Forecasting Tidal Power in Alaska, Maine and Florida

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Introduction

Motivation and Background

Our group, composed of students from the Coastal Marine Systems and Energy concentrations within the MEM program, chose to explore tidal power due to its strong relevance to our academic and professional interests. Tidal energy presents a compelling case as a clean and sustainable energy source, producing zero greenhouse gas emissions while avoiding the environmental drawbacks of traditional hydro-power, such as dams and large reservoirs. Beyond its ecological benefits, tidal power boasts a high energy density and efficiency—unlike intermittent sources like wind and solar, ocean currents remain relatively constant, ensuring continuous power generation without heavy reliance on costly storage systems. This reliability makes tidal energy a valuable asset in balancing energy grids and complementing other renewables. Additionally, the predictability of tidal currents enhances its appeal as a stable energy solution. While the U.S. currently lacks commercially operational tidal power sites, growing interest and investment, including pilot projects in Maine and New York, signal its potential as a key player in the renewable energy landscape. (Sources of references: altenergymag.com)

Project Objectives and Relevance

In this project, we aim to evaluate and compare tidal power potential across three U.S. sites at varying latitudes and coastal conditions. Our assessment focuses on Wave Energy Flux (measured in watts per square meter), which is calculated by Wave Power Density multiplying by Wave Energy Period. We will analyze seasonal and long-term trends in these time-series datasets, apply predictive modeling using training and testing datasets, and compare forecasting results to determine which site offers the most stable and highest Wave Energy Flux. By doing so, we hope to contribute meaningful insights into the feasibility and optimization of tidal energy as a sustainable power source. (Sources of data: NREL Marine Energy)

Dataset information

Data selection and extraction

We first picked 3 sites/ locations/ areas tend to be some of the locations referred to for its tidal power potential in the general Internet searches. These areas are distinct by latitudes and longitudes, as well as different coasts and climatic environments. These three sites are:

- Gulf of Maine (43.68° N, 69.77 ° W)
- ~ 3 km distance into ocean near Miami, Florida (25.74 ° N, 80.11 ° W)
- Cook Inlet, Alaska (59.37° N, 152.64° W)

With the lat-long of these sites, we extracted raw data of 1979-2010 Wave Energy Density and Energy period data in NREL marine energy atlas: http://nrel.gov/marine-energy-atlas/data-viewer (http://nrel.gov/marine-energy-atlas/data-viewer)

Data Wrangling & General Steps of Analysis

1. Calculate the Wave Energy Flux data based on the raw data we extracted.
2. Wave Energy Flux datasets for all 3 sites' are aggregated to daily and monthly view (original series).
3. Split the current full dataset using 80/20 rule into training and testing datasets.
4. Conduct the original time series analysis on all of the sites.
5. Run various models to compare predicting/ forecasting performance on the Maine dataset.
6. Get the top 3 performing models based on the Maine Wave Energy Flux forecasting
7. Use the top 3 performance models (Arima + Fourier k-4, TBATs. and STL+ETS) for the other 2 sites Wave Energy Flux.
8. Compare Wave Energy Flux Results of the 3 sites and determine which site has more potential.

Initial Summary Statistics/ Visualizations of the Datasets

We do a preliminary analysis of the three sites based on summary statistics for monthly mean wave power. We see drastic contracts among them, with the Gulf of Maine delivering the most energetic and variable resource, averaging 8,443.4 W/m. On the other hand, Cook Inlet's sheltered basin gives us only ~16.2 W/m of monthly wave power on average. Thus, based on these observations, we first test out forecasting models using the Gulf of Maine site, and then choose the top three performing models on the other two sites for a final comparison of tidal power potential.

Initial Summary Statistics

Summary statistics of monthly mean wave power by site

Site	Mean (W/m)	Median (W/m)	SD (W/m)	Min (W/m)	Max (W/m)
Alaska	16.2	11.5	15.3	0.0	105.1
Florida	3422.6	3167.6	2271.9	268.7	12334.1
Maine	8443.4	7346.8	4897.7	1528.5	28885.9

Here is the head of our Maine dataset:

Y... <int>	M... <int>	monthly_mean_wave_energy <dbl>	monthly_mean_wave_height <dbl>	monthly_mean_wave_pow <db
1979	1	4.543913	1.060624	6246.53
1979	2	5.557235	1.657162	16710.12
1979	3	4.932436	1.246594	10674.54

Y...	M...	monthly_mean_wave_energy	monthly_mean_wave_height	monthly_mean_wave_pow
<int>	<int>	<dbl>	<dbl>	<db
1979	4	4.948208	1.009137	4120.43
1979	5	5.026293	1.066162	4085.11
1979	6	5.241151	1.089948	4304.46

6 rows

Analysis

Maine

As concluded from the initial summary statistics, we start off with Maine as a test site. The location we chose for Maine is 3 kilometers offshore with reliable wave and wind currents and thus, a good starting point to test our ability to forecast tidal power.

We proceeded with looking at the time series plots for both daily and monthly mean wave power. We also looked at the ACF and PACF plots of both series, so that we can make an informed decision on which time series (daily or monthly) to pursue.

From Figure 1, we see that while the daily series provides a more granular view of the fluctuations in mean wave power, it is subject to extreme outliers that can affect our forecasting ability. Additionally, when compared to the monthly series, there is a lot more noise in the graph, making it harder to discern trends.

The monthly series on the other hand shows a clearer seasonal pattern. Further, by averaging out to a monthly series, the impact of outliers is diminished.

