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Increasing Confidence in Agricultural Crop Forecasts and Climate Adaptation Decisions with Causality Analysis

BY

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Abstract

The Earth system is facing increased pressures from the accelerating world population, rapid depletion of non-renewable, finite resources, and climate change variability. Many resource practitioners, scientists, economists and policy decision-makers argue that we must move beyond traditional correlation or associative-based methods to ones that are causality-based. Causality is a stronger condition imposed on whether variables can be considered to interact in time and space. Causal analysis aims to observe, model and frame policy decisions to explore greater complexity in the structure and functioning of coupled socio-economic and environmental systems. We showcase how such analysis identifies a causal interaction between sea-surface pressure and temperature variability associated with El Niño/Southern Oscillation (ENSO). Greater predictability and opportunities exist to adapt resource-based systems in advance of extreme events and economic shocks. Building causal methods into system models that integrate economic, biophysical and climate variables can increase confidence in adaptation decision-making.

1. Introduction

The notion of cause and effect is fundamental to devising testable scientific hypotheses, guiding sound inference and developing prediction and foresight on the impact, response and adaptive behavior (i.e., resilience) inherent in complex socio-economic and biophysical systems. Causal analysis is concerned with identifying causes and effects of observed phenomena with the purpose of understanding, predicting and eventually intervening on society and on individuals. It involves the cognitive goal to relate to explanation as well as the action-oriented goal to relate to inference and decision-making [1]. Assumptions regarding open versus closed boundaries, degree of modularity and level of complexity in the relationship between interacting components can differ widely between casual and systems-level approaches. Nonetheless, they are highly congruent, compatible and amenable to advance econometric and environmental risk models, for guiding resource decision analytics, and to devise operational solutions of real-world economic, societal and environmental opportunities and problems involving water, food, energy and climate change aspects [2]. Causal and systems analyses both fundamentally embrace broader considerations and assumptions and explore a wider suite of known and unknown observed and/or latent interactions between variables. They also both increasingly involve probabilistic-based, statistical methods. Linear and nonlinear tests have been devised. Existing causal-based methods include: vector autoregressive (VAR) models, parametric and nonparametric decision tree analysis, stochastic simulation, the state contingent approach and mathematical programming-optimization techniques, statistical risk production functions, and Bayesian belief networks [3]. While there have been relatively few major innovations in these methods of decision analysis over recent decades, the availability of Big Data (e.g., sensor-based, remote-sensing based, technological, socio-economic data), computational power and more efficient statistical methods is driving rapid innovation in the integrated modeling of risk. Recently, a detailed review of the importance, need and consequence of causal inference in solving natural resource problems in a wide range of scientific domains suggests that a scientific paradigm shift is needed to move from traditional statistical-based methods inferring correlation/association to those that specify a stronger cause-effect or causal relationship, so as to: 1) more reliably explain interacting processes using multivariate data, 2) to devise more integrative, system-level or multi-scale sustainability assessment frameworks, and, 3) for guiding multi-objective stakeholder decision making and more complex policy evaluation of agricultural or resource economics [1].

We define causality in the statistical sense, such that a variable x(t) *Granger-causes* another variable y(t) (denoted $x(t) \rightarrow y(t)$), if given information of both x(t) and y(t), the variable y(t) can be better predicted in the mean-square-error sense by using only *past values* of x(t) than by not doing so. The null hypothesis here is: x(t) does not Granger-cause y(t). In other words, having knowledge of past values of x(t) improves the ability of a model or index to predict y(t). A weaker condition is of *instantaneous* causality where not only past, but also present values of x(t) improve prediction of y(t). Feedback can occur where x(t) causes y(t) and y(t) causes x(t) [5]. Granger causality statistical tests are sensitive to data availability, random variability, and especially whether the variables arise from a deterministic or stochastic process [6]. Uncertainty in causal relationships can amplify when data is sparse, random variability increases, and the mediating effects of hidden or latent variables that can drive causal relationships (in the bivariate and multivariate sense). Granger causality considers the extent to which the lag process in one variable explains the current values of another variable [7].

