

Variability of extreme wave heights in the northeast Pacific Ocean based on buoy measurements

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[1] Recent studies reveal important trends in mean values and high percentiles of significant wave height in the northeast Pacific. However, changes of the extreme wave heights through time have not received much attention. In this work, the long-term variability of extreme significant wave height along the northeast Pacific is modeled using a time-dependent extreme value model. Application of the model to significant wave height data sets from 26 buoys over the period 1985–2007 shows significant positive long-term trends in extreme wave height between 30–45°N near the western coast of the US averaging 2.35 cm/yr. We also demonstrate an impact of El Niño on extreme wave heights (about 25 cm per unit of NINO3.4 index) in the northeast Pacific as well as important correlations with mid-latitude climate patterns (e.g., NP and PNA indices). **Citation:** Menéndez, M., F. J. Méndez, I. J. Losada, and N. E. Graham (2008), Variability of extreme wave heights in the northeast Pacific Ocean based on buoy measurements, *Geophys. Res. Lett.*, 35, L22607, doi:10.1029/2008GL035394.

1. Introduction

[2] Extreme wave climate is a limiting factor both in the biology and geology of the coastal area and also determines the uses of the coast, making their characterization so necessary for coastal management and maritime works. Within this context, this work focuses on the extreme values of significant wave heights.

[3] There are four major sources of wave data (buoy data, voluntary observing ship (VOS) data, model hindcasts and satellite altimeter data) that can contribute to study wave climate. In this study, we work on buoy data because although they usually present gaps in their records and do not have a homogenous spatial distribution, buoy data are the most reliable records, especially when considering extreme values.

[4] The characterization of extreme wave climate is a challenge from both the statistical and geophysical perspectives. Statistically, the most pervasive problem is that consistent buoy records are rarely over 35 years in length. This means that the extreme values of the sample populations are inherently scarce and the derived parameters may exhibit large uncertainties. Geophysical characteristics pres-

ent other problems: the sparse and uneven coverage of wave buoys makes it difficult to assess spatial patterns; wave model hindcasts [Caires and Sterl, 2005] or VOS visual data [Grigorieva and Gulev, 2006] can be of some assistance in this regard but special caution is required when working with extreme wave heights [Caires and Sterl, 2003].

[5] This work focuses on the eastern North Pacific and fits within the context of other studies which consider the question of wave climate variability in that region [e.g., Allan and Komar, 2000; Gower, 2002; Gulev and Grigorieva, 2004, 2006; Wang and Swail, 2001; Graham and Diaz, 2001]. However, most of these studies are aimed to use some parameters of wave climate (e.g., mean or high percentiles of significant wave height) that do not represent the largest extreme events. In general, the above noted studies find evidence of increasing wave heights over the northeast Pacific during the latter part of the 20th century and most of these authors show a positive association between El Niño activity and wave climate.

[6] We use hourly significant wave height (H) data from twenty six NOAA (<http://www.ndbc.noaa.gov>) and Environment Canada wave buoys in the northeast Pacific (Figure 1) to estimate the seasonal-to-interannual variability of extreme H . In order to consider the same time frame for all 26 buoys, we have selected a common 23-year period (1985–2007), except for the Canadian buoys that start in 1987.

2. Methods

2.1. Extreme Value Model

[7] The early works to define the extreme values of the wave heights consist of choosing the whole data set from the population, fitting an initial value distribution model and calculating return levels, but this method is likely to provide unreliable extreme estimates because most of the sample values are far away from the tail. Another approach would be to use the Annual Maxima Method but the samples used are not suitable because buoy records are short. In order to overcome all these inconveniences, we use an approach based on the Peak Over Threshold (POT) method to study the statistical properties of the peaks of H , analyzing the exceedances $y = H - u$ over a threshold u (see the peaks of the storms (dots) selected in Figure 2). We assume that the number of episodes over level u follows a Poisson distribution with a rate of occurrence, $\nu > 0$ (year⁻¹), and the threshold excesses $y > 0$ are modeled using the Generalized Pareto Distribution (GPD). Our procedure has the advantage that the GPD-Poisson model can be expressed compatibly to the well-known Generalized Extreme Value distribution (GEVD) for annual maxima given by $F(H;\theta) = \exp\{-[1 +$