Daily Mean Wave Power - Maine
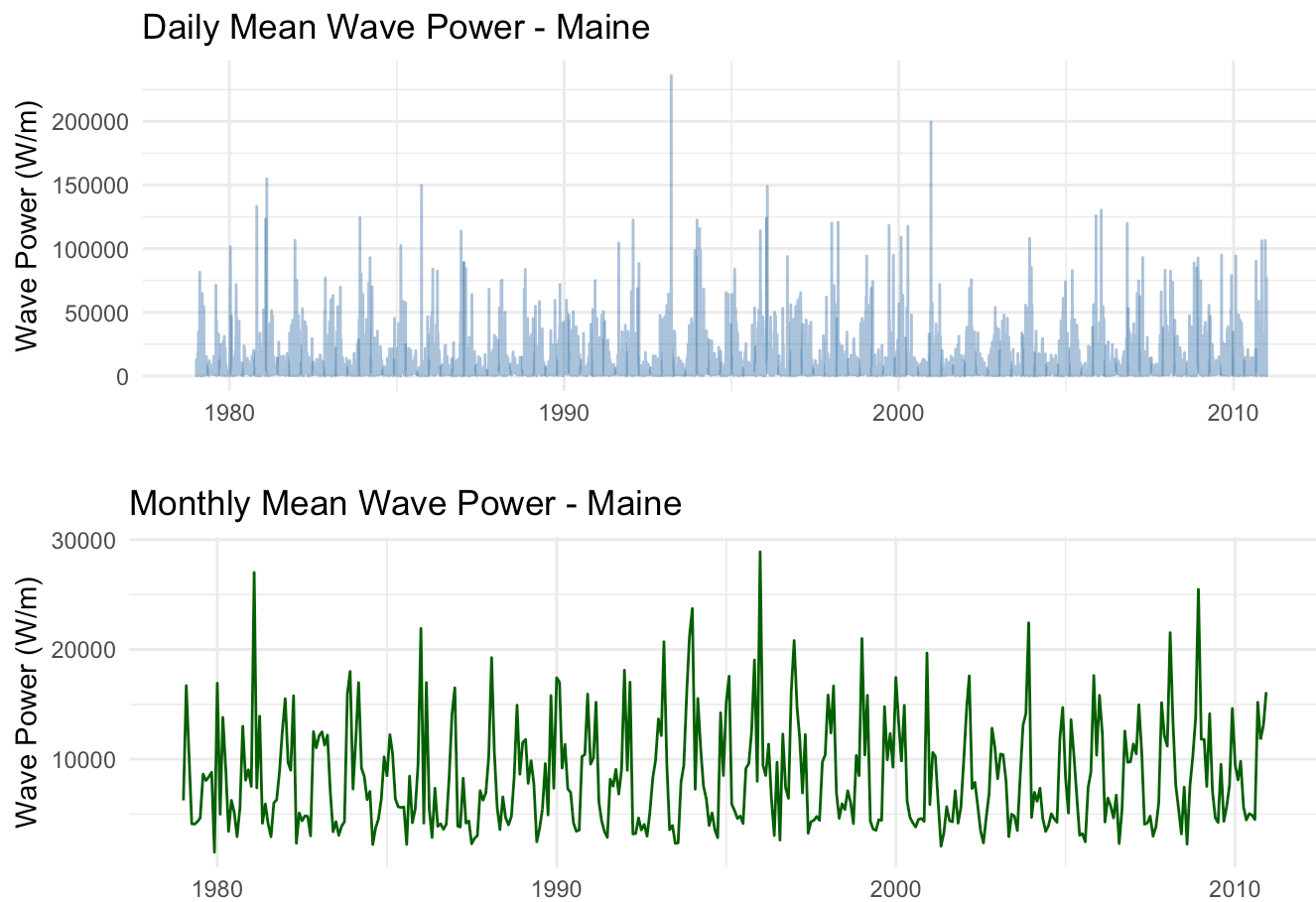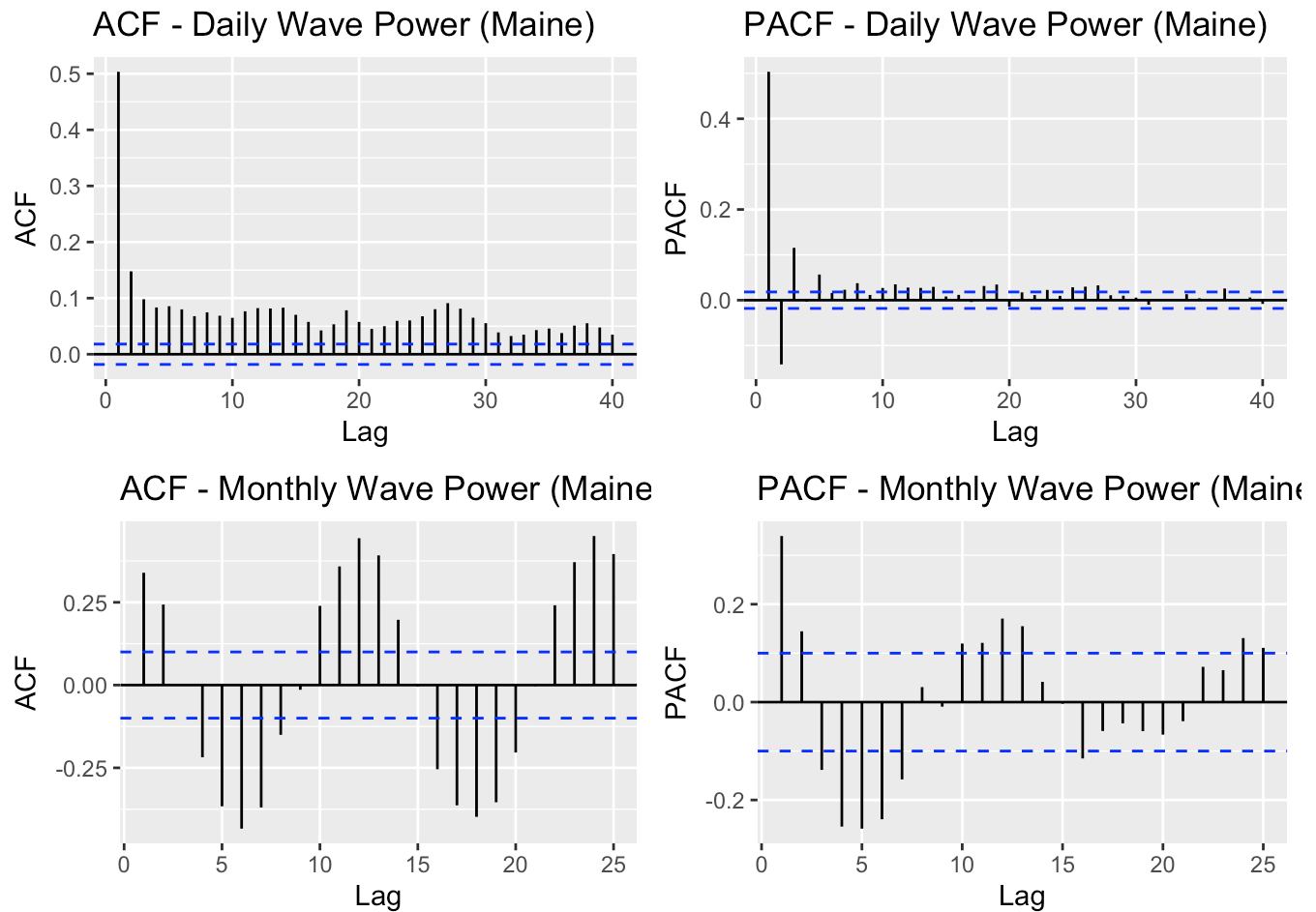

Monthly Mean Wave Power - Maine

Figure 1. Plots for mean wave power in Maine (Daily and Monthly)

From Figure 2, we see that both ACF and PACF plots for the daily series have a sharp drop-off after lag 1, suggesting that past daily mean wave power values do not carry much signal for future values. For the monthly mean wave power, the ACF and PACF plots shows strong seasonality with the wave pattern. The autocorrelation persists over time, which will be ideal for ARIMA/SARIMA and other seasonal models.

Preparing the data

Thus, we will proceed with forecasting for the monthly series. We start by splitting our monthly mean wave power datasets using the 80-20 rule: 80% for training, 20% for testing. Our training dataset for Maine contains mean wave power from January 1979 to December 2003 and our testing dataset for Maine contains mean wave power from January 2004 to December 2010.

We used the decompose() function on our training dataset and performed an additive deomposition. From Figure 3, we can confirm the strong seasonality seen in mean wave power in Maine. We also see that mean wave power peaked from 1995 to around 2000 in Maine. This could be due to climate and oceanographic factors (wind speed, underwater currents) that warrant a further look. Since tidal energy is subject to a whole host of climate and oceanographic factors, our remainder series shows some significant spikes at irregular intervals which could be caused by specific weather events. Further research into Maine's short-term and long-term weather patterns is recommended for future forecasting projects.

