Forecasting High Bay Water Levels that Result in Flooding and Highway Closure

March 2023

A Research Report from the National Center for Sustainable Transportation

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16. Abstract

Like most coastal states in the U.S., California's shoreline communities and ecosystems have been exposed to flooding related to sea level rise and storms, which jeopardize their persistence and well-being. Shoreline transportation is especially vulnerable in certain places to flooding and failure, and because it is part of a continuously used network with little redundancy, it transfers its vulnerability to regional transportation networks. Forward-projected inundation/flooding risk is typically modeled at coarse spatial and temporal scales, which are useful at regional and decadal scales, but less useful for coastal managers and flood responders. This project improved assessment of both overall probability and short-term forecasts of water level for specific locations in San Francisco Bay that are vulnerable to flooding associated with sea level rise. The authors have developed probability assessment and forecasts through developing data-based, site-specific, model-independent approaches, which can be compared with and help to improve regional models of coastal flooding (e.g., CoSMoS). Water level data were collected across fine-scale arrays at fluvial-bay junctures in Sonoma and Marin Counties. The primary analysis is based on deconstructing water level records into multiple quasi-independent signals, which can be better predicted and recombined to produce probability of extreme events and to produce short-term forecasts during a flooding event based on predicted weather, wind, rain, and tide. In addition, real-time water level data are now available to first responders at critical locations in Novato Creek and Petaluma River when there is potential for flooding, as well as during a flood event. This is a pilot project that could be replicated at many other vulnerable locations around San Francisco Bay and elsewhere.

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EXECUTIVE SUMMARY

Climate change is changing our world in many ways. A critical challenge for coastal cities is the increased risk of flooding events that will accompany sea-level rise. Amongst the largest impacts of floods will be disruption of traffic and thus economies and societies as many low-lying highways have been built across tidal lands. While existing scenario-sketching models show the extent of the impact, few short-term forecasts exist and there is very limited real-time data to guide operational decisions in the days preceding and during flood events. Motivated by flood risks for State Highway 37 across the tide lands along the north shore of San Francisco Bay, we have developed an empirical system for site-specific forecast of water levels.

To build a water-level forecast model we have collated existing data and initiated new monitoring sites to track water levels on Novato Creek and Petaluma River. We analyzed these data to validate tidal predictions and fine tune them for specific locations on these waterways. With reliable tidal predictions, one can identify anomalies when water levels are above tidal predictions (i.e., “tidal residuals”). These residuals can explain water level fluctuations of ¾ m (30 inches) at sites near the Bay owing to wind, weather, and ocean effects—and over a meter at sites more influenced by creek flow. We develop a second model to predict tidal residuals, enabling much improved predictions of water level at these sites on Novato Creek and Petaluma, which are close to levee low points that threaten future flooding of Highway 37. Uncertainty in forecasts for less than 3 days is further improved by an autoregressive approach, resulting in 95-percentile errors about 10 cm (4 inches) for near-bay sites and about 27 cm (11 inches) for the site strongly influenced by creek flow, as precise creek flow predictions are not readily available. These water-level forecasts and real-time data are delivered through a website that is updated every four hours, including continual update of the prediction model as new data are included. Over time, as more data are collected while the system is operated, the precision and confidence of forecasted water level will improve at all sites.

These site-specific observations are also used for long-term forecasts of the increases in the probability of flooding as sea level rises. Whereas the highest astronomical tide is rarely exceeded now, this same elevation is expected to be exceeded 12 days a year in Petaluma River with just ¼ m (10 inches) of sea-level rise, expected by mid-century. At Novato Mouth and Rowland Bridge sites, the probability of flooding does not increase much until there is ½ m (20 inches) of sea-level rise, expected before 2100, but then the risk increases rapidly with exceedance expected 10-20 days in a year.

1 Introduction

The global rise in sea level will have many effects on coastal environments and on the people who live there (Chaumillon et al 2017; Griggs et al 2017)—and preliminary impacts are already occurring. The most severe and unavoidable impacts are related to the inundation of low-lying lands, which occurs as flood events that grow in frequency, severity, and duration as the mean sea level rises. Social and economic impacts to low-lying Infrastructure include reversible impacts (transient loss of value that ends as flood waters recede) and irreversible impacts (permanent loss of value). For example, highways will be impassable for some days or weeks as waters drain off the roadway, but they may also be damaged by erosion that needs repair. As sea level rises further, these impacts will occur more often with greater disruption and repair costs.

Low-lying coastal highways are susceptible to flooding, which already impacts routes like Highway-37 that runs across the lowlands at the northern end of San Francisco Bay and is crossed by several creeks/rivers. The road is below normal high-tide water levels for four miles near to the Petaluma River (Figure 1; elevations below 6 ft NAVD88). It is protected by levees and berms, which also protect several residences and businesses in addition to local and private roads. While the increasing frequency of flood events will require alterations to the road, short-term operational forecasts are required in the meantime to enable planning for traffic disruption, evacuation, and protection of property and infrastructure. The reliance on Highway-37 for regional traffic flows make this a high priority site for decision support tools that can provide real-time data and operational forecasts of water level (i.e., flood risk).

Flood events occur when spring high tides occur at the same time as onshore winds, low atmospheric pressure, high fluvial inflows, and/or high ocean water levels—these non-tidal forcing factors result in observed water levels that may be a few feet above water levels predicted from the tide alone. In different locations these multiple factors combine in different ways, requiring a site-specific approach to assess and forecast water level at low points in the landscape that separate highways from tidal waters. In this project we seek to develop an empirical tool for predicting water level at specific locations that enables flood forecasts on the same time horizon as weather forecasts.

In 2017, Highway-37 in Marin County flooded and was closed for 28 days during 3 separate events, primarily associated with Novato Creek and adjoining ditches (section A1, Figure 1). Mitigating the immediate impacts and near-term flooding risk cost $8 million, but this did not address the long-term risk of highway closure, nor the increasing risk associated with sea level rise. One of the flooding incidents was caused by over-topping of a private berm along a channel stemming from Novato Creek. The complex arrangement of private and public berms and levees protecting lands adjacent to Highway-37 results in a high risk due to the conjunction of anomalously high water levels during storms and locally degraded berms/levees. The highway and railroad are exposed to this elevated risk, as are local land uses.

In 2018, the Metropolitan Transportation Commission contracted with Kimley-Horn to complete a corridor plan for Highway-37 to prioritize actions that would reduce flooding impacts (Kimley-Horn, 2018). That plan relies on a prior 5-year study carried out by the UC Davis [Road Ecology Center](#) that highlighted the locations at risk, and strategies highlighted in the plan. A flood was anticipated when water levels were 24" above expected, but not when water levels were 12" above expected. Kimley-Horn (2018) summarizes road and levee elevations (Figure 1), but uncertainty in levee elevations undermines estimates of flood risk. This report focuses on forecasting water level, and the probability of anomalously high water levels, but quantification of flood risk depends on collection of accurate, fine-scale data on levee elevations—specifically at low points in the levee—and on assessment of structural integrity of levees.

In February 2019, Highway-37 flooded again and was closed for 7 days. The highway closed in the same place as in 2017 and for the same reason—the failure of local/private berms to contain water in Novato Creek. As noted by Kimley-Horn (2018): "Many of the levees are privately owned and were not constructed specifically for protecting SR 37 from flooding. Instead, protection of SR 37 is an ancillary benefit of the levees. Neither Caltrans, MTC nor any of the four North Bay Transportation Authorities has a role in managing or maintaining many of the levees responsible for protecting SR 37."

