Newsletter of the Climate Variability and Predictability Programme (CLIVAR)

Exchanges

No 47 (Volume 13 No 4)

October 2008

From Heuser et al., page 20; Numerical Simulations of the Role of Land Surface Conditions on the Climate of Mt. Kilimanjaro Region

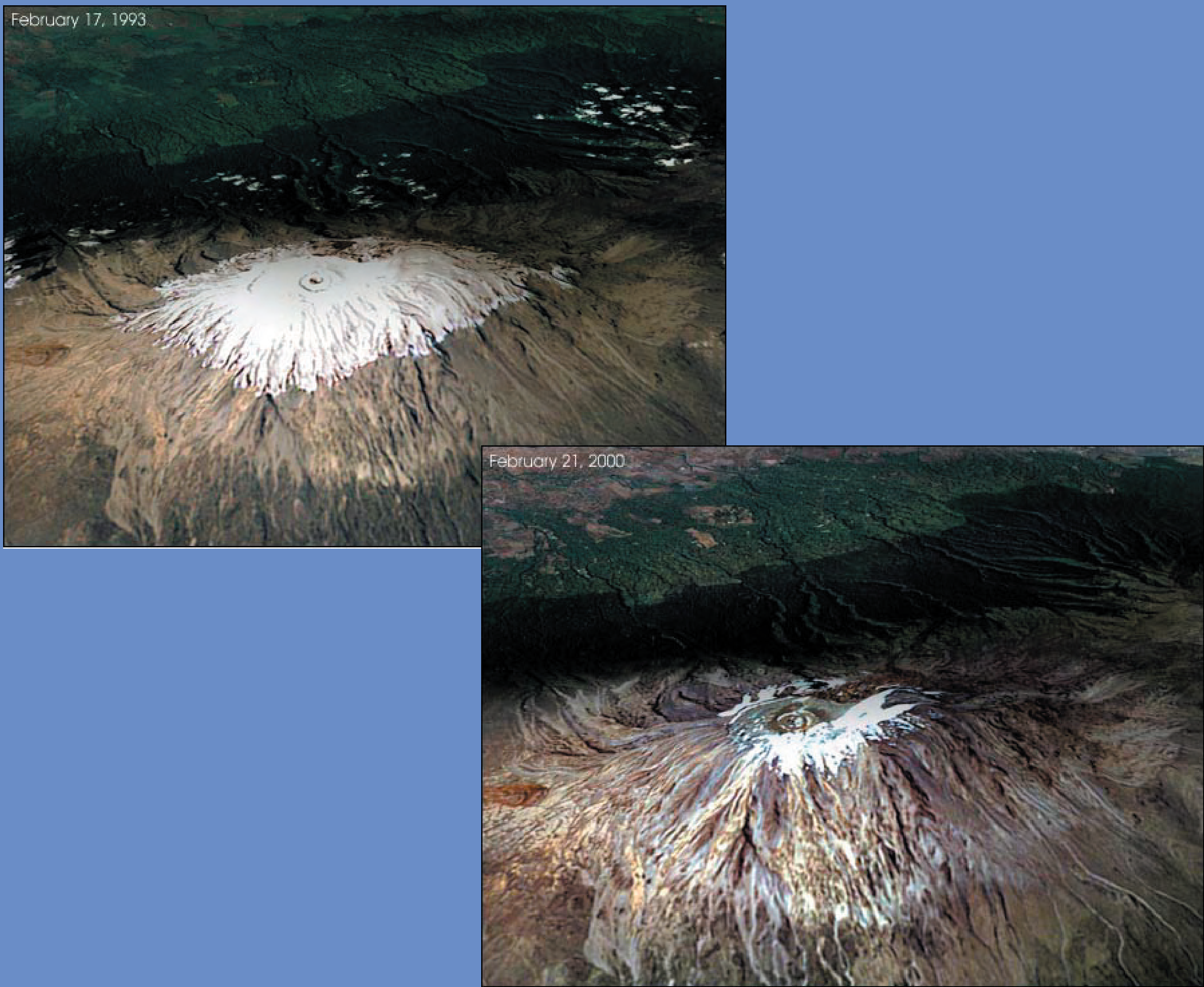

Figure 1: Kilimanjaro Ice Extent: February 1993 and February 2001

CLIVAR is an international research programme dealing with climate variability and predictability on time-scales from months to centuries. CLIVAR is a component of the World Climate Research Programme (WCRP). WCRP is sponsored by the World Meteorological Organization, the International Council for Science and the Intergovernmental Oceanographic Commission of UNESCO.