Decomposition of additive time series
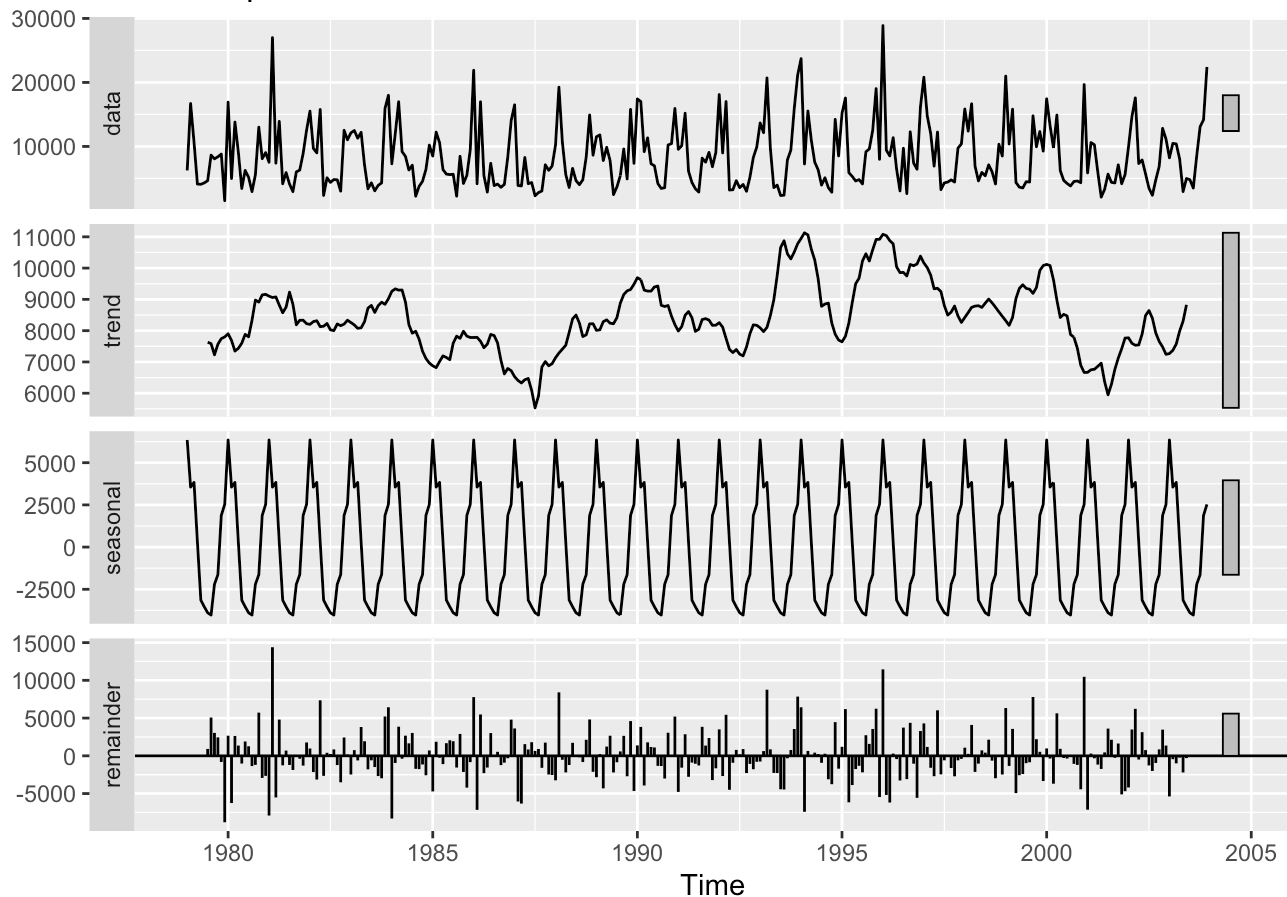
Lastly, we ran a ADF test on our training dataset on Maine, which produced a p-value of 0.01. Thus, we reject the null hypothesis that the Maine monthly mean wave power series has a unit root and is non-stationary.

Start of forecasting models

We proceed by setting the forecasting length to be from January 2004 to December 2010 (testing dataset). We will evaluate our forecasts against values found in our testing datasets.

For forecasting, we trained and tested the following models: - Seasonal Naïve: Used as a preliminary baseline due to strong seasonal patterns in monthly wave power

- ARIMA + Fourier: Applied using auto.arima() function with a fourier term

- ETS + STL: Implements seasonal trend decomposition (Figure 3) and performs exponential smoothing using stlf() function

- SARIMA: Applied a seasonal ARIMA model (due to strong seasonality present) using the auto.arima() function

- ES: Exponential smoothing to use recent, past values of monthly wave power to forecast future ones

- StructTS: Uses a state-space framework to model unobserved components of monthly tidal series. Applied using a Basic Structural Model (BSM).

- TBATS: Used to model complex seasonal patterns present in tidal power

- Neural Network + XREG: Single, hidden-layer neural network (with our training dataset as an external regressor).

Table 1 displays our accuracy metrics for our models.

Judging from the RMSE and MAPE, our 3 best models are STL + ETS, TBATS and ARIMA + Fourier. This is in line with our hypothesis that models that capture the complex seasonality of tidal power would perform best.

Forecast Accuracy for Monthly Wave Power - Maine

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
SNAIVE	-822.5207	4290.692	3202.526	-19.62825	42.60721	0.06549	0.89498
SARIMA	-217.5947	4026.117	3221.739	-29.70686	50.01054	0.32049	0.83462
STL+ETS	-192.9789	3730.735	2709.232	-17.21843	36.39588	0.18831	0.70042
ARIMA+Fourier	736.3832	3690.025	2601.569	-5.30294	31.99013	0.20083	0.72561
ES	4686.0140	5864.526	4762.718	78.82107	80.54519	-0.00122	1.84991
StructTS	4686.0140	5864.526	4762.718	78.82107	80.54519	-0.00122	1.84991
TBAT	569.0860	3728.780	2690.142	-8.37019	33.99924	0.17281	0.70592
NN	-182.0862	4216.735	3019.558	-14.78550	37.99968	0.11474	0.77562

Figure 4 looks at how our models forecast monthly mean wave power for Maine for our top 3 models, and compares it with actual values. We see that all 3 models capture the seasonality of tidal power well. However, they also underestimate its highest peaks on average. This could likely be due to not accounting for the many exogenous variables that can cause spikes in tidal power (powerful rip currents, strong weather storms, sudden changes in wind velocity). Our 3 models are dependable in providing a minimum power generation forecast, which is helpful for energy planners and policymakers who want to understand the cost-benefit analysis of harnessing tidal energy. Additionally, the underestimation of maximum capacity can be beneficial when building power stations as the forecasts can be used to determine safe lower bounds on maximum capacity.

Monthly Wave Power Forecasts - Maine
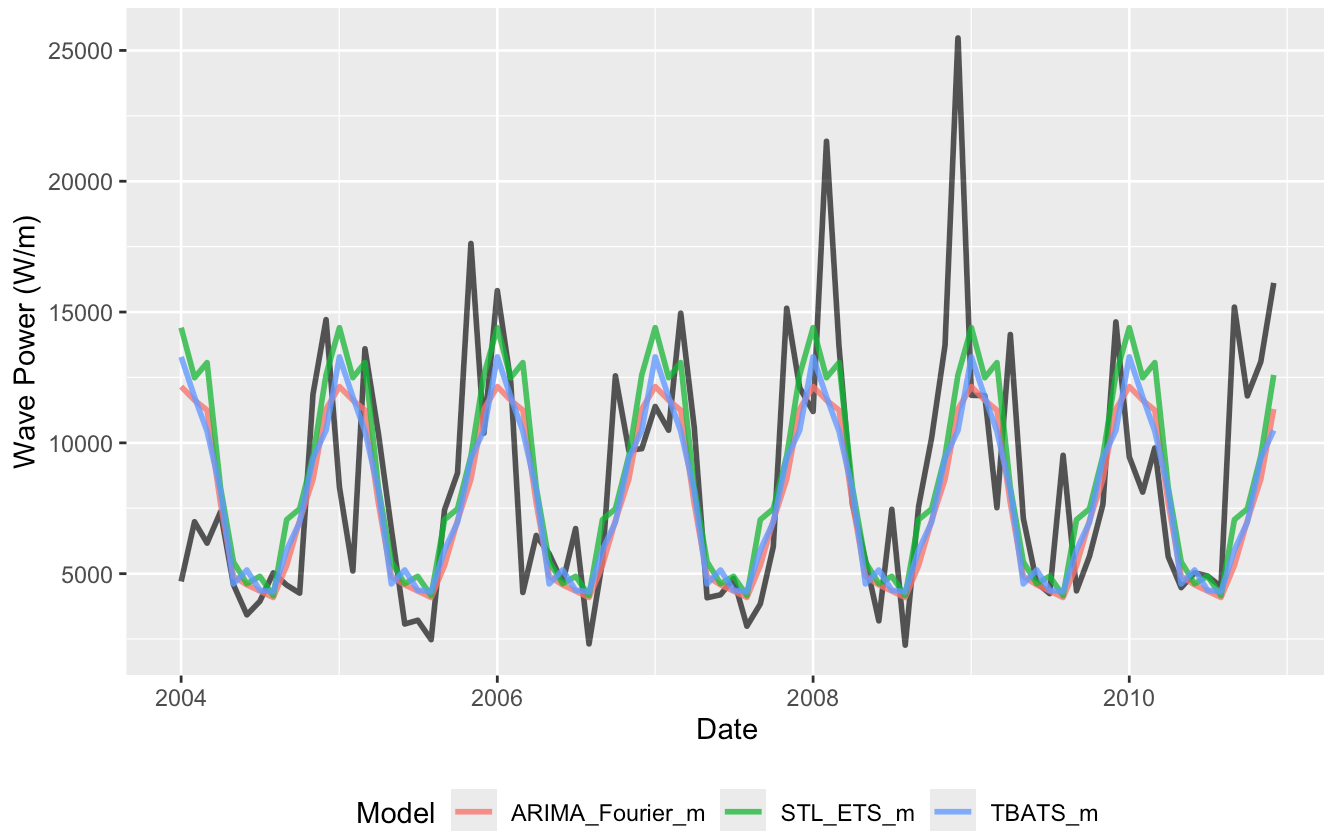### Comparison of Top 3 Models (2004–2010)

Figure 4. Comparing Forecasted Values with Actuals - Maine

Given the performance of our 3 chosen models, we proceed with fitting them on Alaska and Florida.

