PRACTICAL ADVANCES IN SHORT-TERM SPECTRAL WAVE FORECASTING WITH SWRL NET

Chloe Dawson[1] **Noah Reneau**[1] **Brian Hutchinson**[1,2] **Sean Crosby**[3]
[1] Computer Science Department, Western Washington University, Bellingham, WA
[2] Computing & Analytics Division, Pacific Northwest National Laboratory, Seattle, WA
[3] Geology Department, Western Washington University, Bellingham, WA

ABSTRACT

Rapid, accurate wave forecasts are critical to coastal communities and nearshore research. Observational data assimilation improves predictive skill, but is difficult to implement in current adjoint variational systems. Machine learning offers an alternative. Here, a previously proposed framework (SWRL Net Mooneyham et al., 2020) is applied to an array of buoys along the U. S. West Coast to quantify the effect of training data size, determine the impacts of transfer learning using archived wave prediction hindcasts, and evaluate the potential skill on recent wave forecasts. Results across buoy locations show diminishing returns for training data sets greater than 5-years, with error reductions of 10-60%. Experiments trained with shorter (1-year) forecast records have higher error, but the application of transfer learning using wave hindcasts substantially improves model performance.

1 INTRODUCTION

Ocean wave forecasts are critical to public safety by providing timely information and alerts for conditions that can lead to coastal flooding, erosion, property damage, and create navigational and recreational hazards (ECMWF, 2020). Coastal damage losses can be large, for example, the National Oceanic Atmospheric Administration (NOAA) has estimated the annual coastal property loss due to coastal erosion in the United States at 500 million dollars, (NOAA, 2021). Contribution of wave energy to coastal erosion rates has been well documented (Hapke et al., 2006), (Hapke & Reid, 2007). Accurate wave forecasts assist emergency preparedness, planning and mitigation, provide forcing to both nearshore and global ocean models. Additionally, accurate wave predictions are necessary in the development of wave energy resources at the coast (Reguero et al., 2015).

Wave forecasts are typically generated with numerical models (Booij et al., 1999; Tolman, 2009). Development over the last several decades have made significant advancements (Cavaleri et al., 2007), but limitations, whether owing to poorly known boundary conditions (Crosby et al., 2016), unresolved bathymetry and shorelines (Chawla & Tolman, 2008), or parameterized underlying physics (Tolman et al., 2005), reduce predictive skill. Given current limitations, assimilation of observations into operational models is a promising avenue of research. Early approaches utilized comparatively simpler approaches such as optimal interpolations (Hasselmann et al., 1997; Lionello et al., 1992) while more sophisticated techniques have been proposed including the use of adjoint models and variational systems (Veeramony et al., 2010; Orzech et al., 2013).

More recently, ensemble forecasts, *i.e.,* several models run simultaneously with perturbed boundary conditions, combined with machine learning is shown to improve predictive skill (O'Donncha et al., 2018). Prior studies have used neural networks trained on observed data to generate wave forecasts (Deo & Naidu, 1998) and several approaches have been taken to use neural networks to improve wave forecasts (Makarynskyy, 2004), (Campos et al., 2020).

To date, most research has focused on bulk wave parameters such as wave heights and period with some recent studies incorporating partitioned bulk parameters (Song & Mayerle, 2017). In general, assimilation approaches are lacking for wave spectra details that are critical for regional wave model boundary conditions (Crosby et al., 2016; Kumar et al., 2017) and accurate modeling of wave processes at the shoreline such as wave run-up (Fiedler et al., 2018). Recently, Mooneyham et al. (2020) proposed the *SWRL Net* neural network approach to improving wave spectra forecasts with

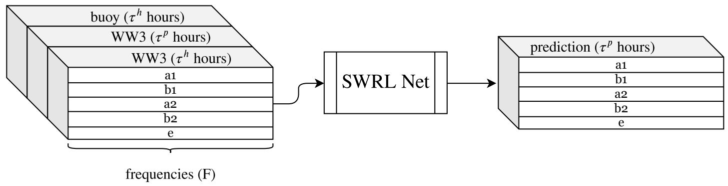

Figure 1: Overview of SWRL Net; figure from (Mooneyham et al., 2020).

wave buoy observations. In this manuscript, we propose and evaluate practical extensions of SWRL Net. The key contributions of this research are as follows:

1. We study the effect of training record length on model performance.
2. We study the model's performance with archived forecasts.
3. We propose and evaluate a transfer learning approach to improve SWRL Net's performance in data-limited scenarios, including buoys with limited hindcast and forecast records.
4. We evaluate model performance at seven U. S. West Coast buoy locations.