WCRP
World Climate Research Programme

CALL FOR CONTRIBUTIONS

We would like to invite the CLIVAR community to submit CLIVAR related papers to CLIVAR Exchanges for the next issue. The deadline for submission is 30th November 2008

Guidelines for the submission of papers for CLIVAR Exchanges can be found under: http//www.clivar.org/publications/exchanges/guidel.php

Editorial

WCRP is considering its future. Hence, a key issue discussed by the Joint Scientific Committee (JSC) for WCRP when it met in Arcachon, France, last April was how to evolve the structure of WCRP to meet changing science priorities and societal needs and how to transition the work undertaken by the WCRP projects (CliC, CLIVAR, GEWEX and SPARC) to meet the challenges of the 21st century. The programme's evolution is seen as taking place on two time horizons – firstly to 2013 (the approximate previously declared "sunset dates" of the projects) and secondly into the next decade beyond. Consequently, all four of the WCRP core projects and the WCRP Working Groups have been asked to contribute to (a) developing a near-term "implementation" plan for WCRP against the priorities set out in the WCRP Strategic Plan 2005-2015 (subtitled "Coordinated Observation and Prediction of the Earth System", COPES [http://wcrp.ipsl.jussieu.fr]); (b) the development of an "accomplishments" document setting out WCRP's achievements for presentation, for example, at the upcoming World Climate Conference-3 (WCC-3) and other climate fora and (c) identifying how WCRP should evolve in the longer-term, beyond the 2013 timeframe.

To gather in the needed views and inputs, CLIVAR together with the other components of WCRP, has been asked to prepare a response to a number of detailed questions including:

1. *What will be the key science issues your project aims to address over the coming years, to 2013?*
2. *What elements of this science do you see as needing to be taken forward beyond thet?*
3. *What new science do you see WCRP needing to address beyond 2013 in the context of your project?*
4. *How is your project addressing the unifying cross-cutting foci of WCRP*
5. *What will be the major key legacy items of your project by 2001, and beyond?*

CLIVAR is addressing these requests by asking its panels and working groups to identify what they see as the "imperatives" and "frontiers of research on climate variability and predictability and the research infrastructure needed to support them". At the same time the ICPO is developing a draft response to the detailed questions from the JSC and which the panel responses will feed into. The resulting document will then be made available for community comment and further input before sending it to the JSC early in the New Year. Further subsequent community discussions can be expected, refining the document for CLIVAR's input to JSC-30 when it meets in Baltimore in April 2009. Outcomes of JSC-30 and the way forward for CLIVAR science will provide the focus for the discussions at CLIVAR SSG-16 in May. Overall this activity is a key opportunity for the CLIVAR community to influence the future of WCRP and its structure, to the benefit of international coordination of climate science. I hope to report on progress in future issues of "Exchanges".

This edition of Exchanges contains papers on various aspects of CLIVAR science demonstrating it's breadth. We welcome further such inputs for future editions (see front cover). In addition, I would be pleased indeed to receive community requests for further "themed" editions such as we have had in the past.

Howard Cattle

Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der hinden, X. Dai, K. Maskell, C.A. Johnson (eds.), 2001: *Climate Change 2001: The Scientific Basis*. Cambridge University Press: Cambridge.

Hemp, A. 2005. Climate change-driven forest fires marginalize the impact of ice cap wasting on Kilimanjaro. *Global Change Biology* **11**:1013-1023.

Indeje, M., F.H.M. Semazzi, and L.J. Ogallo, 2000: ENSO signals in East African rainfall seasons. *Int. J. Climatol*. **20**: 19-46.

Kain, J., and J. Fritsch, 1993: Convective parameterization for mesoscale models: The kain-fritsch scheme. *Meteorological Monographs* **24**: 165-170

Kaser, G., 2004: Modern Glacier Retreat on Kilimanjaro as Evidence of Climate Change: Observations and Facts. *Int. J. Climatol*. **24** : 329-339

Liang, X-Z., K. Kunkel, and A. Samel. Development of a Regional Climate Model for U.S. Midwest Applications. Part I: Sensitivity to Buffer Zone Treatment. *Journal of Climate*. **14**: 4363-4378.

Molg, T., D.R. Hardy, 2004: Ablation and associated energy balance of a horizontal glacier surface on Kilimanjaro. *Journal of Geophysical Research*. **109**

Oerlemans, J., 2001: *Glaciers and Climate Change*. Balkema: Rotterdam.

Schreck, C.J. III and F.H.M. Semazzi, 2004: Variability of the recent climate of Eastern Africa. *Int. J. Climatol*. **24**: 681-701.