Alaska

From figure 6, we see a significant spike at lag 1 in both ACF and PACF plots - this is similar to our ACF and PACF plots for Maine where tidal power does not show strong correlation with recent months. Also, the significant spikes at lag 12 in both ACF and PACF indicate a strong seasonal component (supported by Figure 8), suggesting that our 3 chosen models should fit well as they model complex seasonality well. Figure 7 shows that much like Maine, there is random noise that our decomposition did not account for, and that future analyses should include exogenous variables to better forecast tidal power.
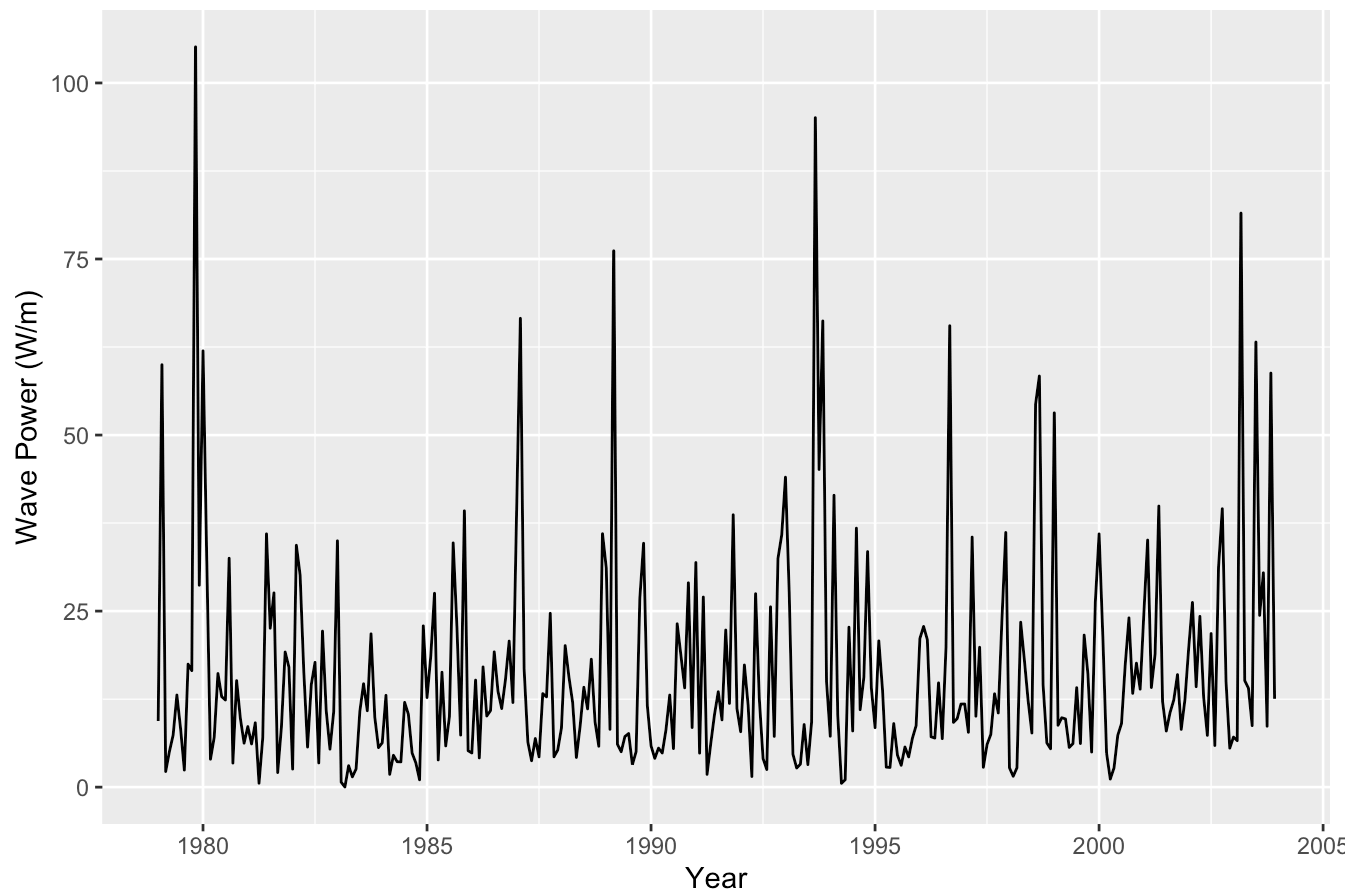
Monthly Mean Wave Power - Alaska (Training)