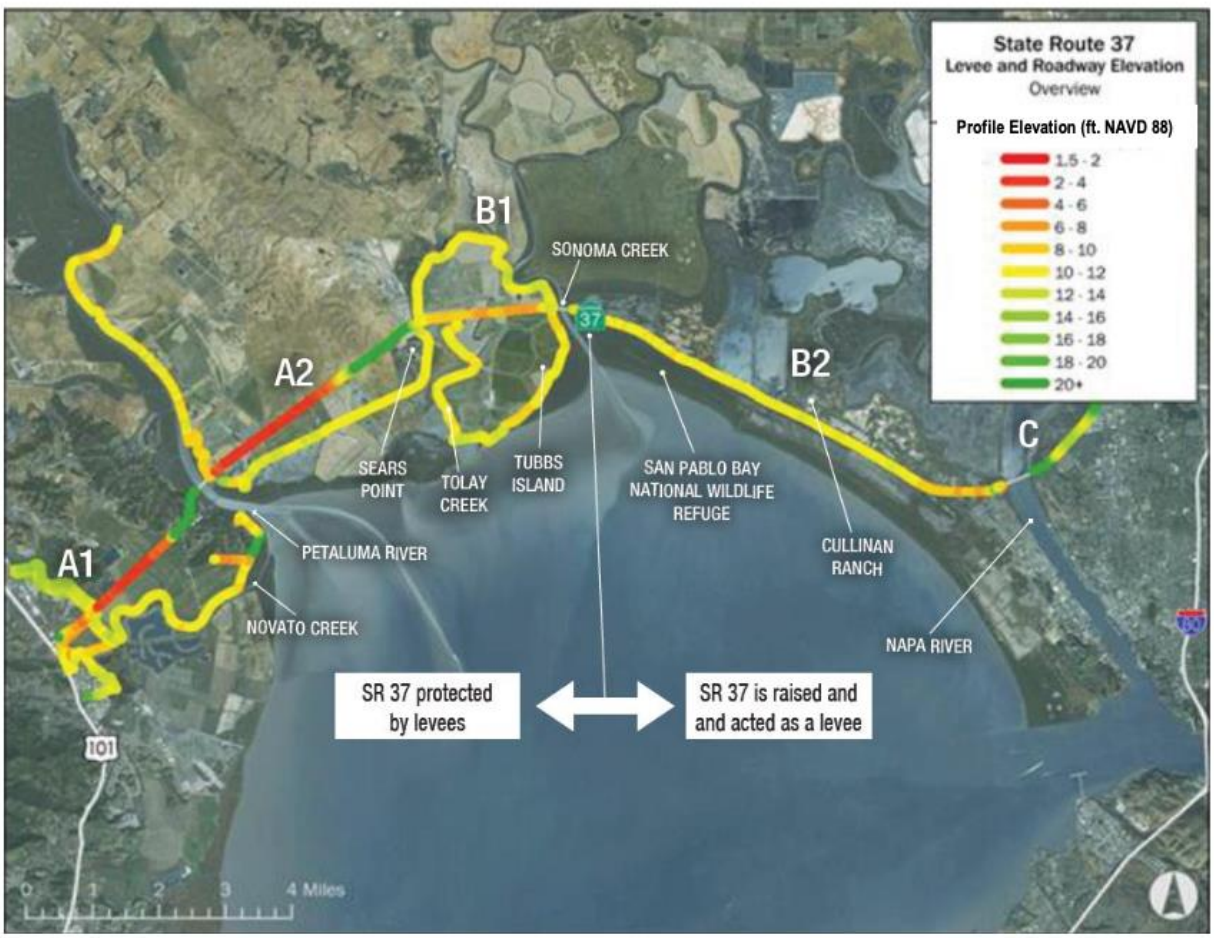

Figure 1. Elevation of Highway-37 roadway and associated levees (Kimley-Horn 2018).

In 2019, the UC Davis Road Ecology Center mapped levee elevations along the east bank of the Petaluma River in response to local concerns about the long-term condition and elevation of the levee. This levee protects an area of land adjacent to Highway-37 which is well below high tide levels in the river and would be flooded if the levee failed or if water overtopped the levee—likely resulting in another highway closure. Low points in the levee are about 3 ft above MHHW, which is about 1.5 ft above the highest astronomical tide level (Figure 2, red circle).

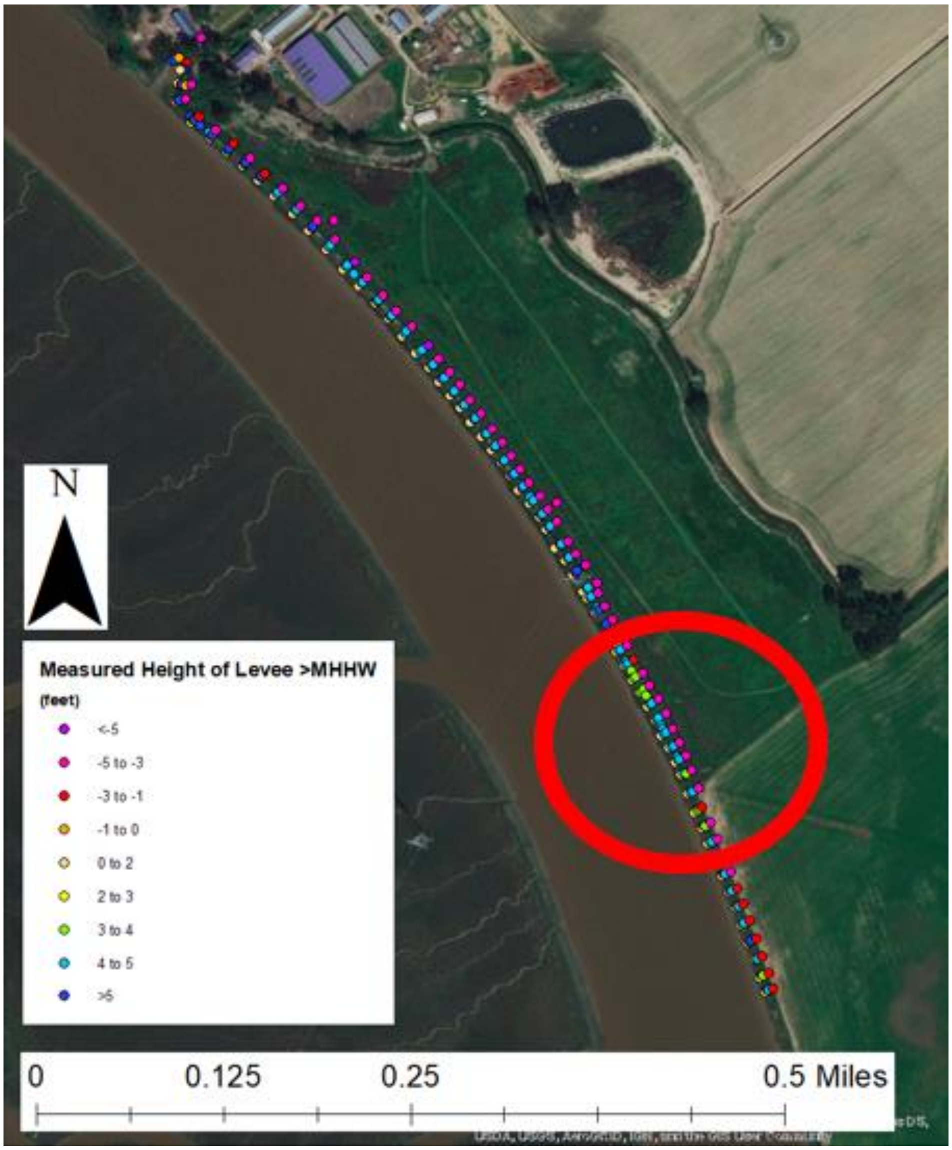

Figure 2. Elevation of levee crest along the east bank of the Petaluma River mapped by UC Davis Road Ecology Center in 2019. Elevations measured by RTK-GPS at 10-meter intervals are shown relative to Mean Higher-High Water (MHHW = NAVD88 + 6.30 ft). In the red circle, crest elevations are about 3 ft above MHHW (about 9.3 ft NAVD88).

The risk of levee overtopping has increased significantly with sea-level rise (about a foot in recent decades) and future risk will increase dramatically with additional sea-level rise (an additional few feet are expected this century: NRC 2012; Griggs et al 2017; OPC 2018). This Highway-37 case study illustrates the importance of hyper-local data to address site-specific risks. However, this is just one road that is vulnerable to flooding and several other roads are also at risk. Not only does each road have knock-on effects on traffic along many other roads, but flooding/closure is likely to occur simultaneously at multiple locations and traffic flow may be completely stalled in major metropolitan areas like the low-lying metropolis surrounding San Francisco Bay.