2 METHODS

SWRL Net Mooneyham et al. (2020) introduced the Spectral Wave Residual Learning Network (SWRL Net), which is the deep learning architecture used in this study. SWRL Net is a deep neural network designed to assimilate spectral data from buoy observations for the improvement of short-term coastal wave forecasts. The architecture is shown in Fig. 1, reprinted with permission from (Mooneyham et al., 2020). It uses τ^h hours of recent observations to improve the performance in the following τ^p hour forecast window. The input to SWRL Net is a $(2\tau^h + \tau^p) \times 5 \times F$ tensor. For any index into the first mode of the tensor, one obtains a $5 \times F$ matrix, containing the energy and four normalized directional moments (e, a_1, b_1, a_2, b_2) (Longuet-Higgins et al., 1963) for each of the the F frequency bands. The first mode concatenates three sets of information:

1. Buoy observations for the most recent τ^h hours.
2. WaveWatch3 (WW3, Tolman, 2009) predictions for the most recent τ^h hours.
3. WW3 predictions for the next τ^p hours.

The model is tasked with predicting corrections to the WW3 forecast for the next τ^p timesteps.

The details of the SWRL Net architecture are shown in Fig. 3 in the supplementary materials. The input is processed by a series of 3×3 2d convolution layers; all but the last convolutional layer is followed by a Leaky Rectified Linear Unit non-linearity. The "spatial" dimensions for the first layer are $5 \times F$, while there are $2\tau^h + \tau^p$ input channels. The output of this series of convolutional layers is a $\tau^p \times 5 \times F$ tensor of residuals (corrections), which is then added to the WW3 forecast of the same shape. Lastly, the energy and moments pass through $ReLU$ and $\tanh$, respectively, to ensure that they remain within valid ranges for those values.

The model is trained using a maximum of 500 epochs with early stopping, and a mini batch size 16. The number of filters for the 9 convolutional hidden layers is (32, 32, 64, 64, 128, 128, 256, 256) with a learning rate in the range of 10^{-4} to 10^{-8}. The optimal learning rate was found to be approximately 10^{-5} via hyperparameter sweep. The history length for the observed data is 6-12 hours and the forecast length for hindcast and forecast data is 12-24 hours (depending on model configuration). The constraint applied to the moments at the output layer of SWRL Net use hard $\tanh$. For additional details on SWRL Net, we refer the reader to Mooneyham et al. (2020).

Data Sources Three *types* of wave data were used: observed, hindcast, and forecast data. Observed data was selected from NOAA's National Data Buoy Center (NDBC) and the Coastal Data Information Program (CDIP) directional wave buoys. Accelerometers on buoys measure the pitch, roll, and heave from which energy (e) and 4 directional moments (a_1, b_1, a_2, b_2) can be estimated as a function of frequency (Longuet-Higgins et al., 1963). Seven nearshore buoys along the coast of California, Oregon, and Washington were selected and available hourly wave observations were used (for more details, see Figure 4 and Table 4 in the appendix).

Dataset	Length	Type	Stations	Train	Dev.	Test
1	>8 yrs	Hindcast	Grays Harbor Point Reyes Harvest	70%	15%	15%
2	2-4 yrs	Hindcast	Columbia River Bar Tillamook Port Orford Crescent City	1st yr	2nd yr	Remainder
3	2 yrs	Forecast	Grays Harbor Point Reyes Harvest	33.3%	33.3%	33.3%

Table 1: Summary of three datasets used, including splits into training, development and test sets.

Wave Spectra hindcasts were extracted from NOAA's WaveWatch3 (WW3, Tolman, 2009) 1979-2009 reanalysis, phase 2 (Chawla et al., 2011) at buoy observation locations. Hindcast predictions are available at 3-hourly resolution in two-dimensional frequency-directional spectra. WW3 spectra were integrated in direction to estimate directional moments consistent with buoy observations. Integrated moments were then interpolated to 1-hour time steps and averaged to frequency bins consistent with buoys observations.