Figure 5. Time Series plot of monthly mean wave power in Alaska
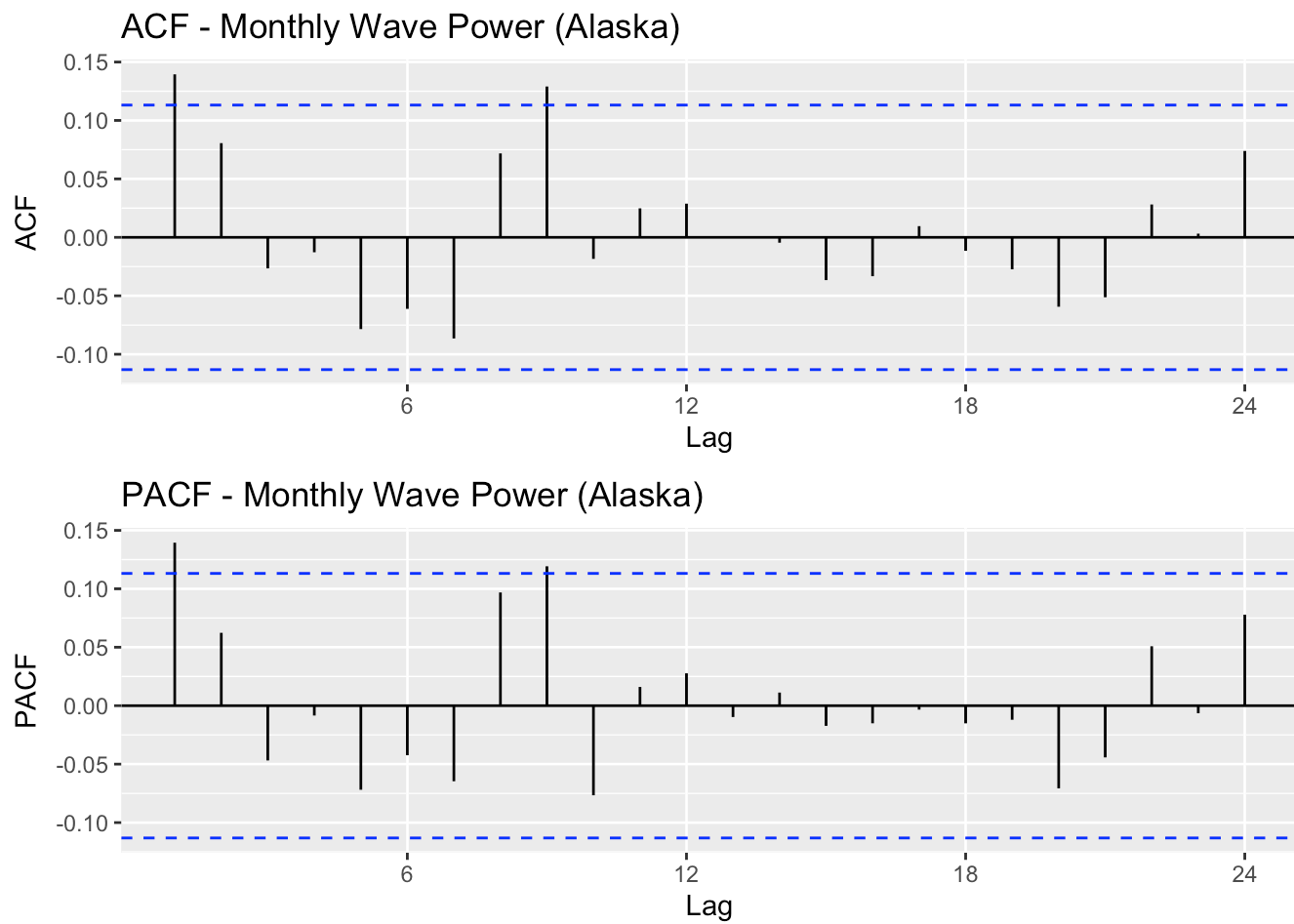
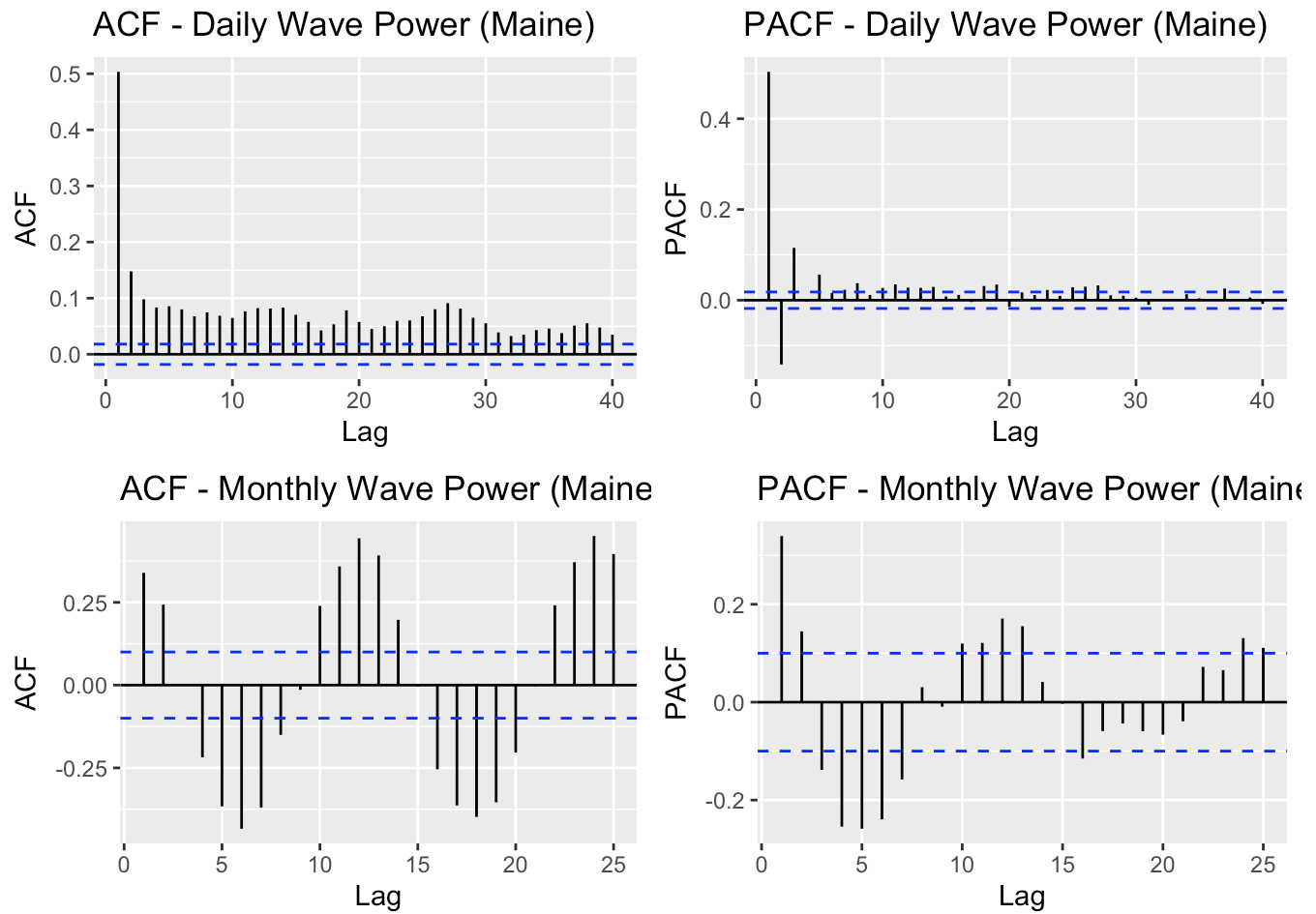Figure 6. ACF and PACF plots of monthly mean wave power in Alaska

Figure 6. ACF and PACF plots of monthly mean wave power in Alaska

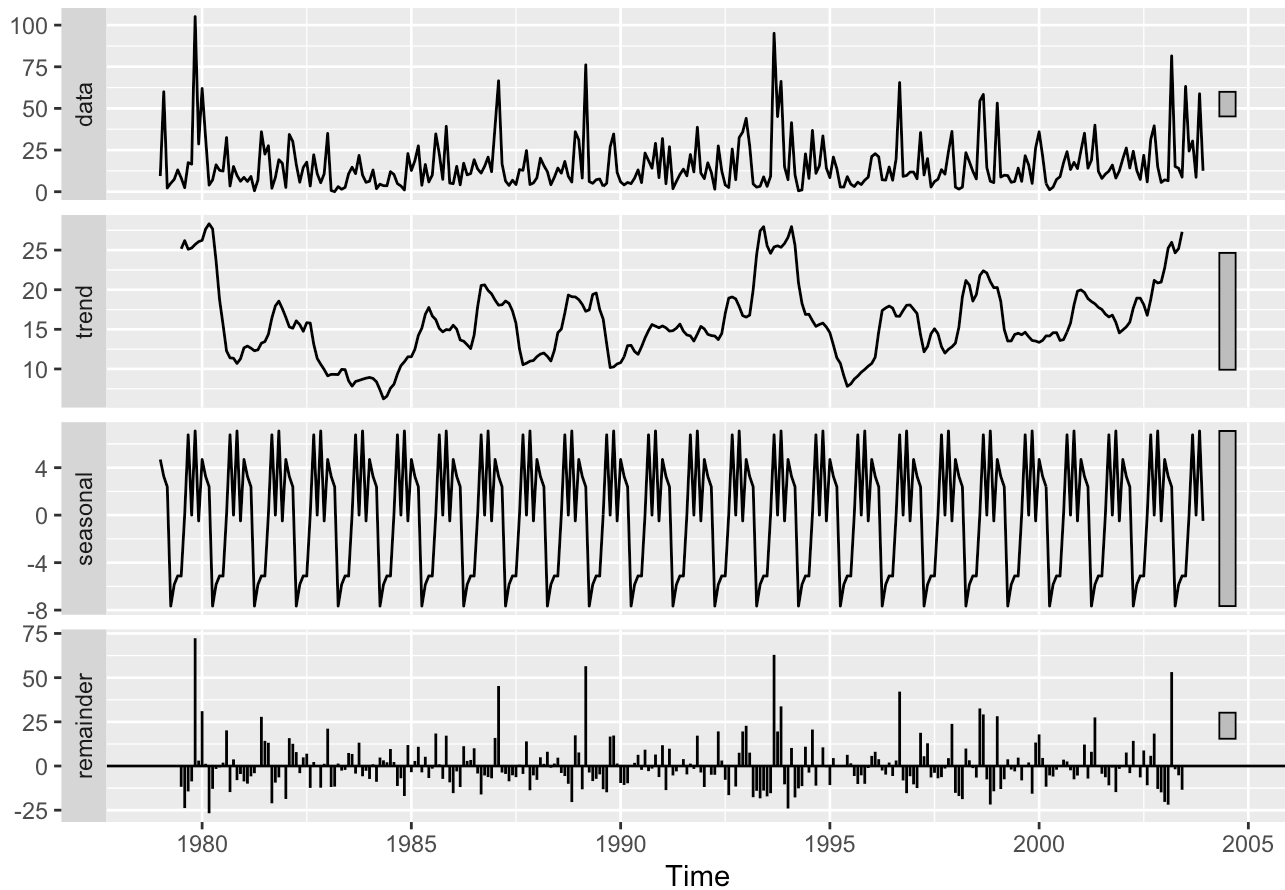## Decomposition of additive time series

Figure 7. Time series plot of decomposed monthly wave power series (Alaska)

The ADF test returns a p-value of 0.01, which is smaller than our chosen significance level of 0.05. We reject the null hypothesis that the Alaska mean monthly wave power series has a unit root and thus, the series is likely stationary and does not need differencing.

