the context of evaluating specific policy options and sensitivity testing and are not intended to show a specific range of values for a particular area.

There are several benefits to the scenario-based approach to forecast uncertainty. One is that it makes it easy to observe and understand the effects of differences in assumptions and/or policies. Another benefit is multiple scenarios give the data user several options from which to choose. Since each series is based on clearly defined assumptions, the data user can make choices based on his/her judgment regarding the validity of those assumptions. This approach also does not require any new models or expertise beyond what is already needed to prepare the forecast, and it is generally the least costly way to examine forecast uncertainty.

The most cited limitation of using scenarios is they do not provide an explicit measure of uncertainty. How likely is it that any particular series will provide an accurate forecast of future change? How likely is it that the future activity will fall within the range suggested by two alternative series? These questions cannot be answered simply with this approach. Although scenarios may provide several reasonable views of the future, they do not provide a means for evaluating what is "reasonable." There is no guarantee that the projected range will encompass the future activity, and it has been found that the scenario approach may understate the true level of forecast uncertainty. Scenarios also typically have smooth time trajectories in their assumptions that fail to capture "real world" fluctuations.

Probability Intervals

The second approach focuses on statistical measures of forecast uncertainty, which address some of the short-comings of the scenario approach. Advances in the theory and methods of forecasting combined with expanding computing power have made probabilistic forecasts of population, housing, and other socioeconomic variable feasible. Probability intervals based on statistical theory and data on forecast error distributions can provide a probability that a given range will contain the future activity. These methods can also provide a forecast value that corresponds to any probability (e.g., the probability is 0.2 that the 2020 population will exceed 3.2 million persons). Two main types of probability intervals have been used with forecasts. The first is based on stochastic models of growth. The second is based on empirical analyses of errors from past forecasts.

Under formal definitions, probability statements about the accuracy of forecasts cannot be made because the distribution of future forecast errors is unknown (and unknowable) at the time the forecast are made. However, it is possible to construct probability intervals based on specific models of change or on the distribution of errors from past forecasts. If current forecast methods are similar to those used in the past, and if the degree of uncertainty is about the same in the future as it was in the past, we can assume that future forecast errors will be drawn from the same distribution as past forecast errors. If this is true, probability intervals can provide a reasonable (albeit imperfect) view of the uncertainty surrounding current forecasts.

Model-Based Intervals

Model-based probability intervals capitalize on the stochastic (or random) nature of population and other processes. They can be developed in a number of ways. Applications have included maximum likelihood estimators of growth rates; Monte Carlo simulation and stochastic models of demographic rates; regression-based forecasting models; models based on experts; and a variety of time series models. Time series models (especially ARIMA models) are most commonly used for developing probabilistic forecast intervals, although, the relatively long time series required for ARIMA models make them impractical for use in subcounty areas. Most research on model-based intervals has focused on the national and international level, but some work has been done at lower levels of geography.[2]

[2] J. Tayman, S. Smith, and J. Lin. 2007. Precision, Bias, and Uncertainty for State Population Forecasts: An Exploratory Analysis of Time Series Models. *Population Research and Policy Rev*iew 26: 347-369; H. Ševčíková, A. Raftery, and P. Waddell. 2007. Assessing Uncertainty in Urban Simulations Using Bayesian Melding. *Transportation Research Part B: Methodology* Vol. 41, No. 6 (652-659).

Model-based probability intervals are valid only to the extent that the assumptions underlying the models are valid. In spite of their objective appearance, they are strongly influenced by the analyst's judgment. The models themselves are often complex, require a substantial amount of expertise often beyond the in-house capabilities of many agencies, and are too difficult to be understood by many users. They are subject to errors in the base data, errors in specifying the model, errors in estimating the model's parameters, and future structural changes invalidating the model's parameter estimates. In addition, many alternative models can be specified and each provides different (perhaps dramatically different) probability intervals. Model-based probability intervals have rarely been used for the production of "official" forecasts. An internet search revealed that only the Netherlands has published fully probabilistic forecasts.[3]

In spite of these problems, model-based probability intervals offer one important benefit: they provide explicit probability statements to accompany point forecasts. These intervals often exceed the low and high projections produced by official statistical agencies. Given that many data users (and producers) tend to overestimate the accuracy of population projections, model-based probability intervals provide an important reality check.

Empirically-Based Intervals

The second type of probability interval is based on empirical analyses of errors from past forecasts. Appendix A discusses the most commonly used measures to assess the error in demographic and socioeconomic forecasts. The empirically-based method attaches probability intervals to a separately generated forecast rather than directly producing a probability distribution of a forecast, like model-based probability methods. Several approaches have been used to develop empirically-based probability intervals.

One calculates the error based on the difference between the actual and forecasted growth rate, using the root mean square error (RMSE). Probability intervals are developed by applying that error to forecasted growth rates. For example if the RMSE was 0.4% and using one standard deviation under a normal curve, for an area forecast to grow by 2% per year for the next 20 years the probability would be approximately 0.66 that the actual growth rate would be somewhere between 1.6% and 2.4%. Given that a large number of past forecasts are required for this approach, it has been used only at the national level.

The second approach bases the predicted distribution of future forecast errors directly on the distribution of past forecast errors. With this approach, error levels associated with a cumulative probability are applied to the forecast. For example, analysis of past forecast errors showed a probability of 0.8 that the error will not exceed 20% over a 10-year horizon. If the forecast population is 200,000 10-years into the future, the probability is 0.8 that it will not be larger than 240,000. An important characteristic of this technique is that it can accommodate any error distribution, including the asymmetric and truncated distributions typically found for forecast errors. This technique has been applied to states, counties, and subcounty areas in San Diego County.

[3] In the early part of this decade, the Census Bureau was developing official probabilistic population forecasts for the U.S. That effort, however, was never completed. In fact, their latest national forecasts released in August 2008 do not even include alternative scenarios and extended only to the year 2050. Previously, four alternatives were published and they each extended to the year 2100.

The final approach, specifically designed for subcounty forecasts, uses a sampling-based methodology.[4]. This method is applied to forecasts for 2000 ft. by 2000 ft. grid cells in San Diego County. From a randomly selected grid cell, forecasts from adjacent grid cells are accumulated until they reach a desired population size. Forecast error is then calculated using the observed value of the accumulated area. Identical-sized areas are created using repeated random sampling techniques and these form the distribution of forecast errors for a given population size. Empirical probability intervals are developed around the average error using standard statistical methodology and for individual forecast errors using the approach described above.

An empirical approach has some advantages over models that incorporate the stochastic nature of the forecasting process and may generally be more useful for small areas. This approach is much less complex and within the capabilities of most agencies preparing forecasts. The problems implementing stochastic models, noted above, are even more difficult because of the lack of time-series data and the lower reliability of rates and statistical parameters based on relatively small areal sizes. However, empirically-based probability intervals require past forecasts whose availability/usability may be an issue, especially in agencies that produce subcounty forecasts.

