

The Value of Long-Term Climate Forecast Information in Weather Index Insurance

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In the paper, preliminary results of the analysis of potential use of climate forecast information in designing rainfall index insurance in the southeastern region of the U.S. are reported. Joint distributions of bi-monthly rainfall and El Nino Southern Oscillation (ENSO) indexes are estimated using copula analysis of historical data. The risk reducing effectiveness of introducing premiums conditional on ENSO forecast is evaluated. The results indicate some dependence of the downward volatility of rainfall on the lagged ENSO (forecast) index, particularly in the coastal areas and in the late winter and spring.

JEL codes: Q14, Q54

Introduction

Over the past decades, several alternative designs of agricultural crop yield and revenue insurance have been tried in an attempt to increase participation rates and to lower the loss ratios. Some programs were aimed at reducing the moral hazard and adverse selection issues inherent in insurance contracts and some tried to make contracts more efficient (cover larger portions of risks born by the producer) by utilizing new methodologies and data. The two objectives are often in conflict as exemplified by the tradeoff between the area-yield (GRP) and farm-level (APH) yield insurance. Up until recently, none of these pilot designs were ultimately successful (Glauber, 2004).

One of the promising venues in the agricultural insurance design is index insurance that largely avoids the moral hazard issues and is especially applicable for crops and areas with limited yield/revenue records. While the GRP has been relatively successful, rainfall index insurance has been showing promise where agriculture is more rainfall dependent and reliable yield records are lacking (Skees, 2008). In the United States, rainfall index (RI) insurance and vegetation index insurance (VI) were offered as pilot programs starting 2007.

The RI insurance started in 2007 as pasture, rangeland, and forage (PRF) crop insurance program in ten states and expanded to another seven by 2009. PRF is a group risk policy that covers livestock grazing and forage land and is based on one of two bi-monthly indices: a Rainfall Index and a Vegetation Index. The Rainfall Index uses National Oceanic and Atmospheric Administration data. Insurance payments to a producer are calculated as a deviation of the actual bi-monthly rainfall index from the covered portion of the normal/average RI within the area. The Vegetation Index uses the Normalized Difference Vegetation Index (NDVI) data from the U.S. Geological Survey Earth Resources Observation and Science data center.

Currently, the premiums for the RI insurance are calculated using historical time series data pooled over all inter-annual climate conditions. However, climate research on the southeastern region of the country indicates a significant relationship between (seasonal) rainfall and continuous El Nino Southern Oscillation (ENSO) index (Hansen, Hodges, Jones, 1998; Gershunov, 1998; Agroclimate.org). The ENSO indexes measure the deviation of the central Pacific sea surface temperatures from normal values and are used in classifying years as El Nino, La Nina, or neutral. The peculiarity of the annual ENSO phenomenon is that the indexes measured in late Fall usually persist for 6-10 months making the indexes a potentially useful forecast information. If the (insurable) rainfall depends on the ENSO index and the index is predictable, incorporating the ENSO forecast information in contract design may increase the efficiency of the RI insurance.

In this research, preliminary results of statistical analysis of bi-monthly rainfall and long-term climate variability (ENSO indexes) are presented along with calculations of risk-reducing effectiveness of incorporating long-term climate forecasts in the RI insurance. The main conclusion is that conditioning the RI insurance premiums on the end of last year ENSO index may increase producer welfare by further reducing the downward volatility of bi-monthly rainfall, at least for the winter and spring seasons and particularly in coastal areas.

The rest of the paper is structured as follows. Section 1 presents a brief methodology description followed by Section 2 describing the data. Results are presented in Section 3.

1. Methodology.

The objective of this research is to evaluate the usefulness of long-term climate forecast information in the RI insurance contract design. A particular aspect of using this information is chosen, which is conditioning the premiums on the forecast. At the present stage, the analysis is abstract from the actual subsidized rates established by the USDA's RMA, focusing instead on the actuarially fair premiums. The rationale behind this approach is that, conditional on no expected income transfer, actuarially fair premiums are the best at consumption smoothing and maximizing the insured's utility. In the framework of basic insurance analysis, charging uniform fair premiums over realizations with different distributions is worse, in terms of consumption smoothing, than charging separate different premiums for each distribution *if* the distribution differences are known. Thus, over a period of numerous realizations of the insured variable, conditioning the premiums on information that affects the variable's distribution increases the expected utility of insured outcome, or certainty equivalent revenue, of a risk-averse agent (while preserving the expected income of the insurer).

At present, the RI premiums are calculated using *pooled* historical rainfall data for the last 50+ years. However, climate research suggests that rainfall in the southeastern region depends on the ENSO phase (El Nino, La Nina, and neutral) the strength of which is measured by the continuous Nino and JMA indexes. The peculiarity of the ENSO phenomenon is that the value of the signal at the end of a calendar year usually persists until the late summer of the next year (hence years are categorically classified as El Nino, La Nina, or neutral). Incidentally, the RI insurance contracts are signed also by the end of the year. Thus, the end of year ENSO index represents forecast information that may affect rainfall distributions. Accommodating this forecast information in the premiums may benefit the producer in terms of further consumption smoothing. Again, the premiums are assumed fair but adding a proportional loading factor would not change the ordinal results. The approach is thus to

- 1) estimate rainfall index distributions conditional on the end of previous year ENSO index representing long-term climate forecast,

- 2) calculate the conditional and unconditional (pooled) premiums, and
- 3) estimate rainfall volatility reduction from applying conditional premiums using reliable historical rainfall index data for four locations in Alabama.

