MULTIDISCIPLINARY CENTER FOR EARTHQUAKE ENGINEERING RESEARCH

A National Center of Excellence in Advanced Technology Applications

ISSN 1520-295X

Updating Real-Time Earthquake Loss Estimates: Methods, Problems and Insights

by

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Technical Report MCEER-01-0005

December 17, 2001

This research was conducted at Natural Hazards Management, Inc., University of Washington and ImageCat, Inc., and was supported primarily by the Earthquake Engineering Research Centers Program of the National Science Foundation under award number EEC-9701471.

NOTICE

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Publication Date: December 17, 2001
Submittal Date: April 7, 2001

Technical Report MCEER-01-0005

Task Number 00-3031

NSF Master Contract Number EEC 9701471

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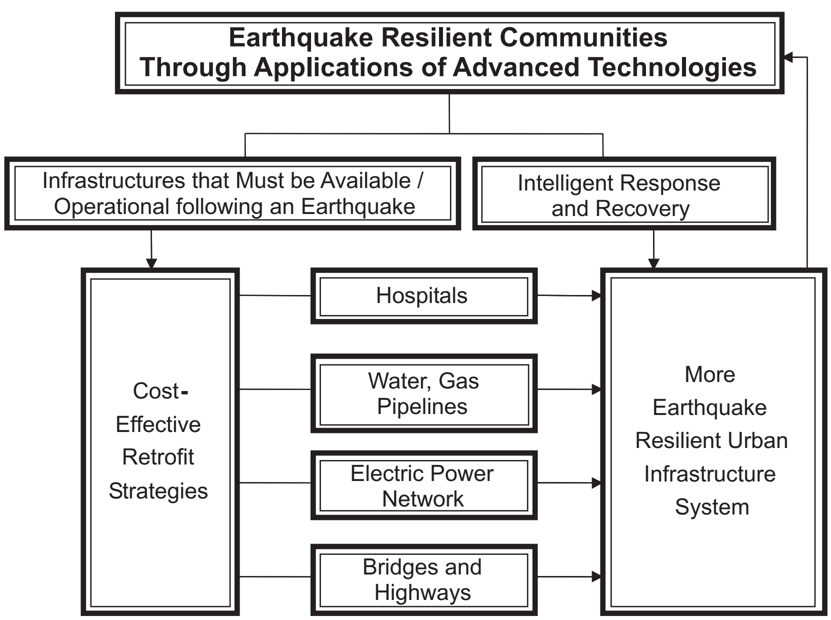
Preface

The Multidisciplinary Center for Earthquake Engineering Research (MCEER) is a national center of excellence in advanced technology applications that is dedicated to the reduction of earthquake losses nationwide. Headquartered at the University at Buffalo, State University of New York, the Center was originally established by the National Science Foundation in 1986, as the National Center for Earthquake Engineering Research (NCEER).

Comprising a consortium of researchers from numerous disciplines and institutions throughout the United States, the Center's mission is to reduce earthquake losses through research and the application of advanced technologies that improve engineering, pre-earthquake planning and post-earthquake recovery strategies. Toward this end, the Center coordinates a nationwide program of multidisciplinary team research, education and outreach activities.

MCEER's research is conducted under the sponsorship of two major federal agencies: the National Science Foundation (NSF) and the Federal Highway Administration (FHWA), and the State of New York. Significant support is derived from the Federal Emergency Management Agency (FEMA), other state governments, academic institutions, foreign governments and private industry.

MCEER's NSF-sponsored research objectives are twofold: to increase resilience by developing seismic evaluation and rehabilitation strategies for the post-disaster facilities and systems (hospitals, electrical and water lifelines, and bridges and highways) that society expects to be operational following an earthquake; and to further enhance resilience by developing improved emergency management capabilities to ensure an effective response and recovery following the earthquake (see the figure below).



A cross-program activity focuses on the establishment of an effective experimental and analytical network to facilitate the exchange of information between researchers located in various institutions across the country. These are complemented by, and integrated with, other MCEER activities in education, outreach, technology transfer, and industry partnerships.

This project reexamined earthquake loss estimation methods by using data collected after the 1994 Northridge earthquake from the California Governor's Office of Emergency Services (OES) and the California Department of Insurance (CDI). In this report, the results of an effort to develop a method for applying Gallup-like statistical procedures to rapidly update earthquake loss estimates are summarized. First, some of the insights gained from an examination of election polling techniques are outlined. Next, the California Governor's Office of Emergency Services (OES) and California Department of Insurance (CDI) loss data are shown to provide an opportunity and motive to develop a rapid loss updating method. At the same time, the diversity of criteria for determining losses underscores the complexity of any updating and, more generally, any loss estimation method. Third, a Bayesian method for rapidly updating losses is outlined. This method is next tested based on a 1995 CDI loss database developed midway before a more finalized 1996 CDI loss summary became available. Further, by examining the Northridge earthquake loss data, the possibility of employing stratification techniques to improve the efficiency of updating methods is explored. Finally, lessons learned and research needs developed from this project are summarized.

ABSTRACT

Loss data that have been systematically collected after the 1994 Northridge earthquake through the California Governor's Office of Emergency Services (OES) and the California Department of Insurance (CDI) provide new opportunities to re-examine earthquake loss estimation methods. In recent years, these loss estimation methods have come to rely more heavily on methods based on expert opinion. OES adjusted initial rapid post-Northridge loss estimates upwards to estimate federal funding requests and discovered later that this upward adjustment was warranted in light of actual loss data systematically collected. Can methods be devised--similar to those in election polls--to improve loss estimates based on early loss data? Can the reliability of these loss estimates be quantified? Once devised, how do these methods fare in practice? Our responses in this report are "Yes, updating methods can be devised" and "They fare only so well--with very wide confidence bounds, wider than statistical methods would imply--owing to the complexity of estimating losses." The development and application of these updating methods--through Bayesian techniques in this report--further accentuates problems of weighting expert opinion in light of actual empirical data.

ACKNOWLEDGEMENTS

We thank Richard Roth Jr., California Department of Insurance, and Dr. David Perkins, United States Geological Survey, for providing California earthquake insurance data, and reviews of an initial draft. The authors also acknowledge the support and encouragement of EQE International, Inc., where the authors performed much of the original work. This report documents work that was sponsored by the Multidisciplinary Center for Earthquake Engineering Research (Grant No. EEC-9701471).

