The studying of the equilibrium model for the coupled air-sea boundary layer in the Tropics

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ABSTRACT

A One-dimensional coupled air-sea boundary layer model is used to study the equilibrium state of the air -sea boundary layer in the Tropics. The atmospheric model is a one-dimensional thermodynamic model for a partially mixed, partially cloud convective boundary layer (CBL). The model includes the effects of the cloud-top subsidence, surface momentum, latent heat flux, sensible heat flux and the radiative transfer (Betts and Ridgway, 1989). The oceanic model is a thermodynamic model for a well-mixed layer, with a closure constraint based on a one-dimensional turbulent kinetic energy (TKE) equation following Kraus and Turner(1967).

The depth of the CBL and the oceanic mixed layer (OML) increase and the upwelling below the OML decrease, corresponding to either increasing SST or increasing surface wind. The deeping of the equilibrium CBL is primarily due to the increase of CBL moisture with increasing SST and surface wind. The increase of the OML depth and the decrease of upwelling are due to the decrease of surface net heat flux with increasing with SST and the increasing of the forced wind stress mixing. We see that, with greater coupling, the CBL depth changes more slowly with SST and drier in the subcloud layer, corresponding to the cloud-top subsidence. The decrease of latent heat flux, will modify the surface net heat flux ,and will influence the development of OML as well. This work suggests that the equilibrium state of the coupled system is very sensitive to the surface net heat flux. Among them, the latent heat flux plays a crucial role in changing the moisture and the radiative flux in the CBL and the thermodynamic budget in the OML.

Interannual Variability of Tropical Cyclone Incidences in the Vicinity of Hawaii Using Statistical Resampling Techniques

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1. Introduction

Tropical cyclones do not form or pass the vicinity of Hawaii very frequently because of the relatively low sea surface temperatures north of 20°N and the large vertical wind shear in this region. However, when they occurred, they caused enormous property damages. The most notable is Hurricane Iniki, which ravaged Kauai and a part of Oahu, Hawaii (Fig. 1), on 11 September 1992, following the wake of the 1991-92 El Niño event. Iniki was a category 4 hurricane on the Saffir-Simpson scale with gust winds up to 64 m s^{-1} recorded. Estimates of damages were about \$2.5 billion for Iniki, the costliest hurricane in Hawaiian history.

Just 10 years prior to Iniki, Kauai suffered major damage approaching \$250 million from another hurricane named Iwa on 23 November 1982. This hurricane occurred when the exceptionally strong 1982-83 El Niño event had nearly reached its maximum intensity. In fact, during July 1982, there were two other tropical cyclones that were less intense than Iwa but were nevertheless close enough to cause major concerns to Hawaii.

A look at the historical records suggest that tropical cyclones tend to occur more often during the El Niño years. Because the sample size of tropical cyclones from the real data is small, it is difficult to determine whether the difference in cyclone numbers between the El Niño and non-El Niño year is significant using the conventional statistical methods. To overcome this problem, modern statistical resampling tehniques such as the nonparametric bootstrap and permutation are used.

2. Data and Cyclone Statistics

The tropical cyclone data are supplied by the National Hurricane Center in Miami, Florida. This dataset contains measurements of latitude, longitude, maximum wind speed, and central pressure at 6-h intervals for all cyclones from 1949 to 1995 over the northeast and north-central Pacific. During the last 47 years, 26 cyclones occurred within 250 n mi of Honolulu, Oahu.

The second dataset is the monthly mean sea surface temperature (SST) series of Niño 3 region. The Japan Meteorological Agency (JMA) defines an El Niño when the 5-month running mean of SST anomalies is greater 0.5°C for at least six consecutive months in the region between 4°N-4°S and

150°W-90°W. We basically adopt the JMA definition but add one more criterion to the Niño 3 region. That is, during the above period SST anomalies are greater than 1°C at least for 1 month. Therefore, our definition for El Niño applies for only pronounced events.

On average, an El Niño event starts in June and ends in the following May or June. The average length of an event is about 12.7 months, or slightly over one year. For simplicity, a year in this study extends from June to May. For example, the 1982 event refers to the period from June 1982 to May 1983. Tropical cyclone data are first classified into El Niño and non-El Niño batches.

3. Bootstrap resampling results

Although the historical cyclone data are used, the sample size is limited; that is, only 11 cyclones during 10 El Niño years and 15 in the other 36 years. In order to make inferences about the frequency distribution of the annual mean number of cylones for each batch, we use the bootstrap technique (Efron and Tibshirani, 1993). O'Brien et al. (1996) used a bootstrap technique to distinguish the relative frequency distribution of Atlantic hurricanes striking the U.S. during El Niño and non-El Niño years.