In addition to that, for the purpose of verifying the existence of a relationship between ENSO indexes and rainfall, bivariate kernel densities are estimated and their plots are examined. As we are interested in the forecast value for insurance, the impact of ENSO on local rainfall is also estimated using quantile regression.

Pending some indications of a relationship, joint densities of historical bi-monthly rainfall and ENSO indexes are estimated using copulas. Copula modeling is employed when

- historical data series are too short for traditional (non-)parametric density estimations. Reliable rainfall data span only 59 years; ENSO-specific series are even shorter
- marginal distributions of jointly distributed variables are of different families, and
- variables are *non-linearly* correlated

Copulas are functions that combine marginal distributions of jointly distributed variables into their joint distributions. The connection between copulas and probability distributions is established by the Sklar's theorem stating that for any group of jointly distributed variables there exists a unique copula (Nelsen, 1999). The usefulness of copulas comes from the fact that, once a copula has been estimated, it can be used to construct joint distributions by combining variables with different marginal (e.g. parametric) distributions, which is handy in cases like farm revenue insurance where yields may be modeled as Beta and prices as log-normal distributions (Tejeda and Goodwin, 2008). Copulas can also be used for generating Monte Carlo series based on estimated marginals and ultimately utilized in contract optimization (Vedenov, 2008). The primary advantage of the copula approach is that it allows for joint distributions with dependence structure other than linear correlation.¹

In order to accommodate seasonal differences in rainfall, annual series are constructed for each insurable bi-monthly period. Parameters of both ENSO index and rainfall marginal distributions are estimated by fitting and choosing among alternative distributions (Beta, Gamma, Lognormal, Normal, and Weibull). Then, cumulative densities are calculated at each observation. According to the probability integral transformation, these densities are then used in estimating the correlation parameters of a copula (Gaussian and t). Then, a large number of jointly distributed draws with uniform marginals are generated from the estimated copula. These draws are then converted into simulated ENSO index and rainfall index data by applying the inverse of the fitted marginal distributions. Conditional distributions of rainfall are formed for an arbitrary number of ENSO index intervals (10 or more, representing long-term forecast) and used for calculating the fair premiums for each interval (forecast). Any consistent patterns in the

¹ For a brief technical description of copulas, see Vedenov. For a detailed discussion, see Nelsen.

ENSO-conditioned premiums (expected loss ratios) would indicate predictable differences in the downward volatility of rainfall and therefore of some value of climate forecast information.

Insurance outcomes are simulated for historical rainfall and ENSO index data using the premiums conditional on the ENSO index and premiums calculated with pooled data. Ideally, a tri-variate density of ENSO index, bi-monthly rainfall index, and hay/forage yield should be estimated, but the lack of monthly yield data made this exercise impossible. Resorting to the second best, volatility of insured rainfall as an (very) imperfect proxy for yields is estimated (yields are positively correlated with rainfall except for floods).

Financial literature uses several measures of performance of risk-reducing innovations (mean-variance analysis) such as value at risk (VAR), mean root square loss (MRSL), and certainty equivalent revenues (CER). In production analysis, comparison of certainty equivalent revenues is perhaps the best indicator of net benefits from risk reduction, as agricultural producers are usually viewed as risk averse and the level of aversion matters (Schnitkey, Sherrick, and Irwin, 2003). For the utility function, constant absolute risk aversion (CARA), or negative exponential, specification of the form $U(R)=1-exp(-A*R)$ is used. A is the coefficient reflecting the level of risk aversion. As assigning different values of A has led to some confusion in interpretation of estimation results (Babcock, Choi, and Feinerman, 1993), assumptions are made about risk premium levels rather than the risk aversion coefficient. Risk premium is a percentage (share) of the expected stochastic income an individual is assumed to be willing to give up in order to eliminate all risk. Most common values for range from 30% to 5% (Vedenov and Barnett, 2004). Having assumed a risk premium of θ , the risk aversion coefficient A is obtained by numerically solving a fixed point problem via function iteration by equating expected utility of revenue to the utility of expected revenue scaled by the risk premium.

2. Data Description.

The states that are currently fully or partially covered by the RI insurance are AL, CO, ID, MO, MT, ND, PA, SC, and TX, KS, NE, NY, NC, OK, OR, SD, VA, WY are covered by the VI insurance. The geographical scope of this research at its current stage is limited to locations in Alabama but the locations present a variety of southeastern regions *ranging from coastal to far inland*, which is important for differentiating the ENSO impact on rainfall that is usually the strongest in the coastal areas. The locations are the four experiment stations in Fairhope (on the Gulf coast), Headland (close to the coast), Chilton (mid-state), and Belle Mina (northern part of the state, inland). Experiment station data was chosen as the most reliable.

Rainfall data are publicly available from the CPC (Climate Prediction Center) and local meteorological sources. Historical data on the rainfall index (RI) are insurance are available from the USDA's RMA online databases. Monthly rainfall data are also available from meteorological databases and is highly correlated with the RMA's RI data. Two ENSO indexes are used for explaining the rainfall: the Nino 3.4 index and the JMA index. The Nino 3.4 index measures SST

anomalies and has been suggested as one of the most suitable for explaining climate variations in the Southeastern United States

(http://gcmd.nasa.gov/records/GCMD_NOAA_NWS_CPC_NINO34.html). The JMA index is highly correlated with the Nino 3.4 index and was designed by the Japan Meteorological Agency (JMA) for determining El Nino and La Nina events. Monthly and weekly data on these indices are available from the NASA online database.