Operational spectral forecasts were saved from October 2019 to February 2021 from NOAA's Global Forecast System at the seven buoy locations. Forecasts are available every 6-hours at 3-hour resolution. Forecasts are similarly integrated to be consistent with directional buoy observations and interpolated onto hourly time steps.

Due to missing data, the data contains seasonal imbalances, especially for locations with limited availability.

Data Processing The frequency range is cropped to 0.04-0.25Hz, where a majority of surface gravity wave energy along the U. S. West coast is observed (Crosby et al., 2016; Adams et al., 2008). In preparation for NN training, data is normalized by dividing each directional wave moment (a_1, b_1, a_2, b_2) by energy (e) so that all values are in the range $[-1, 1]$ and energy is standardized to be zero-mean unit-variance.

Both hindcast and forecasts are reformatted to provide inputs to SWRL Net. For each hindcast hour an "artificial forecast" is generated by using either the prior $\tau^h = 12$ or $\tau^h = 6$ hours as a stand in for the prior forecast and the following either $\tau^p = 24$ or $\tau^p = 12$ hours as a stand in for the current forecast. This one hour offset provides a large amount of overlapping inputs in training. Forecasts, available every 6-hours, provide fewer inputs, however, each input is unique. SWRL Net inputs are created from the first 24-hours of a forecast and the first 12-hours from a forecast 12-hours prior. Both forecasts and hindcasts are paired with observations at the same time steps. If data is missing in an input forecast-observation pair that input is removed.

Available data at each buoy site was split into training (train), development (dev), and testing (test) subsets chronologically. For records with four or more years of data in total (hindcast data for buoys Grays Harbor, Point Reyes, and Harvest), the first 70% of the data was put into train, the next 15% was put into dev, and the last 15% was put into test. Locations with more than 2 years but less than 4 years of data (hindcast data for buoys Columbia River Bar, Tillamook, Port Orford, and Crescent) were split such that the first year's worth of data went into train, then next year to dev, and the remaining data went into test. Locations with 2 years of data or less (forecast data for buoys Grays Harbor, Point Reyes, and Harvest) were split such that the first third of the data was put in train, the next third in dev, and the last third in test. This information is summarized in Table 1.

Transfer Learning via Pretraining and Fine-Tuning Pretraining and fine-tuning was implemented to improve performance for datasets with limited training data available; this is of great practical importance as new buoys are brought online. Pretraining here refers to training the model on a dataset other than the target buoy. Fine-tuning refers to further training of this model on a small amount of target data (e.g., a limited record from a newly launched buoy). In our transfer learning experiments, we consider and compare three variants:

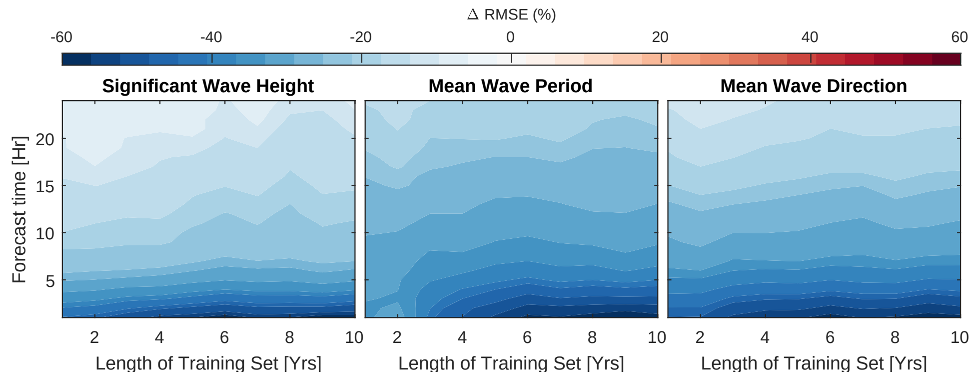

Figure 2: Relative difference between root mean square error (rmse) of SWRL Net and WW3 model at Harvest buoy location for Significant Wave Height (a), Mean Wave Period (b) and Mean Wave Direction (c). Blue indicates lower SWRL Net errors.