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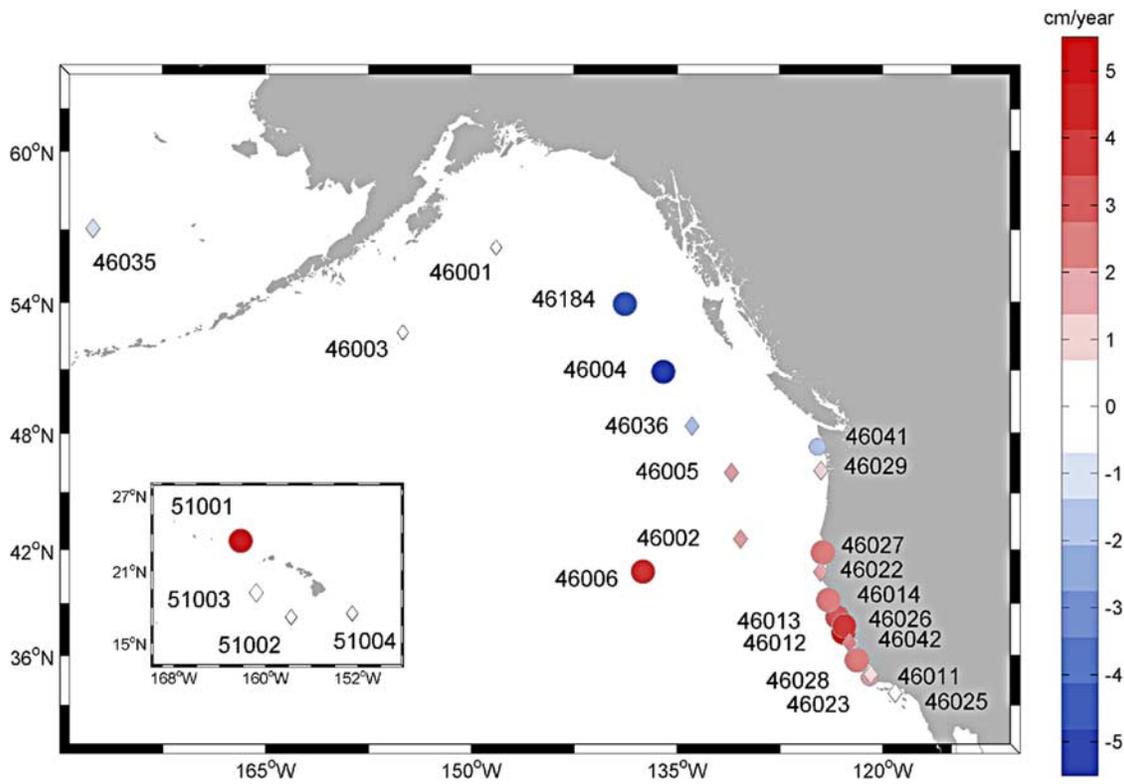


Figure 1. Long-term trends for LT model along the northeast Pacific coast. The two increasing circle sizes mean that the inclusion of the parameter is significant above 95% and 90% levels (coloured diamonds show significances over 50% levels and empty diamonds non-significant values).