Monthly hay yield data would be highly desirable for the analysis of efficiency of rainfall index insurance. Unfortunately, we have not yet been able to procure the data even from the experiment station locations. To the best of our knowledge, simulated data on certain grass yields are being generated at the University of Florida. It is expected that the monthly hay yields are highly correlated with rainfall, which is confirmed by analyzing annual rainfall and annual hay yield data in Alabama available from the NASS database. However, the annual data correlation/distribution was not utilized in this analysis because the joint densities of monthly distributions are likely sufficiently different for the annual data to be of use.

3. Results.

In order to infer the level of dependence of local rainfall on the ENSO signal, a brief examination of the data was conducted. Figure 1 shows bivariate kernel densities of rainfall and Nino 3.4 index averages over October-December of previous year for the most coastal (Fairhope) and most inland (Belle Mina) locations. Last year averages of the Nino index are used as the closest proxy for conditioning the premiums on climate forecast before the contracts come in force. While maybe not easily discernable, the mass is shifting from low Nino 3.4 and low rainfall to high Nino 3.4 and high rainfall indicating a positive dependence, particularly on the coast (results using the JMA index are similar). However, the relationship becomes more and more vague with the lag between the index and the rainfall period (later in the year).

As we are interested in the insurance implications of using climate information and therefore in the downward volatility (expected losses) of the insured variable, quantile regressions were run on lagged values of Nino 3.4 and JMA indexes. A sample of results reported in Table 1 indicate that most of the impact is on the lower to mid quantiles of rainfall distribution and that, at least for the coastal regions, the impact is significant for the index lagged up to 8 months. However, these coefficients should be interpreted with caution because of the seasonality of ENSO impacts.

For the copula analysis, several types of distributions were fitted to the data. The skewness and kurtosis and Shapiro-Wilk tests reject the normality hypothesis for both RI and ENSO index data. Out of the alternatives of Beta, Gamma, Log-Normal, and Weibull distributions, the lognormal was chosen for the ENSO and Weibull for the rainfall indexes

according to the p-values of the parameter estimates. 50,000 draws from joint Nino 3.4 and rainfall index distributions for 10 Nino 3.4 index intervals were generated using Gaussian and t copulas. The results of Gaussian copula analysis conducted according to the description in the methodology section are as follows.

The coastal areas in Alabama are the most consistent. Figure 2 shows expected rainfall for insurable bi-monthly periods from January to December by intervals of the Nino 3.4 index range (using the JMA index produces similar results). Again, the index values are averages over the last three months of the previous year representing the forecast made available before signing the contract.² The average winter rainfall values show the strongest dependence on the ENSO index. At least for the first four months of the year, the higher the (lagged) index, the higher the expected rainfall (rainfall is proportional to the index). The *downward* volatility of rainfall, however, is inversely related to the index: the lower the index, the higher the volatility and, hence, the riskier the hay production. This is reflected in the actuarially fair premiums (expected losses for full coverage over expected rainfall) calculated for the index intervals shown in Figure 3: the premiums decrease with the index indicating that the index is a predictor of production risk. These results are largely consistent with those of climate research.

However, starting from the May-June period, the index-rainfall dependence disappears, which should be expected considering the lower impact of ENSO index on rainfall in the southeast in the summer and because the lag between the index used here (end of last year) and current period increases. By the end of the year, when the next ENSO phase comes into effect, both average rainfall and rainfall volatility become almost flat, indicating no impact of the forecast (last year index). Similar patterns exist for the other three locations, with the significance of the relationship between the ENSO signal and rainfall decreasing not only with the lag but also with the distance from the coast, as should be expected.

With regard to insurance, accommodating the ENSO index information in the premiums, provided the demand is unaffected by premium changes, seems to make a positive difference for the producer. The certainty equivalences for rainfall corresponding to rate setting methodology provide only an inference for possible consideration. Due to unavailability of monthly hay yield data, the certainty equivalences are calculated in inches/year. An alternative would be to use the Base County Values (BCVs) defined by the RMA that represent the \$ value of expected rainfall. Still, without knowing monthly yields, converting the deviations of RI from normal into dollar values would require making additional assumptions but would not change the ordinal properties of the results.

² This of course contradicts the design of many insurance contracts but, in this case, availability of the forecast information to both the insurer and the insured may be beneficial and not cause additional agency problems.

The results presented in Table 2 are extremely sensitive to the utility function parameter and dependent on the risk aversion assumptions. Nevertheless, preliminary estimates indicate sizeable (loosely defined) benefits from accommodating ENSO forecast information in the insurance contract design only in the beginning of the contract year and in the coastal areas where rainfall is more susceptible to the ENSO signal. The certainty equivalent rainfall (calculated according to the methodology described above) is the highest for the rainfall index insured using ENSO index-contingent (conditional) premiums and the lowest for the uninsured rainfall series. Interestingly, the volatility of rainfall (not shown here) declines, making insurance less desirable, in the warm season (April-October). The gains from additional “rainfall income” smoothing due to making premiums conditional on lagged ENSO indexes increase with the number of index intervals. This introduces a tradeoff between the gains and the costs of data processing.

Due to the lack of monthly hay yield data, it is impossible to calculate certainty equivalent revenues from rainfall insurance. Nevertheless, the results presented here only suggest some potential for improving the efficiency of the rainfall index insurance in the beginning of the year by using climate forecast information. In later months, forecasts become largely irrelevant for rainfall distribution. Thus, unless further refinements in the methodology produce better rainfall distribution predictability, incorporating ENSO forecast information in premiums may be of limited practical use. However, it is impossible to infer the proper value of forecasts without knowing the relationship between rainfall and hay yields.

Conclusion.