The mean growth rate of global crop production must reach roughly 2.4% per year, to meet the global demand for major agricultural food crops and is expected to increase by 110% by 2050 [8]. It is widely agreed that by reducing the impacts of climate variability, by adjusting crop selection, planting dates, sequences and rotations, alongside more efficient use and application of fertilizer, chemicals and water/irrigation will have a major contribution to increasing yields, especially in areas that have low yields today [9]. A recent systems analysis of agricultural production has combined climate, crop and economic models to explore the consequences of different global climate scenarios, climate and crop models and their assumptions [10]. Based on the Intergovernmental Panel on Climate Change (IPCC)'s representative concentration pathway with end-of-century radiative forcing of 8.5 W/m^2, and with no incremental CO_2 crop fertilization assumed, this study predicts a 17% reduction in global crop yields by 2050, relative to a baseline scenario with unchanging climate. Endogenous economic responses reduce yield to 11%, increase area of major crops by 11% and reduce consumption by 3%, but these variables also have high variability. This major study identifies substantial disagreement on the relative responses of crops to climate variability and extreme events ('shocks') and highlights the need to improve the representation of agricultural adaptation responses to climate change [10]. To address this need, a causal analysis of the status (e.g., onset and decay timing, lead time and variance) of inter-annual climate variability tracked by atmospheric/climate teleconnection indices, such as the El Niño/Southern Oscillation (ENSO), integrated into seasonal crop forecasts, may increase the predictability of seasonal crop forecasts by improving their causal assumptions and representation, and enable such systems to be used with more confidence in framing and guiding adapting decisions to ensure agricultural crop production systems can better respond to both positive and negative anticipated impacts.

El Niño (EN) is an episode of higher than normal sea-surface temperatures over the eastern tropical Pacific, and higher than normal pressure over Indonesia and northern Australia. This is also closely linked to a negative phase of a global atmospheric oscillation known as Southern Oscillation (SO), whereby weaker than normal near-surface equatorial easterly (east-to-west) winds. Hence, the close interaction and climate variability that links both EN and SO is known as ENSO variability. ENSO disrupts the ocean-atmosphere system in the Tropical Pacific and has important consequences for weather and climate around the globe. Warm episodes of ENSO generally increases and decreases precipitation across California and the Pacific Northwest, respectively. Further north, it leads to a milder than normal winter across western Canada, but in the eastern United States favors more coastal storms, and more hurricanes in the eastern Pacific (www.elnino.noaa.gov/).

Variability in the timing, intensity evolution and spatial impacts of ENSO activity exists, and alternative causal assumptions can have a large influence on the reliability of forecasts based on standardized teleconnection indices. This, in turn, can change our confidence in climate forecasts and early warning systems. A palaeoclimate study of ENSO variability through the Holocene epoch indicates ENSO oscillates over a period of 2-8 years, with warm ENSO episodes becoming less frequent [11]. This study involved a wavelet statistical analysis of sedimentation core data recording fluctuations in alluvial deposits within the Laguna Pallcacocha drainage basin, an area strongly influenced by ENSO variability within southern Ecuador. However, considerable model and measurement-based uncertainties suggest significant variance exists, such that a decadal trend in warm episodes may exist over a slower time range of 4-15 years, with faster oscillations occurring every 9-12 months.

The Oceanic Nino Index (ONI) also known as the monthly Niño3.4 OISST index is the current international standard for identifying El Niño (warm) and La Niña (cool) events in the tropical Pacific. It is the running 3-month mean SST anomaly for the Niño 3.4 region (i.e., 5^oN-5^oS, 120^o-170^oW). Events are defined as five consecutive overlapping three-month periods at or above the $+0.5^o$ C anomaly for warm (El Niño) events and at or below the $-0.5\ ^o$ C anomaly for cold (La Niña) events. This event threshold is further broken down into weak (0.5 to 0.9), moderate (1.0 to 1.4) and strong (≥ 1.5) ONI events. The years 2009-10 marked a moderate warm, and 2010-12, a strong cool episode. The current status and prediction of ENSO activity indicates neutral conditions are persisting, but that sea surface temperatures (SST) are above-average across the equatorial Pacific Ocean, tropical rainfall is enhanced over Indonesia and the western tropical Pacific, and the net chance of El Niño is 70% during the Northern Hemisphere summer, predicted to rise to 80% during the fall and winter (US Climate Prediction Centre or CPC June 2014 Report, www.cpc.ncep.noaa.gov/).

Causality analysis was recently applied to investigate the interaction between globally-averaged land surface temperature observations (GT) and total radiative forcing (RC) as a proxy for observed atmospheric carbon dioxide [12]. This study revealed that RC granger causes GT, with jump in correlation significance in the early 1970's, and that more than one variable may granger cause GT, besides RC, such as ENSO. The data did not meet the stationarity and no heteroscedasticity assumptions for applying a Granger F-test. Also, a significant Granger-causal influence of SST on the North Atlantic Oscillation (NAO) teleconnection signal at lags longer than ten days with slower-than-exponential decay was detected in another recent climate causal analysis [13]. This suggests higher predictability of ENSO activity and confidence in decision analytics involving ENSO could be achieved by applying causal modeling instantaneous and lead-lag interaction of multiple climate teleconnections [14].