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SECTION 1
INTRODUCTION

In this report, the results of an effort to develop a method for applying Gallup-like statistical procedures to rapidly update earthquake loss estimates are summarized. First, some of the insights gained from an examination of election polling techniques are outlined. Next, the California Governor's Office of Emergency Services (OES) and California Department of Insurance (CDI) loss data are shown to provide an opportunity and motive to develop a rapid loss updating method. At the same time, the diversity of criteria for determining losses underscores the complexity of any updating and, more generally, any loss estimation method. Third, a Bayesian method for rapidly updating losses is outlined. This method is next tested based on a 1995 CDI loss database developed midway before a more finalized 1996 CDI loss summary became available. Further, by examining the Northridge earthquake loss data, the possibility of employing stratification techniques to improve the efficiency of updating methods is explored. Finally, lessons learned and research needs developed from this project are summarized.

1.1 The Relevance of Election Polls

"Scientific" polling, that is, polling using random samples, gained instant credibility after the 1936 election between Franklin Delanor Roosevelt and Alf Landon. Using a "straw poll," a non-random poll of three million people with 2.4 million respondents, *The Literary Digest* predicted a landslide victory, 57% of the vote, for Alf Landon. The landslide went in the opposite direction, as Landon received only 38.5% of the vote. In the straw poll, prospective respondents were selected among those who owned either automobiles or telephones, which represented only 60% of the population during this Depression period. The fledgling scientific polls predicted the winner, while *The Literary Digest* and its methods went into demise. This early effort indicated that *the size of the sample does not necessarily predict the outcome of a poll.* Today, election polls may require only 1,000 to 1,500 respondents (Field, 1983, pp. 198, 199; Bradburn and Sudman, 1988, p. 19; Nieburg, 1984, pp. 174, 175).

Although scientific polling has proven to be very useful, it has also had setbacks. The most famous is probably the pre-election polls that led the *Chicago Times* to run the infamous headline "Dewey Wins" in the 1948 election between Harry Truman and Thomas Dewey. Interviewers had quotas, or targets, in the population that they were to interview, but were allowed non-randomly to select how they met these targets. So, they chose safer respondents. The likelihood of voting was neglected: methods of allocating undecided voters were inadequate (Field, 1983, p. 200; Bradburn and Sudman, 1988, pp. 29, 30; Nieburg, 1984, p. 64).

More recently, the debacle witnessed in Florida during the 2000 Presidential elections accentuated some of the weaknesses inherent in modern day election calling. Based on early exit poll results, the State of Florida was initially "awarded" to Vice President Gore even before voting had officially closed for the State. Within hours, this "call" was reversed in favor of then Governor Bush, only to be taken away once again because actual vote counts indicated that the election in Florida was "too close to call." In many respects, the confusion could be attributed in large part to the media and their race to be the first to call the election. It should be noted, however, that reversal of early calls (e.g., winner too close to call) occurred in other states as well, such as Oregon and New Mexico.

The overall success rate of election polls that result from comparing estimates with actual returns, shows that the *random or statistical methods used to estimate confidence levels somewhat overestimate the reliability of the estimates.* In one examination of the actual reliability of pre-election polls, the authors found them to deviate by an average of 2.8 percent, even though the confidence level is generally stated as +/- 3 percent. Standard deviation of the errors for winning parties turns out to be twice what is expected--based on pure statistical methodology (Levy, 1983, p. 65; Buchanan, 1986, p. 225).

At first blush, exit polls, performed immediately after the election, appear to have more significant parallels with the loss updating problem than do pre-election polls. However, the important lesson to be learned from the slight divergence of both pre-election polls and exit polls from actual returns is that *we are dealing with a complex inference*, involving both random and systemic elements. As one pair of authors state, nonsampling error has been significant and this pertains to matters "we don't talk about and can't begin to estimate--non-response bias, sample design and weighting factors, interviewer bias and error, question wording, screening techniques, etc." (Taylor and Krane, 1993, p. 11).

1.2 Opportunities and Challenges: 1994 Northridge Earthquake Loss Data

After the 1994 Northridge earthquake, OES saw the wisdom in soliciting rapid loss estimates and in pursuing systematic loss data collection as well. Rapid loss estimates were used to refine regional response and recovery plans as well as to estimate how much initial disaster relief funding to request from the federal government. Also assisting in regional recovery planning, the OES loss database consisted of over 100,000 buildings in the affected area, and contained basic building data derived from the County Tax Assessor along with various loss estimates, especially preliminary building damage inspection reports (EQE and OES, 1995; Eguchi and others, 1998; Goltz, 1996).

After the 1989 Loma Prieta earthquake, CDI had begun its systematic collection of insurer loss data, and collected this information again following the Northridge earthquake. Both CDI and OES efforts follow many years of recommendations that empirical loss data should be systematically collected after major events to improve loss estimation procedures, which are too often based on anecdotal or biased experience along with expert opinion (National Research Council, 1989; Eguchi and others, 1989).

The various loss databases also include Small Business Administration (SBA) loss data, Federal Emergency Management Agency (FEMA) payout data for individual and public assistance programs, and building permit data. While the OES and CDI loss databases provide an opportunity for putting loss estimation procedures on a sounder footing, the various databases also pose the problem--still to be researched--as to how to reconcile loss data developed based on diverse loss and damage criteria (i.e., SBA versus building permit versus insurance adjustment versus building inspection criteria). This issue was certainly paramount in a recent NRC report on loss estimation (NRC, 1999). Early building inspection data, for instance, appear at first glance to lead to much lower estimates of loss than do CDI loss summaries (Eguchi and others, 1998).

Since the Northridge earthquake, official estimates of total loss have been increased periodically as applications for assistance and other new information continues to be received. Initial figures released by the Governor's office on February 8, 1994 estimated $12.5 to $22.5 billion in property damage to structures and contents. Two years after the disaster, government and insurance sources reported the total cost of the earthquake at roughly $24 billion, which can be considered a lower bound estimate since not all capital losses are included. If adjustments are made for unreported losses, specifically insurance deductibles and otherwise uncompensated losses borne by uninsured property owners, actual losses may amount to as much as $44 billion (Eguchi and others, 1998).