Expert Judgment

Experts can play a key role in the forecasting process and their tasks include: 1) helping to select a model and its key drivers; 2) defining key assumptions; and 3) reviewing the forecast. Many agencies producing official forecasts incorporate expert opinion through technical or advisory committees. While these experts may improve the quality of the forecast, they do provide it additional credibility that is very valuable when defending a forecast in the public arena. A common use of experts is defining assumptions about the most likely future values of key assumptions, but experts can also help determine alternate scenarios, ranges for assumptions, the shape of assumption distributions, and probability statements about assumption ranges. Expert panels have been used to create probabilistic forecasts and estimates in public sector applications.[5]

Structured, iterative procedures, such as the Delphi method, have often been found to lead to more accurate judgments than can be obtained from individual experts or from other ways of eliciting expert opinion. The Delphi method is designed to maximize the positive aspects of interactions among a group of experts (e.g., collecting opinions from a variety of knowledgeable sources, synthesizing information) while minimizing the negative aspects (e.g., political or personality conflicts, domination by particular group members). This type of an approach also allows incorporation of non-conformist or minority views, which are often disregarded.

[4] J. Tayman, E. Schafer, and L. Carter 1998. The Role of Population Size in the Determination and Prediction of Population Forecast Errors: An evaluation Using Confidence Intervals for Subcounty Areas. *Population Research and Policy Review* 17(1): 1-20.

[5] San Diego County Water Authority. 2002. Regional Water Facilities Master Plan, Appendix C. Development of Probabilistic Water Demand Forecast; San Diego Association of Governments. 2006. Economic Impacts of Wait Times on the San Diego-Baja California Border.

There are issues in using experts. Defining who is an expert and establishing adequate criteria for selection. Even qualified experts are never free of personal biases in their opinions. Most experts tend to think conservatively and in terms of the status quo, which can limit the possibilities of more radical changes or future discontinuities from being discussed. Therefore, it is most useful to use rigorous procedures that challenge prevailing views and do not allow dominant personalities to take over the interaction.

Expert judgment offers some advantages over other approaches to understanding forecast uncertainty. This approach can use the same models, assumptions, and committee structure of the “official forecast,” elaborating on the uncertainty inherent in the assumptions. The official forecast is still treated as most likely and becomes the median variant within a range. It may be also be the least costly alternative because of the resources required to implement stochastic models and to store, retrieve, and analyze past forecast errors.

State and Regional Agency Practices

A survey was sent to 18 regional agencies and 17 state agencies that produce official forecasts. A non-probability judgment scheme was used to select the sample. These 35 agencies have long-standing, well respected forecasting programs and are similar in stature to the forecasting program at MAG. Eleven of the 18 regional agencies responded, a response rate of 61%, and 12 of the 17 state agencies returned the survey. The state agency response rate was higher at 71%. The survey instrument and list of respondents is contained in Appendix B. The survey questions focused on three areas: 1) how forecast quality is assessed; 2) how uncertainty is incorporated into the forecasting process; and 3) general characteristics of the forecasting process. The first two areas are the most relevant to forecast uncertainty, and a summary of these results is presented below. Appendix C contains detailed results and tables from the survey, including the general characteristics of regional and state agency forecasts.

Assessing Forecast Quality

The quality of the population forecast is assessed by all state agencies and with one exception is the only variable assessed (see Table C-1). Employment is the only forecasted variable assessed for quality by all regional agencies. Most regional agencies also assess the quality of their population and housing forecasts. About half of the regional agencies assess their land use forecasts and smaller percentages assess income and housing price forecasts.

Only one state agency assesses the quality of its subcounty forecast since their primary focus is on state- and county-level forecasts (see Table C-2). All states assess the quality of their county forecasts and 11 of the 12 states assess their state forecast. About half of the state agencies evaluate forecast quality for multi-county regions. Most regional agencies evaluate forecast quality for multi-county region, county, and subcounty areas, with one agency also evaluating the quality of its state forecast.

In both regional and state agencies, by far the most common approach used to assess forecast quality is to examine the quality of past forecasts (see Table C-3). More state agencies rely on internal/external review, while more regional agencies use expert panels. Published research is used about the same in both regional and state agencies.

Incorporating Uncertainty into the Forecasting Process

Migration is the greatest source of forecast uncertainty for both regional and state agencies (see Table C-4). For state agencies, future fertility and mortality trends rank second and third most important. Taken together these three factors account for 84% of the sources of uncertainty cited by state agencies. For regional agencies, economy/labor force and land use are cited the most behind migration and are ranked high as important sources of uncertainty.

More regional than state agencies currently incorporate uncertainty into their forecasting process (see Table C-5). State agencies use a single approach, while regional agencies tend to use multiple ways when incorporating uncertainty in their forecasting process. In terms of specific approaches, alternative scenarios are the most used in both regional and state agencies (see Table C-6). Range of values and expert panels are also used by regional agencies, but by only one state agency. Probability intervals are used by relatively few state and regional agencies.

A cross-classification of current incorporation of uncertainty status by anticipated changes to current practices show that two-thirds of agencies who anticipate changes currently do not incorporate uncertainty into their process (see Table C-7). Of agencies not anticipating changes, 91% currently incorporate uncertainty and only 9% do not. Put another way, of the 9 agencies that currently do not incorporate uncertainty into their forecasting process 8 are planning to do so in the future. These data suggest a continuing and increasing desire to incorporate uncertainty into state and regional agency forecasts.

Of the new approaches being considered by agencies who anticipate changing practices, for regional agencies alternative scenarios is the most often cited new approach followed by range of values and expert panels (see Table C-8). State agencies considering new approaches are focusing on range of values, but 50% have not yet identified approach(s) they are considering.

In terms of spending priorities, state and regional agencies differ somewhat (see Table C-9). Both would spend 63 cents of every dollar on model enhancement and data development activities, with model enhancement the highest priority. State agencies place more value on activities dealing with forecasting uncertainty and error rather than on database systems. Regional agencies show the opposite spending priority in this regard, which is indicative of the greater data management challenges faced by regional agencies

Implementation Guidelines and Options

General Approach

MAG currently relies on expert panels and internal/external review to assess the uncertainty of their forecasts. The guidelines and options suggested are designed to enhance MAG's current approach for assessing the uncertainty of its SEMS. To be successful, these enhancements must have clear advantages; be cost-effective; be consistent with the MAG's mission and philosophy regarding the uses and roles of forecasting; and be understandable to management, stakeholders and the general public (USERS). Based on these criteria, it is suggested that MAG take a phased approach to enhancing the uncertainty assessment of its SEMS. Three identifiable phases are suggested and in order they are: 1) alternative scenarios-policy analysis and sensitivity testing (ASPAST); 2) alternative scenarios-explicit ranges (ASER); and 3) probability intervals (PI).