In this paper, we present a causal analysis of sea-level pressure and temperature variables and agricultural crop forecasting and adaption decision making. We demonstrate the application of causal analysis in linking sea-surface pressure and temperature variability associated with El Nino Southern Oscillation (ENSO). We show how variability between these two variables is linked at extended time-lags, and thus infer that greater predictability and opportunities exist for adapting agricultural and resource-based systems in advance of extreme events and shocks, strengthened by ENSO activity. Building causal analysis into agricultural and forestry-sector system models, which integrate economic, biophysical and climate variables, may thus increase their predictive power and usefulness as tools for guiding adaption decisions with added confidence. We highlight current challenges and major benefits in applying causal analysis to address complex environmental problems in the agricultural and resource sector.

2. Materials and Methods

2.1. Data sources

Historical (1950-2013) (i.e., 63 years) monthly standardized Niño 3 sea-surface temperature (SST) (Niño3 SST) for the eastern Pacific (CPC) and standardized sea-surface pressure (SLP) for south-eastern Australia (Australian Bureau of Meteorology) were assimilated. The monthly mean (Mean.Niño3), anomoly (Std.Niño3), difference (i.e., monthly change in SST, diffNiño) and three-month running mean (Std.N22mo) were each separately considered as the dependent variable, y(t). For the independent or explanatory variable, x(t), the anomoly in pressure (Std.SEAP), and its three-month (threemoSEAP) and five-month (fivemoSEAP) running mean values were computed.

2.2. Causal model

A general equation for a spatio-temporal (ST) process, X(s,t), where s denotes space and t, time, can be expressed as,

$$X(s)_t = \mu + \sum_{i=1}^{p} \phi_i X(s)_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

This representation is termed a vector autoregressive model (VAR) and factors observed ST variability into three main effects – one attributed to autoregressive (AR(p)) or autocorrelation over months, another involving a shifting baseline or moving average (MA(q)) variability, and residual stochastic variability (i.e., ε_t term). This general equation is termed an ARMA(p,q) type VAR model.

We re-express the general representation, given by Equation 1, by setting k=p=q (i.e., that assumes equal autocorrelation and moving-average lags), as a bivariate VAR(k) model that couples SST with SLP, given by,

$$\begin{aligned} S_t &= \sum_{i=1}^{k} \alpha_i S_{t-i} + \sum_{i=1}^{k} \beta_i P_{t-i} + \varepsilon_t \\ P_t &= \sum_{i=1}^{k} \gamma_i S_{t-i} + \sum_{i=1}^{k} \delta_i P_{t-i} + \eta_t \end{aligned} \quad (2)$$

Here the signal term, S(t) denotes either SST or an SST-derived variable at time (i.e., month) t, P(t) is the SLP or SLP-derived variable for month t, and the lag order of the model is k, where $k \geq 1$. The noise or residual terms, ε_t and η_t are assumed to be distributed with mean zero and stationary covariance. Lag order k is the delay between events in time that have a dependency, while lead-time is the overlap between events that have a dependency. Lead-lag effects in coupled ST processes can occur, which combine both lag and lead effects. In the current model, both S(t) and P(t) are assumed to have the same lag order k, i.e. VAR model with symmetric lag length. However, one could also specify an asymmetric lag order [15]. Lead-lag relationships in resource pricing and commodity economic markets refer to the tendency of prices to be determined in one market, and after some interval of time, such information then passed on during a lag period to a corresponding market. When space, in addition to time, is also involved, lead-lag relationships can be mediated by a complex array of feedbacks, and interaction of signal variability coupled to noise or stochastic fluctuations involving multiple interacting processes operating within a system.