The issue of definitive loss estimates for the disaster is further clouded by significant discrepancies between major data sources, as described in Eguchi and others (1998). Table 1-1 shows that according to the Los Angeles County Building & Safety Department database (May 1995), inspectors checked 97,000 buildings and estimated total structural loss at $2.6 billion. On the other hand, the CDI insurance database (March 1995) records 333,000 claims paid or outstanding with total loss valued at $10.2 billion, almost four times the inspection estimate. Note that this total includes nonstructural and contents loss which are not reflected in the inspection totals; if these are excluded and adjustments made for insurance deductible payments, average estimated losses for the two databases are not so disparate. These average estimated losses, of course, are based on 330,000 samples in the insurance database, but only 97,000 in the building inspection database. The former database included many buildings not inspected presumably because their apparent damages were less. Reasons for the differences between the two data sources include the purpose, thoroughness, and criteria of the damage inspections and loss estimates. Study of the Los Angeles City building permit database for repairs to earthquake-damaged property further indicates that some 30 percent of buildings in that database had not had a safety inspection performed, no doubt primarily because they suffered only minor damage. On the other hand, some 60 percent of homeowners in the impacted region did not have earthquake insurance.

TABLE 1-1 Comparison of Insurance and Inspection Databases[a]

	Insurance database	Inspection database
No. buildings damaged[b]	333,000	97,000
Total estimated loss	$10.2 billion	$2.6 billion
Average loss per building (unadjusted)	$31,000	$26,000
Average loss per building (adjusted)	$28,000	$26,000

(a) Source: Eguchi et al. (1998).
(b) Number of claims paid or outstanding (insurance database); number of dwellings with damage estimates (inspection database).

The Northridge earthquake represents the first time that analysts have had information available to make assessments of post-disaster loss estimates. The upward-trending nature of loss estimates over time reinforces the need to update initial post-disaster loss estimates, as better and more complete data become available, either as damage records are added to databases or damage surveys are conducted. The discrepancies between major data sources emphasize that each incorporates certain biases that may affect the reliability of statistically based procedures for updating loss estimates.

Faced with the significant challenges of selecting test databases from so many diverse and idiosyncratic sources, the databases chosen for this research were: (1) an early 1995 CDI detailed residential loss database from a small group of insurers and (2) the summary 1996 CDI residential loss database. The former database is used to construct an example of an "early" or "partial" sample of losses; the latter database is used to construct a "final" estimate of losses. Both databases come from the insurance industry and to that extent reflect more consistent loss criteria than a database mixing loss estimates from different sources such as the Small Business Administration, municipal building permit data, damage inspection data, as well as insurance data. The choice of test databases thus eliminates much of the systematic ambiguity resulting from databases developed using diverse criteria of losses, an ambiguity described more fully in Eguchi and others (1998).

SECTION 2
SIMPLIFIED BAYESIAN METHOD
FOR UPDATING LOSS ESTIMATES

Bayesian methods have often been construed as requiring a “subjective” view of probability. In application to this project, we concur that the Bayesian methods as applied here introduce the use of “prior” estimates based on expert opinion. Bayesian methods as used here require that these prior estimates, based on expert opinion, be given a “weight” that can be compared with the empirical weight added by actual loss data. This prior weight might be very low, if the expert opinion is largely arbitrary. Or, this prior weight might be considerable if the expert opinion is significantly informed by experimentation, analysis, and actual loss experience. Still, this prior weight cannot be sufficient to rule out the use of empirical data. Ironically, then, in the context of earthquake loss methodologies heavily dependent on expert opinion, the Bayesian methods discussed here focus on the use of empirical data to reassess expert opinion (Press, 1989, p. 16) In this context, expert opinion refers to the early post-earthquake loss estimates, which are based on prior models of earthquake damageability applied to rapid estimates of the earthquake magnitude and epicenter.

The basic Bayesian theorem, derivable by mathematical induction from set-theoretic definitions of conditional probability, is as follows:

$$P(B_i / A) = \frac{P(A / B_i) P(B_i)}{\sum_{j=1}^{k} P(A / B_j) P(B_j)} \qquad \text{(2-1)}$$

in which:

$P(B_i / A)$, the *posterior* probability estimate, is the probability that B_i will occur given some event A,

$P(A / B_i)$, called the *likelihood function*, is the likelihood or probability that A will occur given some event B_i,

$P(B_i)$, the *prior* probability estimate, is the probability that B_i will occur, and

$B_1, ..., B_j, ..., B_k$ are mutually exclusive events whose union is the Universal set.[1]

In this context, the finite population methods in Hays (1973) and Hansen and others (1953) are followed in transforming the problem from one of probabilities to one of statistics. In finite population methods, as will be seen, factors involving T, or the total number in the universe, modify formulas used in sometimes more familiar infinite population methods. With respect to the fundamental theorem expressed in Equation (2-1), employing a *prior* estimate of an overall loss in combination with an early sample of losses (event A) to derive a *posterior* estimate (some B_i that serves as a best estimate) of overall loss will be examined.

To illustrate the application of simplified Bayesian methods to the updating problem, the tasks below will be performed for selected zip codes:

1) outline, from the 1996 CDI database, known population characteristics, namely, exposure at risk (e.g., number of insurance policies, values in these policies, locations of insured residences),
2) use the 1995 partial CDI database (a posterior database) to estimate for the entire population at risk the mean total loss and its standard error, and the mean loss ratio and its standard error,
3) develop for the population at risk the prior ("expert judgment") estimate of the mean loss ratio and its standard ratio, and
4) combine prior and posterior estimates in (3) and (4) to derive estimates of the posterior mean loss ratio and its standard error.

---

[1] An example of Equation (2-1) arises if we assume that either Jack (B_1) or Jill (B_2) is in charge of the production line and that (A) the part produced is defective. Then, let us wonder what the probability is of Jack's being in charge if the part produced is defective. By Equation (2-1), we can assess this probability as the probability that the part is defective if Jack is in charge (say, 10%) times the probability that Jack is in charge (say 50%) divided by the sum of the probability that the part is defective if Jack's in charge times the probability that Jack is in charge and the probability that the part is defective if Jill's in charge (say 5%) times the probability that Jill is in charge (say 50%). Hence, the probability that Jack's in charge if the part is defective is

$$\frac{0.1 * 0.5}{0.1 * 0.5 + 0.05 * 0.5}, \text{ or } 0.67.$$

Jack's more likely to be in charge because he is more likely to produce defective parts.

Afterwards, the results obtained will be compared to the final loss estimates found in the 1996 CDI database. Hence, the 1995 partial sample of losses along with prior estimates of losses will be evaluated to determine how well they capture the "actual" or "final" losses as determined by the 1996 database.