In general, this progression represents an increasing commitment in terms of resources and a greater enhancement of current practices. This "try before you buy" approach should be undertaken gradually and cautiously, not abruptly. In that way, MAG can decide how far along the forecast uncertainty road map it wants to travel without committing resources up front. It also would allow MAG to gain the necessary skills to apply the increasing more powerful and complex ways of dealing with forecast uncertainty should it chose to go in that direction. Finally, USERS will face a learning curve on how to use and interpret the additional information on forecast uncertainty. A gradual process of implementation would help ease their transition.

Forecast uncertainty under the ASPAST phase for the County and subregional areas is relatively straightforward and should pose no significant challenges. MAG has experience with these types of scenarios and the idea here is to analyze a broader and more comprehensive set of alternatives and policy questions.

Moving to ASER and PI will be more complex and technically challenging, especially for subregional areas. The UrbanSim framework and its underlying assumptions are more intricate and highly interconnected than the cohort-component framework and other methods used to derive County forecast totals. Subregional forecasts are also subject to constraints (e.g., space, land use, pricing), which will impact the creation of forecast ranges and their probabilities.

For the ASER and PI phases, MAG should consider a tiered approach that would focus first on forecast uncertainty for the County and next moving to the RAZ. MAG should examine forecast uncertainty at the SAZ only if useful results are obtained for the RAZ. MAG should also consider first examining a limited perspective on forecast uncertainty in subregional geographies before trying to capture its full extent. Ranges under this perspective might focus, for example, on just the uncertainties inherent in local general plans.

Role of Experts

Extensive input and review is an important part of MAG's forecasting process and its current approach for assessing forecast uncertainty. The POPTAC Ad Hoc Subcommittee, which provides more in depth input on the development of socioeconomic information, is a likely candidate to provide further and enhanced guidance on subregional forecast uncertainty. Given the economic and pricing framework of UrbanSim, MAG should consider expanding the composition of this subcommittee to provide a broader range of expertise. A wider perspective could also facilitate more "out of the box" thinking that would benefit the current forecasting process and additional efforts related to forecast uncertainty. MAG should also consider a Delphi-like approach for gathering expert opinions if it moves to the ASER and/or PI phases.

An appropriate group of experts will be needed to provide guidance on County forecast uncertainty. The State Population Technical Advisory Committee or a smaller subcommittee from its members could serve in this capacity. Since MAG is mandated to use the County population forecast prepared by the DOC, MAG should consider if and how to involve the DOC in their efforts related to understanding forecasting uncertainty.

Implementation Phases

Phase 1 Alternative Scenarios-Policy Analysis and Sensitivity Testing

Probability free scenarios for policy analysis and sensitivity testing are a logical first step to enhancing MAG's assessment of forecast uncertainty. This approach can be accomplished with existing models and databases. It is a relatively benign way to illustrate future uncertainties to USERS that would be easy for them to understand. Scenarios are benign in the sense that they are less likely to raise questions about model credibility, as their focus is on What If questions rather than on providing robust measures of forecast uncertainty. Some additional scenarios MAG might consider are:

1. Varying regional control totals (e.g., alternate views of U.S. immigration policy).
2. Assuming change in the planned land use characteristics;
3. Varying "build out" capacity using the low density and high density for both residential and non-residential uses;
4. Varying different transportation system assumptions (e.g., no build versus the RTP network); and
5. Varying assumptions about pricing and cost signals.

Phase 2 Alternative Scenarios-Explicit Ranges

Developing explicit ranges requires more comprehensive alternatives than used in Phase 1. In moving to this phase, a range of forecasts would be developed for each geographic area. Each alternative should be interpreted as providing a reasonable view of the future, but the most likely series would be preferred to all others. The assumption set should be specified so the high and low series provide a "reasonable" range, and that the range will contain the future activity observed in the target year. MAG would still follow its current, familiar process of developing a most likely forecast. The ranges provide information to augment rather than change that process.

A first look at ranges could focus only on the uncertainty of the County forecast and how that impacts the subregional forecast. This would require low and high ranges to be placed around the most likely County population forecast and the other derived County totals. UrbanSim would then be run twice using the County totals that reflect the low and high ends of their respective ranges. Subsequent analysis could then incorporate subregional forecast uncertainty into the ranges.

Phase 3 Probability Intervals

Expert-based. An expert-based approach should be undertaken first if MAG decides to develop probabilistic measures of forecast uncertainty. The experts helped to develop the non-probabilistic ranges in Phase 2, and this effort would build on that work. It would provide information on distributional shape and parameters for the key assumptions, which are used to derive the probabilities attached to the forecast. Software such as @Risk (a Microsoft Excel add-in) can be used to simulate a probability distribution of the forecast based on random sampling rules applied to the uncertainty inputs.

Empirically-based. MAG should also consider exploring empirically-based probability intervals. This is a longer term option since it will take time for MAG to gather needed data for this approach using UrbanSim. An exciting prospect would be a replication of the repeated sampling method using aggregations of parcels. In addition to insights into forecast uncertainty, analyses of past forecast errors can help guide and prioritize model development and enhancement efforts. As such, MAG should ensure its forecast archiving system allows easy retrieval and manipulation of past forecasts.

Model-based. Model-based probability intervals are the least attractive option for MAG at this time. Probability intervals around the County forecast could be developed using stochastic time series-based models. However, the efficacy of such intervals around County forecasts has not yet been demonstrated. The research of Waddell and his colleagues cited in footnote 2 offers one way of developing probabilistic intervals inside UrbanSim, but it not close to practical application. Further efforts along these lines might yield fruitful results that could eventually become part of the UrbanSim framework. If that were to happen, measuring the uncertainty of a forecast based on UrbanSim would be a relatively low cost and easy to implement option.

Appendix A
Measuring Forecast Error

Introduction

Given the widespread use of forecasts—and the many planning decisions and funding allocations tied to those forecasts—it is important to evaluate the error (accuracy and bias) of forecasting methods. Accuracy is how close the forecast is to its intended target regardless of whether it is too high or two low, while bias shows the tendency of a forecast to be too high or too low. Forecasts are most often evaluated on a post-hoc basis by looking at how well past forecasts have performed. For example, a population forecast for the year 2000 done in 1980 would be compared to the 2000 census count or a 2007 employment forecast done in 1990 with the 2007 employment estimate from the Bureau of Labor Statistics. This Appendix discusses the most commonly used measures of forecast accuracy and bias in demographic and socioeconomic forecasts and the criteria for selecting among them.[1]

Defining Forecast Error

Forecast Error (E) as the difference between the forecast (F) for a particular geographic area (i) in a particular target year (t) and the actual activity (A) for the same area and year:

$$E_{it} = F_{it} - A_{it}.$$

For example, if the population of a county had been projected to be 55,000 in 2000, and the actual population turned out to be 50,000, the forecast error would be 5,000. If the population had been projected to be 45,000, the forecast error would be –5,000.