Here we develop a site-specific method that can be implemented at multiple vulnerable sites around San Francisco Bay and in other low-lying coastal areas across the State of California. This method is based on direct observations of water level at the site, independent of large computer simulations, and analyses are based on open-source statistical models and publicly available software. This empirical method for site-specific (hyper-local) operational forecasts complements bay-scale generalized future scenarios generated by regional models like CoSMoS (Barnard et al 2014, 2019). Historic data are used to quantify each of the primary controls on water level at a specific site (i.e., tides, local winds, atmospheric pressure, river inflow, ocean water levels), allowing real-time forecast of water levels, similar to weather forecasts. Data and model-based forecasts point to a sharp contrast between sites that are close to one another owing to small-scale effects of tide, wind, and creek inflow. By using historical and contemporary data at three specific project sites, we forecast water levels out to 4 days in the future with errors of 10 cm (0.33 ft) in open tidal waters, which is smaller than the uncertainty in topographic low points, and 27 cm (0.89 ft) at sites on the interface of creek and tidal waters, where error comes from uncertainty in creek flow predictions. In the report below we outline the model developed, the data collected, and the results obtained. Forecasts are available on the project website.

We deployed water level sensors or used existing sensors that telemeter data in real-time and developed operational water-level forecasts for three specific locations on Petaluma River and Novato Creek (Figure 3). At each site the water level is controlled by a unique combination of bay tides, ocean conditions, atmospheric conditions, and land runoff (fluvial controls).

- ***Novato Mouth.*** The station at the mouth of Novato Creek exhibits water levels that are primarily controlled by Bay conditions, although low-tide water levels are often above Bay water levels due to the ebb tide shoal that has formed off the mouth of the Creek. Water level data have been collected here since December 2018 by Marin County.
- ***Rowland Bridge.*** The station near Rowland Bridge is located about 1 mile upstream of the station at the mouth of Novato Creek. Data are also available since December 2018 (collected by Marin County), but the site had been recently vandalized and at the time of writing this report and real-time data were not available. Water levels at this site are characterized by weaker tidal variability and a strong fluvial effect. As the creek is constrained by artificial embankments, the stage is very sensitive to creek flow rate.
- ***Petaluma River.*** The station on Petaluma River is adjacent to Sonoma Horse Park, about a mile from the mouth of the river. Water level data have been collected here since October

2020 by UC Davis Bodega Marine Laboratory. Water levels at this site exhibit strong tidal variability without the low-tide control observed at Novato Mouth. Although influenced by river flow, the response is weak as the river is surrounded by extensive tidal wetlands.

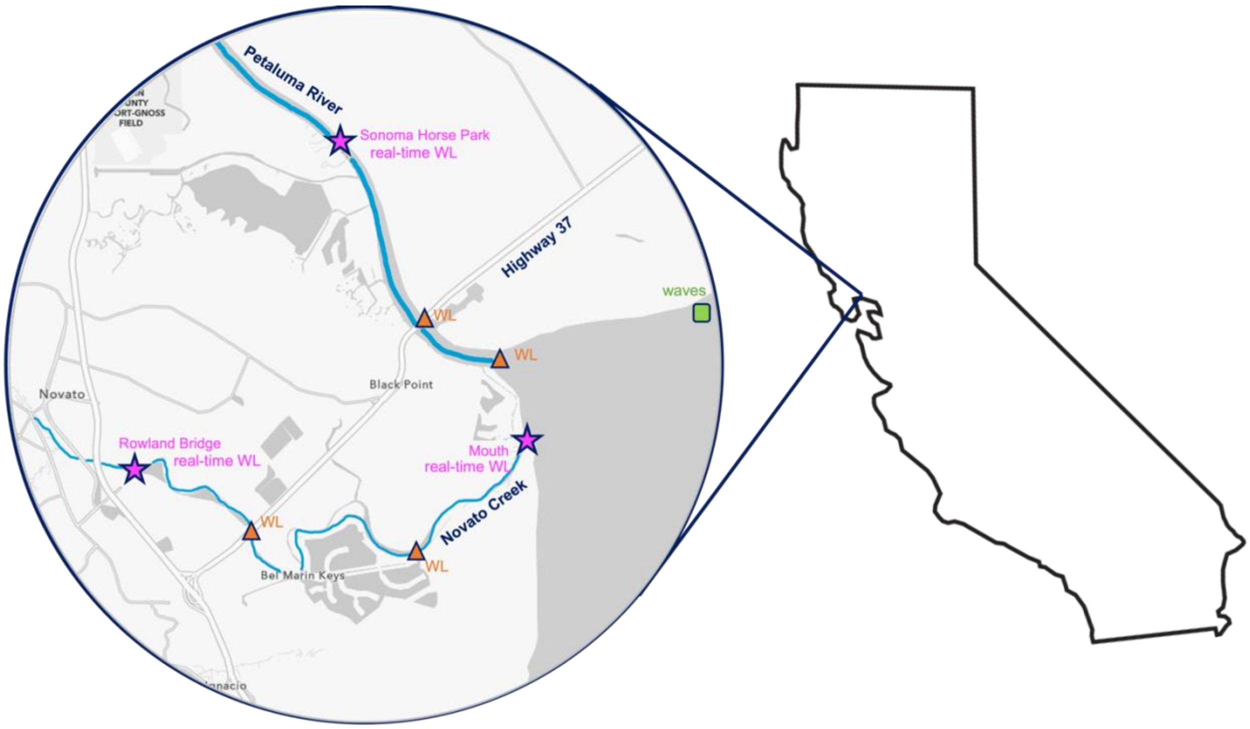

Figure 3. The study region: magenta stars indicate the location of water-level (WL) monitoring stations for which operational water level forecasts have been developed: Rowland Bridge and Novato Mouth on Novato Creek; Sonoma Horse Park on Petaluma River. Water level data were also collected at sites marked by orange triangles and wave data were collected at the site marked by a green square. Data from these secondary sites were used in analyses but not available in real-time and not used in water level forecasts at the three primary sites.

Additional long-term water level data are available elsewhere in San Francisco Bay (e.g., NOAA tide stations, like Richmond and additional short-term water level data were collected on Petaluma River and Novato Creek by UC Davis Bodega Marine Laboratory during this study (but not available in real-time). These additional sites in Petaluma River and Novato Creek provided additional data for analysis and development of forecast methodology, but they are not used in the final model and not addressed further in this report.

As described below, the highest water levels occur when storm conditions occur at the same time as spring high tides. While the influence of spring tides on water level varies little across the seasons, the influence of local winds, atmospheric pressure, river inflow, and ocean water levels is more important in winter, accounting for significant positive anomalies in water level (i.e., observed water levels are much higher than tidal predictions). Thus, the greatest risk of flooding is in winter, associated with winter storms but only weakly associated with rainfall and runoff. As the 2020-2022 project period was characterized by weak winter storms, our data set is limited, and our model should improve in precision and confidence as more storm data become available in future years.

2 Methodology

2.1 Stakeholder Engagement

We leveraged prior relationships with landowners in the vicinity of Novato Creek and Petaluma River to gain access to the levee on the Petaluma River (i.e., Sonoma Horse Park) and to engage the landowners in discussions of the purpose and likely outputs of the project. We maintained this stakeholder engagement as much as possible during COVID, meeting with landowners at the Petaluma River site and remotely (via Zoom) during 2020 and early 2021. At the same time, we leveraged existing relationships with the Transportation Authority of Marin, Marin County Public Works, Sonoma County, and other local agencies to inform them of the study. Several stakeholders requested a workshop following completion of the model and submission of the final report.

2.2 Model Rationale and Overview

Flood prediction is fundamentally complex because of the compounding interaction of multiple effects that can account for higher or lower water level. Traditional physically based numerical simulation models resolve key processes and exhibit great predictive capability when the dominant processes are included—and when there is an extensive data set that can be used for both model calibration and validation. However, high-resolution simulation models are computationally expensive which limits their performance and availability for short-term and localized forecasting. Data-driven approaches have long been used for river flood prediction (Mosavi et al, 2018) and tidal predictions (Hibbert et al 2015), but they are less commonly used in predicting coastal flooding. The advantage of an empirical modeling (statistical model based on direct observations) over simulation modeling is that it does not need to make a priori decisions about which processes to include, it is less computational and can output predictions quickly and affordably for specific sites. While existing numerical simulation models quantify San Francisco Bay water levels for generic scenarios, existing site-specific operational forecasts only account for tidal fluctuations in water level and omit meteorological and fluvial effects which are a key factor in coastal flooding. The primary objective of this project was to develop and assess the skill of a data-driven approach for operational *forecasting of water levels* in sheltered bay and estuarine waters (an operational model for *forecasting flood risk* would require more precise and reliable data on levee elevations). The ultimate aim is to implement a flood forecast model that is easy to implement, with low computational cost and fast training and testing.