Here, 5000 bootstrap replications of size n_{nino}=10 and $n_{non\text{-}Nino}$ =36 are generated from the cyclone data corresponding to the El Niño and non-El Niño batches, respectively. The (1-α) x 100% confidence intervals for boostrap estimates are obtained using the percentile method. For details, see Chu and Wang (1997).

Figure 2 shows the probability distribution of the number of cyclones per year from 5000 bootstrap realizations for El Niño and non-El Niño batches, respectively. It is clear that distributions are quite different between El Niño and non-El Niño batches. For the non-El Niño batch, the distribution is tight and around the mean value while for the El Niño batch, the distribution spreads out far more and is relatively flat.

4. Hypothesis testing using two-sample permutation procedures

The permutation procedure operates in the following way. As two different batches are compared, they are combined to form a large batch. The pooled batch is resampled to form a new pair of batches. The test statistic is recomputed from these new batches and then the above steps are repeated a large number of times. The collection of the test statistic from the simulation is used to produce an empirical estimate of the reference distribution. If the test statistic from the actual observations falls outside the central 95% of the reference distribution, the permutation rejects the null hypothesis at a 5% level.

Table 1 indicates that the actual test statistic lies outside of the central 95% confidence intervals of the bootstrap estimates. This suggests that the annual mean number of tropical cyclones during the El Niño and non-El Niño batches are significantly different from each other at the 5% test level.

5. Summary

Results from the bootstrap method show that sampling distributions of the yearly occurrence of tropical cyclones in the vicinity of Hawaii during El Niño is quite different from the non-El Niño condition. The procedures to compare the means are applied to the two-sample data batches generated from the permutation. The difference in the annual mean number of cyclones during El Niño and non-El Niño years from the real sample is unusual relative to that from the simulated sample, suggesting that there are indeed more tropical cyclones observed during an El Niño year than during a non-El Niño year, and this difference is statistically significant. The current results, which are based on actual observations using nonparametric resampling techniques and hypothesis testings, thus lend support to the GCM simulations (e.g., Wu and Lau, 1992).

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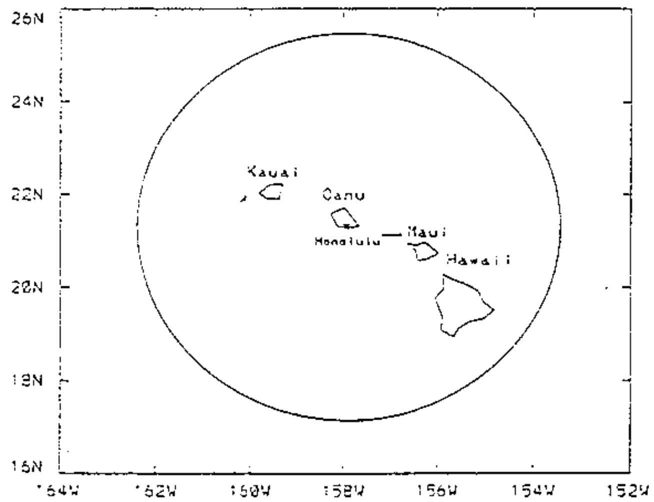

Fig. 1. Map of the major Hawaiian islands and the scan radius of 250 n mi from Honolulu.

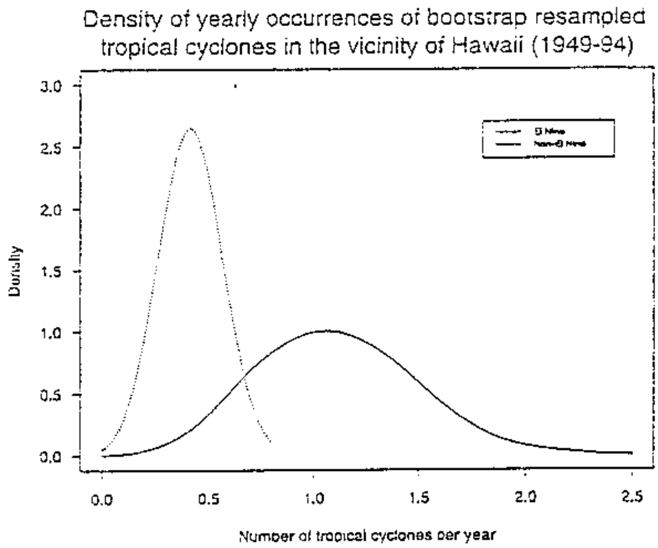

Fig. 2. Density distribution of the annual mean number of tropical cyclones in the vicinity of Hawaii for the El Nino and non-El Nino batches simulated by bootstrap.

Table 1. Test statistic of the annual number of tropical cyclones and their corresponding 95% confidence intervals between El Nino and non-El Nino batches based on actual observations and permutation tests.

batch	Test statistic from observations	The 95% confidence interval for test statistic from simulations
Nino/non-Nino	1.744	(-0.928, 1.341)