The "classical" statistics on the early sample will be developed as a means to compare the classical approach to the Bayesian approach with respect to their capacities to estimate final losses. In effect, a classical approach will give no weight whatsoever to prior estimates of loss.

This initial attempt is regarded as simplified because many of the complications that arise in adjusting the methods to a specific problem are not explored. More complex formulas are required, for instance, if the variance of the prior estimate is unknown or if the sampling distribution of the mean is not normal. Efforts to explicitly develop strata, and then to combine results from different strata, are not presented. No attempt has been made to correct systematic temporal biases in the loss data related to the timeframe in which they were reported. This initial attempt is designed to show the feasibility of Bayesian methods, not to develop a more in-depth method to implement them in practice.

2.1 Estimating Population Characteristics, the Mean Total Loss, its Standard Error, the Mean Loss Ratio and its Standard Error

Table 2-1 summarizes the 1996 CDI population data for selected zip codes. Pertinent characteristics that can be inventoried before a damaging earthquake include number of policies (or, equivalently for survey purposes, residential building structures), number of policies with earthquake coverage, average structure replacement cost based on fire coverage, and average structure replacement cost for policies with earthquake coverage. For instance, zip code 91301 contains 8,479 residential policies, or dwellings, with an average replacement value or cost of $209,892. Of these, 4,064 dwellings had earthquake insurance coverage at the time of the Northridge earthquake. The total value of the structures at risk in the zip codes surveyed can be derived by multiplying average replacement cost by the number of structures. For example, in zip code 91301, this would be 8,479 times $209,892, for a total structural replacement cost of

$1.78 billion. Relevant to using earthquake insurance loss estimates for the population indicated in Table 2-1 is that buildings insured for earthquake coverage tended to have somewhat higher structure replacement costs than average residential buildings.

TABLE 2-1 Population Characteristics for Selected Zip Codes (Source: 1996 CDI summary survey)

Zip Code	Number of Policies	Number of Policies with Earthquake Coverage	Average Structure Replacement Cost [a] ($000s)	Total Structure Replacement Cost ($M)
91301	8,479	4,064	$210	$1,780
91302	4,623	2,501	$316	$1,462
91303	1,661	631	$122	$ 202
91304	7,113	3,386	$161	$1,147
91306	7,084	3,033	$134	$ 951
91307	6,293	3,103	$169	$1,065

(a) Fire coverage limits for the structure.

From the 1995 CDI partial database, the average earthquake structure loss per insured building is calculated. Table 2-2 summarizes these results, which also permit one to estimate the average loss ratio, or the ratio of losses to values at risk. In zip code 91301, the partial sample contains 506 earthquake insurance policies (about one-eighth of all such policies in the zip code), and the average loss for these dwellings was $27,659, or 11.9 percent of their structural replacement value. To illustrate the contrast between "classical" and Bayesian methods, classical methods as applied to total losses are used, and in contrast, Bayesian methods as applied to loss ratios are used.

2.2 Classical Estimates for Loss Totals

The classical approach to estimating overall losses merely takes the sample (the 1995 partial CDI loss data) and uses it to extrapolate to the entire population. Prior estimates of losses are ignored.

TABLE 2-2 Partial Average Loss Estimates for Selected Zip Codes (Source: 1995 partial CDI database)

Zip Code	Sample Size: Number of Policies	Average Loss Per Building Sampled	Average Loss Ratio: Total Losses Divided by Total Value of Buildings
91301	506	$27,700	0.119
91302	448	$54,769	0.160
91303	90	$28,984	0.199
91304	397	$28,123	0.142
91306	460	$26,903	0.176
91307	490	$42,937	0.184

In greater detail, then, using the loss ratios derived for each zip code, one may thus obtain the total expected loss from the total values at risk in the zip code. This derivation is shown in Table 2-3. For example, in zip code 91301, the total structure value, $1.78 billion, is multiplied by the average loss ratio for the early sample, or 0.119, which results as a best estimate of the loss total as being $211,781,238.

TABLE 2-3 Estimates of Total Losses Based on Partial Sample Survey (Sources: Tables 2-1 and 2-2)

Zip Code	Total Structure Value ($M)	Average Loss Ratio for Sample	Estimate of Total Loss ($M)
91301	$1,780	0.119	$212
91302	$1,462	0.160	$234
91303	$ 202	0.199	$ 40
91304	$1,147	0.142	$163
91306	$ 951	0.176	$167
91307	$1,065	0.184	$196

Other techniques are possible for developing the best estimate, as an average. One alternative method would be to compute the "average" of the loss ratios for each policy. This alternative has the disadvantage that high loss ratios for lower valued dwellings (or, in the opposite way, high loss ratios for higher valued dwellings) can greatly skew the results even within a zip code. Nonetheless, as a point of comparison, in zip code 91301, the use of the average of the loss ratios for each policy yields an average loss ratio of 0.13, and hence a best estimate of total loss of $231 million for the zip code. In general, use of this alternative way to estimate losses will not greatly change the overall conclusions of this study, but some of the conclusions of this alternative loss-ratio averaging method will be indicated as the study proceeds.

The biased sample variance S^2 of loss per building is defined as:

$$S^2 = \frac{\sum (L_i - L_{ave})^2}{N} \qquad (2\text{-}2)$$

where L_i refers to a sample loss estimate for building I, L_{ave} is the average of building loss estimates for the sample, and N refers to the number of buildings observed.

For a finite population, the standard error of the mean estimate of overall losses is defined as the square root of the variance of the sampling distribution of the mean, where this variance is derived as follows:

$$\frac{(T-N)(S^2)}{(N-1)(T)} = \left(1-\frac{N}{T}\right)\left(\frac{S^2}{N-1}\right) \qquad (2\text{-}3)$$

in which T refers to the total number of buildings (or, for residences, policies) in the sample and $\left(1-\frac{N}{T}\right)$ is a deflationary factor for finite populations.

Table 2-4 summarizes this "classical" statistical approach to estimating biased sample variances and derived standard errors for selected zip codes and per building. Individual loss totals are used to estimate means, sample variances, and standard errors, expressed in terms of total losses. For zip code 91301, for instance, the biased sample variance is $363 million and the deflationary factor is 0.00186. The variance of the sampling distribution of the mean is $675,000, resulting in a standard error of $820 per building. By way of comparison, if one uses the alternative method for computing average loss ratios as mentioned above, then the standard error per building is $904. These statistics indicate that the 1995 partial CDI sample database provides a large sample size for estimating overall losses.