1. Fine-tuning only: the model is simply trained on the target buoy; training begins with randomly initialized weights.
2. Pretraining only: a model is trained on a non-target buoy with a longer record, and evaluated on the target buoy with no further training.
3. Pretraining and fine-tuning: a model is pretrained on a non-target buoy and then fine-tuned and evaluated on the target buoy.

3 Results

We conducted and report here results from three sets of experiments to assess SWRL Net's skill.

Effect of training record length on skill with hindcasts SWRL Net is trained with varying lengths of training data to determine the data length required to achieve good model performance. This experiment is run only with Dataset 1 (Table 1) because of the sufficiently long records. Models are trained with most recent N years of data, for $N = 1, 2, \ldots$ until we reach the maximum training set size permitted by the data (9 years for Grays Harbor and Point Reyes, and 10 years for Harvest). As expected, results show a greater reduction of SWRL Net prediction error as the training period grows. As shown in Fig. 2, at the Harvest buoy site the trends are consistent across wave height, mean period, and mean direction. There are diminishing returns on error reduction, or skill improvement, for using more than 5-years of training data. The improvement with increasing training data is more pronounced for mean wave period, suggesting that errors in wave periods may be more variable; this is consistent with previous observations (Adams et al., 2008). Results are similar at Greys Harbor and Pt. Reyes, however the magnitude of improvement is lower (see Fig. 5 in the appendix). Because the largest gains are observed for the first 12 forecast hours, we limit our analyses to this forecast range for the remaining experiments.

Effect of cross-buoy transfer learning on skill with hindcasts To determine how well SWRL net can perform on buoys with less data, we evaluate performance using the hindcast datasets for buoy locations Columbia River Bar, Tillamook, Port Orford, and Crescent City were selected (i.e., Dataset 2). The length of these datasets range from just over two years to almost four years. First, a model for each of the four buoy locations was trained and evaluated with their respective datasets. Next, a model pretrained on hindcast data from Grays Harbor, Point Reyes, and Harvest (i.e., Dataset 1), which have the longest datasets, was evaluated on each of the four shorter buoy datasets. Finally, the each of the pretrained models was fine-tuned and then evaluated on each of the four shorter buoys. The results are shown in Table 2. First, we note that all of the pretraining and fine-tuning variations substantially outperforms the WW3 baseline (with no corrections). We observe that pretraining nearly always helps, regardless of the target buoy (columns) or the buoy it was pretrained on (rows). We note that for each of the four target buoys, the best performance is achieved using both pretraining and fine-tuning, although for Port Orford, this same result can be achieved by pretraining on Grays Harbor *without any fine-tuning*. Fine-tuning appears to be particularly important for the

Pretrain?	Fine-tune?	Port Orford	Crescent City	Columbia River	Tillamook
(None)	✓	0.112	0.108	0.056	0.090
Grays Harbor		**0.094**	0.113	0.062	0.101
Grays Harbor	✓	0.097	0.099	**0.042**	0.091
Point Reyes		0.098	0.105	0.120	0.087
Point Reyes	✓	0.097	0.100	0.046	**0.085**
Harvest		0.096	0.100	0.092	0.093
Harvest	✓	**0.094**	**0.095**	0.046	0.089
WW3 Baseline	N/A	0.195	0.263	0.211	0.214

Table 2: Test set mean squared error for Port Orford, Crescent City, Columbia River and Tillamook stations (from Dataset 2, Hindcasts); with or without fine tuning and with or without pretraining on one of Grays Harbor, Point Reyes, or Harvest (from Dataset 1, Hindcasts). Bold values are the lowest MSE per station

Pretrain?	Fine-tune?	Grays Harbor	Point Reyes	Harvest
	✓	0.249	0.212	0.224
✓		**0.117**	0.223	**0.179**
✓	✓	0.240	**0.207**	0.222
Baseline	N/A	0.598	0.571	0.564

Table 3: Test set mean squared error for Grays Harbor, Point Reyes, and Harvest stations (from Dataset 3, Forecasts); with or without fine tuning on Dataset 3 training data, and with or without pretraining on hindcast data from the same buoy (from Dataset 1). Bold values are the lowest MSE per station

Columbia River and Tillamook stations; each performs worse with pretraining only than they do training on their own limited record (fine-tune only).