2.3 Model application, significant testing

We tested the assumption of stationarity of order two (i.e., a process having a constant mean *and* variance), including auto-covariance that does not depend on time) on all combinations of the selected x(t) and y(t) variables. The Augmented Dickey-Fuller (ADF) test for stationarity applying the adf.test() function available in the tseries R library package [16, 17]. The VARS modelling package (Version 1.5-2) that computes test statistics for Granger- and instantaneous causality for a VAR(k) bivariate model was then used to implement our model (i.e., Equation 2) using the R Statistical Language, Version 3.1.0 [18,19]. Standard F test statistics for linear, Granger and instantaneous causality were computed for the simplest possible VAR model having lag order k=1. For this significance test, the higher the F statistic and lower the p-value, the stronger the Granger-causality. Next, we tested Granger causality for higher-order or extended-lag VAR models. An ADF test for stationarity was applied to each of the individual (i.e., univariate) time-series with different lag order k. The best-fit VAR model and its lag was then determined as the model having the strongest stationarity (most negative value of the ADF test statistic). Sample size was 765, so critical value of the Dickey-Fuller t-distribution of 3.98 (1%, with trend) and -3.44 (1%, without trend) were specified. The VAR.select() procedure, available in the VARS R Package, was run to determine the best-fitting bivariate VAR model that minimized AIC (Akaike's Information Criterion). Bootstrap simulations (n=100) were performed in determining the p values.

3. Results and Discussion

Standard F test statistics for linear, Granger and instantaneous causality were first computed for the simplest possible VAR model having lag order k=1 (Tables 1 and 2). In the causality significance testing, the higher the F statistic and lower the p-value, the stronger the Granger-causality. Causality was detected at the 95% confidence level between the three-monthly averaged SEAP and monthly-difference in SST, and the five-month averaged SEAP and monthly-difference in SST, respectively (i.e., two causal linkages) (Table 1). In the case of the instantaneous causality that incorporates present values of the variables (Table 2), seven significant causal linkages were detected, with the highest significance (at 99% confidence level) between three- and five-monthly averaged SEAP indices and the monthly difference in SST, and five-monthly averaged SEAP and the monthly mean and difference of SST.

Results of the ADF test for stationarity on the individual (i.e., univariate) time-series with different lag order k are summarized in Table 3. All the univariate SST and SLP derived-variable time-series were deemed stationary, because the value of the chi-square test-statistic was more negative than the tabulated critical values. Also, associated p values were less than 0.01, whereby the null hypothesis of a so-called ‘unit root’ (that indicates non-stationarity) is rejected at the 95% confidence level. Results for Granger causality of higher-order or extended-lag VAR models between SST and SLP were obtained. The best-fit VAR model and its lag were determined as corresponding to the VAR model having the strongest stationarity (most negative value of the ADF test statistic). For the SST variables, lag ranged from 1-6 (or 2-12 months maximum possible lead-time), and for SLP variables, lag ranged from 1-4 (or 1-20 months). Given such extended lags in each of the individual time-series, further causality testing for *bivariate* combinations of SST and SLP variables was conducted at extended or higher-order lags.

A total of nine causality links between SST and SLP variables were found (Table 4). Significant causality was found between sdtSEAP and sdtNiño, diffNiño at the 99% confidence level, and between sdtSEAP and threemoNiño at the 95% confidence level, corresponding to a lag range between 6-17 (or maximum possible lead time of 6-22 months). Three month-averaged SEAP was found to significantly Granger cause sdtNiño, diffNiño and threemoNiño at extended lags ranging between orders of 16-20, or maximum possible lead times of 20-25 months. Similarly, five-month averaged SEAP Granger caused the same three SST variables between orders of 17-20, or maximum possible lead-times of 23-27 months.

4. Conclusions

Our analysis results indicate that there is significant Granger causality extending up to maximum possible lead times of 7-22 months between SST and SLP. The findings reported here from a causal analysis of ENSO variability have been further incorporated into a new operational prediction index of ENSO activity that embeds extended lead-time of 15-18 months, called the El Niño Prediction Index (EPI). This index is measured 12-15 months before El Niño peaks, and occurs within this maximum lead time range of 7-22 months within which significant Granger causality between SST and SLP persists. This EPI index is also based on new evidence that strong El Niños are preceded by a standing wave in planetary Rossby waves within the Southern Hemisphere that are coupled to the Southern Oscillation [20].

Further testing of the reliability of the Granger causality test results here could be undertaken as part of future work by employing a de-noising algorithm that has been developed to mitigate measurement noise contamination in Granger causality testing, called the KEM (Kalman smoother combined with use of the Expectation-Maximization (EM) algorithm)[21]. The EM algorithm is used in conjunction with a Kalman smoother, because a Kalman filter cannot be directly applied to de-noise experimental or observed data since it assumes knowledge of the model describing the state-space dynamics - and such knowledge is typically not known or available. A multivariate Granger causality test, such as the one developed by Bai et al., (2011), could be used to further explore and test the causal linkage detected between SST and SLP [7]. This would require identifying latent or intermediate variables that may influence causality between SST and SLP along with additional observational time-series data. Given that the accuracy of VAR models and their use in causality and forecasting can vary substantially for alternative lag lengths and depending on whether symmetric or asymmetric lag lengths are assumed [22], further testing could also be undertaken for asymmetric VAR models.