Thompson, L.G., Mosley-Thompson. E., Davis, M.E., Henderson, K.A., Brecher, H.H., Zagorodnov, V.S., Mashiotta, T.A., Lin, P-N., Mikhalenko, V.N., Hardy, D.R., Beer, J. 2002. Kilimanjaro Ice Core Records: Evidence of HoloceneClimate Change in Tropical Africa. *Science*. **298**: 589

Yu, L.S. and M.M. Rienecker. 1999. Mechanisms for the Indian Ocean warming during the 1997-1998 El Nino. *Geophysical Research Letters*. **26**: 735-738.

Quantifying climate–related risks and uncertainties using Cox regression models

Maia, A.H.M.[1] and H. Meinke[2]
[1]Embrapa Meio Ambiente, Jaguariúna, SP, Brazil; [2] Centre for Crop Systems Analysis, Plant Sciences Group, Wageningen University, PO Box 430, NL 6700 AK Wageningen, The Netherlands; holger.meinke@wur.nl
Corresponding author: ahmaia@cnpma.embrapa.br

Abstract

For applied climate risk management the probability distributions of decision variables such as rainfall, likely dates of climatic events (e.g. frost, onset of the wet season), crop yields or economic returns can be expressed as cumulative distribution functions (CDFs) or probability exceeding functions (PEFs). Such functions are usually derived from empirical or modelled time-series. For forecast purposes in regions impacted by e.g. the El-Nino Southern Oscillation (ENSO), such functions can be categorised by oceanic or atmospheric indexes (e.g. sea surface temperature anomalies, southern oscillation index). These then allow objective climate impact assessments. Although intuition suggests that the degree of uncertainty associated with CDF estimation could impact decision making, quantitative information regarding the uncertainties surrounding these CDFs is rarely provided. Here we propose Cox-type regression models (CRMs) as a powerful statistical framework for making inferences on CDFs in the context of seasonal climate risk assessments. CRMs are semi-parametric approaches especially tailored for modelling CDFs and associated risk measures (relative risks, hazard ratios) and are usually applied to time-to-event data in other domains (e.g. medicine, engineering, social and political sciences). Beyond providing a powerful means to estimate CDFs from empirical data, the Cox approach allows for ranking and selecting multiple potential predictors and quantifying uncertainties surrounding CDF estimates. Well-established and theoretically sound methods for assessing skill and accuracy of Cox-type forecast systems are also available. To demonstrate the power of the Cox approach, we present two examples: (i) estimation of the onset date of the wet season (Cairns, Australia) and (ii) prediction of total wet season rainfall based on historical records (Quixeramobim, Brazil). This study emphasises the methodological aspects of CRMs and does not discuss the merits or otherwise of the ENSO-based predictors. We conclude that CRMs could play an important role in making GCM output more relevant for decision makers through the provision of application-oriented downscaling techniques.

Introduction

Managers of climate-sensitive industries can incorporate probabilistic forecasts of alternative management options as long as the associated uncertainties are clearly spelled out (Nelson et al., 2007). This is particularly true for agriculture and related sectors where proactive adaptation to climate risk is becoming increasingly important (Meinke and Stone, 2005; Howden et al., 2007). Operational climate risk management requires knowledge about the likely consequences of the future state of the climate systems. Often variables of interest (Y), such as time of onset of the wet season (Lo et al., 2007), rainfall, crop yields (Meinke et al., 1996) or return on investment (Twomlow et al., 2008) are provided as CDFs [$P(Y \leq y)$] or PEFs [$P(Y>y)$]. Such probabilistic representation of decision variables helps risk managers to conduct rapid assessments of management options. CDFs/PEFs are particularly convenient to summarise time series that are not or only weakly auto-correlated. However, if time series are moderately to strongly auto-correlated, a CDF/PEF summary will result in the loss of some information. The decision variables in our study (likely time to wet season onset and seasonal rainfall amounts) are at most weakly auto-correlated, thus allowing the CDF/PEF representation to convey seasonal climate information (Maia et al., 2007).

Here we propose the use of Cox-type regression models (CRMs), a statistical approach that includes the Cox regression model (Cox, 1972) and its generalizations. By using theoretically sound likelihood-based methods, CRM allows for estimating CDFs and their uncertainties, ranking and selecting multiple risk factors and quantifying their impacts on probabilistic outputs of seasonal forecast systems. CRMs are semi-parametric approaches especially tailored for modelling CDFs and associated risk measures (relative risks, hazard ratios) arising from time-to-event data in other domains (e.g. medicine, engineering, social and political sciences; Allison, 1985).