From Table 2, we see significantly lower RMSE and MAPE values, suggesting that perhaps our models are better able to capture monthly mean tidal power trends in Cook Inlet, Alaska. However, Figure 8 paints a different picture.

Forecast Accuracy for Monthly Wave Power - Alaska

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
STL+ETS	0.41065	14.12462	10.06050	-118.37052	148.4886	0.24409	0.44005
ARIMA+Fourier	2.70368	13.68095	9.00760	-79.91860	115.1316	0.19990	0.39252
TBAT	3.71047	14.20461	8.81815	-71.65192	107.4045	0.18163	0.41341

Figure 8 compares the forecasted values for Alaska with the actual values from the test period. The models are unable to reproduce not just the higher peaks, but also miss the troughs. It is likely that our models capture the seasonality of tidal power in Cook Inlet well but not its fluctuations. This shows that the wave power is highly unpredictable, at least at the site of Cook Inlet. Thus, this would require further investigation into other possible sites if we were to consider Alaska as a potential source for tidal energy development.

Monthly Wave Power Forecasts - Alaska
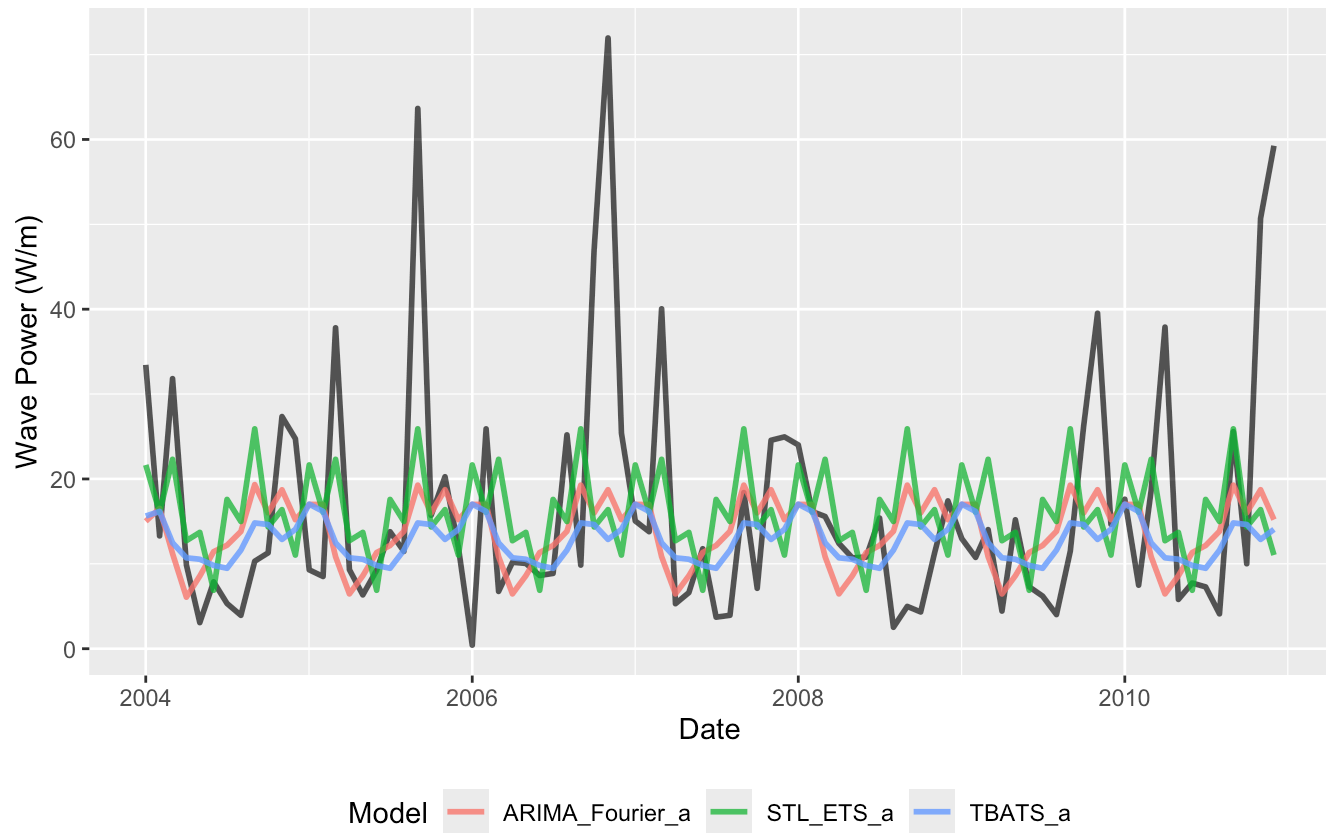Comparison of Top 3 Models (2004–2010)

Figure 8. Comparing Forecasted Values with Actuals - Alaska

Florida

Similar to Alaska and Maine, we see significant spikes at lag 1 in both ACF and PACF plots -tidal power does not show strong correlation with recent months. We also see significant spikes at lag 12 in both ACF and PACF plots, indicating a strong seasonal component. Lastly, Figure 11 shows that there is random noise that our decomposition does not account for (likely due to exogenous factors).
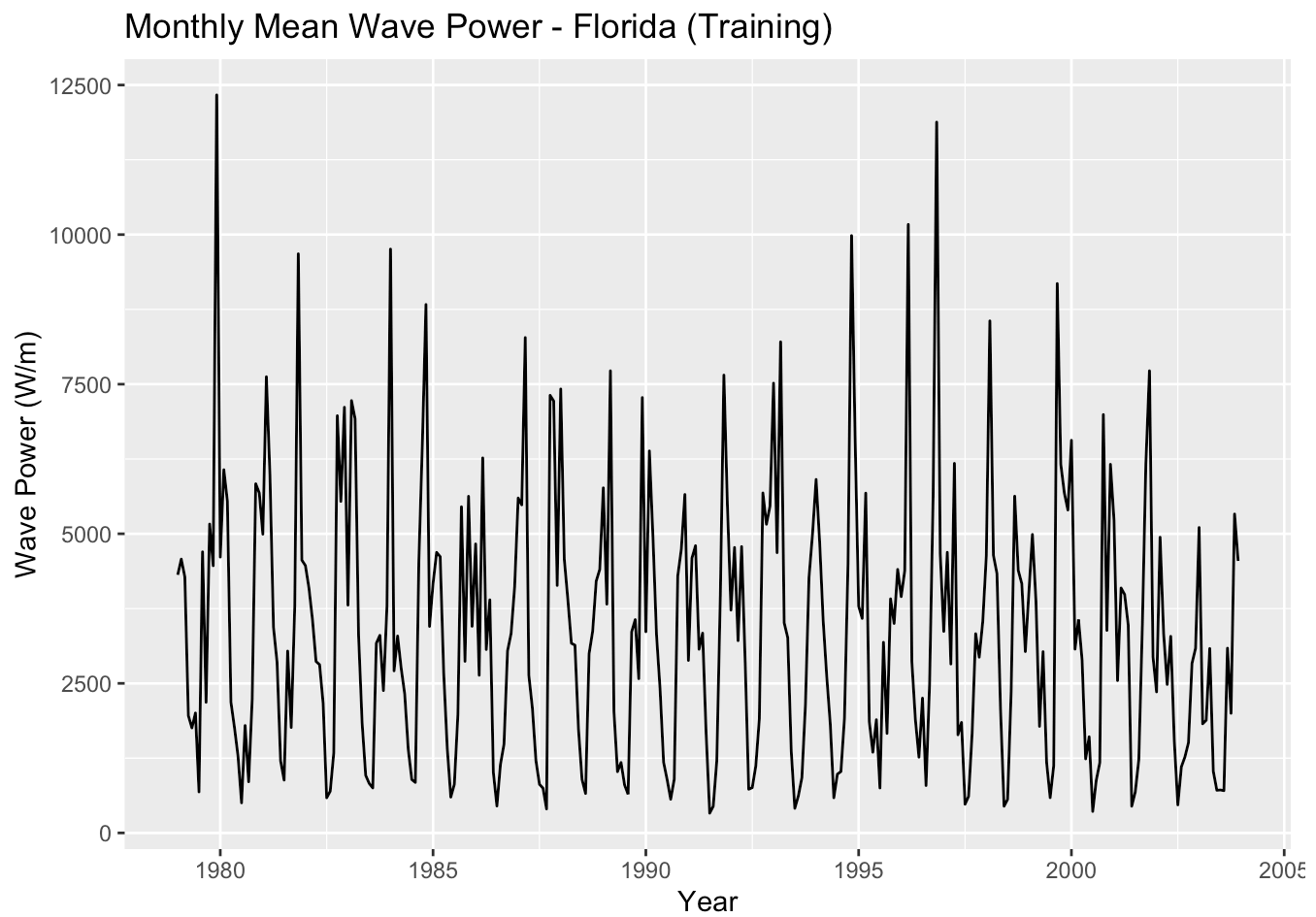
Monthly Mean Wave Power - Florida (Training)