Statistical approaches can be divided into correlative models and machine-learning models. Both approaches aim to fit the best mathematical model to a set of data. While machine learning algorithms are specifically constructed for the best predictive accuracy, they are somewhat obscure and lack interpretability. Statistical models on the other hand are often easier to interpret and relationships between the variables can be easily visualized and interpreted in terms of well-established physical processes. In this project we combined a relatively simple statistical model (multiple-linear regression) with a forecast error correction inspired by the autoregressive moving average method (ARMA) commonly used in time-series forecasting (Hibbert et al 2015).

In tidal waters like the San Francisco Bay, tidal fluctuations dominate the water level signal (AECOM 2016), accounting for the majority of variance. Tidal analysis is well established, and tidal predictions are available for many locations in San Francisco Bay and globally. While tides are large and well predicted, non-tidal influences on water level are typically small and poorly predicted at specific sites. However, non-tidal signals can be large during weather-related events, accounting for water levels well above expected tidal levels and consequent flooding events—these events are referred to as “extreme tides” in AECOM (2016), which is an unusual and misleading term as the events are due to a combination of tidal and non-tidal effects. The difference between the observed water level (“stage”) and the predicted tide is known as the “tidal residual” (or sometimes the tidal anomaly or tidal deviation). The challenge is to predict this non-tidal residual, which is a response to forcing by onshore wind stress, low atmospheric pressure, high river inflow, and/or fluctuations in coastal sea levels (related to large-scale wind and runoff as well as seasonal effects, El Niño cycles and sea-level rise). Our model uses a record of past water level fluctuations at a specific site to predict future water levels with a forecast horizon limited by reliable weather predictions (i.e., similar to weather forecasts). It is comprised of three steps: (i) develop a tidal prediction model for the observation site, (ii) calculate tidal residual and develop a model that predicts this residual as a response to meteorological and hydrological conditions, and (iii) use an autoregressive model to account for slowly varying background effects. The third step assumes that the difference between today’s observed values and the tide-and-weather-based prediction is primarily due to large-scale, slowly varying effects such as seasonal or interannual fluctuations in coastal ocean sea level and seasonal fluctuations in the inflow of aggregated land runoff to the Bay. This error-reduction approach is commonly used in time-series forecasting (Hibbert et al 2015) and is effective in reducing short-term forecast error, as it does in our model.

The workflow for this forecast model is summarized in Figure 4. Once sufficient data are available for a given location, one can use this water level record to calculate the predicted tide. Then one can calculate the tidal residual from the difference between observed and predicted water level and regress this time-varying residual against parallel data on creek flows, local winds, atmospheric pressure, and ocean sea level. By combining the tidal prediction model and the model that relates the tidal residual to meteorological and hydrological forcing, one can make hindcasts of water level and compare those to past observations to estimate the uncertainty in model prediction (model error). Given the slowly varying nature of the error, one can make an autoregressive correction to the hindcast and again compare to past observations to quantify corrected error. Finally, one can calculate how corrected error increases with the forecast horizon (i.e., days into the future).

Once the model is fully trained and error bounds are quantified, it can be implemented as an operational tool for forecasting water level at the observation site. The quality of forecasts for a specific location depends on high-quality meteorological and hydrological forecasts (which are typically available for only a few days into the future) and real-time water level observations (to allow for autoregressive corrections).

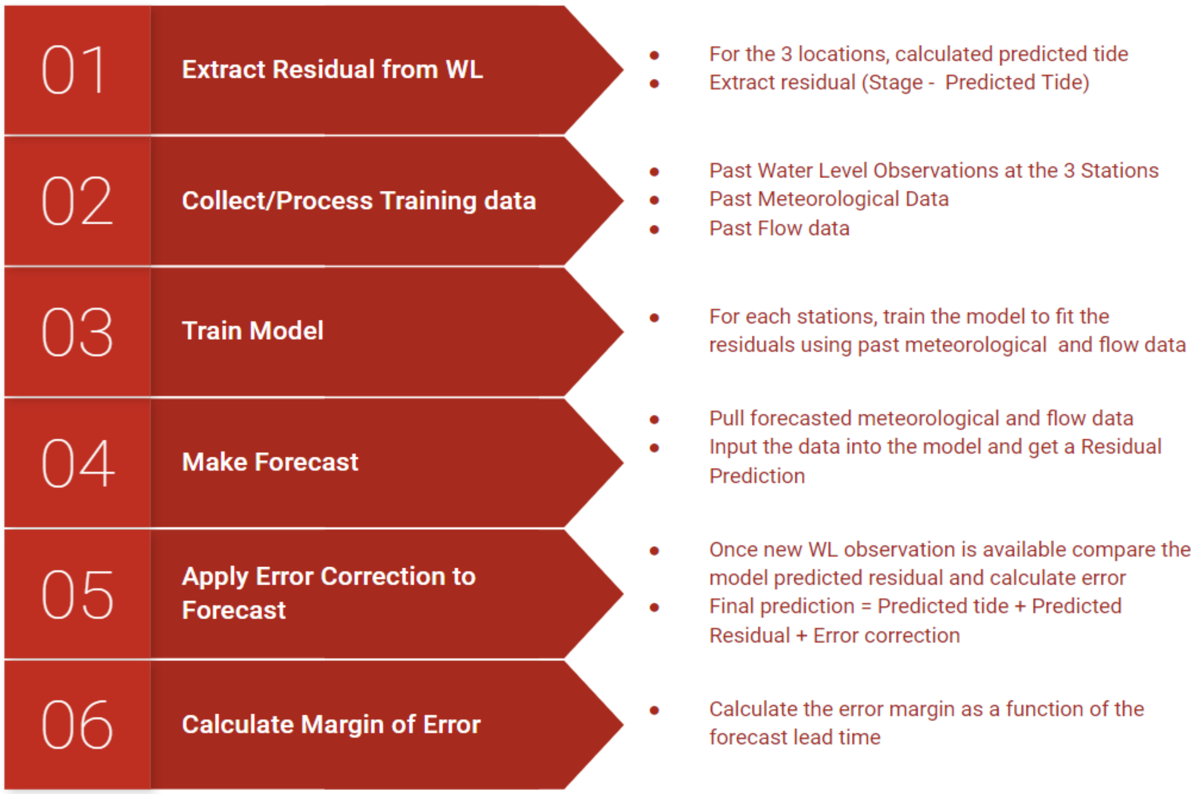

Figure 4. Schematic summary of workflow for developing and implementing a water-level forecast model from water level observations.

2.3 Tidal Analysis and Extracting Tidal Residual Signal

The tide accounts for the largest contribution to the variance in the water level signal. The first step is to remove the tide and calculate the residual. The tide signal is composed of a number of predetermined harmonics of different phase and amplitude. Harmonic analysis allows one to determine the unique phase and amplitude for each tidal constituent at a specific location. The tidal signal can then be predicted as a sum of harmonic signals. Several prepackaged routines are available to determine coefficients for each tidal constituent. In this project, we use a publicly available Python routine based on a well-documented Matlab routine called Utide (http://www.po.gso.uri.edu/~codiga/utide/utide.htm). Utide was selected as it provided the best results for tidal prediction in shallow waters like in Novato Creek.

To optimize determination of the tidal signal, we removed the strongest non-tidal influences from the data record before applying the Utide analysis to determine the persistent tidal signal. For example, on inspection of water level data at Novato Mouth, it is evident that the lowest water levels are frictionally controlled by an ebb-tide deltaic shoal off the mouth of the creek, so that the inclusion of these data contort the harmonic analysis, which is not well-suited to friction-dominated drainage flows. For water levels below 0.6 m NAVD88, the tidal drop in water level slows down as the water level asymptotes towards the elevation of the crest of the shoal. We thus exclude this non-tidal effect from the analysis by only including data for water levels above 0.75 m NAVD88 (i.e., only considering the well-behaved tidal curve at mid/high tide). This approach focused the analysis on performing best for high tides, which is when flooding events occur. We also removed data collected during times of significant creek flow to exclude fluvial effects contaminating tidal analysis (data only included from periods when creek flow less than 25 cfs). This fluvial effect was most important to exclude in analysis of water levels from the Rowland Bridge site, where fluvial effects dominate tides during flow events (Figure 5). At Rowland Bridge and Petaluma River sites, the tidal signal did not show low-tide friction effects as at Novato Mouth, which meant that low-tide data were not excluded, and the tidal predictions performs well at both high and low tides.