Our main objectives are to (i) introduce the Cox approach to climate scientists; (ii) demonstrate the power of CRMs for statistical climate forecasting and suggest its use for downscaling GCM output, (iii) provide methods for quantifying the degree of uncertainty of probabilistic forecasts and (iv) extend the use CRMs by replacing time-to-event variables with other quantities of interest (e.g. rainfall). Using examples from two locations (Cairns, Australia and Quixeramobim, Brazil), we outline in detail the use of these techniques, including their potential pitfalls.

Background

CDFs are commonly used to summarize information from studies in biomedical, social and engineering research where the objective is to model the time until the occurrence of a certain event such as death, equipment/component failure, divorce or unemployment. The statistical approaches for making inferences about CDFs are referred to as survival analysis, reliability analysis or event history analysis in the fields of medicine (Collett, 1994), engineering (Crowder et al., 1991) and social sciences (Yamaguchi, 1991), respectively. Survival analysis comprises many tools, including parametric, semi-parametric and non-parametric methods for estimating and comparing CDFs (Lawless, 1982). Survival analysis also allows for the inclusion of incomplete information, referred to as censored data[1] . For instance, when studying wet season onset, censored data can occur, when in dry years the criteria for 'onset' is not reached until the end of the defined wet season period (Lo et al., 2007).

Recently, some authors have proposed the use of survival analysis as an innovative tool for modelling time-to-event variables in natural sciences: Anthony et al. (2007) used a CRM to assess the risk of coral mortality in response to temperature, light and sediment regime, while Gienapp et al. (2005) discuss the utility of survival approaches for predicting phenology under climate change scenarios. In spite of its traditional use and recent extensions to other domains, survival analysis has rarely been used for seasonal climate risk assessments (e.g. Maia and Meinke, 1999; Maia et al., 2007). Here we focus on Cox regression models (Cox, 1972) as a methodological framework for empirical-statistical seasonal forecasts of climate-related variables. However, the approach could equally be applied to CDFs generated by other means, such as coupled ocean-atmosphere models.

The original Cox model assumes proportional hazards (PH), a property related to the absence of interaction between predictor and predictant. This constitutes the simplest Cox-type model and will hereafter be referred to as CoxPH model. In the absence of an appropriate time-dependent covariate, Cox models simply assume an average effect over the range of observed data (Allison, 1995). However, a great variety of generalizations for the CoxPH model are available, allowing for adequate modelling of non-proportional hazards, if necessary.

In summary, the main advantages of using the Cox approaches in climate risk assessments include:

- CRMs do not require assumptions regarding the type of underlying probability distributions of the climate-related variable being modelled (in contrast to, for instance, ordinary least squares multiple linear regression, logistic regression or parametric survival analysis);
- the validity of proportional hazards assumption can be tested and, if needed, CoxPH models can be generalised to more flexible Cox-type non-proportional hazard models;
- estimates of probabilities of exceeding [P(Y>y)] can be simultaneously obtained for multiple thresholds (y), an advantage compared to the alternative approach based on, for instance, logistic regression (Lo et al., 2007) where PEFs were composed by individual estimates of [P(Y>y)] arising from logistic functions, estimated one at a time.
- the influence of many potential predictors on climate risks can be investigated simultaneously - the contribution of each potential predictor can be objectively evaluated via likelihood tests;
- methods for assessing model skill and predictive accuracy are readily available.

For demonstration purposes we use CRMs to estimate time to wet season onset in Northern Australia, based on the state of two ENSO-based predictors prior to the commencement of the wet season. We then extend the method beyond its usual application to time-to-event data by assessing the probabilities of exceeding threshold values of rainfall amounts for the wet season in North-eastern Brazil based on similar predictors.

Further, we provide associated uncertainties for estimated CDFs (predictive accuracy) that might guide decision makers in their choice between alternative decisions that could be based on this information. To our knowledge, this study is the first using CRMs to analyse the linkage among oceanic/atmospheric indexes and climate risks thereby extending the methods to the domain of seasonal climate risk assessments.

Data and Methods

To demonstrate the utility of the approach, we present two examples where we investigate the influence of predictors based on oceanic/atmospheric phenomena such as the Southern Oscillation and warming/cooling of surface water in the Pacific basin (El Niño/La Niña) on rainfall-related variables:

Example I. For Cairns (Northern Australia, 16.93°S, 145.78°E) we quantify the influence of the Southern oscillation Index (SOI) (mean of June to August monthly SOI, JJA SOI) and the first rotated principal component (SST1) of large scale SST anomalies (JJA SST1) on time to onset of the wet season (Drosdowsky and Chambers, 2001). We adopted one of the criteria presented by Lo et al. (2007) for defining wet season onset: the date at which 15% of the long term mean of total summer rainfall (September to April) is first reached (after 1 September and before 31 March). We used a high quality, daily rainfall data set (Haylock and Nicholls, 2000) to calculate the time to wet season onset for each year (1948 to 2004). The monthly SOI series is available at

www.bom.gov.au/climate/current/soihtm1.shtml.

