

統計的波浪モデルの開発と気候変動への応用  
Development of statistical wave model for climate projection

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Future wave climate projection is important for climate impact assessment of the coastal environment and hazards. The statistical wave model is developed to reduce computational costs. In this study, the monthly averaged wave heights are estimated by a linear multi-regression model with atmospheric data as explanatory variables. The present statistical model considers the local atmospheric information (wind speed at 10 m height, sea level pressure) and the large-scale atmospheric information obtained by the principal component analysis (PCA) of the global sea level pressure and wind field. The representation of swell in the lower latitude is greatly improved by introducing the large scale atmospheric information from the PCA. The present statistical model was applied to the results of Japan Meteorological Research Institute's Atmospheric General/Global Circulation Model (MRI-AGCM) climate change projection.

### 1. Introduction

Climate change is highly expected to give significant impact on coastal hazards and environment. The future projections of wave climate under global warming scenarios have been carried out and shows changes in wave heights depending on the regions (e.g., Hemer et al., 2013). Annual to decadal changes are also important to understand variability. However, variability of wave climate is not well understood over the globe, quantitatively. Additionally, the standard coastal engineers regard stationary process for wave environment for solving coastal problems.

The statistical wave model is developed analyzes global wave climate variability based on principal component analysis of atmospheric forcing (sea surface winds  $U_{10}$  and sea level pressure SLP).

### 2. Methods

The statistical analysis was conducted to estimate contribution of  $U_{10}$  and SLP for  $H_s$ . The linear multivariate regression model for monthly mean significant wave height  $H_s$  combining local grid based atmospheric information  $U_{10}$  and SLP, and the global scale principal component analysis (PCA) for pressure field SLP and wind field  $U_{10}$  was developed based on the previous model (Kishimoto et al., 2017) and calibrated by the dynamic wave hindcast results by

spectral wave model, WaveWatchIII v4.18 (denotes WW3).

$$H_s = \sum_j^n a_j F_j + \sum_i^{ddm} \sum_j^n b_j^i PC_j^i \quad (1)$$

where  $F_j$  the local forcing such as spatial gradient of  $P$ ,  $PC_j^i$  the  $j$ -th mode principal component (PC) of  $i$ -th variable,  $a_j$  and  $b_j^i$  the turning coefficients  $F_j$  or  $PC_j^i$  respectively. The SLP,  $U_{10}$  and their gradient or latitudinal/longitudinal components were used for local forcing. The PC modes for SLP and  $U_{10}$  are considered to introduce the large-scale atmospheric patterns to each grid information.

The target of wave climate is monthly mean significant wave height  $H_s$ . The numerical analysis was conducted to understand long-term changes and variability of wave climate. First the 55 years wave hindcast ( $\Delta x=60\text{km}$ ) was conducted by WW3 forced by JRA-55 reanalysis over the globe.

### 3. Discussion

The global wave climate characteristics was analyzed in detail. Figure 1 shows the RMSE of global wave hindcast depends on local forcing. The use of SLP, gradient of SLP and wind speed  $w_{10}$  significantly improve the global averaged RMSE. The use of wind speed components both latitudinal and longitudinal

components do not contribute improvement of model performance but it gives significant impact on the local accuracy near the coast.

Figure 2 shows the RMSE of global wave hindcast depends on number of PCA modes. Here we only used SLP for PCA term and use of  $U_{10}$  does not contribute model performance. As increasing the number of PC modes, the RMSE is reduced until  $n=30$  and it turns out to increase for large number of PC modes. As the PCA term gives spatial and temporal variability in the model, the model accuracy will be saturated for large number of PC modes.

Figure 3 shows the spatial distribution of  $R^2$  between statistical wave model and dynamic wave model around Japan. The statistical model gives enough accuracy in the Sea of Japan but  $R^2$  becomes smaller in the Pacific Ocean side. The long propagating swells are significant in the Pacific side and it reduces the accuracy of the statistical model.

### Conclusion

The dynamic and statistical wave climate analysis were conducted based on 55yrs wave hindcast. The large-scale atmospheric information is estimated by the PCA for pressure fields. The application to climate projection will be presented at the conference.

### References

Kishimoto, R., T. Shimura, N. Mori and H. Mase (2017) Statistical modeling of global mean wave height considering principal component analysis of sea level pressures and its application to future wave height projection, *Hydrological Research Letters*, Vol.11(1), pp.51-57.

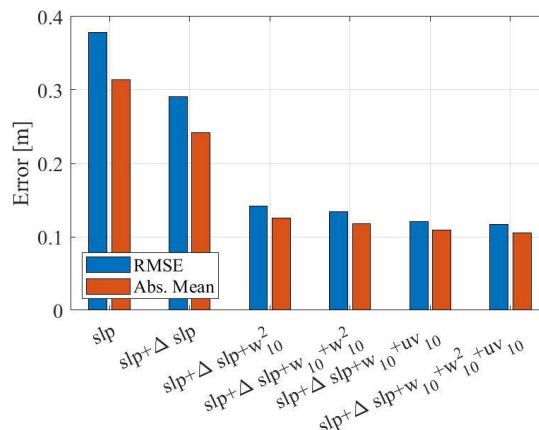


Figure 1 – RMSE of global wave hindcast depends on local forcing.

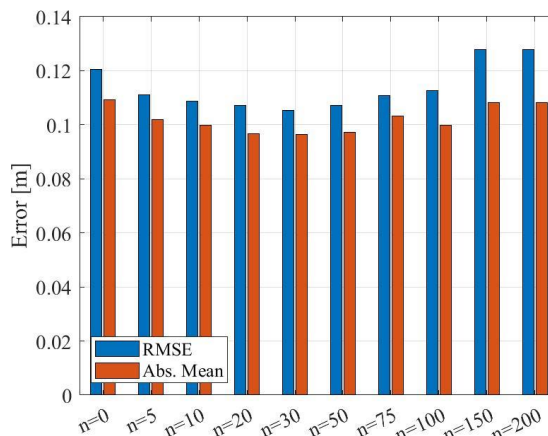


Figure 2 – RMSE of regional hindcast depends on number of PCA modes.

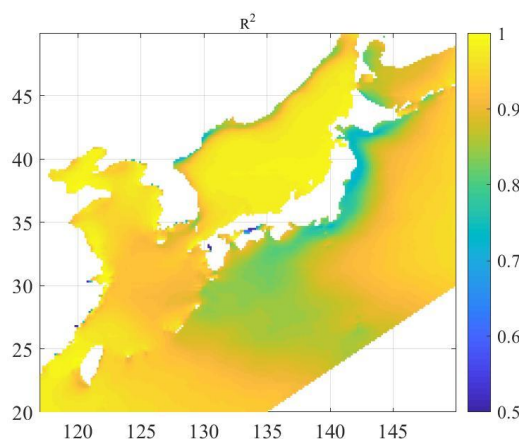


Figure 3 – Spatial distribution of  $R^2$  between statistical wave model and dynamic wave model.