One of the promising venues in agricultural insurance development is index insurance which largely avoids the moral hazard issues and is especially applicable for crops and areas with limited yield/revenue records. In the United States, rainfall index (RI) insurance and vegetation index insurance (VI) were offered as pilot programs starting 2007. Currently, the premiums for the RI insurance are calculated using pooled time series. However, climate research on the southeastern region of the country indicates a significant relationship between seasonal rainfall and continuous El Nino Southern Oscillation (ENSO) index. The objective of this research is to evaluate the risk-reducing effectiveness of incorporating long-term climate forecasts in the RI insurance contract design. This is accomplished by (1) estimating rainfall index distributions conditional on the end of previous year ENSO index, (2) calculating conditional and unconditional (pooled) premiums, and (3) estimating rainfall volatility reduction changes from applying conditional premiums using historical rainfall index data for the four locations in Alabama. Preliminary results indicate some potential for improving the efficiency of the rainfall index insurance in the beginning of the year by using climate forecast information. In later months, forecasts become largely irrelevant for rainfall distribution. Thus, unless further refinements in the methodology produce better rainfall distribution predictability, incorporating ENSO forecast information in premiums may be of limited practical use.

References

- Agroclimate.org. Impacts of ENSO on southern agriculture are listed at www.agroclimate.org
- Babcock, B.A., E.K. Choi, and E. Feinerman. "Risk and Probability Premiums for CAM Utility Functions." *J. Agr. and Resour. Econ.* 18,1(1993):17-24.
- CPC (Climate Prediction Center). ENSO Impacts on the U.S., Alabama are listed on the CPC website at www.cpc.ncep.noaa.gov/products/predictions/threats2/enso/el_nino/al_bar.html
- Carriquiry, Miguel and Daniel E. Osgood. "Index Insurance, Probabilistic Climate Forecasts and Production." Working Paper 08-WP465, Center for Agricultural and Rural Development, Iowa, March 2008.
- Gershunov, A. 1998. "ENSO Influence on Intra-Seasonal Extreme Rainfall and Temperature Frequencies in the Contiguous United States: Implications for Long-Range Predictability." *Journal of Climate*, American Meteorological Society, 11:3192-3203.
- Glauber, J. 2004. "Crop Insurance Reconsidered," *American Journal of Agricultural Economics*, 86(5):1179-1195.
- Hansen, J.W., A.W. Hodges, and J.W. Jones. 1998. "ENSO Influences on Agriculture in the Southeastern United States," *Journal of Climate*, 11:404-411.
- Magrin, G.O., M.I. Travasso, W.E. Baethgen, and R.T. Boca. "Improving Applications in Agriculture of ENSO-Based Seasonal Rainfall Forecasts Considering Atlantic Ocean Surface Temperatures." In Mannava V. K. Sivakumar and James Hansen (Eds.) *Climate Prediction and Agriculture Advances and Challenges*. Springer, Berlin Heidelberg, 2007.
- NASA online database: http://gcmd.nasa.gov/records/GCMD_NOAA_NWS_CPC_NINO34.html
- Rainfall Index Insurance policy explanation is available at the RMA website at www.rma.usda.gov/policies/pasturerangeforage.
- RMA. Data for specific Grid locations are available from the RMA website at <http://prfri-rma-map.tamu.edu>.
- Schnitkey, G. D., B. J. Sherrick, and S. H. Irwin. 2003. "Evaluation of Risk Reductions Associated with Multi-Peril Crop Insurance Products." *Agr. Fin. Rev.*, 63:1-21.
- Skees, J. "Innovations in Index Insurance for the Poor in Lower Income Countries," *Agricultural and Resource Economics Review* 37, April 2008.
- Tejeda, H.A., and B.K. Goodwin. 2008. "Modeling Crop prices through a Burr distribution and Analysis of Correlation between Crop Prices and Yields using a Copula method," paper presented at the 2008 AAEA Meetings in Orlando, FL.
- Vedenov, D. 2008. "Application of Copulas to Estimation of Joint Crop Yield Distributions," paper presented at the 2008 AAEA Meetings in Orlando, FL.
- Vedenov, D.V., and B. J. Barnett. 2004. "Efficiency of Weather Derivatives as Primary Crop Insurance Instruments," *Journal of Agricultural and Resource Economics*, 29(3):387-403.

FIGURES AND TABLES.

Figure 1. Joint Kernel Densities of Bi-Monthly Rainfall Index (RI) and Nino 3.4 Index.