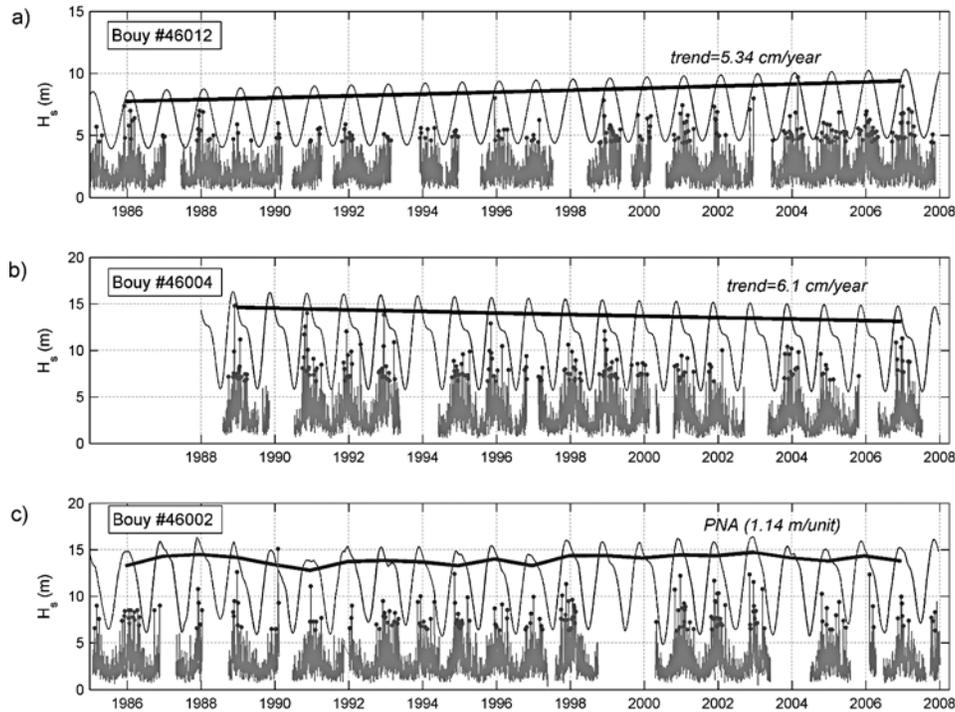


Figure 2. Hourly time series (grey lines) of H at buoys (a) #46012, (b) #46004 and (c) #46002. Dots represent the events that exceed the u_{98} threshold. Solid lines stand for the 20-year time-dependent quantiles for LT model (#46012 and #46004) and CP model (#46002). The bold lines represent the annual 20-year return level values.

$\xi(H - \mu)/\psi]_{+}^{-1/\xi}$, where $\theta(\mu, \psi, \xi)$ is the vector parameter, $[x]_{+} = \max(0, x)$, μ is a location parameter that informs about the origin of the distribution, $\psi > 0$ is a scale parameter, and ξ is a shape parameter which determines the bounded (if the value is negative), light (null value) or heavy (positive values) nature of the upper tail of the distribution. This equivalence between GPD-Poisson model and GEVD (e.g., $v = (1 + \xi(u - \mu)/\psi)^{-1/\xi}$) greatly facilitates the derivation of annual statistics.

[8] The selected threshold is the 98th percentile of all H data for every buoy (u_{98}) and the time span to assure independence between consecutive episodes of high waves is three days. We use the maximum likelihood (ML) method to obtain the vector parameter estimates $\hat{\theta}$. Statistical significance and confidence intervals are estimated according to likelihood ratio test which relates deviance function to chi-squared distribution [see *Coles*, 2001]. Estimates of the extreme return levels are obtained by inverting the GEVD function.

2.2. Non-stationary Approach

[9] The basic idea of the approach in this work is to consider that the probability of exceedance of a certain extreme event varies through time [*Méndez et al.*, 2006]. Consequently, variability is represented in the model allowing the parameters in the GEVD to be time-dependent, using parametric expressions for the location and scale parameters ($\mu(t)$ and $\psi(t)$). Three different models have been proposed to analyze the seasonal-to-interannual variability of extreme events of H : S Model for seasonality (intra-annual variability), LT Model to study long-term trends and CP Model for climate patterns (interannual climate variability).

[10] The variability within a year is introduced in the model by means of sinusoidal functions that represent the annual cycle (first harmonic), and a possible semiannual cycle (second harmonic). The best combination of annual and semiannual cycles for the location and the scale parameters ($\mu_s(t)$ and $\psi_s(t)$) is obtained using an automatic selection mechanism [*Menéndez et al.*, 2008].