Forecast errors are often expressed as percent differences rather than as absolute differences. This specification is useful when measures of relative error rather than absolute error are needed. The use of percent errors (PE) is particularly helpful when making comparisons across regions because—without adjustments for the size of an area—errors for larger places would dominate the effects of errors for smaller places.

$$PE_{it} = [(F_{it} - A_{it}) / A_{it}] * 100.$$

In the above example, if the population of a county had been projected to be 55,000 in 2000 and the actual population turned out to be 50,000, the percent error would be (5,000 / 50,000) * 100 = 10%. If the population had been projected to be 45,000, the percent error would be (-5,000 / 50,000) * 100 = -10%.

Counts from the decennial census are often used as proxies for the "actual" population, housing, and socio-economic variables of an area. For postcensal or intercensal years, estimates produced by the state and federal agencies or private data companies are typically used. These proxies are not perfect, of course. Census counts are subject to errors that may be substantial for some places

[1] This Appendix is adapted from pages 301-307 in S. Smith, J. Tayman, and D. Swanson. 2001. S*tate and Local Population Projections: Methodology and Analysis*. New York: Kluwer Academic/Plenum Publishers.

or demographic groups; estimates are subject to even larger errors. Enumeration and estimation errors undoubtedly have an impact on individual forecast errors. They can either raise or lower forecast errors, depending on whether they reinforce or offset the differences between projected and actual activities. Because of these offsetting effects, the impact of enumeration/estimation errors on average forecast errors is probably not very great, especially for longer projection horizons. Most empirical studies do not attempt to adjust for enumeration or estimation errors when evaluating forecast accuracy.

Summary Measures of Forecast Error

E_{it} and PE_{it} represent the individual forecast errors for the observations under study and form a distribution of forecast errors. These error distributions can then be analyzed using summary measures including means, medians, and standard deviations. Table A-1 illustrates the computations of commonly used summary measures for a sample of counties in Florida.

The first two measures refer to the average error for a set of n individual forecasts:

$$\text{Mean Error (ME)} = 1/n * \Sigma(E_{it}); \text{ and}$$
$$\text{Mean Absolute Error (MAE)} = 1/n * (\Sigma|E_{it}|).$$

The first is a measure of forecast bias and takes account of the direction of errors; consequently, positive and negative errors offset each other. In fact, they could offset each other completely, resulting in a ME of zero even when individual errors are large. For example, three forecasts with errors of 400, 200, and –600 would yield a ME of zero.

The second is a measure of forecast accuracy and ignores the direction of the error, so positive and negative errors do not offset each other. This measure—sometimes called the mean absolute deviation—shows the average difference between forecasted and actual populations, regardless of whether the forecasts were too high or too low. Using the example cited above, forecasts with errors of 400, 200, and –600 would yield a MAE of 400.

These measures are based on the numerical differences between projected and actual populations; they do not account for differences in the size of the activities being projected. Yet a forecast error of 1,000 has a very different meaning for a place with 2,000 residents than a place with 200,000 residents. The next two measures account for activity size by focusing on percent errors rather than numerical errors:

$$\text{Mean Algebraic Percent Error (MALPE)} = 1/n * (\Sigma(PE_{it})); \text{ and}$$
$$\text{Mean Absolute Percent Error (MAPE)} = 1/n * (\Sigma|PE_{it}|).$$

The MALPE (often called the mean percent error) is a measure in which positive and negative values offset each other. Consequently, it is often used as a measure of bias. A positive MALPE reflects a tendency for forecasts to be too high and a negative MALPE reflects a tendency for forecasts to be too low. The proportion of positive errors (%POS) is another commonly used as measures of bias. In this measure, a value of 50% would indicate an unbiased forecast; values exceeding 50% would indicate a positive bias; and values less than 50% a negative bias.

Table A-1. Measures of Forecast Error, Selected Counties in Florida[1]

County	2000 Census (A)	Forecast (F)	E	abs(E)	PE	abs(PE)	abs(PE)^2
Bay	148,217	147,684	-533	533	-0.4	0.4	0.1
Brevard	476,230	504,263	28,033	28,033	5.9	5.9	34.7
Broward	1,623,018	1,469,802	-153,216	153,216	-9.4	9.4	89.1
Dade	2,253,362	2,173,098	-80,264	80,264	-3.6	3.6	12.7
De Soto	32,209	28,290	-3,919	3,919	-12.2	12.2	148.0
Flager	49,832	46,423	-3,409	3,409	-6.8	6.8	46.8
Hillsborough	998,948	970,405	-28,543	28,543	-2.9	2.9	8.2
Jefferson	12,902	13,169	267	267	2.1	2.1	4.3
Manatee	264,002	260,334	-3,668	3,668	-1.4	1.4	1.9
Monroe	79,589	90,470	10,881	10,881	13.7	13.7	186.9
Nassau	57,663	53,016	-4,647	4,647	-8.1	8.1	64.9
Sarasota	325,957	339,398	13,441	13,441	4.1	4.1	17.0
Sumter	53,345	37,491	-15,854	15,854	-29.7	29.7	883.3
Suwannee	34,844	30,921	-3,923	3,923	-11.3	11.3	126.8
Wakulla	22,863	17,052	-5,811	5,811	-25.4	25.4	646.0
Total	6,432,981	6,181,816	-251,165	356,409			
		Mean	**-16,744** **ME**	**23,761** **MAE**	**-5.7** **MALPE**	**9.1** **MAPE**	**12.3** **RMSPE**
		Median	**-3,919** **MEDME**	**5,811** **MEDAE**	**-3.6** **MEDALPE**	**6.8** **MEDAPE**	
		% Positive	**26.7%**				

[1] Forecasts produced by the Bureau of Economic and Business Research at the University of Florida and reflect a 10-year forecast horizon.

The MAPE, on the other hand, is a measure in which positive and negative values do not offset each other. It shows the average percent difference between forecasts and actual activities regardless of whether the individual forecasts were too high or too low. The MAPE is a widely used measure of forecast accuracy in the general forecasting literature.

Sometimes it is important to use error measures that give more weight to large errors than to small errors; for example, when a large error has a disproportionately large impact on the cost of being wrong. Although the Mean Square Error and Root Mean Square Error Mean Squared Error are commonly used in general forecasting applications, they are less useful for evaluations of population, housing, and socioeconomic forecast errors because results for large areas swamp the results for small areas. This problem can be dealt with by using percent errors rather than absolute errors as in the Root Mean Squared Percent Error (RMSPE):

$$\text{RMSPE} = [1/n\ \Sigma(\text{PE}_{it})^2]^{1/2}.$$

Some accuracy measures focus on other aspects of the error distribution rather than the mean value. For example, the median absolute percent error (MEDAPE) is the percent error which falls right in the middle of the distribution: half the absolute percent errors are larger and half are smaller. Median error is useful when the objective is to highlight the "typical" error and ignore the effects of outlying errors. As seen in Table A-1, outliers, such as Wakulla and Sumter counties, can inflate the mean because forecast error distributions are typically right-skewed.[2] Moreover, the effect of outlying errors increases as activity levels decrease in size.