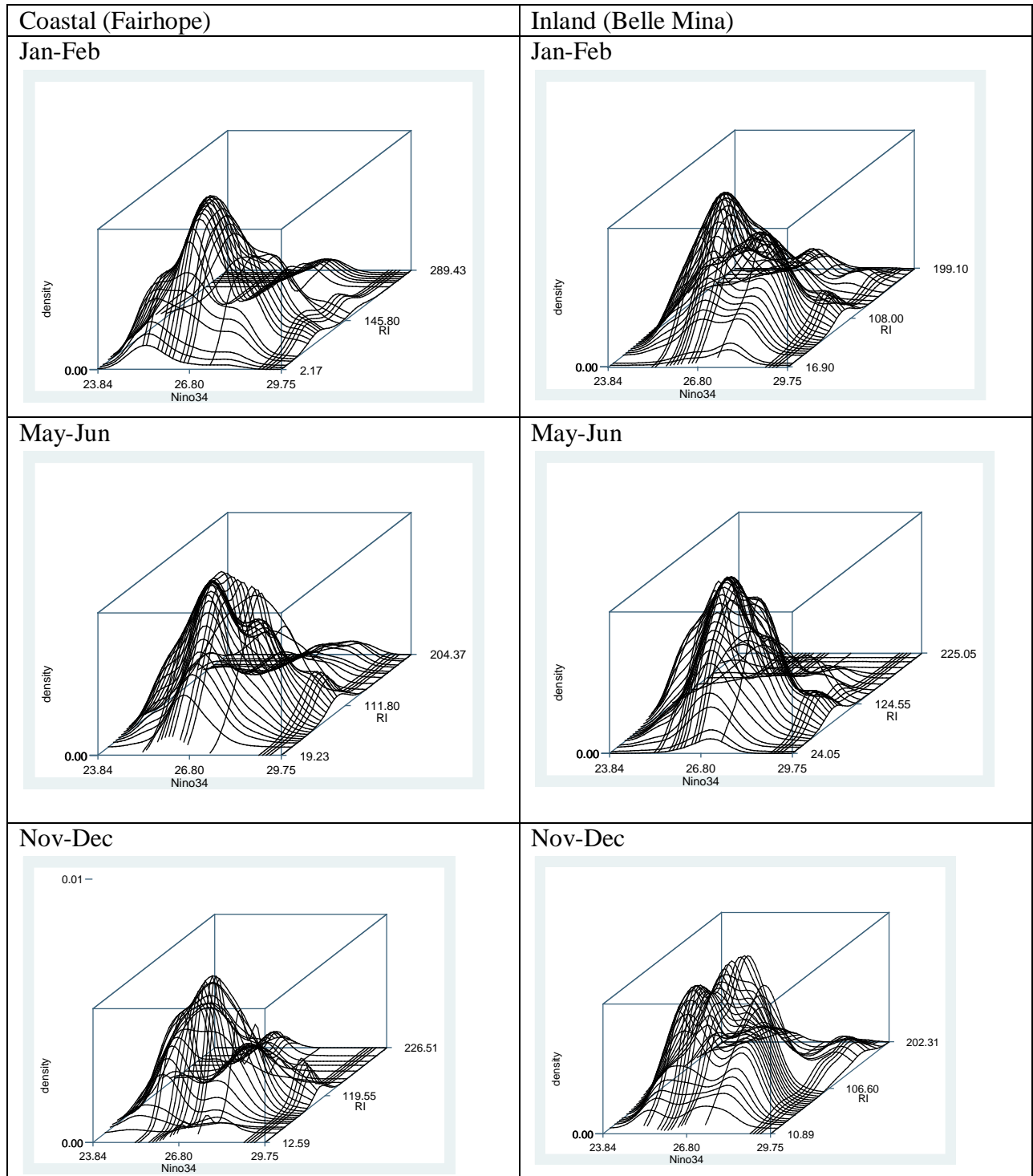


Figure 2. Average Rainfall by the Nino 3.4 Index for Bi-Monthly Insurable Periods.