Example II. For Quixeramobim (Northeastern Brazil, 5.08°S, 38.06°W) we quantify the influence of SST anomalies (average Oct - Feb) in the Niño 3.4 region (SST3.4, 5°N to 5°S; 170-120° W) and SOI (average Dec- Feb) on the wet season

[1]In the context of survival analysis, 'censored data' means that some units of observation have incomplete information regarding time-to-event.

(MAMJ) rainfall amount (1950 to 2007, from Funceme, Ceará's state meteorological agency; www.funceme.br). SST anomaly data for the same period, are available at www.cpc.noaa.gov/data/indices/sstoi.indices.

For both cases, PEFs and associated uncertainties were estimated via CoxPH models, where the probability of T exceeding a particular value t, given a predictor value of x is given by

$$PEF(t, x) = [PEF_0(t)]^{\exp(x.\beta)}$$

where t is the time to event, $PEF_0(t)$ is the baseline survival function, and β is the unknown model parameter that quantifies the influence of the predictor on the $P(T>t)$. The derivative of $PEF(t,x)$ with respect to t is the so called hazard function $h(t, x)$ that represents the instantaneous failure rate at each time t, for $X=x$. Under the proportional hazards assumption, the hazard ratio $[h(t, x_i)/ h(t, x_j)]$ is supposed to be constant over time for any pair (x_i, x_j) of predictor values.

Here we adopt a terminology more adequate for climate studies, using $PEF(t, x)$ instead the classical notation $S(t, x)$. Further, by replacing the time variable $T=t$ with any other quantity $Y=y$ (as in the case of Quixeramobim, where rainfall is the predictant) we can use CRMs for modelling PEFs for important climate dependent variables such as water stress, crop yields or even economic measures (e.g. farm income). For such variables, the hazard function $h(t,x)$ cannot be interpreted as an instantaneous failure rate, but the methods for estimating PEFs and associated uncertainties remain valid. Confidence bands for PEFs were calculated following methods described in Allison (1995). Here we only present a model for a single predictor, although the model can easily be generalized for multiple predictors.

Results and Discussion

Table 1 shows parameter estimates and respective likelihood tests for CoxPH models used to quantify the average (over time) influence of: (a) June - August average SOI or SST1 on time to onset of the wet season at Cairns (models A1 and A2, respectively) and (b) December – February SOI or October – February SST3.4 anomalies on the seasonal rainfall (MAMJ) at Quixeramobim (model B1 and B2, respectively).

Table 1: Parameter estimates and respective standard errors (SE) for CoxPH models fitted for quantifying the influence of atmospheric/oceanic predictors on the PEFs for time to onset of the wet season at Cairns, Northern Australia (models A1 and A2) and wet season rainfall amount at Quixeramobim, North-eastern Brazil (models B1 and B2).

Model	Predictor	b	SE	$exp(b)$	p*
A1	SOI	0.065	0.017	1.067	0.0002
A2	SST1	-0.757	0.199	0.469	0.0001
B1	SOI	-0.028	0.014	0.972	0.0421
B2	SST3.4	0.862	0.143	3.920	0.0478

** Nominal significance levels arising from the maximum likelihood chi-square tests for the hypotheses $\beta = 0$ (no predictor influence). Estimates for β and the hazard ratio (HR) are denoted by b and exp(b), respectively.*

In Figure 1 (page 16) we show PEF estimates derived from fitted CoxPH models for some specific SOI (-15, 0, and +15)