The measures discussed above examine a forecast's accuracy and bias for a particular observation. Another perspective views the misallocation of a forecast across a set of observations. This aspect of forecast error is especially pertinent for forecasting models that allocate activities from larger units to smaller units such as a county to a RAZ or a RAZ to a parcel. The Index of Dissimilarity can be used to measure the extent that the forecast misallocates activities:

$$\text{IOD} = (0.5 * (\Sigma \left| F_{it} / F_t - A_{it} / A_t \right|)) * 100.$$

The IOD compares the forecast share of activity in the i^{th} observation with the observed share. It sums the absolute value of those differences across the observations and multiplies that sum by 0.5. One advantage of the IOD is its relatively straightforward interpretation; it gives the percent (0 to 100) that the two distributions would have to change in order to match.

The measures previously discussed focus on differences in activity levels in a target year. This is the approach most commonly used to evaluate forecast error. An alternative approach focuses on differences between projected and actual growth rates rather than differences between projected and actual activity sizes. Seeing how well the forecast change matches or predicts the observed change is a more rigorous test. A target year forecast includes both activities in the launch year and forecast change, which confounds the measurement of the error caused solely by the forecast method.

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[2] J. Tayman, D. Swanson, and C. Barr. 1999. In Search of the Ideal Measure of Forecast Accuracy for Subnational Demographic Forecasts. *Population Research and Policy Review* 18: 387-409.

A parametric approach to evaluating forecast change uses a regression model that predicts the observed growth rate from the forecast growth as the independent variable. A different, and perhaps more useful perspective, is to take a more general look at this relationship using non-parametric techniques. The growth rate variable is defined by broad categories rather than by its original interval form. These redefined variables are cross-classified as shown in Table A-2, which facilitates analysis of the conditional relationships within different growth rate categories. Also shown is Kendall's Tau, which measures the strength of the relationship between the forecast and observed growth rates. Of particular interest is the percentages shown in the diagonal of the table, which represent the success of the forecast growth rate category in predicting the same growth rate category as observed. If the forecast growth rate category is a perfect predictor, each diagonal cell would contain 100%.

Table A-2. Relationship between the Observed and Forecast Growth Rate, Census Tracts in San Diego County[1]

	Forecast			
Observed	Decline	0 to 19%	10 to 49%	50+%
Decline	**26%**	17%	8%	4%
0 to 19%	36%	**41%**	24%	10%
10 to 49%	24%	31%	**41%**	19%
50+%	14%	11%	27%	**67%**
	100%	100%	100%	100%

Kendall's tau^b = 0.325

[1] Taken from J. Tayman. 1996. The Accuracy of Small Area Population Forecasts Based on a Spatial Interaction Land-Use Modeling System. *Journal of the American Planning Association* 62(1): 85-98.

Measures of Relative Forecast Error

Forecast error is the typical and often the only standard for judging the adequacy or quality of a given forecast. This expectation has served to support the demand of many users that forecasts meet standards of accuracy that exceed those commonly accepted as reasonable by forecasters. It also underscores the reluctance of agencies to rigorously evaluate their forecasts and publically disclose their error, especially the error for subcounty areas. Forecast error is an important characteristic, but it not the only criterion upon which a forecast should be judged. Forecasts can also be judged according to their overall "utility," or their value-added in improving the quality of information upon which decisions are based.

To measure the "utility" or potential gain in information from a forecast, measures have been developed that compare the errors from a formal forecasting model to a no or low-cost naïve model. Theil's U-statistic is used extensively to evaluate time series forecasting models. This statistic squares the errors so that large errors are given heavier weights than small errors. Theil's U ranges from 0 to 1.0, where the upper bound indicates no improvement over the naive model. The proportionate reduction in error (PRE) also shows the extent to which a forecast from a formal model can improve on the naïve model, but without giving heavier weights to large errors:

PRE = ((Naïve Model Error – Formal Model Error) / Naïve Model Error) * 100.

A PRE value of zero indicates the formal model does not improve on the naïve model. Values between 0 and 100% represent the percentage gain of information from the formal model, while negative vales indicate the formal model performs worse than the naïve model. As shown in Table A-3, the formal model does add value or knowledge over the naïve model for both forecast bias and accuracy.

Table A-3. Proportionate Reduction in Error,
Selected Counties in Florida

	2000			
County	Census (A)	Naive (F)[1]	PE	abs(PE)
Bay	148,217	140,216	-5.4%	5.4%
Brevard	476,230	455,230	-4.4%	4.4%
Broward	1,623,018	1,463,281	-9.8%	9.8%
Dade	2,253,362	2,334,730	3.6%	3.6%
De Soto	32,209	28,764	-10.7%	10.7%
Flager	49,832	34,593	-30.6%	30.6%
Hillsborough	998,948	964,323	-3.5%	3.5%
Jefferson	12,902	13,615	5.5%	5.5%
Manatee	264,002	255,165	-3.3%	3.3%
Monroe	79,589	94,040	18.2%	18.2%
Nassau	57,663	52,961	-8.2%	8.2%
Sarasota	325,957	262,453	-19.5%	19.5%
Sumpter	53,345	38,059	-28.7%	28.7%
Suwannee	34,844	32,277	-7.4%	7.4%
Wakulla	22,863	17,117	-25.1%	25.1%
		Naïve Method Means	-8.6%	12.3%
		Formal Method Means	-5.7%	9.1%
PRE (MALPE) =	**34.0%**	((-8.6 -(-5.7)) / -8.6) * 100		
PRE (MAPE) =	**25.7%**	((12.3 - 9.1) / 12.3) * 100		

[1] Naïve forecast is the 1990 census controlled to the 2000 population forecast for Florida.

Selection Criteria

Several criteria used to select measures of forecast error are mentioned frequently. Error measures should be reliable; that is, repeated applications should yield similar results. They should be valid, in the sense that they actually measure what they are purported to measure. They should convey as much information about forecast errors as possible and should be easy for the data user to understand. They should be sensitive to differences in error distributions, but should not be unduly influenced by outliers.

A survey of the literature on population forecasting reported that the MAPE was used far more frequently than any other measure of error, followed by the RMSPE, and Theil's U-statistic.[3] The MAPE is a good choice as a general accuracy measure because it incorporates the best characteristics among the various accuracy criteria and provides a reasonable measure for evaluating accuracy under a wide variety of circumstances. Because of the impact of a few large errors, however, the MAPE may overstate the "typical" error in a set of projections and should be accompanied by a more robust measure of central tendency such as the median error. The MALPE is fairly widely used as a measure of bias and provides a useful way to investigate the tendency for projections to be too high or too low.