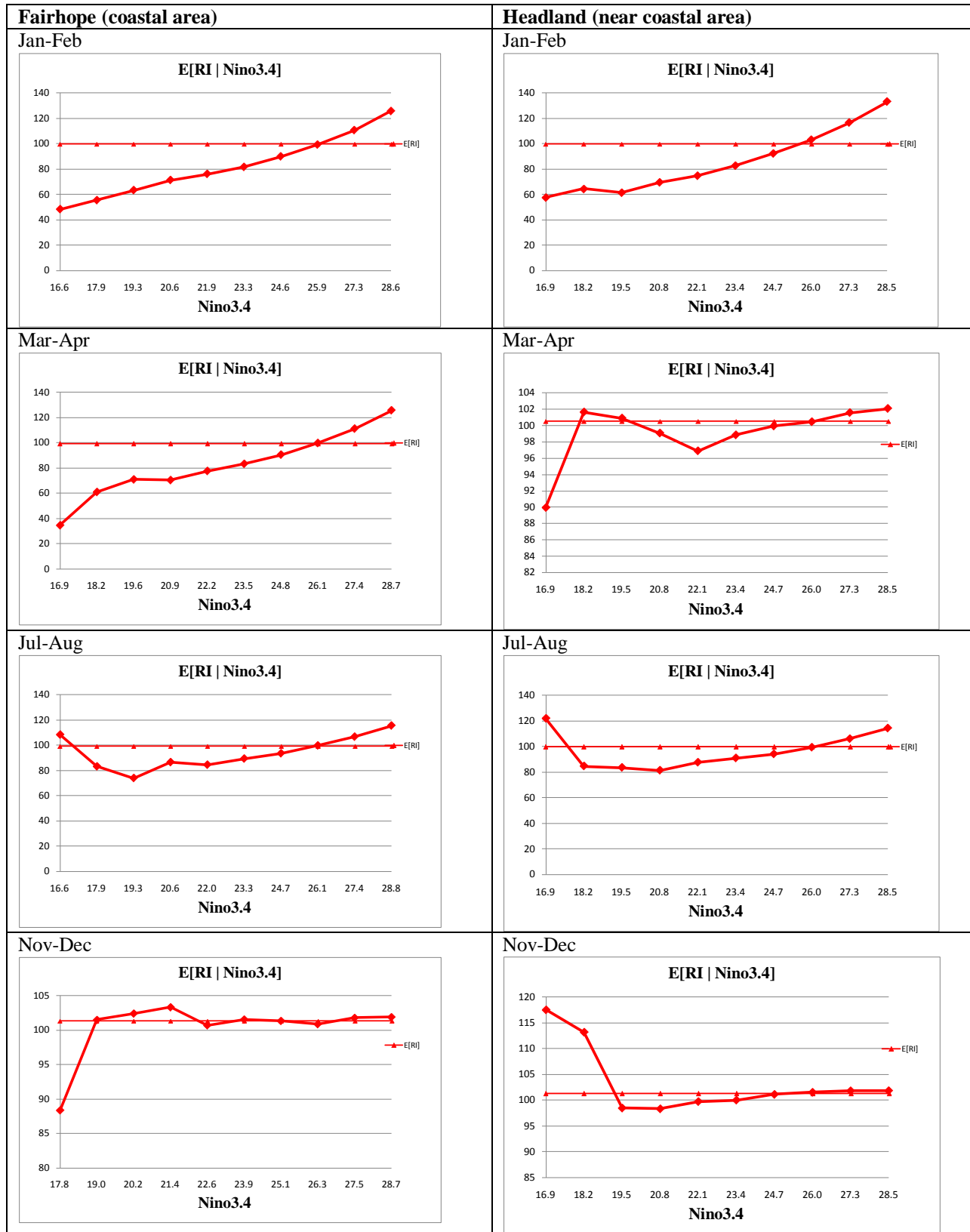


Figure 2 (continued)

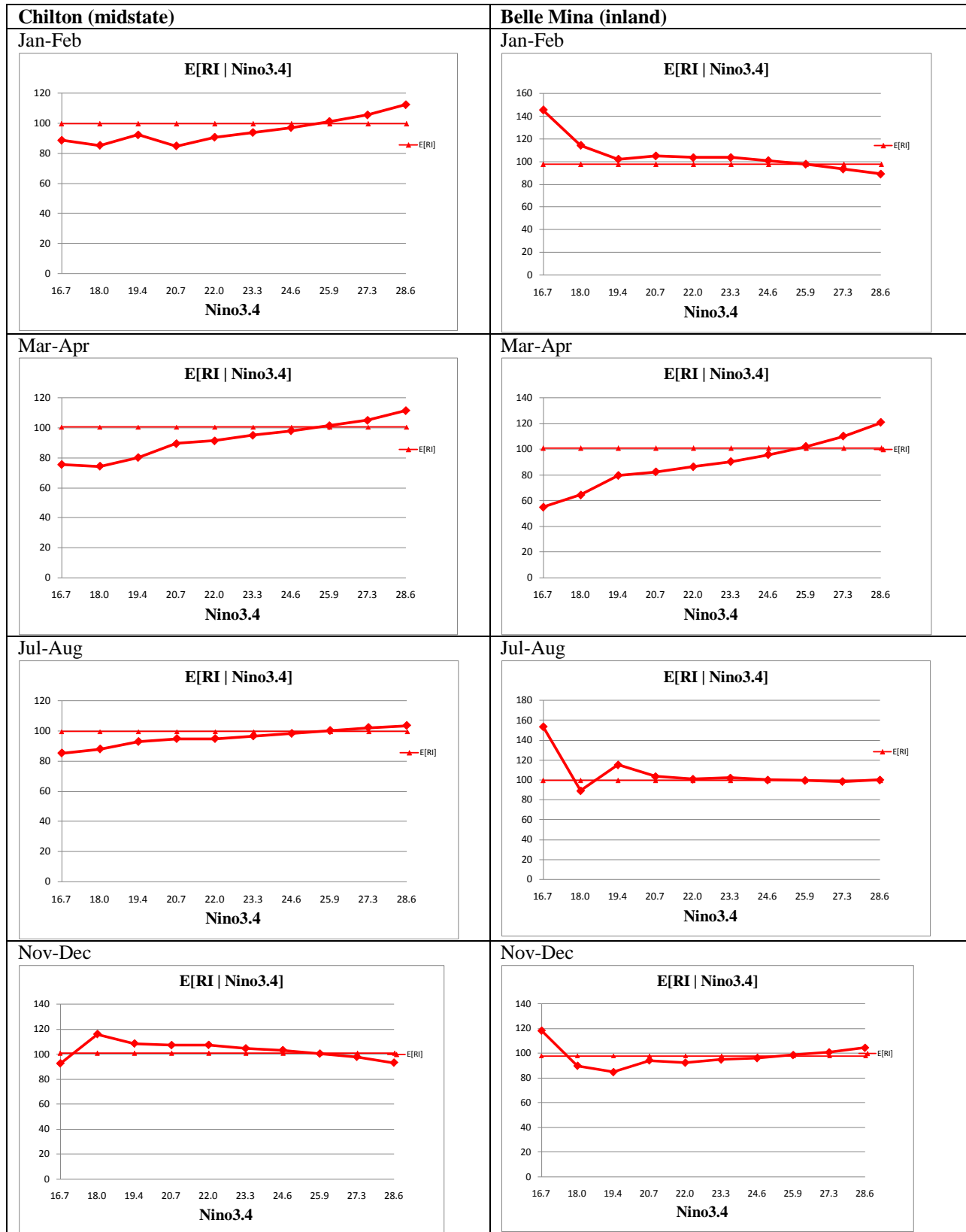


Figure 3. Expected Losses for Full Coverage by Nino 3.4 Index for Bi-Monthly Periods.