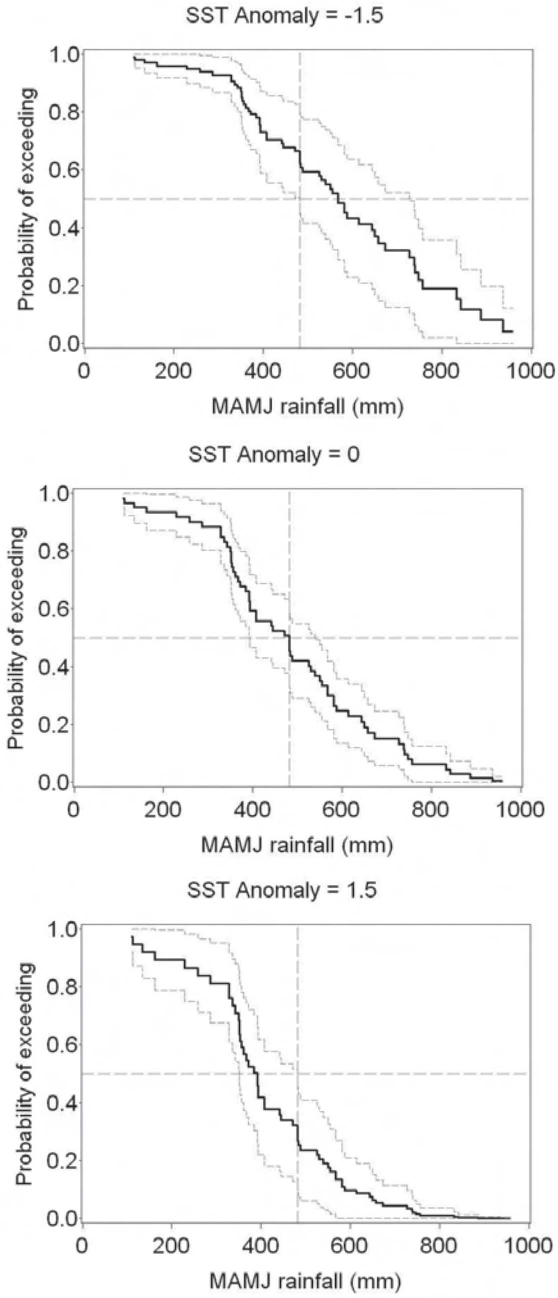

Figure 2: Probability of exceeding functions for MAMJ rainfall at Quixeramobim (Brazil) with respective 95% confidence limits for preceding (October – February) SST3.4 values, estimated via CPH models (as Figure 1B1 and 1B2, page 16).

and SST anomaly values (-1.5, 0 and 1.5) at both locations. PEFs could also be easily obtained for any other predictor value.

Using the hazard ratio (HR) estimates from Table 1, we objectively quantify the influence of predictors on PEFs for the climate-related variables. When the HR estimate is grater than one (positive b), for each unitary increase in the predictor, the baseline PEF, $PEF_0(y)$ is powered by the corresponding hazard ratio. As $PEF_0(t)$ has a value between 0 and 1, this results in a decrease in $Prob(Y>y)$.

This occurs for model A1 (Cairns, SOI), for which increases in SOI lead to lower probabilities of late onset and model B2 (Quixeramobim, SST), where increases in SST3.4 lead to lower probabilities of rainfall exceeding a threshold y, respectively. Conversely, if HR is lower than one (models A2 and B1), unitary increases in predictors lead to increases in *Prob(Y>y)*. These results are consistent with the well known influences of ENSO on the North Australia, where La Niña conditions (positive SOI, negative SST1) favour an earlier than normal start of the wet season (Lo et al., 2007) and on North-eastern Brazil, where El Niño conditions (negative SOI, positive SST3.4 anomalies) lead to low probabilities of substantial wet season rainfall (Coelho et al., 2002).

So far, the PEFs in Figure 1 do not contain any uncertainty estimates. In a final step we expand the risk analysis arising from Model B2 (Quixeramobim, predictor -SSTs.4) by providing their respective 95% asymptotic confidence bands (Figure 2). The width of the confidence limits depends on the series length, the signal strength of the predictor SST3.4 and the predictor value at which the PEF was evaluated.

Given that the main objective of this paper is to show the power of the Cox approach for the generation of seasonal forecasts, we used its simplest form, which assumes proportionality of hazards. Such model might be not able to adequately reproduce some patterns of ENSO influence. In a subsequent step we will refine the risk modelling process by using more flexible non-proportional hazard (NPH) models able to capture nonlinear and possible disproportional influences of ENSO on rainfall-related variables. The use of such models for climate risk assessment as well as a complete evaluation of their skill and predictive accuracy forms part of our ongoing research.

Concluding remarks

In this paper we demonstrate the power of survival analysis, a statistical approach commonly for risk modelling in domains such as medicine, engineering and social sciences. So far these techniques have been undervalued in the domain of climate science, a situation that is likely to continue given the strong focus on dynamical modelling without due attention to the provision of probabilistic forecasts of decision variables such as crop or pasture yields, income or environmental indices, to name just a few. However, particularly for the emerging field of adaptation science, simple, yet locally relevant evaluation techniques are needed. The current trend towards ever increasing complexity in GCM-based modelling without an equal attention to the information needs of decision makers is unlikely to produce such decision-relevant outcomes (Pielke and Sarewitz, 2002).