[11] A significant fraction of the data variance at short time scales is due to the intra-annual variations. Therefore, once the best model considering the intra-annual variability has been obtained, the magnitude and the statistical significance of the long-term trend of the extreme events of H can be analyzed. We include long term variability in the location parameter, $\mu_{LT}(t) = \mu_s(t)\exp[\beta_{LT}t]$. For example, for Buoy 46014 the annual variation of $\hat{\beta}_0\hat{\beta}_{LT}$ is 2.6 cm yr^{-1} (which in this case is significant above the 99% level). Figures 2a and 2b show the results of the LT model in two buoys.

[12] To study interannual variability in extreme H , different climate indices are used as predictors (the NINO3.4 index and two mid-latitude patterns: PNA and NP indices). The study of interdecadal variability in this area is not considered because buoy records are relatively short.

[13] We formulate the CP model in the form of an additive covariate to the location parameter, so that $\mu_{CP}(t) = \mu_s(t) + \beta_{CP}^{Climate\ Index(t)}$, where the climate index can be NINO3.4, PNA or NP indices. As before, we obtain the magnitude and the statistical significance of β_{CP} to describe

the relation between extreme wave heights and a certain climate index.

3. Results and Discussion

[14] For the buoys used in this analysis, the extreme wave climate of the North Pacific is defined primarily by five factors: 1) sea and/or swell from strong mid-latitude cyclones, 2) the annual cycle of the storm track position, 3) strong northwest winds along the coast of Oregon and California, 4) tropical cyclones near the Hawaiian Islands and 5) the location exposure of each buoy. With these factors in mind we have divided the set of buoys into three groups; Area I: the nine buoys in the Gulf of Alaska, Bering Sea and western Canadian coast, Area II: the near-coastal buoys in the western US coast, and Area III: the four buoys near Hawaiian Islands.

[15] Figure 3a shows the main characteristics of the wave environment by means of basic and stationary statistics: first stack represents averaged wave climate conditions; second and third stacks inform about the most probable value and the variance of extreme H respectively; fourth stack shows the 20-year return-level values and their 95% confidence intervals and asterisks point the maximum H for the analyzed period.

[16] A different spatial behavior between mean and extreme values is observed. The relative difference between mean and extreme events is smaller in the Hawaiian Islands than in Area II (up to 30°N). A clear pattern in extreme waves shows more severe conditions to the North. Local characteristics also appear in several buoys, for example, buoy #46006 shows larger extreme wave climate due to its relative proximity to the mean North Pacific winter cyclone track, and buoy #46025 presents lower values in extreme waves due to its sheltered position off Point Concepcion.

3.1. Intra-annual Variability

[17] Figure 4 shows sample results from the S Model for three buoys. These results are shown in terms of frequency (Figure 4 (left)) and magnitude (Figure 4 (right)). They are representative of those obtained for other buoys in each Area and give an idea of the quality of the fitted models. When referring to the magnitude, the results show dominance of the annual cycle, with peaking around January. The semiannual cycle tends to have larger relative amplitude and is more uniformly significant for locations farther north. These features apparently relate primarily to the seasonal migration of the storm track from a more northern position in boreal autumn, to a more southerly position in mid-winter, and northward again in spring. The importance of the semiannual cycle may also reflect the impact of mid-winter suppression of cyclone growth at higher latitudes [*Nakamura*, 1992]. Also apparent in Figure 4 are the effects of extreme waves generated by tropical cyclones that occasionally affect the Hawaiian Islands region during boreal summer.