Can valid conclusions be drawn when only a few error measures are analyzed? They can in most instances. Although different error measures provide different perspectives on forecast accuracy and bias, error patterns are found to be quite stable across a variety of error measures. That is, the impact of factors such as size, growth rate, or length of forecast horizon on forecast accuracy is generally about the same regardless of which error measure is used. The same is true for alternative measures of bias. Because of these similarities, it is not necessary to analyze a wide variety of error measures to achieve valid conclusions.

When population projections are used to guide real-world decision making, however, the analyst should consider more than a single measure of error. In particular, it is important to consider the cost of being wrong. When forecasts are used for planning the location of a retail outlet, constructing a new electric power plant, or adding a lane to a freeway, for example, what are the implications of inaccurate forecasts? Will the cost of forecasting too little growth be considerably greater than the cost of forecasting too much growth? Will small errors have little impact on costs, but large errors have a disproportionately large impact? These are the types of questions that should be answered before using population forecasts to guide decision making.

[3] D. Ahlburgh. 1995. Simple versus Complex Models: Evaluation, Accuracy, and Combining. *Mathematical Population Studies* 5:281-290.

Appendix B
State and Regional Agency Survey Instrument and Respondents

Uncertainty in Forecasting
State-of-the-Practice in Regional and State Agencies

This brief eleven question survey aims to identify the general characteristics and state-of-the-practice in assessing the quality and uncertainty of official forecasts produced by regional and state agencies. You have been selected to participate in this survey because of your expertise in forecasting.

As you go through the questionnaire,
please mark the "closed-ended" responses by bolding your choice(s).

1. What variables are included in the long-range forecast?*(Please mark all that apply by* ***'bolding'*** *your choice(s))*
    a. Total population
    b. Age and sex
    c. Race/ethnicity
    d. Households
    e. Housing units
    f. Employment
    g. Income
    h. Other *(Please list other variables below)*

2. What is the typical forecast horizon?

    (Please record the typical forecast horizon length here, preferably in years)

3. How often is the forecast updated?

    (Please record the frequency of forecast updates here, preferably in years)

(Please continue answering questions on the next page)

4. Are economic factors considered in the forecast? *(Please' **bold'** your choice)*

   a. No

   b. Yes *(If yes, please describe how)* ➷

5. How is the quality of the long-term forecast assessed? *(Please mark all that apply by **'bolding'** your choice(s)*)

   a. Using past forecasts produced by your agency

   b. Using published research

   c. Using an expert panel

   d. Other *(Please describe below)* ➷

(Please continue answering questions on the next page) ☞

6. At what level of geography is the forecast assessed? (*Please mark all that apply by **'bolding'** your choice(s)*)

   a. State
   b. Multi-county region
   c. County
   d. Subcounty

7. What forecasted variables are assessed? (*Please mark all that apply by **'bolding'** your choice(s)*)

   a. Population
   b. Housing
   c. Employment
   d. Income
   e. Land Use
   f. Other *(Please list other variables below)* ➷

8. What are the major sources of uncertainty in the long-term forecast (e.g., migration assumptions or land use assumptions)? *(Please list the source and its rank, with 1being the most important source)* ➷

Sources	**Rank**

(Please continue answering questions on the next page) ☞

9. How is uncertainty incorporated into the current forecasting process? *(Please mark all that apply by* ***'bolding'*** *your choice(s))*

   a. Currently not incorporated
   b. Using alternative scenarios
   c. Using a range of forecast values
   d. Using empirically-based probability intervals
   e. Using model-based probability intervals
   f. Using an expert panel
   g. Other *(Please describe below)* ➷

10. How will uncertainty be incorporated into future forecasting processes? *(Please mark all that apply by* ***'bolding'*** *your choice(s))*

   a. No changes are anticipated
   b. Using alternative scenarios
   c. Using a range of forecast values
   d. Using empirically-based probability intervals
   e. Using model-based probability intervals
   f. Using an expert panel
   g. Other *(Please describe below)* ➷

(Please continue answering questions on the next page) ☞

11. How would you spend $100 on the following areas? *(Please put whole dollar amounts in the boxes and ensure they sum to $100)*

Area	**Funding**
Model Enhancement	
Forecast Uncertainty and Error	
Data Development	
Database Management and Integration Systems	
Total Spent	**$100**

Thank you very much for taking the time to complete this survey. Your responses are very important, so please check it to make sure that you completed all 11 questions.

When done, please email your completed survey back to me by December 17th through my email address, jtayman@san.rr.com
Thanks again, Jeff Tayman

Survey Respondents

Regional Agencies	State Agencies
Atlanta Regional Commission	Alaska- Department of Labor
Baltimore Metropolitan Council	Arkansas- College of Business Administration, University of Arkansas at Little Rock
Houston-Galveston Area Council	California- Department of Finance
Mid-America Regional Council	Florida- Bureau of Economic and Business Research, University of Florida
PIMA Association of Governments	Indiana- Indiana Business Research Center, Indiana University
Portland Metro	Minnesota- Department of Administration
Puget Sound Regional Council	New Jersey- Department of Labor
San Diego Association of Governments	New Mexico- Bureau of Economic and Business Research, University of New Mexico
So. California Association of Governments	New York- Program on Applied Demographics, Cornell University
SE Michigan Council of Governments	Texas- Institute of Demographic and Socioeconomic Research, University of Texas at San Antonio
Wasatch Front Regional Council	Washington- Office of Financial Management
	Wisconsin- Department of Administration

Appendix C: State and Regional Agency Survey Results

A survey was sent to 18 regional agencies and 17 state agencies that produce official forecasts. A non-probability judgment scheme was used to select the sample. These 35 agencies have long-standing, well respected forecasting programs and are similar in stature to the forecasting program at MAG. Eleven of the 18 regional agencies responded, a response rate of 61%, and 12 of the 17 state agencies returned the survey. The state agency response rate was higher at 71%. The survey instrument and list of respondents is contained in Appendix B. The survey questions focused on three areas: 1) how forecast quality is assessed; 2) how uncertainty is incorporated into the forecasting process; and 3) some general characteristics of the forecasting process.

Assessing Forecast Quality

Three questions were asked regarding the assessment of the quality of the forecast. These questions pertained to the variables assessed, the geography assessed, and the approach used to conduct the assessment.

Table C-1. Assessing Forecast Quality: Variables[1]

	Percent			Number		
Variables	Regional	State	Total	Regional	State	Total
Population	26%	92%	42%	10	12	22
Housing	23%	0%	17%	9	0	9
Employment	28%	8%	23%	11	1	12
Income	8%	0%	6%	3	0	3
Land Use	13%	0%	10%	5	0	5
Housing Price	3%	0%	2%	1	0	1
All Responses	100%	100%	100%	39	13	52

[1] Respondents could select more than one variable.

Source: 2008 survey of state and regional agencies.