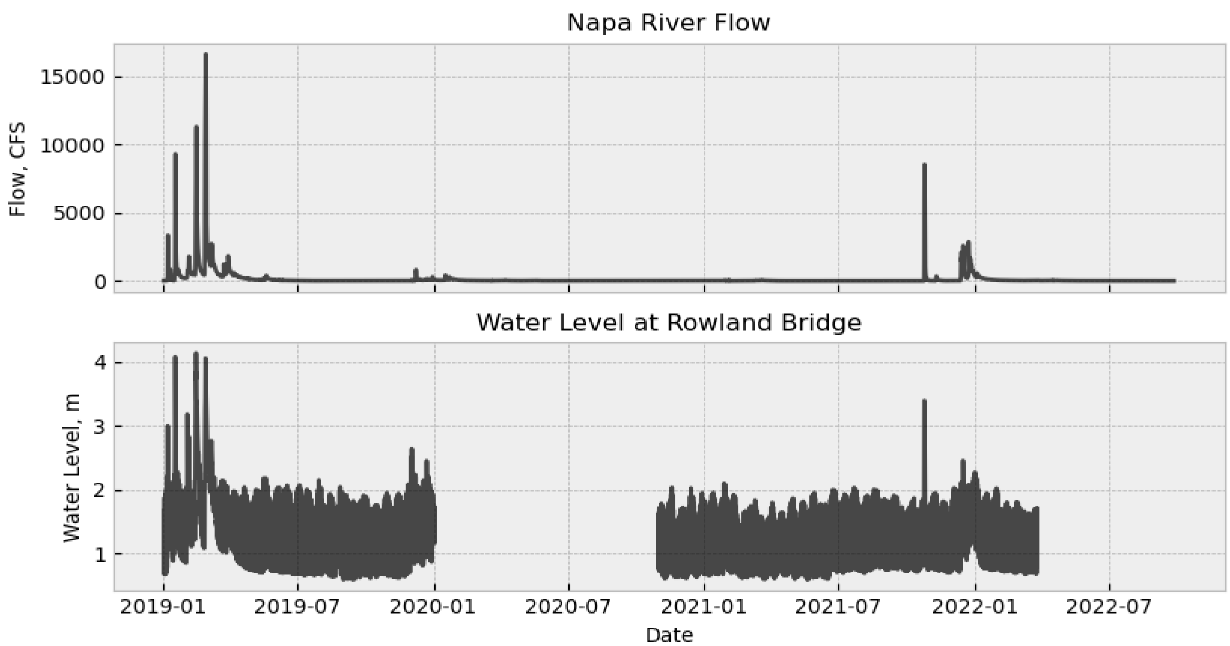

Figure 5. Flow in Novato Creek and water level at Rowland Bridge from January 2019 to March 2022. During spring-summer-fall months with negligible flow in the creek, water levels exhibit a tidal signal, but during flow events water levels have little relation to tide as they are controlled by river flow.

We adopted different approaches for obtaining a residual signal at different sites. At Novato Mouth the residuals calculated at low tide often exhibit large error, given that the tidal analysis excluded low-tide data. To exclude this effect, we only calculated residuals at high tide (i.e., about twice a day, Figure 6), which is the time when the tidal prediction is most accurate. The 12-hour time series was then smoothed with a 3-point window. At Petaluma River and Rowland Bridge sites, the residual was extracted from the entire signal (all tidal stages) and smoothed with a 3-hour window. This 3-hour smoothing removes any irregularities from the noise in the observations and removes the effect of a small lag that is sometimes evident during rapidly rising and falling tides. Longer windows reduce the variance in the residual signal and shorter windows exhibit a tidal signal in the residual (owing to the small lag during rising and falling tides).

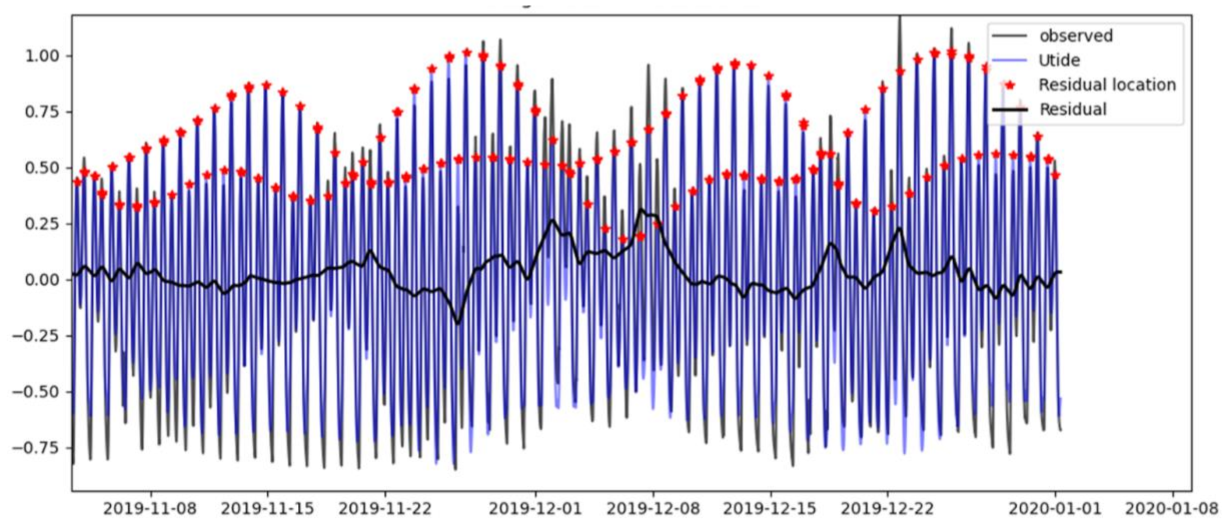

Figure 6. Observed and Utide-predicted water levels for Novato Mouth during November and December 2019, with red symbols marking the 12-hour residual values and black line showing the 3-point smoothed tidal residual signal.

2.4 Factors Controlling Tidal Residual

Deviations of observed water level from tidal predictions are primarily due to meteorological and hydrological effects. The foremost factors are onshore wind stress that tilts the bay surface and piles up water at the observation site, atmospheric pressure that depresses water level at the site, land runoff that accounts for water level gradients in confined channels, and water levels in the coastal ocean that set the base level for the bay. While cumulative inflow to the Bay also can affect Bay water levels, this effect was weaker than others, difficult to predict, and slowly varying so that it was addressed more effectively through the autoregressive error correction. Likewise, most ocean influences were weak, difficult to predict, and slowly varying (i.e., best handled by the autoregressive error correction). However, local wind forcing accounts for significant short-term storm surge in the Gulf of Farallones, which correlates well with winds over the ocean and is an important factor in explaining tidal residuals in the Bay (this effect is not slowly varying and colloquially referred to as the "wind tide").

The data used to develop the model are listed in Table 1 (i.e., training data) and plotted in Figure 7. For each station, the residual signal was related to four primary factors:

- Local wind – onshore component of wind measured at Gnoss Field or Napa Airport.
- Local atmospheric pressure – measured at Gnoss Field or Napa Airport.
- Local runoff – creek flow measured on Novato Creek or Napa River.
- Coastal ocean water level – tidal residual from NOAA tide gauge at Point Reyes that is well correlated with onshore wind at NDBC Buoy 46026 in the Gulf of Farallones.

While the model was initially trained with the data from sites closest to the water-level observation site (Figure 6), it was later retrained with data that are predicted by meteorological and hydrological models (Figure 9), thus allowing water level forecasts. Firstly, the model was retrained for each site using Napa River flow as it is predicted and well correlated with variability in flows in Novato Creek and Petaluma River (Figure 7). Secondly, coastal ocean residuals at Point Reyes and San Francisco tide gauges were well correlated with onshore winds in the Gulf of Farallones, which are predicted in weather forecasts. Local winds and atmospheric pressure are also predicted.