Effect of transfer learning on skill with forecast data Lastly, we evaluate SWRL Net's skill on archived forecast data for buoy locations Grays Harbor, Point Reyes, and Harvest (i.e., Dataset 3). As before, these locations were selected for this experiment because they have the largest hindcast datasets available for pretraining. First, models trained were trained on forecast data alone. Next, models were trained with hindcast data and evaluated on the forecast data. Finally, hindcast models were fine-tuned with forecast training data and the skill of each was evaluated. Results for the three approaches (forecast only training, hindcast only training, and hindcast pretraining with forecast fine-tuning) suggest that the shorter forecast training sets may not be adequate. In general, errors are generally much higher for forecasts than for the hindcast predictions Table 3. While at Grays Harbor and Harvest models pretrained on hindcasts yields have the smallest errors, fine tuning does reduce errors at Point Reyes, likely owing to the larger forecast training set at this location. These results indicate the need for model reforecasts that could provide larger training sets.

4 Conclusions and Future Work

In this paper we advanced the practical application of SWRL Net to short-term coastal wave forecasting in several key ways. First, we quantified the effect of the training set length on model skill, finding modest degradation with shorter training records. Second, we proposed and evaluated a transfer learning approach to mitigate this behavior, finding it to improve performance for buoys with short training records. Third, we offer the first evaluation of SWRL Net on real (archived) forecasts, finding that longer archived forecast datasets are needed. We propose and evaluate a transfer learning approach in which models are first pretrained on hindcasts, finding it to improve model skill – however, whether or not fine-tuning helps appears to be buoy dependant.

There are many ways this work could be extended. First, one promising direction would be to explore the space of model architectures; e.g., recurrent models designed for learning temporal behavior, or Transformer-based models that allow more flexible access to the relevant inputs for any given datapoint. Another important area of extension would be to evaluate performance of SWRL Net on other coastal regions, such as the U. S. East coast.

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A MODEL DETAILS

Fig. 3, reprinted with permission from Mooneyham et al. (2020), shows the details of the SWRL Net architecture. The input is processed by a series of 3×3 2d convolution layers, resulting in an output $\tau^p \times 5 \times F$ tensor of residuals (corrections). This is then added to the WW3 forecast of the same shape.

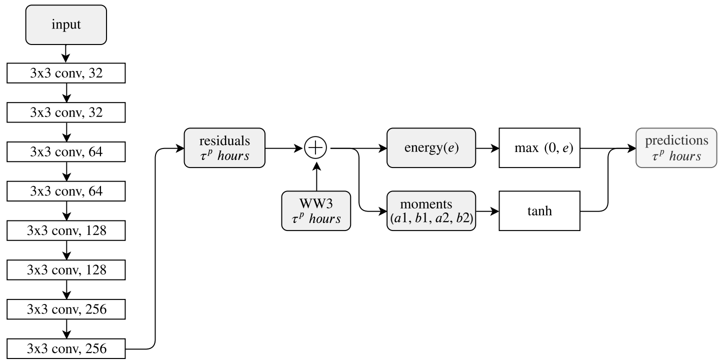

Figure 3: SWRL Net model architecture details; figure from (Mooneyham et al., 2020).

B BUOY DETAILS

Buoy locations were chosen along the west coast from southern California to Washington state. The buoy station information and location are recorded in Table 4, and the buoy locations are displayed in Fig. 4.

Station ID	Station Name	State	Latitude	Longitude
46211	Grays Harbor	WA	46.857	-124.244
46029	Columbia River Bar	OR	46.143	-124.485
46089	Tillamook	OR	45.933	-125.785
46015	Port Orford	OR	42.752	-124.844
46027	Crescent City	CA	41.852	-124.380
46214	Point Reyes	CA	37.937	-123.463
46218	Harvest	CA	34.452	-120.780

Table 4: Buoy stations used in this research.

C ADDITIONAL RESULTS

Fig. 5 presents the full set of results from the first analysis in Sec. 3, here including the Point Reyes and Grays Harbor buoys.