TABLE 2-4 Biased Sample Variances and Derived Standard Errors of Loss for Selected Zip Codes

Zip Code	Estimate of Total Loss ($M) (from Table 2-3)	Biased Sample Variance ($M) = $\frac{\sum (L_i - L_{ave})^2}{N}$	Coefficient for Deriving Standard Error = $\frac{(T-N)}{(N-1)(T)}$	Standard Error Per Building
91301	$211	$ 363	0.00186	$ 820
91302	$234	$2225	0.00207	$2146
91303	$ 40	$1059	0.01063	$3355
91304	$163	$1110	0.00238	$1625
91306	$167	$ 262	0.00204	$ 731
91307	$196	$1936	0.00188	$1907

2.3 Bayesian Approach Using Loss Ratios

Instead of using the approach described in the previous section for Bayesian analysis purposes, an approach employing loss ratios is used. This is exemplified in Table 2-5. The basis for the table is the approximate formula for the standard error of the loss ratio (LR), given as the square root of

$$\frac{((LR)^2)(1-N/T)[(COV_L)^2+(COV_E)^2]}{N} \qquad (2\text{-}4)$$

in which COV refers to the covariances of individual building losses (L) and exposures or values at risk (E), respectively, and the loss-ratio, LR, refers to the average loss ratio as indicated in Table 2-3, the sum of losses over the sum of exposures.

The above formula results from examining a sample of building losses and exposures in the database and finding that the correlation coefficient between them--surprisingly enough--was too small to affect the above result. For ease of reference, Equation 2-4 is used (rather than the more precise formula including correlation coefficients) to backcalculate the sample variance for the average loss ratio and then derive the standard deviation for this loss ratio. In zip code 91301, for instance, the covariance (COV) for the exposed values (E) is 0.507 and the covariance (COV) for losses (L) is 0.689. From Table 2-2, the N is 506 and from Table 2-1 the T is 8,479. The resulting standard error of the average loss ratio is 0.0044. One can then use Equation 2-4 to compute the sample variance for the average loss ratio, which turns out to be 0.010. Standard deviations in Table 2-5 hover near the average loss ratios. So, for example, the average loss ratio for zip code 91301 is 0.119 and its standard deviation is 0.102.

TABLE 2-5 Empirical Estimates of Mean Loss Ratios, Their Standard Errors, Sample Variances, and Standard Deviations (Basis: 1995 CDI partial sample)

Zip Code	Average Loss Ratio (See Table 2-3)	COV(E)	COV(L)	Standard Error of the Average Loss Ratio (See Equation 2-4)	Sample Variance for the Average Loss Ratio (See Equation 2-3)	Standard Deviation of the Loss Ratio
91301	0.119	0.507	0.689	0.0044	0.010	0.102
91302	0.160	0.685	0.861	0.0080	0.031	0.176
91303	0.200	0.465	0.841	0.0197	0.036	0.191
91304	0.142	0.592	1.186	0.0092	0.033	0.181
91306	0.176	0.361	0.602	0.0056	0.015	0.123
91307	0.183	0.746	1.026	0.0101	0.054	0.232

To develop prior estimates, it is assumed that the zip codes are mostly in intensity VIII regions and loss estimation models from ATC-13, *Earthquake Damage Evaluation Data for California*, are used as applied to average wood frame construction to derive the approximate loss ratio of 0.055. To derive a variance for this estimate, it is arbitrarily assumed that the estimate is worth a small sample of 20 buildings. Table 2-6 is then derived, analogous to Table 2-5, on the assumption that the covariances for losses and exposures or values at risk are the same as in Table 2-5. For zip code 91301, the covariances for Exposed Values (E) and Losses (L) are assumed to be 0.507 and 0.689, respectively. T is 8,479 and LR is assumed to be 0.055. Before an earthquake, in principle, information on the covariances of values at risk is accessible. However, assumptions as to the covariances in losses would at this stage be based on prior experience with other earthquakes.

TABLE 2-6 Prior Estimates of Mean Loss Ratios, Their Standard Errors, Sample Variances, and Standard Deviations (N assumed to be 20)

Zip Code	Average Loss Ratio	Standard Error of the Average Loss Ratio (Equation 2-4)	Sample Variance for the Average Loss Ratio (See Equation 2-3)	Standard Deviation for the Average Loss Ratio
91301	0.055	0.011	0.0021	0.046
91302	0.055	0.014	0.0035	0.059
91303	0.055	0.012	0.0027	0.052
91304	0.055	0.016	0.0050	0.071
91306	0.055	0.009	0.0014	0.037
91307	0.055	0.016	0.0046	0.068

This arbitrary estimate of a sample size of 20 in each zip code could be modified with higher estimates, significantly decreasing the standard error and slightly increasing the standard deviation, but it is not known how to exactly estimate the random uncertainty in such an example. It cannot straightforwardly be assumed that the variability in expert opinions, which are the basis for these prior estimates, reflects the random uncertainty in such an estimate (NRC, 1996).

The uncertainty associated with a prior estimate of a loss ratio is not wholly concerned with a presupposition as to the validity of prior loss ratios. A prior estimate of the hazards affecting a building from a given earthquake also plays a role in the uncertainty of the prior estimate of the loss ratio. Rapid early estimates of Modified Mercalli Intensity (MMI) are developed based on preliminary estimates of the location and size of an earthquake, along with prior estimates of how the earthquake waves attenuate through rock and how local soft soils amplify the incoming seismic waves. These uncertainties have not been examined in this project.

To combine the prior and empirical estimates into posterior estimates, the symbol V is used to represent the variance of the sampling distribution of the mean, which equals the standard error squared. Then, the following formulas are employed:

Posterior Loss Ratio =

$$\frac{LR(data)/V(data) + LR(prior)/V(prior)}{1/V(data) + 1/V(prior)} \tag{2-5}$$

and, Posterior Standard Error is the square root of

$$\frac{V(data) * V(prior)}{V(data) + V(prior)} \tag{2-6}$$

These equations result from various assumptions, including the simplifying assumption that the sampling distribution of mean loss ratio estimates is assumed to be normal. Further research would be desirable to test this assumption in greater depth and alternative, more complex mathematical formulations of the posterior estimates. Our final loss estimates for the Northridge earthquake will indicate some questions pertaining to the assumption of normality of the sampling distribution of mean loss ratio estimates.

