With over 15,000 km of coastline and around 150,000 people living in low-lying coastal areas, coastal inundation is a major hazard to New Zealand. The cost to defend the associated buildings, infrastructure and assets is of the order of $10 billion. With global sea level rise and the increase in the intensity and frequency of extreme weather events, the threat posed by coastal flooding is only expected to become greater.

Storm surge is the rise in water level generated by wind and atmospheric pressure changes associated with tropical or mid-latitude storms. In conjunction with tides, it is one major driver of coastal flooding associated with storms events. Because local inundation is strongly modulated by the local shape of the coastline and the bathymetric slope, accurate storm surge prediction by the mean of traditional numerical models requires the use of very fine grids and is hence very resource intensive. This means that the performance of a live prediction system based on such methods will likely be subject to a trade-off between prediction accuracy, prediction speed and cost (Wang et al., 2009).

Several publications have demonstrated the potential of machine learning approaches for the prediction of storm surge (e.g. (Tiggeloven et al., 2021), (Cagigal et al, 2020)). However, the developed methods often focus on local predictors and aim at predicting storm surge at a single location at a time. In this study, we explore the use of several data driven methods as an alternative to numerical methods to predict storm surge along the coast of New Zealand.

The study uses numerical model data from a global atmospheric reanalysis as predictors and data from a regional high resolution hydrodynamic hindcast for predictand. Building up on an initial study involving linear methods for site prediction of storm surge and aiming at identifying optimal predictors, we develop a fully non-linear model that predicts the daily maximum storm surge at a resolution of 5km along the coast of New Zealand.

We tested a number of different methods to use as a basis for the predictor. In principle, we extract local grids from global sea level pressure fields and winds, to drive the predictors, trialing different spatial scales of the local grid. To remove noise, only the larger principle components of the atmospheric data. For the prediction, we use regression analysis, KNN and decision trees, trained on numerical hindcast storm surge times series (aiming to predict the daily maximum storm surge). The training timeseries dataset was produced by the Moana project. Preliminary results of the optimal prediction are shown in Figure 1. We are now working on using neural network predictions to see if we can improve performance, prior to operationalizing the predictions as part of the Meteorological Service of New Zealand’s services.

REFERENCES