[18] Two further important points that relate to the model utility of the non-stationary GPD-Poisson approach concern the shape parameter, ξ_o . First, we find that both the statistical significance and spatial homogeneity of ξ_o markedly increase when the seasonal variability in location and scale parameters are included. Second, the prevalence of

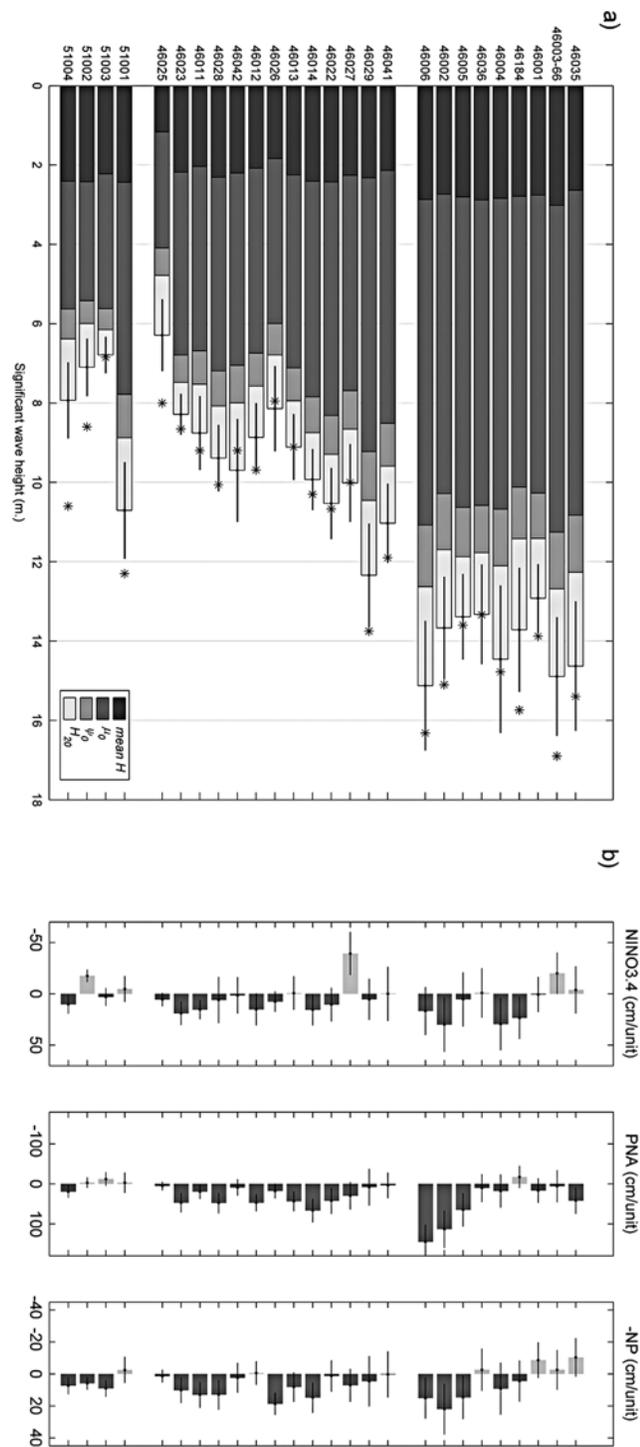


Figure 3. (a) From darker to light: averaged wave climate conditions, most probable extreme H and variance of extreme H . Midpoints: 20-year return-level values. The asterisks are the maximum H registered at every buoy time series. (b) Contribution of different climate indices: NINO3.4, NPA and NP index. Horizontal bars stand for the 95th confidence intervals.

negative values of ξ_o indicates that the upper tail of the extreme distribution of H is bounded for nearly all of the buoys used in our study.

3.2. Long-Term Trends

[19] The most relevant results for the analyses of LT Model are the statistically significant positive trends obtained at most sites along the coast of California (Figure 1). In most of the buoys, these trends range from about $2\text{--}4\text{ cm yr}^{-1}$ or about 0.2 to 0.9% per year for the 23-year analysis period. Buoys around Alaska (Bering Sea and Gulf of Alaska) show small and no significant trends. However, trend results of Canadian buoys point out a decrease in extreme H (Figure 2b). In buoys near Hawaiian Islands, the trends obtained are not statistically significant except for those of the northern buoy, #51001, which presents a similar increase as that of the mid-latitudinal buoys.