It has been suggested that using GCMs to predict the driving forces of climate variability might be more robust than carrying the prediction through to highly complex variables such as rainfall (Stone et al., 2000). Given the additional benefit that can be derived from such simple, statistical procedures, we suggest to combine the approaches suggested here with GCM-derived estimates of predictors such as SSTs or SOI to be used as input into statistical models. Such 'downscaling' techniques would enable the provision of information at spatial and temporal scales relevant for decision makers – usually at station to regional scale with a time horizon of up to several years. For practitioners, these are the spatial and temporal scales that really matter and where decisions are made. The statistical techniques presented here also intrinsically account for trends in empirical data. This means that non-stationarity in, for instance, SSTs or SOI values that might be a consequence of climate change are captured by the model. This feature makes it even more attractive to investigate the feasibility of developing a rigorous GCM-CRM interface for provision of user-relevant forecasts risks.

Acknowledgements

HM initiated this work while employed by the Queensland Department of Primary Industries, Australia. The research was financially supported by Land and Water Australia (Managing Climate Variability Program, Project QPI62 - Improving Prediction of the Northern Australian Wet Season). We thank Francis Zwiers for valuable comments on an earlier draft.

References

Allison, P.D., 1995: Survival Analysis Using the SAS® System: A Practical Guide. SAS Institute Inc., 292 pp.

Anthony, K.R.N., S.R. Connolly, O. Hoegh-Guldberg, 2007: Bleaching, energetics, and coral mortality risk: Effects of temperature, light, and sediment regime. *Limnol. Oceanogr.*, **52**, 716-726.

Coelho, C.A.S., C.B. Uvo, and T. Ambrizzi, 2002: Exploring the impacts of the tropical Pacific SST on precipitation patterns over South America during ENSO periods. *Theoret. Appl. Climatol.*, **1**, 185-197.

Collett, D., 1994: Modelling Survival Data in Medical Research. Chapman and Hall.

Cox, D.R., 1972: Regression models and life-tables (with discussion). *J. Royal Stat. Soc.*, **34B**, 187-220.

Crowder, M.J., A.C.Kimber, R.L. Smith, and J. Sweeting, 1991: Statistical Analysis of Reliability Data. Chapman and Hall.

Drosdowsky, W. and L. E. Chambers, 2001: Near-global sea surface temperature anomalies as predictors of Australian seasonal rainfall. *J. Climate*, **14**, 1677-1687.

Gienapp, P., L. Hemerik, and M.E. Visser, 2005: A new statistical tool to predict phenology under climate change scenarios. *Global Change Biol.* **11**, 600-606.

Haylock, M., and N. Nicholls, 2000: Trends in extreme rainfall indices for an updated high quality data set for Australia, 1910-1998. *Int. J. Climatol.*, **20**, 1533-1541.

Howden, S.M., J. F. Soussana, F.N. Tubiello, N. Chetri, M. Dunlop, and H. Meinke, 2007: Adapting agriculture to climate change. *Proc. Natl. Acad. Sci.*, **104**, 19691-19696.

Lawless, J.E., 1982: Statistical Models and Methods for Lifetime Data, John Wiley & Sons.

Lo, F., M. Wheeler, H. Meinke, and A. Donald, 2007: Probabilistic forecasts of the onset of the north Australian wet season. *Month. Weather Rev.*, **135**, 3506-3520.

Maia, A. de H.N., and H. Meinke, 1999: Non-parametrical survival analysis as a statistical tool in agricultural decision making. International Symposium, Modeling Cropping Systems, Proc. Eur. Soc. for Agron. Div. Agroclimatology and Agronomic Modeling, Lleida, Spain, 21-23 June 1999, 103-104.

Maia, A. H. N., H. Meinke, S. Lennox, and R. C. Stone, 2007: Inferential, non-parametric statistics to assess quality of probabilistic forecast systems. *Month. Weather Rev.*, **135**, 351-362.

Meinke, H., and R. C. Stone, 2005: Seasonal and inter-annual climate forecasting: The new tool for increasing preparedness to climate variability and change in agricultural planning and operations. Clim. Change, 70, 221-253.

Meinke, H., Stone, R.C. and Hammer, G.L., 1996. Using SOI phases to forecast climatic risk to peanut production: a case study for northern Australia. *Int. J. Climatology*, **16**, 783-789.

Nelson, R., P.Kokic, and H. Meinke, 2007: From rainfall to farm incomes - transforming policy advice for managing climate risk in Australia. Part II: Forecasting farm incomes. *Aust. J. Agric. Res.*, **58**, 1004-1012.