The quality of the population forecast is assessed by all state agencies and with one exception is the only variable assessed (see Table C-1). Employment is the only forecasted variable assessed for quality by all regional agencies. Most regional agencies also assess the quality of their population and housing forecasts. About half of the regional agencies asses their land use forecasts and smaller percentages assess income and housing price forecasts.

Table C-2. Assessing Forecast Quality: Geographic Areas[1]

	Percent			Number		
Geographic Areas	Regional	State	Total	Regional	State	Total
State	4%	37%	21%	1	11	12
Multi-county region	30%	20%	25%	8	6	14
County	33%	40%	37%	9	12	21
Subcounty	33%	3%	18%	9	1	10
All Responses	100%	100%	100%	27	30	57

[1] Respondents could select more than one variable.

Source: 2008 survey of state and regional agencies.

As expected, relatively few state agencies assess the quality of subcounty forecasts since their primary focus is on state- and county-level forecasts (see Table C-2). All states assess the quality of their county forecasts and with one exception the state as well. About half of the state agencies evaluate forecast quality for multi-county regions. Most regional agencies evaluate forecast quality for multi-county region, county, and subcounty areas, with one agency also evaluating the quality of its state forecast.

Table C-3. Assessing Forecast Quality: Approach[1]

	Percent			Number		
Approach	Regional	State	Total	Regional	State	Total
Past Forecasts	42%	53%	47%	10	10	20
Published Research	17%	16%	16%	4	3	7
Expert Panel	29%	11%	21%	7	2	9
Internal/External Review	4%	21%	12%	1	4	5
Sensitivity Testing	4%	0%	2%	1	0	1
Compare to Other Forecasts	4%	0%	2%	1	0	1
All Responses	100%	100%	100%	24	19	43

[1] Respondents could select more than one variable.

Source: 2008 survey of state and regional agencies.

In both regional and state agencies, by far the most common approach used to assess forecast quality is to examine the quality of past forecasts (see Table C-3). More state agencies rely on internal/external review, while more regional agencies use expert panels. Published research is used about the same in both regional and state agencies.

Incorporating Uncertainty into the Forecasting Process

Four questions were asked regarding the uncertainty of the forecast. An open-ended question asked respondents to list and rank the major sources of uncertainty in their forecasts. A second question asked how uncertainty is incorporated into the current forecasting process. A third question asked about plans for incorporating uncertainty in future forecasts. The final question asked respondents to allocate $100 between four activities related to the forecasting process with uncertainty and error being one of the choices.

Table C-4. Major Sources of Uncertainty in the Long-range Forecast[1]

	Rank (1 Highest)[2]			Percent			Number		
Uncertainty Sources	Regional	State	Total	Regional	State	Total	Regional	State	Total
Migration	1.7	1.0	1.3	22%	46%	33%	7	12	19
Fertility	4.0	2.0	2.3	3%	23%	12%	1	6	7
Mortality	2.0	3.0	2.7	6%	15%	10%	2	4	6
Economy/Labor Force	1.8	2.0	1.8	16%	4%	10%	5	1	6
Land Uses	1.9	–	1.9	22%	0%	12%	7	0	7
Administrative/Regulatory	2.0	2.0	2.0	3%	8%	5%	1	2	3
Commuting Patterns	2.0	3.0	2.5	3%	4%	3%	1	1	2
Model Specification	3.0	–	3.0	6%	0%	3%	2	0	2
Availability of Infrastructure	2.0	–	2.0	3%	0%	2%	1	0	1
U.S. Forecasts	3.0	–	3.0	3%	0%	2%	1	0	1
Prices, Costs	4.0	–	4.0	3%	0%	2%	1	0	1
Household Size/VR	5.0	–	5.0	3%	0%	2%	1	0	1
Aging of Households	3.0	–	3.0	3%	0%	2%	1	0	1
Changes in Technology	4.0	–	4.0	3%	0%	2%	1	0	1
All Responses				100%	100%	100%	32	26	58

[1] Respondents could select more than one variable.
[2] Average of ranks

Source: 2008 survey of state and regional agencies.

Migration both international and domestic is the greatest source of forecast uncertainty for both regional and state agencies (see Table C-4). For state agencies, future fertility and mortality trends rank second and third most important. Taken together these three factors account for 84% of the sources of uncertainty cited by state agencies. For regional agencies, economy/labor force and land use are cited the most behind migration and are ranked high as important sources of uncertainty. Commuting patterns, infrastructure availability, and administrative/regulatory decisions have average ranks of 2.0 for regional agencies, but these factors are only cited by one agency.

Table C-5. Uncertainty Incorporated into Current Forecasting Process[1]

	Percent			Number		
	Regional	State	Total	Regional	State	Total
Yes	73%	50%	61%	8	6	14
No	27%	50%	39%	3	6	9
All Responses	100%	100%	100%	11	12	23

Source: 2008 survey of state and regional agencies.

Table C-6. Uncertainty in Current Forecasting Process: Approach[1]

	Percent			Number		
Approach	Regional	State	Total	Regional	State	Total
Alternative Scenarios	35%	33%	35%	6	2	8
Range of Values	24%	17%	22%	4	1	5
Expert Panel	29%	0%	22%	5	0	5
Empirical Intervals	6%	17%	9%	1	1	2
Model Intervals	6%	17%	9%	1	1	2
Past Forecasts	0%	17%	4%	0	1	1
All Responses	100%	100%	100%	17	6	23

[1] Respondents could select more than one variable.

Source: 2008 survey of state and regional agencies.

More regional than state agencies (73% versus 50%) currently incorporate uncertainty into their forecasting process (see Table C-5). State agencies use a single approach, while regional agencies tend to use multiple ways when incorporating uncertainty in their forecasting process. Two regional agencies use a single approach, four use 2 approaches, one uses 3 approaches, and one uses 4 approaches (data not shown). In terms of specific approaches, alternative scenarios are the most used in both regional and state agencies (see Table C-6). Range of values and expert panels are also used by regional agencies, but by only one state agency. Probability intervals, either empirically- or model-based, are used by two state and regional agencies.

Table C-7. Current Status by Anticipated Changes to Incorporating Uncertainty

	Changes Anticipated				Changes Anticipated		
Currently Incorporated	Yes	No	Total	Currently Incorporated	Yes	No	Total
Yes	33%	91%	61%	Yes	4	10	14
No	67%	9%	39%	No	8	1	9
All Responses	100%	100%	100%	All Responses	12	11	23

Source: 2008 survey of state and regional agencies.

Table C-8. Uncertainty in Future Forecasting Process: Approach[1,2]

	Percent			Number		
Approach	Regional	State	Total	Regional	State	Total
Alternative Scenarios	44%	17%	33%	4	1	5
Range of Values	22%	33%	27%	2	2	4
Expert Panel	22%	0%	13%	2	0	2
Empirical Intervals	0%	0%	0%	0	0	0
Model Intervals	11%	0%	7%	1	0	1
Do Not Know	0%	50%	20%	0	3	3
All Responses	100%	100%	100%	9	6	15

[1] Respondents could select more than one variable.