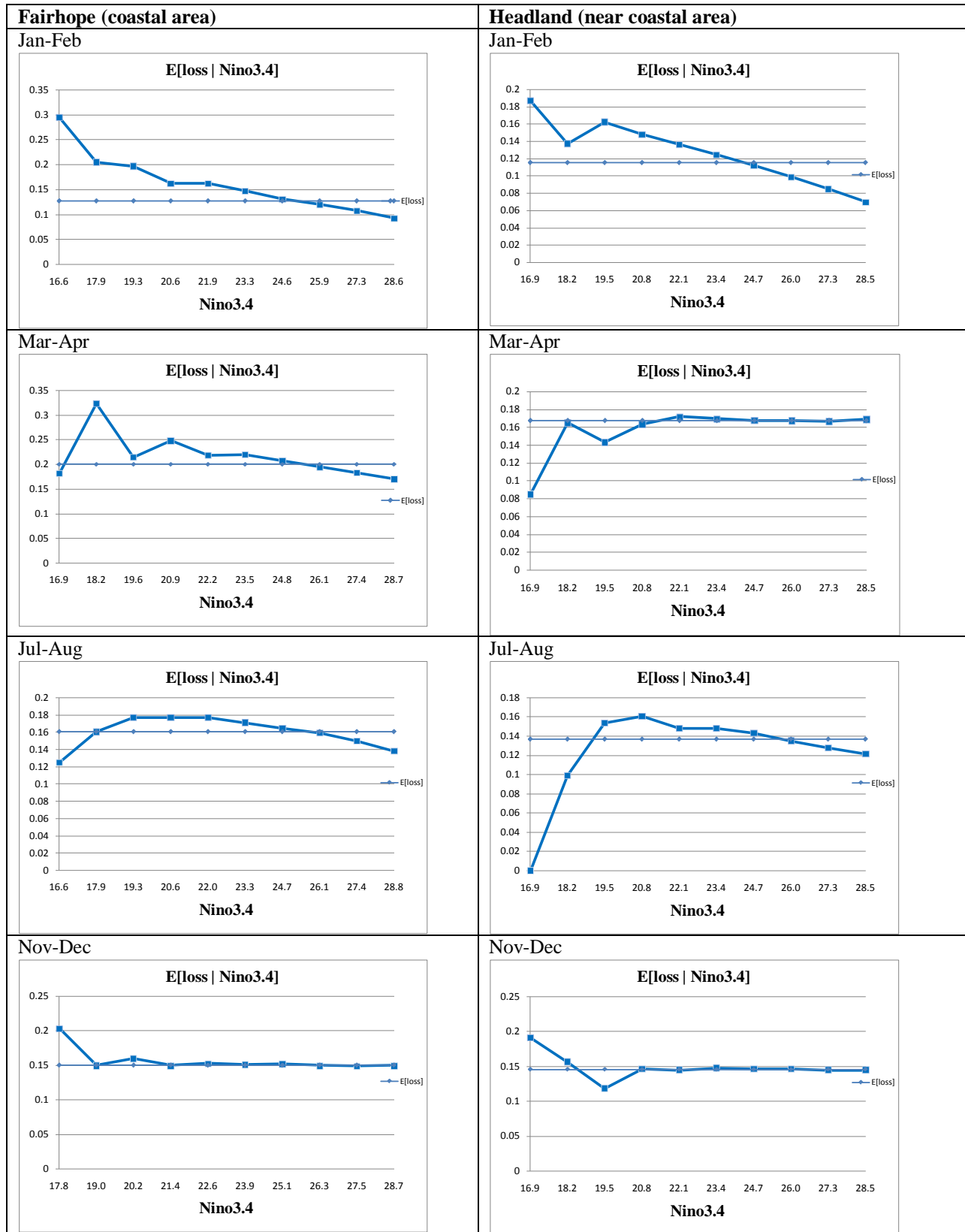


Figure 3 (continued).