Pielke, R. (Jr); D. Sarewitz, 2002: Wanted: Scientific Leadership on Climate. *Issues in Science and Technology*, **19**: 27.

Stone, R. C., I. Smith, and P. McIntosh, 2000: Statistical methods for deriving seasonal climate forecasts from GCM's. In: Applications of Seasonal Climate Forecasting in Agricultural and Natural Ecosystems, G. L. Hammer, N. Nichols, and C.Mitchell, Eds., Kluwer Academic, 135–147.

Twomlow, S., F. T. Mugabe, M. Mwale, R. Delve, D. Nanja, P.Carberry and M. Howden, 2008: Building adaptive capacity to cope with increasing vulnerability due to climatic change in Africa – a new approach. *Physics and Chemistry of the Earth*, **33**, 780–787.

Yamaguchi, K., 1991: Event history analysis. *Appl. Soc. Res. Meth.*, **28**. Sage Publications.

Report on the CLIVAR Pacific Panel Summer School on "ENSO: dynamics and predictability" in Puna, on the Big Island of Hawai'i.

Timmerman, A. and S. Power
on behalf of the organising committee
Corresponding author: axel@hawaii.edu

Fundamental advances have been made in understanding the basic dynamics and predictability of the El Niño-Southern Oscillation (ENSO) phenomenon in recent decades. The breakthroughs strongly depended on (i) the availability of improved observational data sets including the TAO-Triton array, satellite altimeter and SST data, ARGO floats and drifters, wind-stress products, and numerous other atmospheric data sets), (ii) the use of a hierarchy of models from simple analog models, through intermediate coupled models, to coupled general circulation models, and (iii) the insights of researchers over past decades.

While fundamental advances in our understanding have been made, many important questions still remain unanswered. For example:

1. Is ENSO a stable, stochastically, excited mode, or a deterministic unstable oscillation whose amplitude is damped by nonlinearities?
2. What determines the amplitude and skewness of ENSO?
3. Why does ENSO vary on decadal timescales?
4. What is the role of westerly wind-bursts (WWBs) in triggering/driving ENSO variability?
5. How does ENSO interact with the annual cycle
6. How does ENSO respond to paleo-climate change?
7. How does ENSO respond to global warming?
8. What processes lead to different ENSO "flavours"?

To raise awareness of the advances and the important outstanding issues amongst the next generation of climate scientists, the CLIVAR Pacific Panel organised a summer school on "ENSO: dynamics and predictability" for young aspiring international students. The lush jungles of Puna on the Big Island of Hawaii provided an ideal setting. This region is under the spell of ENSO, and is subject to the whims of the Hawaiian volcano goddess Pele. The summer school was located a mere 5 miles from where the active and spectacular Kilauea Lava flow spills into the ocean.

Sixteen outstanding students and 6 lecturers from 11 different countries participated. All students had a strong background in meteorology, oceanography or geology. The lecturers included 4 members of the CLIVAR Pacific Panel (Magdalena Balmaseda - ECMWF, Mike McPhaden-NOAA PMEL, Scott Power- Bureau of Meteorology and Axel Timmermann - IPRC), Fei-Fei Jin from the University of Hawaii and Richard Kleeman from the Courant Institute (NYU). Topics covered during 4 hours of daily lectures included ENSO theory (Fei-Fei Jin), ENSO phenomenology (Mike McPhaden), ENSO prediction (Magdalena Balmseda), paleo ENSO (Axel Timmermann), decadal changes in ENSO and the impact of global warming on ENSO (Scott Power) and ENSO predictability theory (Richard Kleeman). The lectures were complemented by challenging student research projects, evening presentations, field excursions to the Mauna Loa CO_2 observatory and the Volcano National Park. Energizing brain fuel consisted of fresh goat milk kefir, locally grown vegetables and fruits and freshly caught fish from the deep blue Pacific.

The research projects engaged the students in investigations of e.g.: the effect of multiplicative weather "noise" on ENSO variability and predictability; the impact of El Niño on Antarctic climate; evidence for the origin of a megadrought 4,200 years ago in existing hydrological paleo-data sets; the role of wave dynamics in the dynamics of ENSO using TAO-Triton data; the termination mechanism for the 2006-2008 ENSO event; and the nature of warm pool El Nino events. Students applied the concepts taught during the lectures to their research projects.

More details on the student projects as well as pdf-files for all lectures can be found on: http://iprc.soest.hawaii.edu/~axel/ENSOsummerschool.html

The summer school was generously supported by WCRP, PAGES, NOAA, ARCNESS, the Australian Bureau of Meteorology, the International Pacific Research Center and Mathworks.

Participants at the ENSO Summer School