Table 2-7 first provides the results from applying Equations 2-5 and 2-6 to derive posterior estimates and then, to put these estimates into perspective, back-calculated estimates of the sample variance and the standard deviation. For zip code 91301, the posterior loss ratio is computed through Equation 2-5 given the values of the loss ratio for the partial sample of 0.119 (see Table 2-5), the sample variance of the loss ratio for the partial sample of 0.010 (see Table 2-5), the loss ratio of the prior estimate of 0.055 (see Table 2-6), and the sample variance for the prior loss estimate of 0.0021 (see Table 2-6).

TABLE 2-7 Posterior Estimates of Mean Loss Ratios, Their Standard Errors, Sample Variances, and Standard Deviations

Zip Code	Average Loss Ratio (See Equation 2-5)	Standard Error of the Average Loss Ratio (Equation 2-6)	Sample Variance for the Average Loss Ratio (See Equation 2-3)	Standard Deviation for the Average Loss Ratio
91301	0.110	0.0040	0.0089	0.094
91302	0.133	0.0069	0.0228	0.151
91303	0.093	0.0101	0.0115	0.107
91304	0.121	0.0080	0.0274	0.166
91306	0.140	0.0047	0.0109	0.104
91307	0.145	0.0085	0.0380	0.195

Relative to Table 2-5 (classical statistical estimates), Table 2-7 (Bayesian estimates) shows that the posterior estimates slightly reduce the loss ratios derived from a partial sample (as expected) and also the standard errors. For zip code 91301, the posterior average loss ratio is 0.110 as opposed to 0.119 based on the partial sample. The posterior sample variance is 0.0089 as opposed to 0.010.

Relative to Table 2-6 (prior estimates), Table 2-7 (posterior estimates) shows that the posterior estimates increase the loss ratios and also generally decrease the standard errors, while increasing the standard deviations. For zip code 91301, the prior average is 0.055 and the prior sample variance is 0.0021, both lower than the posterior average loss estimate of 0.110 and the posterior sample variance of 0.0089.

2.4 Comparing Classical and Bayesian Estimates with "Final" Loss Estimates

The 1996 CDI survey provides illustrative "final" estimates of losses that will be used to test both the classical and Bayesian methods. To develop final estimates of losses, it is assumed in all cases that the final loss ratio for insured buildings is the same as the final loss ratio for all buildings in the zip code, and minor errors that may result from applying final estimates to all buildings (T = 8479 in zip code 91301) rather than only to insured buildings (4,064 in zip code 91301) are ignored.

Table 2-8 shows the estimates of final or actual loss ratios in the selected zip codes. For example, in zip code 91301, the average structure loss is $33,136 with an average structure value of $225,343, for a loss ratio of 0.147.

TABLE 2-8 Derivation of Final or Actual Loss Ratio Estimates for Selected Zip Codes

Zip Code	Average Structure Loss	Average Structure Value for Dwellings with Earthquake Insurance	Earthquake loss ratio
91301	$33,136	$225,343	0.147
91302	$64,804	$341,566	0.190
91303	$33,005	$129,606	0.255
91304	$32,449	$172,869	0.188
91306	$29,518	$138,660	0.213
91307	$35,772	$184,432	0.194

Table 2-9 summarizes the best estimate of loss ratios relative to final or actual loss ratio estimates. For zip code 91301, the final or best estimate of the loss ratio is 0.147. This compares to a classical loss ratio estimate of 0.119 and a Bayesian loss estimate of 0.110. Standard errors of loss ratios and standard deviations of loss ratios are provided for the classical and Bayesian approaches, respectively. Very significantly, the standard deviations in Table 2-9 are high enough that all but one of the final loss ratios (for zip code 91303 with respect to the Bayesian estimate) are within one standard deviation of the loss ratio estimates.

TABLE 2-9 Comparisons of Classical and Bayesian Loss Ratio Estimates with Final CDI Loss Ratios

Zip Code	Final Loss Ratio	Classical Loss Ratio Estimate	Bayesian Loss Ratio Estimate	Classical standard error of the loss ratio	Bayesian standard error of the loss ratio	Classical standard deviation of the loss ratio	Bayesian standard deviation of the loss ratio
91301	0.147	0.119	0.110	0.0044	0.0040	0.102	0.094
91302	0.190	0.160	0.133	0.0080	0.0069	0.176	0.151
91303	0.255	0.200	0.093	0.0197	0.0101	0.191	0.107
91304	0.188	0.142	0.121	0.0092	0.0080	0.181	0.166
91306	0.213	0.176	0.140	0.0056	0.0047	0.123	0.104
91307	0.194	0.183	0.145	0.0101	0.0085	0.232	0.195

Table 2-10 summarizes the best estimates of total losses relative to these final total loss estimates. For all zip codes surveyed, the final loss estimate is $1.215 billion. Using classical statistical methods, the estimate is $1.01 billion. Using the Bayesian approach, the estimate is $0.84 billion. The alternative method for calculating the classical estimate yields $1.09 billion. Standard deviations as provided by the classical statistical approach are included, which are very large.

As noted in the previous discussion, early building damage inspection reports would have yielded even lower estimates of total losses and loss ratios than the 1995 partial CDI data. Loss estimates for the Northridge earthquake appear to be upward-trending. This upward-trending feature calls into question whether or not the sampling distribution of the mean estimates should be treated as being normal.

TABLE 2-10 Classical and Bayesian Total Loss Estimates and Classical Standard Deviations

Zip Code	Final Loss Estimate ($M)	Classical Loss Estimate ($M)	Classical Standard Deviation ($M)	Bayesian Loss Estimate ($M)
91301	$262	$211	$161	$196
91302	$277	$234	$101	$194
91303	$ 52	$ 40	$ 10	$ 19
91304	$215	$162	$157	$139
91306	$202	$167	$113	$133
91307	$207	$196	$159	$154
Summations for six zip codes	$1215	$1011		$835

Indeed, many of the difficulties in this project may have arisen because the sampling distribution of the mean estimates are not normal (or else the samples are not random). Assuming normality of this sampling distribution along with the Tchebycheff inequality leads, for instance, to the equation (Hays, p. 283):

$$|\text{final estimate - sample mean estimate}| < 1.96*(\text{standard error}) \quad (2\text{-}7)$$

for 95 percent of all cases. That is, in 95 percent of all cases, the sample mean estimate should be relatively close (within 1.96 times the standard error) to the final estimate.