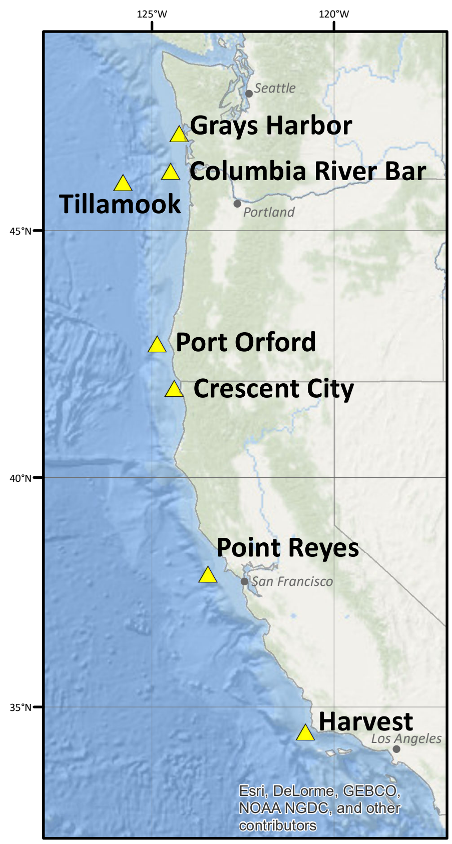

Figure 4: Directional wave buoy locations (yellow triangles) along U. S. West Coast

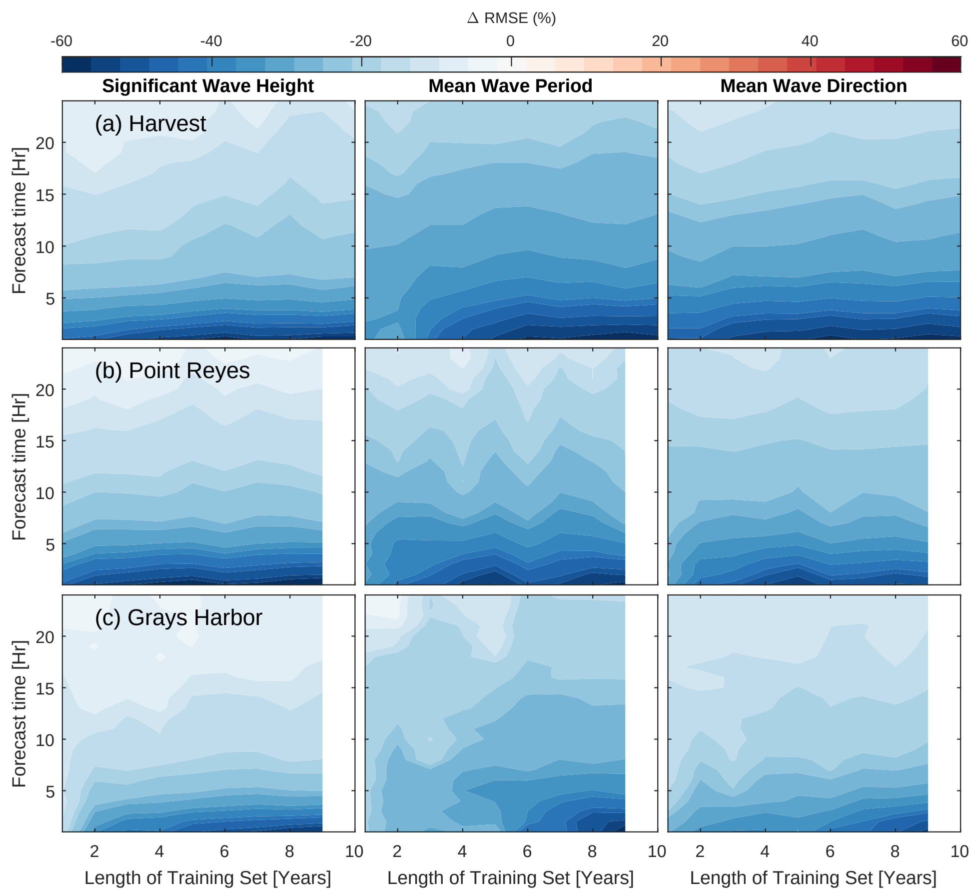

Figure 5: Relative Difference in RMSE for Significant Wave Height, Mean Wave Period, and Mean Wave Direction (columns) between SWRL Net and WW3 for Harvest (a), Point Reyes (b) and Grays Harbor (c). Blue colors indicate lower SWRL Net errors.