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気候変動による太平洋の波浪長期変化
Climate change impact on mean wave climate change

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Long-term and future wave climate projections are important for climate impact assessment of the coastal environment and hazards. The statistical wave model is developed to reduce computational costs. This study estimates the monthly averaged wave heights 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 large-scale atmospheric information from the PCA. The model is validated by the long-term wave hindcasts by JRA-55.

1. Introduction

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

The statistical wave model is developed to analyze 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 the 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).

$$Hs = \sum_{\mathrm{j}}^{\mathrm{n}} a_{\mathrm{j}} F_{\mathrm{j}} + \sum_{i}^{ddm} \sum_{\mathrm{j}}^{\mathrm{n}} b_j^i \, PC_j^i \qquad (1)$$

where F_{j} the local forcing, such as the 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 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 wave climate variability. First, the 55-year wave hindcast (Δx=60km) was conducted by WW3 and forced by JRA-55 reanalysis over the globe.

3. Discussion

The global wave climate characteristics were 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 w10 significantly improve the global averaged RMSE. The use of both latitudinal and longitudinal wind speed components does not contribute to the improvement of model performance but significantly impacts the local accuracy near the coast.

Figure 2 shows the RMSE of global wave

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

Figure 3 shows the spatial distribution of R^2 between the statistical and dynamic wave models. The statistical model gives enough accuracy in most regions, but R^2 becomes smaller in the lower latitude. The long propagating swells are significant and reduce the statistical model's accuracy.

Conclusion

The dynamic and statistical wave climate analysis used a 55-year wave hindcast. The PCA estimates the large-scale atmospheric information 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.

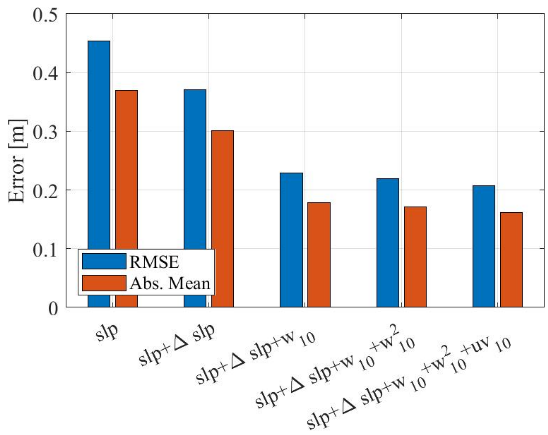


Figure 1 – RMSE of global wave hindcast depends on local forcing.

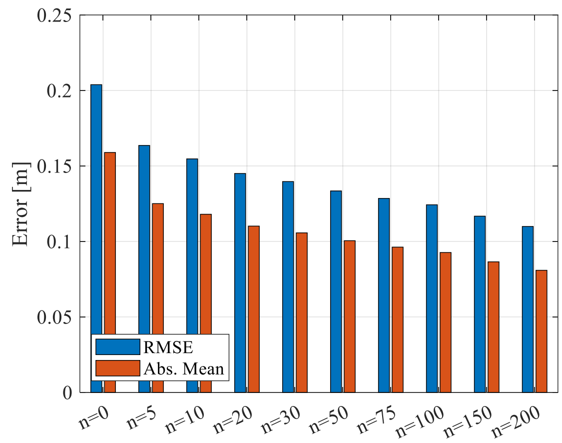
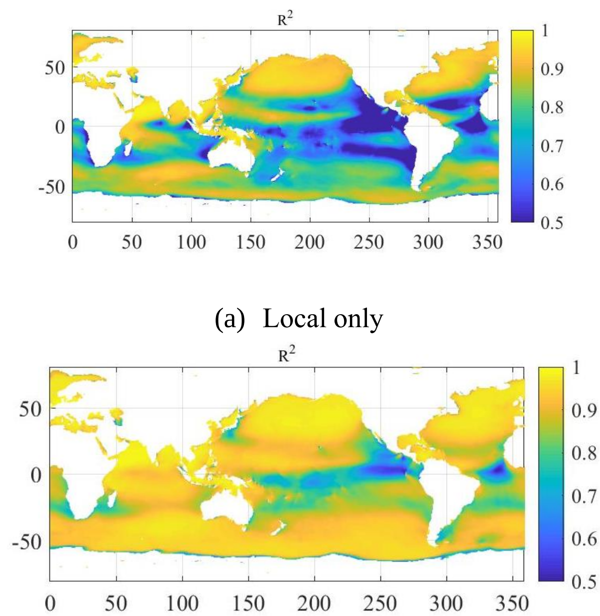


Figure 2 – RMSE of regional hindcast depends on number of PCA modes.



(a) Local only

(b) Full model

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