However, an examination of Table 2-9 reveals that the above equation does not hold true in any of the zip codes surveyed (whether classical or Bayesian statistics are used). For instance, for zip code 91301, the classical standard error of the loss ratio is 0.0044. Multiplied by 1.96, this yields

0.0086. Yet the difference between the classical estimate and the final or actual estimate is 0.147 minus 0.119, or 0.028. This is 6.4 times the standard error. Table 2-11 summarizes, in terms of multiples of the standard error, the divergencies between the classical and Bayesian loss estimates, respectively, relative to the final loss estimate. In all cases, the classical loss estimates tend to diverge more than expected, with possible explanations that the sampling distribution of the mean is not normal and/or that the loss estimates exhibited over time show an upward trend. The Bayesian estimates diverged even more from the final loss estimate. The weight of 20 samples, as given to the Bayesian loss estimates, produced no increase—and actually a decrease-- in the reliability of the total loss estimates as measured by the final loss estimates.

TABLE 2-11 Actual Standard Errors of the Classical and Bayesian Loss Estimates

Zip Code	Classical standard error of the loss ratio (Table 2-9)	Bayesian standard error of the loss ratio (Table 2-9)	Final loss ratio (Table 2-9)	Classical loss ratio estimate	Bayesian loss ratio estimate	Number of Standard Errors: Classical minus Final loss ratio estimate[a]	Number of Standard Errors: Bayesian minus Final loss ratio estimate[a]
91301	0.0044	0.0040	0.147	0.119	0.110	6.36	9.25
91302	0.0080	0.0069	0.190	0.160	0.133	3.75	8.26
91303	0.0197	0.0101	0.255	0.200	0.093	2.79	16.04
91304	0.0092	0.0080	0.188	0.142	0.121	5.00	8.38
91306	0.0056	0.0047	0.213	0.176	0.140	6.61	15.53
91307	0.0101	0.0085	0.194	0.183	0.145	1.09	5.76

(a) Calculated by first taking the difference between the loss ratio estimate and the final loss ratio and then dividing this difference by the standard error (for the loss ratio estimate).

The puzzling results in conjunction with Table 2-9, Equation 2-7, and Table 2-11 do not arise because high loss levels (or else loss ratios) do not appear in the 1995 partial database. Another possible explanation is that the 1995 CDI partial database contains insurers that do not have losses that represent the industry-wide average. This may result from divergent underwriting and claims adjustment practices and procedures within the companies sampled and the insurance industry as a whole. Alternatively, the losses represented in 1995 for the few insurers may have risen later with more complete adjustments. One way or another, the sample used may not be random.

SECTION 3

SAMPLING AND STRATIFICATION OF LOSSES

The problem of developing random early samples for overall loss and damage estimates is clear and needs to be addressed in future work. Here, one element of the problem has been addressed, developing meaningful loss strata to reduce the uncertainty associated with estimating and updating loss ratios (L/E). Structural engineering assessments of building performance in earthquakes, embodied in expert-based loss estimation methodologies such as ATC-13 (1985), indicate that ground shaking levels (e.g., MMI) and structural type (e.g., unreinforced masonry construction) are two important determinants of structural performance and hence, prime candidates for stratification. Previous study of damage patterns in the Northridge earthquake (EQE/OES 1995) demonstrated that average loss ratios also differ significantly between building usage category (e.g., multi-family residential) and vintage class (e.g., pre-1940 construction). From the perspective of developing efficient loss stratification schemes to assist in early post-disaster loss and damage sampling, this study is interested in discerning strata for which loss ratios exhibit significant variation between strata but low variation within a given stratum. The discussion here is limited to analysis of stratification by MMI. Once again, the Northridge CDI and Los Angeles Building & Safety Department databases provide an unprecedented basis for this analysis.

One question that arises with regard to using MMI for stratification for early post-disaster loss estimates is the extent to which MMI can be accurately estimated soon after the disaster. Evidence from an early post-earthquake damage assessment tool (EPEDAT) developed for OES indicates that MMI patterns can be reasonably accurately estimated based on knowledge of the epicentral location, magnitude and depth of the earthquake source (available in southern California within minutes of an earthquake occurrence) and models of ground motion attenuation. Furthermore, with the introduction of "Shake Maps" (http://pasadena.wr.usgs.gov/shake/) which interpolate real ground motion values from triggered accelerographs, it is reasonable to assume that accurate intensity maps will be available in near real-time. Table 3-1 shows total estimated structural losses for Northridge using (1) the "actual" map of MMI contours from USGS, (2) the EPEDAT MMI contour map using a point source model of the earthquake, and (3) the EPEDAT map using a planar source model that more accurately models the seismic source. The planar source estimate gives a close approximation to the results using the "actual" MMI contour map, indicating that the uncertainty in early post-earthquake MMI estimation should not disqualify MMI as a stratification scheme in damage or loss sampling.

TABLE 3-1 Estimated Total Losses Using Actual and Estimated Ground Motion

MMI Estimate Basis	EPEDAT Estimate of Structural Loss
USGS Dewey MMI contour map ("actual")	$5.7 billion
EPEDAT point source	$6.9 billion
EPEDAT planar source	$5.6 billion

Table 3-2 shows the average loss ratios for MMI levels in the Northridge impacted area based on structural losses and exposure values, reported at the zip code level in the CDI summary database (3/95). Recall that this information pertains only to single-family residential buildings. MMI here indicates the average ground shaking intensity level for the zip code. The table shows that while MMIs VIII and IX accounted for only about 16 percent of total exposure value in the region, they accounted for some 68 percent of loss. Note that these loss values reflect actual payouts and neglect damages under deductibles. The final column in the table demonstrates the expected exponential increase of average loss ratio (L/E) with MMI ground shaking intensity.

To evaluate the variability of loss ratios within the MMI strata, a partial CDI database (9/94) is used, which contains information on roughly 12,000 policies in 43 high shaking intensity zip codes (MMI ≥ VII), including losses before deductibles. This sample suffers from several limitations: it appears to be biased toward higher-loss policies, does not include those with small or no losses (which were not reported), and includes a few policies with losses only to nonstructural categories such as contents. It is therefore difficult to compare this information to that presented in Table 3-2. However, it is useful for examining the variability of loss ratios at the policy level. Table 3-3 shows the mean and standard deviation of policy loss ratios by MMI and demonstrates that the variability of loss ratios within each MMI far exceeds that across MMIs. For example, the standard deviation of loss ratios for policies in MMI VII is 0.12, whereas the difference between average loss ratios in MMIs VII and VIII (0.023 and 0.076, respectively) is 0.053.