Figure 9. Time Series plot of monthly mean wave power in Florida

ACF - Monthly Wave Power (Florida)

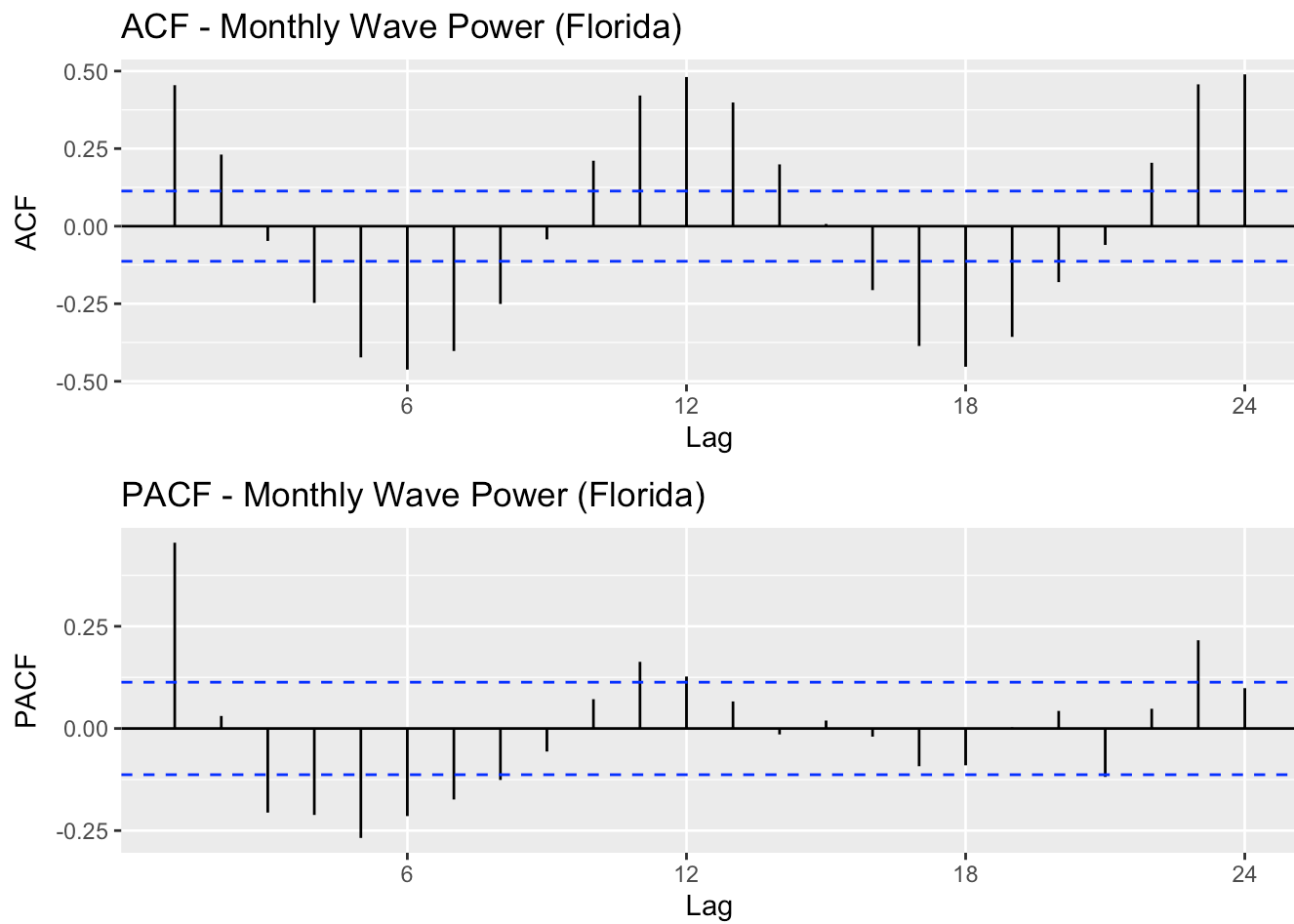## PACF - Monthly Wave Power (Florida)

Figure 10. ACF and PACF plots of monthly mean wave power in Florida
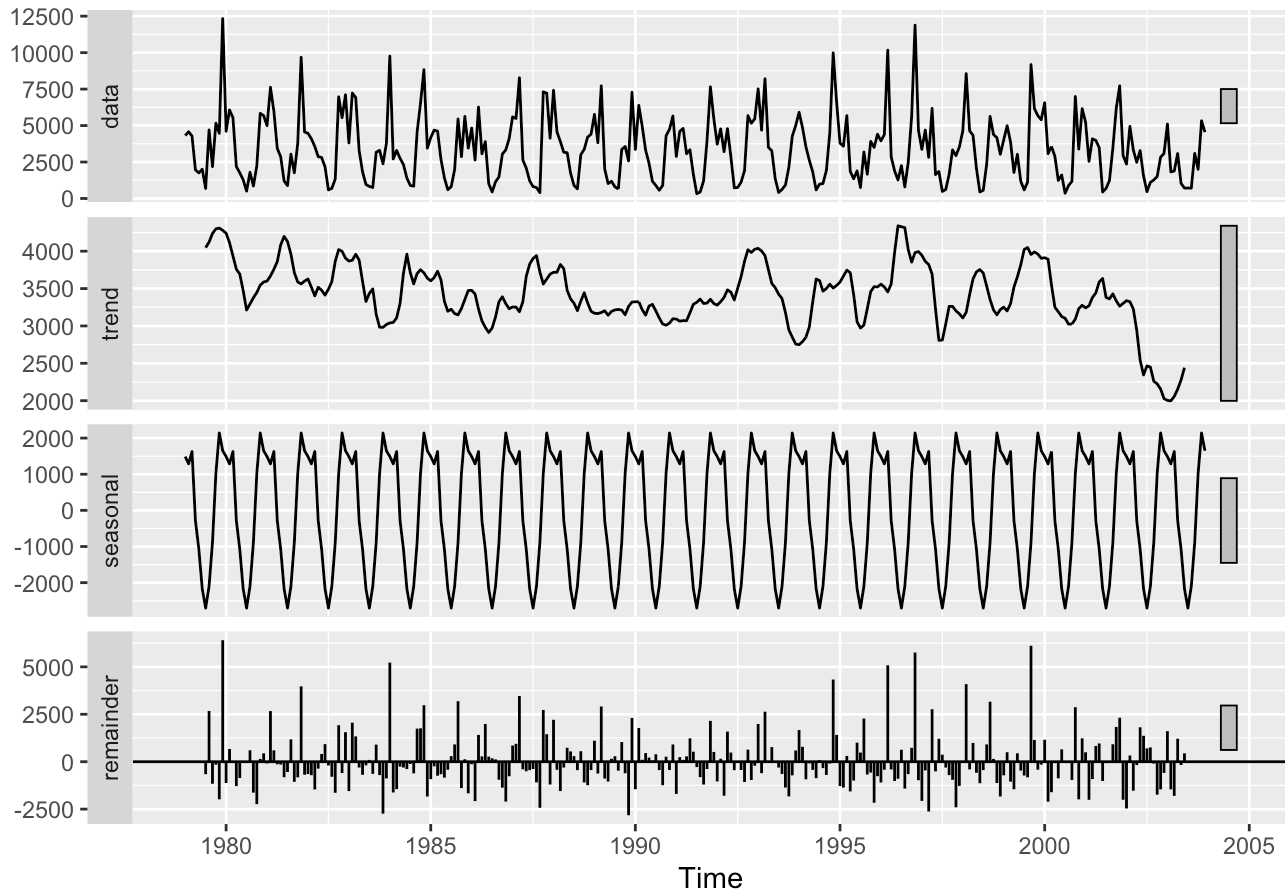
Decomposition of additive time series

Figure 11. Time series plot of decomposed monthly wave power series (Florida)

The ADF test returns a p-value of 0.01, which is smaller than our chosen significance level of 0.05. We reject the null hypothesis that the Alaska mean monthly wave power series has a unit root and thus, the series is likely stationary and does not need differencing.