Table 1. Data Sources for Factors that Influence Water Level

Location	Type	Data Sources
Novato Creek	Flow	USGS NWIS https://waterdata.usgs.gov/nwis/uv?site_no=11459500
Napa River	Flow	USGS NWIS https://waterdata.usgs.gov/ca/nwis/uv?site_no=11458000
Chip Island	Delta Outflow	DWR CDEC https://cdec.water.ca.gov/dynamicapp/staMeta?station_id=DTO
Point Reyes	WL residuals	NOAA tide gauge https://tidesandcurrents.noaa.gov/noaatidepredictions.html?id=9415020
Buoy 46026	Atmospheric pressure, Wind, SST	NOAA NDBC https://www.ndbc.noaa.gov/station_page.php?station=46026
Napa Airport	Atmospheric pressure, Wind, precipitation	NOAA NCEI https://www.ncei.noaa.gov/maps/lcd/
Gnoss Field	Atmospheric pressure, Wind, precipitation	Sonoma county https://sonoma.onerain.com/site/?site_id=155&site=b4e33d63-e909-4ecd-bb2b-1ee2c587bb00

Table 2. Data Sources for Water Level

Location	Type	Data Sources
Mouth of Novato Creek	Stage	https://marin.onerain.com/site/?site_id=16808&site=a88e57c5-06b1-4855-a65c-92ef0063e6bb
Novato Creek at Rowland Bridge	Stage	https://marin.onerain.com/site/?site_id=16809&site=82b05ca8-3c86-49cc-9660-63ca3abd3e35
Petaluma River at Horse Ranch	Stage	https://coastalocean.ucdavis.edu/ocean-observing/hwy37

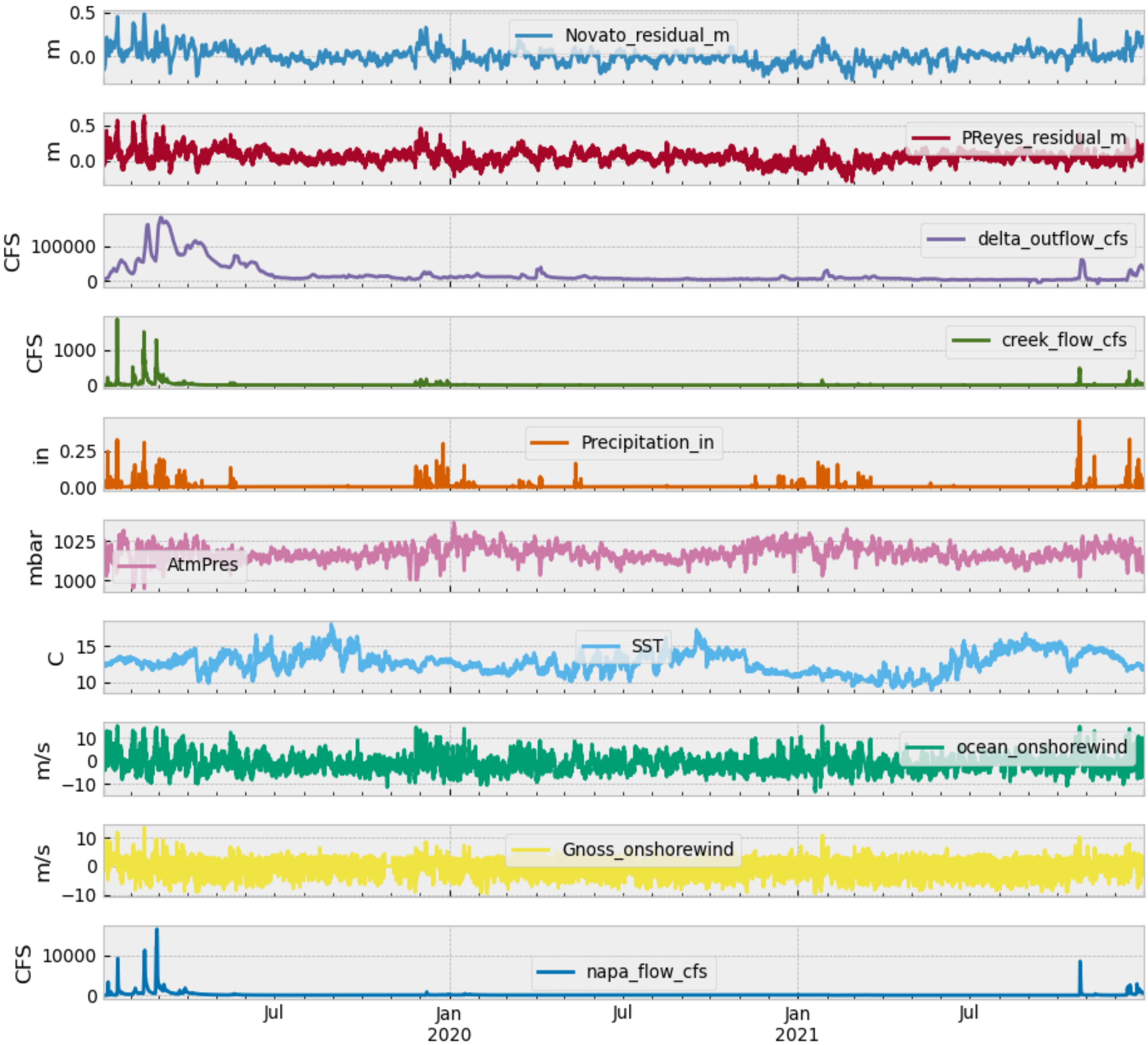

Figure 7. Time series of data used in analyses (January 2019 to December 2021).

While initial analyses of water level at the mouth of Novato Creek conducted in 2021 were based on a 2-year record of observations starting in January 2019, the final model is based on more than 3 years of data from 2019 to 2022. Prior to analyses, all data were processed to be regularly spaced with outliers removed and gaps filled. For wind, the “onshore component” was found by iteratively correlating different components to the residual signal to identify the orientation of the component that has the most influence on the residual.

Table 3 lists the correlation coefficient r^2 for single-factor correlations with the residual signal at Novato Mouth. Correlations between the residual at Novato Mouth and different factors can also be visualized in scatter plots (Figure 8).