[20] The magnitude of the trends noted here, especially upward trends between latitudes $32\text{--}42^\circ\text{N}$, agree qualitatively with those reported by *Allan and Komar* [2000], *Gower* [2002], and *Bromirski et al.* [2005], and hindcast analysis by *Graham and Diaz* [2001] and *Wang and Swail* [2001].

3.3. Associations With Climate Indices

[21] The NINO3.4 index is a widely used area-average measure of eastern tropical Pacific sea surface temperature (SST). It is well established that SST in the equatorial Pacific plays an important role in altering winter circulation and storm activity over the North Pacific [*Bjerknes*, 1966, and references therein] and via that linkage, wave climate. The strength of the North Pacific westerlies is usually characterized by the North Pacific (NP) Index [*Trenberth and Hurrell*, 1994] or the Pacific-North America (PNA) Index [*Wallace and Gutzler*, 1981].

[22] The regression parameter β_{CP} of the CP model shows a general positive association with the NINO3.4, PNA and NP indices for the buoys located in NE Pacific off the west coast of US (Figure 3b). This common pattern proves the tropical and extratropical relationships in the atmosphere-ocean circulation.

[23] Results for NINO3.4 emphasize the response of the extreme wave heights to El Niño activity. This pattern is consistent with the tendency for an expanded and deepened Aleutian Low during El Niño years [*Horel and Wallace*, 1981], and consequently rougher wave conditions in the eastern and central North Pacific. However, the spatial distribution of the influence of NINO3.4 presents less statistical significance in extreme waves than PNA or NP indices. This is because NINO3.4 explains a global-scale spatial variation directly related to the ocean-atmosphere phenomenon of “El Niño/La Niña”. Consequently the influence of NINO3.4 over extreme H is explained because it can produce wind patterns in the Pacific Ocean that can force extreme wave events in the NE Pacific basin. The uncertainty obtained for influence of PNA and NP indices is smaller since they represent the decadal (NP index) and high-frequency (NPA) variability directly in the North Pacific extratropics, i.e., in the predominant region of generation of extreme wave height values. The stronger influence over extreme H is obtained using the PNA index, with a maximum influence of 1.5 m per unit of index and a standard error of 28 cm for buoy #46006 (see also the results for #46002 in Figure 2c). PNA influence is also positive for most of the buoys in Area I: Bering Sea, Gulf of Alaska and open ocean buoys. The open ocean buoys show