[2] Includes respondents who indicated a change in practices and only new approaches not currently being used.

Source: 2008 survey of state and regional agencies.

Table C-7 shows the cross-classification of current incorporation of uncertainty status by anticipated changes to current practices for state and regional agencies combined. Two thirds of agencies who anticipate changes currently do not incorporate uncertainty into their process, while the other third are considering changes to augment current processes. Of agencies not anticipating changes, 91% currently incorporate uncertainty and only 9% do not. Put another way, of the 9 agencies that currently do not incorporate uncertainty into their forecasting process 8 are planning to do so in the future; the one exception is a state agency. These data suggest a continuing and increasing desire to incorporate uncertainty into state and regional agency forecasts.

Table C-8 shows the new approaches being considered by the 12 agencies who anticipate changing practices. For regional agencies, alternative scenarios are the most often cited new approach followed by range of values and expert panels. One regional agency is considering model-based intervals. State agencies considering new approaches are focusing on range of values. Three state agencies have not yet identified the approach(s) they are considering, and one state agency is considering using alternative scenarios.

Table C-9. Forecast Process Spending Priorities[1]

Activity	Regional	State	Total
Model Enhancement	$37	$37	$37
Uncertainty and Error	$16	$22	$19
Data Development	$26	$26	$26
Database Management and Integration Systems	$21	$15	$18
	$100	$100	$100

[1] Average of dollar amounts allocated.

Source: 2008 survey of state and regional agencies.

In terms of spending priorities, state and regional agencies differ somewhat (see Table C-9). Both would spend 63 cents of every dollar on model enhancement and data development activities, with model enhancement the highest priority. State agencies place more value on activities dealing with forecasting uncertainty and error rather than on database systems ($22 versus $15). Regional agencies show the opposite spending priority in this regard ($16 versus $21), which is indicative of the greater data management challenges faced by regional agencies.

General Characteristics of the Forecasting Process

Four questions were asked about the general characteristics of forecasts prepared by state and regional agencies. These questions pertained to the variables forecasted, length of forecast horizon, frequency of forecast updates, and the consideration of economic factors into the forecast.

Population is universally forecast and age/sex is produced by every state agency and 64% of regional agencies (see Table C-10 on the next page). Race/ethnicity is forecast by 58% of the states and 54% of regional agencies. States produce little information beyond these variables, while regional agencies provide a wider range of information. Most all regional agencies forecast housing units, households, employment, and income in large part to support the demands of travel models. More regional agencies produce these variables than either age/sex or race/ethnicity. A few regional agencies forecast other variables the most prevalent being prices, costs, and values and housing and labor force characteristics.

No regional agency produces a forecast less than 30 years into the future, while 25% of state forecasts have shorter horizons (see Table C-11 on the next page). Conversely, twice as many state agencies have forecasts that extend 40 or more years into the future. As a result, both state and regional agencies have a median forecast horizon length of 30 years.

Table C-10. Variables Included in the Long-range Forecast[1]

Variables	Percent Regional	Percent State	Percent Total	Number Regional	Number State	Number Total
Population	14%	32%	20%	11	12	23
Age/Sex	9%	32%	16%	7	12	19
Race/Ethic	8%	19%	11%	6	7	13
Households	14%	8%	12%	11	3	14
Housing Units	13%	3%	9%	10	1	11
Employment	14%	0%	9%	11	0	11
Income	11%	0%	8%	9	0	9
Labor Force Characteristics	4%	5%	4%	3	2	5
Housing Characteristics	5%	0%	3%	4	0	4
Prices, Costs, Values	4%	0%	3%	3	0	3
Energy	1%	0%	1%	1	0	1
Day-time Population	1%	0%	1%	1	0	1
Other Economic Factors	3%	0%	2%	2	0	2
License Drivers	1%	0%	1%	1	0	1
All Responses	100%	100%	100%	80	37	117

[1] Respondents could select more than one variable.
[2] Age of householder, housing tenure, household size and vacancy rate
[3] Regional GDP, retail sales, and poverty rate

Source: 2008 survey of state and regional agencies.

Table C-11. Typical Horizon Length in the Long-range Forecast

Horizon Length (Years)	Percent Regional	Percent State	Percent Total	Number Regional	Number State	Number Total
20	0%	17%	9%	0	2	2
25	0%	8%	4%	0	1	1
30	64%	42%	52%	7	5	12
35	18%	0%	9%	2	0	2
40	9%	17%	13%	1	2	3
50+	9%	17%	13%	1	2	3
All Responses	100%	100%	100%	11	12	23

[1] The regional agency forecast horizon was 60 years.

Source: 2008 survey of state and regional agencies.

Table C-12. Update Frequency of Long-range Forecast

Frequency (Years)	Percent Regional	State	Total	Number Regional	State	Total
1	9%	17%	13%	1	2	3
2	0%	17%	9%	0	2	2
3	36%	8%	22%	4	1	5
4	55%	17%	35%	6	2	8
5	0%	33%	17%	0	4	4
10	0%	8%	4%	0	1	1
All Responses	100%	100%	100%	11	12	23

Source: 2008 survey of state and regional agencies.

All but one regional agency updates their forecasts every 3 to 4 years (see Table C-12). The one exception does annual updates only if necessary. The update schedule for states is more varied with every 5 years being the most frequent occurrence. One third of the states update their forecasts every one or two years, but one state does updates only after each decennial census.

Table C-13. Economic Factors Considered in the Long-range Forecast

	Percent Regional	State	Total	Number Regional	State	Total
Yes	82%	50%	65%	9	6	15
No	18%	50%	35%	2	6	8
All Responses	100%	100%	100%	11	12	23

Source: 2008 survey of state and regional agencies.

All but two regional agencies consider economic factors in their long-range forecast, while only half of the demographic forecasts prepared by state agencies take economic factors into account (See Table C-13). The 15 agencies who considered economic factors in their forecasts were asked how these factors were considered. Table C-14 on the following page contains the answers to this question. Two-thirds of regional agencies used an integrated econometric-demographic model, such as REMI. The other third uses shift-share methods or determines the level of migration that balances future labor supply and demand. In general, state agencies rely on less rigorous methods when they consider economic factors. Two states use an integrated econometric-demographic model, while 50% rely on more qualitative approaches based on expert judgment and local review.

Table C-14. Approach used to Consider Economic Factors in the Long-range Forecast

	Percent			Responses		
Approach	Regional	State	Total	Regional	State	Total
Econometric Model	67%	33%	53%	6	2	8
Balance Labor Supply/Demand	22%	17%	20%	2	1	3
Shift-Share	11%	0%	7%	1	0	1
Local Input	0%	17%	7%	0	1	1
Expert Judgment	0%	33%	13%	0	2	2
All responses	100%	100%	100%	9	6	15

Source: 2008 survey of state and regional agencies.