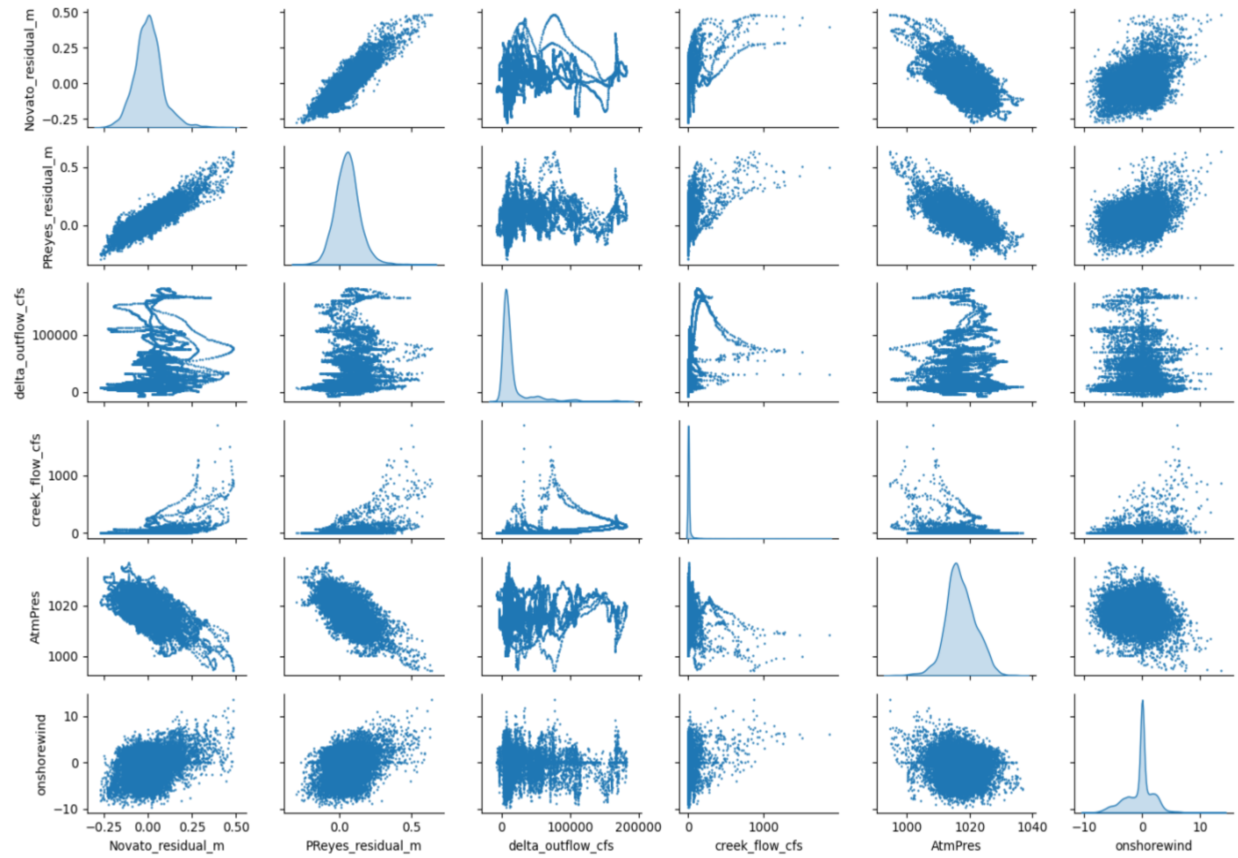

Figure 8. Association between tidal residual at Novato Mouth *Novato_residual* with (i) tidal residual at Point Reyes *PReyes_residual*, (ii) Delta outflow *delta_outflow*, (iii) Novato Creek flow *creek_flow*, (iv) atmospheric pressure *AtmPres*, and (v) onshore wind *onshorewind*. Panels along the diagonal show the distribution of values for each parameter and off-diagonal panels show scatter plots of relationships between pairs of parameters.

The strongest association and most linear relation are between residuals at Point Reyes and Novato Mouth (i.e., the ocean effect) as Bay water level rises in concert with ocean water level. There is also a significant (negative) linear relationship between Novato Mouth residual and atmospheric pressure as bay hydrodynamics is controlled by sub-surface pressure such that water level rises to increase sub-surface pressure due to water head to compensate for any drop in atmospheric pressure (i.e., a simple barometer effect). A clear but weaker relationship between Novato Mouth residual and onshore wind is observed due to onshore wind stress piling up Bay waters along the shore (i.e., wind setup). For creek flow, the relationship is highly nonlinear with little response to weak flows and strong response to occasional high flows, due to the frictional effects on fluvial flows. At other sites the relationships are qualitatively similar, although the dependence of the residual on creek flow is much stronger at Rowland Bridge.

Table 3. Correlation coefficient (r^2) quantifying relationship between tidal residual at the mouth of Novato Creek and various datasets

Datasets	Correlation to Residual at Mouth of Novato, m
Residual at Point Reyes, m	0.85
Delta Outflow, CFS	0.28
Novato Creek flow, CFS	0.39
Napa Airport Precipitation, in	0.29
Atmospheric Pressure, mBar	-0.57
Sea Surface Temperature (SST), C	0.23
Ocean, Onshore Wind, m/s	0.53
Gnoss Field, Onshore Wind, m/s	0.24
Napa River Flow, CFS	0.35
Napa River Stage, ft	0.45

Two criteria were used in selection of training data for the final model development:
(i) how well the residual is correlated with this parameter, and (ii) how well the parameter is reliably predicted out to 3-5 days in the future. Based on these criteria, four parameters were selected for the model (Figure 9):

- Flow in Napa River
- Atmospheric pressure at the mouth of the Bay
- SSW onshore wind stress over the ocean in the Gulf of Farallones
- SE local onshore wind stress at Gnoss Field

The strongest predictors are atmospheric pressure and wind over the ocean, with a weaker dependence on river flow and local onshore wind. However, these four factors are themselves correlated, specifically during rain-bearing, low-pressure storms in winter. Thus, while the model works well, the attribution of variance in residual signal to specific factors may not be precise. The SSW onshore wind over the ocean also may be a proxy for other influences on water level, including water temperature, Ekman upwelling, and geostrophic setup related to alongshore currents (which are correlated with wind strength and orientation). This is question of attribution and the relative phasing of non-tidal forcing will be addressed in future work.

Figure 9. Data used in final model training, based on over 3 years of data from January 2019 to September 2022: (i) Atmospheric pressure *Baro_pressure*, (ii) Onshore wind over Gulf of Farallones *Ocean_wind*, (iii) Onshore wind at mouth of the creek *Local_wind*, and (iv) land runoff as indexed by Napa River flow *napa_flow_cfs*.

2.5 Selecting and Training the Tidal Residual Model

The predictive model for the tidal residual, combined with the predictive model for tides, is the engine of the forecasting method. Tidal-residual model selection and training used the [scikit learn] python package and a different model was built for each location using the same training data set (described above). The target variable was the residual at a selected location. Amongst the many different model types, we selected a model that was simple and easy to replicate across these three sites (and potentially more sites in the future). We selected a Multiple Linear Regression (MLR) model, to which we applied a few modifications:

- Min-Max scaling
- Polynomial transformation
- Correction for estimated error

Before fitting the model, the input data were normalized with a Min-Max scaler which transforms all factors so that data values lay between 0 and 1. This normalization ensures that the calculated weights are all within the same range. Initially we used a linear model where the target value y is expected to be a linear combination of the factor values x_i with coefficients w_i and intercept w_0. In the case of only 2 factors, the equation is:

$$\hat{y}(w, x) = w_0 + w_1 x_1 + w_2 x_2$$

The model solved for w_i and w_0 by minimizing the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation—i.e., finding the model that minimizes the mean squared error. In Figure 10 the model prediction is shown for the tidal residual at Novato Mouth using this scaled MLR approach for a 4-month period in early 2019 that included several large storms.

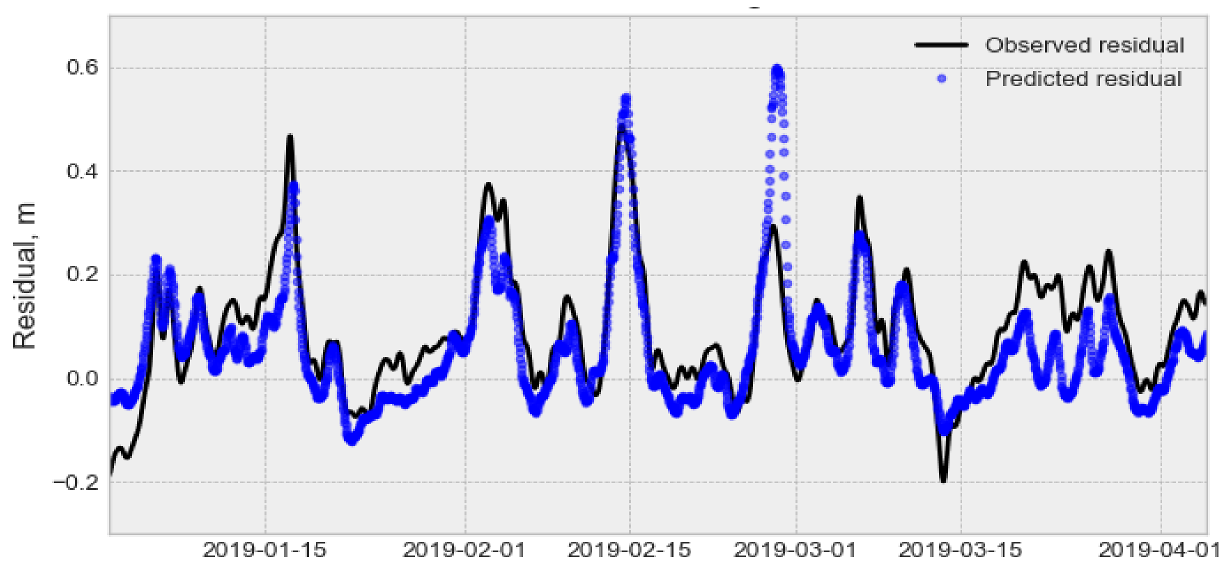

Figure 10. Observed and predicted residuals at Novato Mouth with predictions using a linear regression model.