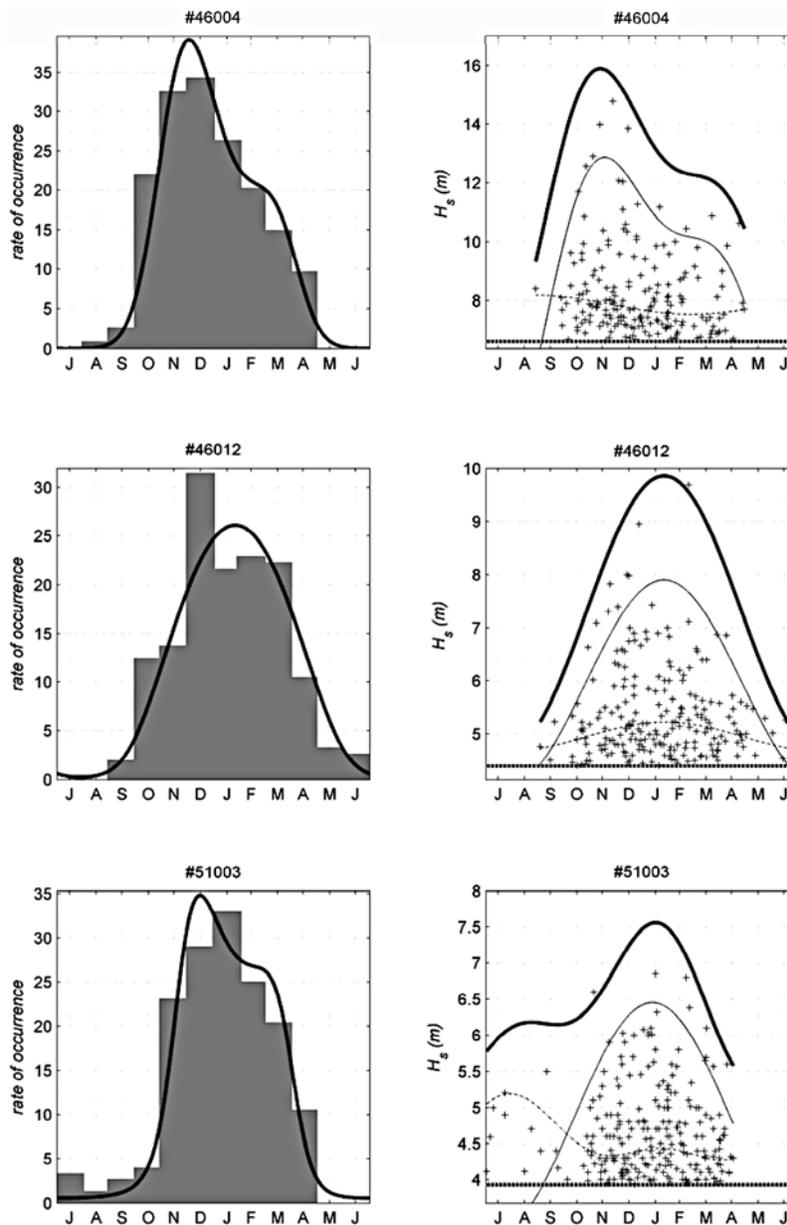


Figure 4. (left) Empirical distribution of the rate of occurrence of threshold excesses (bars) and time-dependent event rate modeled within a year (solid line). (right) Exceedances over the 98 percentile threshold (crosses) and time-dependent location parameter (solid line), scale parameter (dashed line) and instantaneous 20-year quantile (bold line). Results are for S model for NOAA buoys #46004, #46012 and #51003.

stronger influence of PNA and NP indices, possibly due to the fact that they are less influenced by local mechanisms near the coast, such as shallow water effects or sheltered areas.

4. Conclusions

[24] We describe the use of a new methodology to characterize the climatology and variability of extreme H at 26 wave buoys in the Northeast Pacific over the 23-year period 1985–2007. The technique is an application of the combined GPD-Poisson methodology that allows for time-dependent modulation of the parameters that describe extreme distributions. This new method has the advantage

of allowing the application of well supported extreme value theory to geophysical variables. It arises not only from the widespread presence of non-stationary behavior, but also from the fact that allowance for non-stationary behavior can considerably enhance the statistical significance and stability of the results.

[25] Results of this work show seasonal, long-term trends as well as the effect of interannual variability associated to El Niño and midlatitudinal climate patterns of extreme values of significant wave heights at all buoys studied. Although the period designated for our analysis is relatively short, the results provide some new information and extend the results of Méndez *et al.* [2006] by showing that the

methodology can be applied usefully to cases in which non-stationarity is an issue.

[26] As would be expected, the analysis of seasonality shows that extreme H in the Northeast Pacific and Bering Sea are most severe and variable between October and March (boreal “winter”). They are larger in the north than farther south and for open ocean locations than for coastal sites. An especially interesting result of the seasonality analysis is the higher relative importance of the semiannual component for the buoys in the higher latitudes of the North Pacific, a feature that is most likely related primarily to the seasonal (meridional) migration of the preferred cyclone track, but which may also reflect the impact of the suppression of the mid-winter cyclone activity.

[27] The measured trends indicate a well-defined region of significant upward trends in the eastern North Pacific off Washington, Oregon and California (Area II), with magnitudes ranging between 5–21% over the analysis period. The buoys off the west coast of Canada revealed an interesting region of negative trends not previously observed.