TABLE 3-2 Insured Structural Loss, Exposure, and Average Loss Ratio by MMI

MMI	Loss (L) ($M)	Loss (%)	Exposure (E) ($M)	Exposure (%)	L/E (%)
Not available	6.7	0.2%	486.2	0.3%	-
<VI	18.7	0.5%	69,957.2	39.1%	0.00
VI	118.8	3.5%	38,818.0	21.7%	0.003
VII	954.7	28.0%	41,321.3	23.1%	0.023
VIII	2,012.6	59.0%	26,468.5	14.8%	0.076
IX	302.2	8.9%	1,848.6	1.0%	0.163
Total	3,413.7	100.0%	178,900.0	100.0%	-

TABLE 3-3 Loss Ratio Variability for Partial Insurance Data

MMI	No. policies[(a)]	Loss ratio mean (μ)	Loss ratio standard deviation (σ)	Loss ratio coefficient of variation (σ/μ)
VII	2,749	0.166	0.120	0.722
VIII	8,355	0.218	0.146	0.668
IX	1,108	0.290	0.169	0.581

(a) Excludes policies with fire structure limit less than $30,000 and/or less than structural loss.

Similar trends are found by examining Los Angeles City inspection data. Since the Building & Safety database does not include information on uninspected buildings, average loss factors are obtained by a weighting scheme that adjusts for the size of the total building inventory in the city. This inventory data derives from the County Tax Assessor's office. For this purpose, it is assumed that all buildings in the Assessor's database and not in the Building & Safety database suffered no damage. This assumption clearly underestimates actual losses, as was noted earlier. Loss values consist of inspectors' judgments, while exposure values are calculated based on building information in the Assessor's database. MMI levels are zip code averages, as in the urance data analysis above. Table 3-4 shows the mean and standard deviations of building loss ratios. The mean loss ratios are much lower than the corresponding values from the insurance database and may reflect biases in the two databases as discussed earlier. However, of interest here is the variability of loss ratios within the strata. The MMI strata appear to be more distinct in terms of the spread of building loss ratios than with the insurance data. For example, the average MMI VIII loss ratio (0.019) is over one standard deviation away from the average MMI VII loss ratio.

TABLE 3-4 Loss Ratio Variability for Inspection Data

MMI	No. buildings	Loss ratio mean (μ)	Loss ratio standard deviation (σ)	Loss ratio coefficient of variation (σ/μ)
VII	25,970	.007	.009	1.39
VIII	44,213	.019	.012	0.61
IX	4,861	.041	.007	0.18

SECTION 4
LESSONS LEARNED AND RESEARCH NEEDS

Independent actions and efforts by OES and CDI have provided the means and motivation for a more in-depth examination of earthquake loss methods. The problem of the reliability of rapid early loss estimates arises in the practical context of decision makers requesting federal assistance and developing detailed plans for response and recovery. The OES and CDI databases are able to respond to this long-standing need as well as improve the basis for earthquake loss estimates.

The foregoing analysis presents a preliminary examination of the feasibility of employing Bayesian methods to rapidly update loss estimates and develop confidence levels for these estimates. We have shown that there is at least one possible way to develop these estimates. The method developed so far is rendered tractable in terms of the tables and formula as applied to six selected zip codes affected by the Northridge earthquake. The test case used for this preliminary methodological development is derived from 1995 partial CDI loss data and 1996 "final" CDI loss data.

The procedures developed in this report warrant future refinements owing to the many challenges faced in the course of this project. These challenges illuminate some of the lessons learned from this project.

First, loss estimates from various sources with diverse criteria for estimating losses have been difficult to reconcile. In practical terms, this means that biases in estimating losses may arise from the application of diverse and hence potentially conflicting criteria for evaluating loss. In terms of the examination in this report, this means that we were unable to use, for instance, building damage and inspection loss data as a means to rapidly update losses in the zip codes surveyed--at least not if we wanted to account for claims paid by insurers and losses borne through self-insurance (e.g., losses under deductibles or losses on properties that were uninsured). *If surveys are to be made to improve initial estimates of loss, then various forms of* *bias need to be minimized.* These include biases in the selection of criteria for "loss" or "damage," biases in the buildings selected for surveying, and so on. Lessons learned from election polling are helpful in this matter.

Second, we do not know exactly how to ascribe random uncertainties to the loss estimates of experts. As the NRC has pointed out, an important difference exists between the variability in expert opinion and the data itself. The method outlined in this report presupposes that there is a prior knowledge of the covariances of values at risk, a plausible assumption, and a prior knowledge of the covariances of losses (as well as of the correlation between losses and values at risk), a less plausible assumption. Testing of expert opinions against actual data, as performed in this report, provides another means of refining the weight that should be given to these opinions.

Third, we found that the reliability of loss estimates was generally low, and needs to be improved. One means of improving this reliability is to develop a stratification approach. For various strata, we could, for instance, derive some index such as:

(Value at risk) times (standard error)

to determine which strata should be examined in greater depth, such as through a random survey. Alternatively, examination of land use patterns could improve our understanding of the seismic vulnerability of buildings. In general, we have not, in this report, addressed the ubiquitous needs of improving hazard and vulnerability models, and how their improvement may occur in a rapid updating process.

Fourth, there is an apparent upward trend in the loss estimates for the Northridge earthquake. The prior estimates are lower than the posterior or else classical estimates which are in turn somewhat lower than the overall or final loss estimates. Such a trend is mirrored in actual loss estimates after the Northridge earthquake, which began at about $17 billion, rose to $30 billion, and now seems likely to be above $40 billion (Eguchi and others, 1998). Can early damage surveys help to identify such a trend? How can the simplified Bayesian methods be modified to incorporate a possible trend?

Fifth, we have used various assumptions--the normality of the mean distribution of all loss estimates--that have not yet been validated. The presence of a likely upward trend in loss estimates is one indicator that the sampling distribution of mean estimates may not be normal. What alternative assumptions are available that may fit the Northridge experience, and how can they be incorporated into a Bayesian updating method? Could it instead be that future efforts should work to ensure randomness in the sample, since as we have learned from election polling, it is not the size of the sample that counts?

SECTION 5

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ISSN 1520-295X