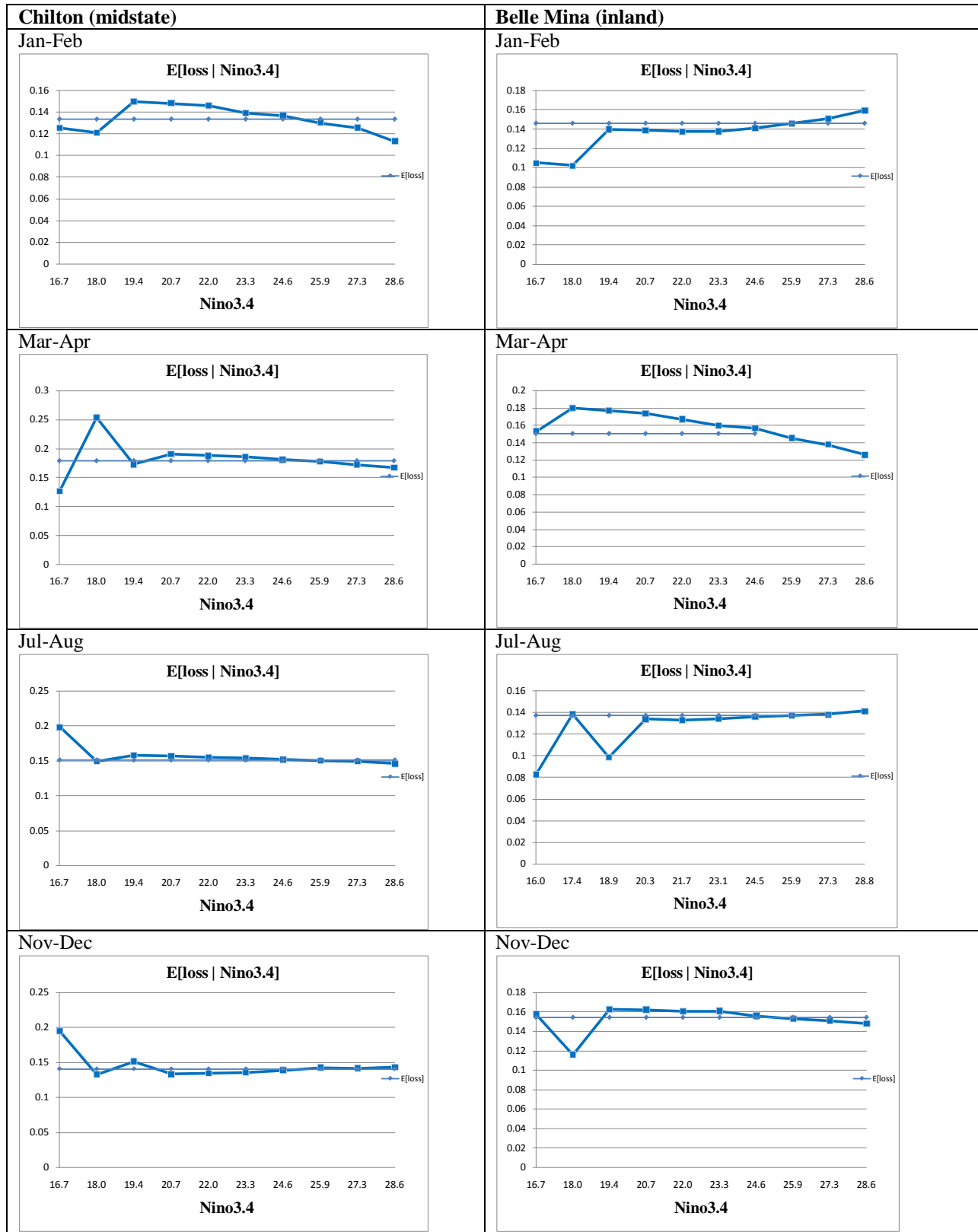


Table 1. Quantile Regression Coefficients for Monthly Rainfall.

Fairhope (costal)	nino34	l1nino34	l2nino34	l3nino34	l4nino34	l5nino34	l6nino34	l7nino34	l8nino34
q10	0.183*	0.223**	0.633***	0.485***	0.269	0.247	0.383**	0.478***	0.698***
q30	0.381**	0.364*	0.631***	0.627***	0.443**	0.320	0.473**	0.503**	0.872***
q50	0.545***	0.434***	0.482***	0.444***	0.461***	0.412**	0.395***	0.375	0.545***
q70	0.410	0.274	0.301	0.364	0.269	0.134	0.153	0.109	0.282
q90	0.950***	0.657*	0.502	0.778**	0.663	0.584	0.721	0.495	0.218
Headland	nino34	l1nino34	l2nino34	l3nino34	l4nino34	l5nino34	l6nino34	l7nino34	l8nino34
q10	0.0579	0.0794	0.148	0.208	0.118	0.132	0.132	0.191	0.367
q30	0.315**	0.421**	0.626***	0.542**	0.316*	0.118	0.121	0.163	0.464*
q50	0.589***	0.508***	0.536***	0.612***	0.630***	0.317	0.338	0.372*	0.644***
q70	0.511**	0.507***	0.491**	0.578***	0.452	0.271	0.340	0.353	0.520
q90	0.182	0.383	0.357	0.313	0.308	0.331	0.280	0.452	0.882**
Chilton	nino34	l1nino34	l2nino34	l3nino34	l4nino34	l5nino34	l6nino34	l7nino34	l8nino34
q10	0.313**	0.173	0.262*	0.312*	0.375**	0.163	0.132	0.265	0.352*
q30	0.307***	0.263*	0.370***	0.418***	0.225	0.213	0.0309	0.168	0.458**
q50	0.271	0.184	0.303	0.251	0.165	-0.0152	-0.0203	0.0163	0.515
q70	0.373**	0.206	0.216	0.197	0.225	0.101	0.0183	0.0792	0.287
q90	0.641	0.141	0.0735	-0.194	-0.413	-0.513	-0.556	-0.840	-0.330
Belle Mina (inland)	nino34	l1nino34	l2nino34	l3nino34	l4nino34	l5nino34	l6nino34	l7nino34	l8nino34
q10	-0.197	-0.194*	-0.0541	-0.0703	-0.172*	-0.203	-0.195	-0.126	-0.145
q30	0.0535	0.0478	0.0701	0.123	0.131	0.111	-0.0323	0.0602	-0.154
q50	-0.0250	-0.145	-0.113	-0.101	-0.127	-0.145*	-0.141	-0.113	0.0426
q70	-0.275	-0.269	-0.205	-0.100	-0.459*	-0.527 ***	-0.376	-0.0585	0.145
q90	-0.126	-0.0762	-0.0318	0.00948	0.0690	0.00633	0.239	0.300	0.745**

Note: *'s define significance (1, 5, and 10%). l# defines the number of lags for Nino3.4 index.

Table 2. Certainty Equivalent Rainfall Values (calculated in in/yr)

	No Insurance	Pooled Premium	Premium Conditional on ENSO Index	No Insurance	Pooled Premium	Premium Conditional on ENSO Index
Fairhope			Chilton			
Jan-Feb	78.81	89.49	97.83	78.79	93.14	95.43
Mar-Apr	78.34	87.96	98.01	76.49	92.71	94.95
May-Jun	76.93	91.04	96.26	75.04	89.97	92.15
Jul-Aug	75.42	91.43	94.63	75.42	91.62	93.86
Sep-Oct	75.84	90.93	94.55	74.85	85.74	86.70
Nov-Dec	77.03	92.35	93.43	77.83	94.32	94.62
Headland			Belle Mina			
Jan-Feb	79.46	95.07	98.18	75.77	90.54	92.05
Mar-Apr	78.85	92.86	95.89	77.17	92.52	93.11
May-Jun	75.25	90.93	92.70	75.96	91.07	92.29
Jul-Aug	77.10	92.09	94.83	78.64	91.96	92.54
Sep-Oct	77.92	92.14	96.09	75.57	90.70	89.94
Nov-Dec	78.81	94.15	98.10	76.51	91.74	91.15