10. References

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Table 1. Granger causality results for VAR(k) model of lag order 1.

Causal variable	Granger causality (F, p values)
sdtSEAP	does not Granger-cause MeanNiño (0.3105, 0.5775) does not Granger-cause sdtNiño (3.4672, 0.06279) does not Granger-cause diffNiño (3.7701,0.05236) does not Granger-cause threemoNiño (0.1411,0.7073)
threemoSEAP	does not Granger-cause MeanNiño (0.3642,0.5463) does not Granger-cause sdtNiño (3.4672, 0.06279) does Granger-cause diffNiño (7.8298,0.005204)** does not Granger-cause threemoNiño (0.1104, 0.7397)
fivemoSEAP	does not Granger-cause MeanNiño (0.5104, 0.4751) does not Granger-cause sdtNiño (3.4672, 0.06279) does Granger-cause diffNiño (10.1226,0.001494)** does not Granger-cause threemoNiño (0.3152,0.5746)

**Significant at 99% confidence (0.01) level ($p < 0.01$)
*Significant at 95% confidence (0.05) level ($p < 0.05$)

Table 2. Instantaneous causality results for VAR(k) model of lag order k=1 between SST and SLP derived variables.

Causal variable	Instantaneous causality (χ^2, p values)
sdtSEAP	no instantaneous causality with MeanNiño (0.969, 0.3249) no instantaneous causality with sdtNiño (2.3009, 0.1293) no instantaneous causality with diffNiño (0.6604,0.4164) with instantaneous causality with threemoNiño (6.3673,0.01162)*
threemoSEAP	with instantaneous causality with MeanNiño (5.7757,0.01625)* no instantaneous causality with sdtNiño (2.3009, 0.1293) with instantaneous causality with diffNiño (6.3782,0.01155)* with instantaneous causality with threemoNiño (15.9412,6.534e-05)**
fivemoSEAP	with instantaneous causality with MeanNiño (8.24,0.004098)** no instantaneous causality with sdtNiño (2.3009, 0.1293) with instantaneous causality with diffNiño (11.777,0.0005997)** with instantaneous causality with threemoNiño (35.4376,2.634e-09)**

**Significant at 99% confidence (0.01) level ($P < 0.01$)
*Significant at 95% confidence (0.05) level ($P < 0.05$)

Table 3. Results of the Augmented Dickey-Fuller unit-root (ADF) test with null hypothesis - non-stationarity and alternative hypothesis - stationarity.

Causal variable	Value of the ADF test-statistic	Best-fit lag order k	Best-fit lead-time (months)
MeanSST	-15.7365	2	2
sdtNiño	-8.2934	6	6
diffNiño	-17.95	1	2
threemoNiño	-9.6574	4	12
sdtSEAP	-15.8297	1	1
threemoSEAP	-12.7321	2	6
fivemoSEAP	-10.5346	4	20

Table 4. Granger causality results for a VAR(k) model with extended lag order k. The lag order was determined based on the best-fitting bivariate model that minimized AIC (Akaike's Information Criterion). Lead-time is the maximum possible lag length over which significant causality persists (months).

Causal variable	Granger causality (F, p value)	Lag-order	Lead-time (months)
sdtSEAP	does not Granger-cause MeanNiño (1.4446,0.107)	17	17
	does Granger-cause sdtNiño (3.3416, 0.001543)**	7	7
	does Granger-cause diffNiño (6.3789,1.207e-06)**	6	6
	does Granger-cause threemoNiño (1.7787,0.02579)*	17	22
threemoSEAP	does not Granger-cause MeanNiño (1.5267,0.06782)	19	24
	does Granger-cause sdtNiño (2.8246,0.0001537)**	16	20
	does Granger-cause diffNiño (3.5516,2.437e-06)**	16	22
	does Granger-cause threemoNiño (2.1138,0.002835)**	20	25
fivemoSEAP	does not Granger-cause MeanNiño (1.6036,0.05598)	17	22
	does Granger-cause sdtNiño (2.9179,3.928e-05)**	18	23
	does Granger-cause diffNiño (3.2965,6.24e-06)**	17	24
	does Granger-cause threemoNiño (2.5235,0.0002289)**	20	27

**Significant at 99% confidence (0.01) level ($p < 0.01$)
*Significant at 95% confidence (0.05) level ($p < 0.05$)