From Table 3, our RMSE values for Florida are the highest amongst the chosen states (across all 3 models).

Forecast Accuracy for Monthly Wave Power - Florida

	ME	RMSE	MAE	MPE	MAPE	ACF1	Theil's U
STL+ETS	260.0615	1884.797	1242.601	-22.94636	48.47699	0.04601	0.78809
ARIMA+Fourier	377.5698	2019.667	1254.629	-13.78776	42.55154	0.03404	0.85821
TBAT	644.5316	2081.479	1271.549	-4.49300	39.17815	0.02116	0.86973

Figure 12, comparing the forecasted values with the actual Florida wave power numbers, shows that Florida's cycles are much more predictable, especially in the recent few years. The lows, especially, are very well produced by all three methods. However, the large RMSE values could be caused by a large understimation of Florida's peaks in tidal power, a problem that was present with the other 2 states.

Monthly Wave Power Forecasts - Florida
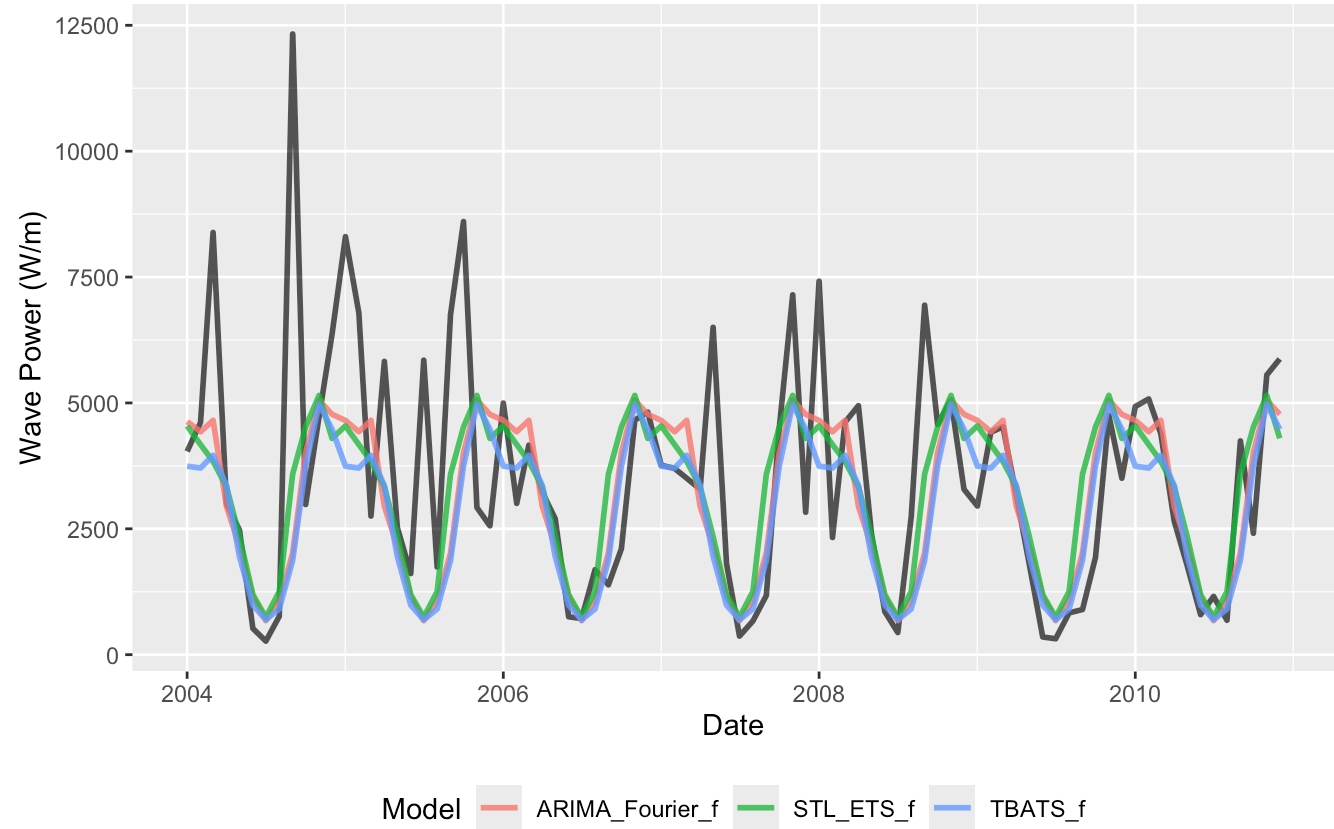### Comparison of Top 3 Models (2004–2010)

Figure 12. Comparing Forecasted Values with Actuals - Florida

Conclusion & Discussion

Forecast performance by site

Site	Best Model	Mean Power (W/m)	RMSE	MAPE (%)
Maine	ARIMA+Fourier	8443.415	3690.025	31.990
Alaska	ARIMA+Fourier	16.232	13.681	115.132
Florida	STL+ETS	3422.569	1884.797	48.477

We see that Maine not only delivers the highest monthly wave power, but also results in the most reliable forecasts as it has the lowest relative error (MAPE %). Florida forecasts show ~50% error on average, which means that they might be good for a baseline analysis. However, it indeed shows more stability than the Maine forecasts, and thus, could be a good alternative site choice if the forecasting or simulation goal targets more stable, sub-seasonal behavior instead of purely accuracy score. Alaska's Cook Inlet site is highly unpredictable, with a MAPE of 115%, which indicates that the one-year ahead forecast did not perform well and was affected by too much random variations/ noise. This is likely due to the geography of the location. Large mountains make incoming winds variable and a more open ocean site would provide more stability in tidal power generation.

Limitations and Future Analyses

Currently our models are purely univariate as we use the monthly mean wave power as a proxy for tidal power potential. Overall, they capture the seasonal patterns of tidal power across all 3 states well. However, they consistently underestimated peaks in tidal power and this is likely due to the large number of exogenous variables that affect the wave patterns, such as wind speed, sea surface temperature and weather events. These could have significant impacts on the forecasts, especially at highly variable sites. Also, our current dataset spans the time period from 1979-2010, which does not capture the recent climate change impacts. Future analyses should involve digging up more recent data and redoing our analysis based on that to see how the conditions have changed and aim to forecast to at least 2028, as we prepare for a federal administration that is hopefully more supportive of renewable energy sources like tidal power. Apart from extending our models temporally, we could also incorporate a wider spatial component, wherein we take the wave potential from a defined area rather than point estimates.

References and Datasets

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- Marine Energy Atlas. Innovative Data Energy Applications. (n.d.). https://maps.nrel.gov/marine-energy-atlas/data-viewer/download?vL=WavePowerMerged&b=%5B%5B-150.717111%2C43.537926%5D%2C%5B-114.418117%2C51.672586%5D%5D (https://maps.nrel.gov/marine-energy-atlas/data-viewer/download?vL=WavePowerMerged&b=%5B%5B-150.717111%2C43.537926%5D%2C%5B-114.418117%2C51.672586%5D%5D)