[28] The study of the influence of associated climate indices (NINO3.4, PNA and NP) over extreme wave heights shows a clear spatial distribution in the NE Pacific for each one. The PNA pattern produces a strong influence for almost all studied buoys except for those around the Hawaiian Islands. The decadal oscillation in North America is affecting the buoys off the northwestern American coast and Hawaiian Islands. The analysis of the relationship between extreme wave heights and El Niño variability showed modest but statistically significant positive relationship for the buoys in the eastern North Pacific off the US West Coast, consistent with previous studies.

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References

Allan, J. C., and P. D. Komar (2000), Are ocean wave heights increasing in the eastern North Pacific?, *Eos Trans. AGU*, *47*, 561–567.
Bjerknes, J. (1966), A possible response of the atmospheric Hadley circulation to equatorial anomalies in ocean temperature, *Tellus*, *18*, 820–829.

Caires, S., and A. Sterl (2003), Validation of ocean wind and wave data using triple collocation, *J. Geophys. Res.*, *108*(C3), 3098, doi:10.1029/2002JC001491.
Caires, S., and A. Sterl (2005), 100-year return value estimates for ocean wind speed and significant wave height from the ERA-40 data, *J. Clim.*, *18*, 1032–1048.
Coles, S. G. (2001), *An Introduction to Statistical Modeling of Extreme Values*, Springer, London.
Bromirski, P. D., D. R. Cayan, and R. E. Flick (2005), Wave spectral energy variability in the northeast Pacific, *J. Geophys. Res.*, *110*, C03005, doi:10.1029/2004JC002398.
Gower, J. F. R. (2002), Temperature, wind and wave climatologies, and trends from marine meteorological buoys in the northeast Pacific, *J. Clim.*, *15*, 3709–3717.
Graham, N. E., and H. F. Diaz (2001), Evidence for intensification of North Pacific winter cyclones since 1948, *Bull. Am. Meteorol. Soc.*, *82*, 1869–1893.
Grigorieva, V., and S. K. Gulev (2006), Extreme wind waves worldwide from the VOS data and their changes over the last 50 years, paper presented at the 9th International Workshop on Wave Hindcasting and Forecasting, Environ. Can., Victoria, B. C., Canada.
Gulev, S. K., and V. Grigorieva (2004), Last century changes in ocean wind wave height from global visual wave data, *Geophys. Res. Lett.*, *31*, L24302, doi:10.1029/2004GL021040.
Gulev, S. K., and V. Grigorieva (2006), Variability of the winter wind waves and swell in the North Atlantic and North Pacific as revealed by the voluntary observing ship data, *J. Clim.*, *19*, 5667–5685.
Horel, J., and J. M. Wallace (1981), Planetary scale atmospheric phenomena associated with the Southern Oscillation, *Mon. Weather Rev.*, *109*, 813–829.
Méndez, F. J., M. Menéndez, A. Luceño, and I. J. Losada (2006), Estimation of the long-term variability of extreme significant wave height using a time-dependent Peak Over Threshold (POT) model, *J. Geophys. Res.*, *111*, C07024, doi:10.1029/2005JC003344.
Menéndez, M., F. J. Méndez, C. Izaguirre, A. Luceño, and I. J. Losada (2008), The influence of seasonality on estimating return values of significant wave height, *Coastal Eng.*, doi:10.1016/j.coastaleng.2008.07.004.
Nakamura, H. (1992), Midwinter suppression of baroclinic wave activity in the Pacific, *J. Atmos. Sci.*, *49*, 1629–1642.
Trenberth, K. E., and J. W. Hurrell (1994), Decadal atmosphere-ocean variations in the Pacific, *Clim. Dyn.*, *9*, 303–319.
Wallace, J. M., and D. S. Gutzler (1981), Teleconnections in the geopotential height field during the Northern Hemisphere winter, *Mon. Weather Rev.*, *109*, 784–812.
Wang, X. L., and V. R. Swail (2001), Changes of extreme wave heights in Northern Hemisphere oceans and related atmospheric circulation regimes, *J. Clim.*, *14*, 2204–2221.

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