Similar MLR models were applied to Rowland Bridge and Petaluma River. The corresponding weights for each of the three target stations are listed in Table 4.

Table 4. Coefficients (w) of the Multiple Linear Regression for each site

	Mouth Novato	Petaluma River	Rowland Bridge
Barometric Pressure	-0.303	-0.146	-0.346
Ocean Wind	0.214	0.178	0.339
Local Wind	0.084	0.151	0.137
Napa River Flow	0.441	0.654	4.498

While the MLR model captures much of the variance and resolves high-residual events, there is a tendency to overestimate the residual when there is high creek flow (Figure 10; e.g., late February). This is because the residual does not have a linear relationship with flow, as seen in scatter plots above (Figure 8). We thus used a polynomial model that includes linear and quadratic terms for each factor. In the case of only 2 factors, the equation is:

$$\hat{y}(w,x) = w_0 + w_1x_1 + w_2x_2 + w_3x_1x_2 + w_4x_1^2 + w_5x_2^2$$

So, in this example, the model solves for 5 weights while still using the ordinary-least-square method:

$$z = [x_1, x_2, x_1 x_2, x_1^2, x_2^2]$$

Ultimately, we used a 3rd degree polynomial with 4 input factors, which resulted in a solution with 34 weights. Sensitivity analysis was performed on the order of the polynomial, and we found that a 3rd degree polynomial gives the best fit to the data while avoiding overfitting (model fits training data well but yields poor predictions). In Figure 11 we show the fit of the model (scaled MLR) on the same data using the 3rd degree polynomial relation. The model now resolves the high-flow events much better.

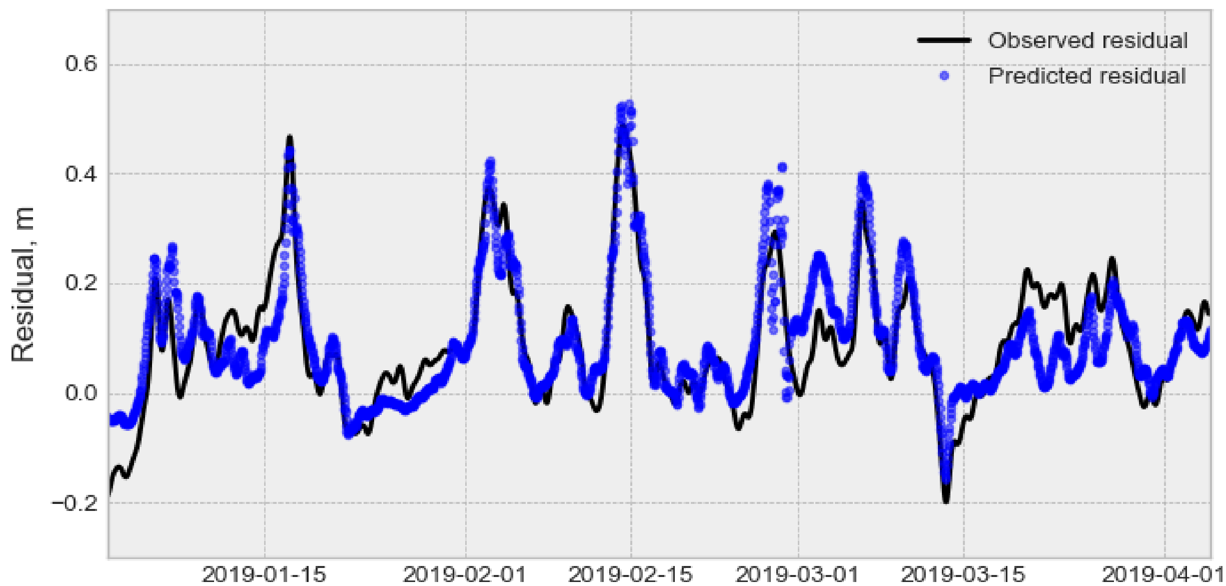

Figure 11. Observed and predicted residuals at Novato Mouth with predictions using a 3rd degree polynomial model.

2.6 Model Forecasts

Once the model is trained, it can be used to forecast water level by inputting predicted values of the four primary factors. Predicted values for input factors were obtained from data sources listed in Table 5.

Table 5. Input Data Sources

Location	Type	Data Sources
NOAA Buoy 46026	Atmospheric Pressure (regional)	https://openweathermap.org/ API
NOAA Buoy 46026	Offshore Wind (ocean setup)	NOAA National Weather Service API https://www.weather.gov/documentation/services-web-api
Gnoss Field	Local Wind (bay setup)	NOAA National Weather Service API https://www.weather.gov/documentation/services-web-api
Napa River	Land runoff (flow rate)	NOAA advanced hydrologic prediction service water.weather.gov/ahps2/hydrograph.php?gage=apcc1&wfo=mtr

The final step in developing a forecast is to correct for the error due to long-term, large-scale influences that are not well resolved by the regression approach. This correction was made using the assumption that the model error tomorrow will be the same as it is today. This is reasonable when the error is slowly varying (Figure 12: see that 12-hour error only occasionally deviates significantly from 7-day error). Here we used the average error over the last 12 hours to correct predictions for tomorrow as well as for days beyond that (the entire forecast period).

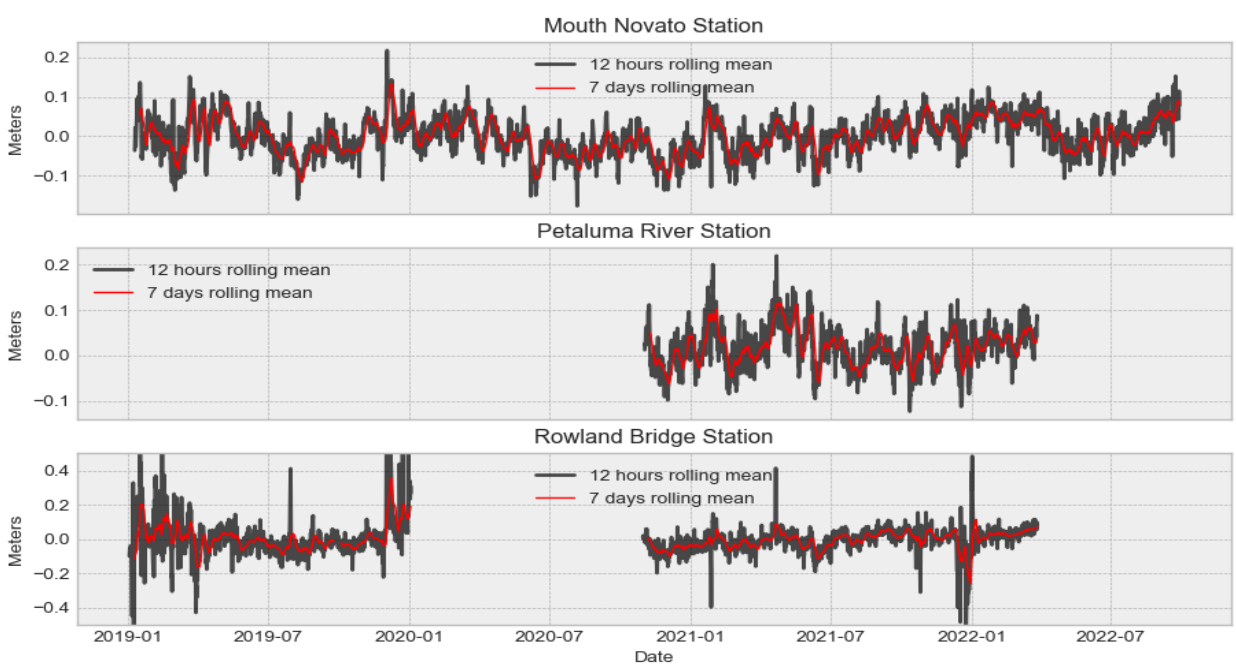

Figure 12. Time-series of the error calculated from observed minus predicted value. Black is the mean error of the previous 12 hours, and red is the mean error of the previous 7 days.

The predicted residual using autoregressive error correction (Figure 13) is significantly improved with respect to prior predictions without error correction (Figure 11). While this correction is very effective in reducing short-term forecast error through accounting for slowly varying effects (weekly to seasonal), it is not useful for long-term forecasts which will need to include additional terms to account for these slowly varying effects (e.g., ocean currents).

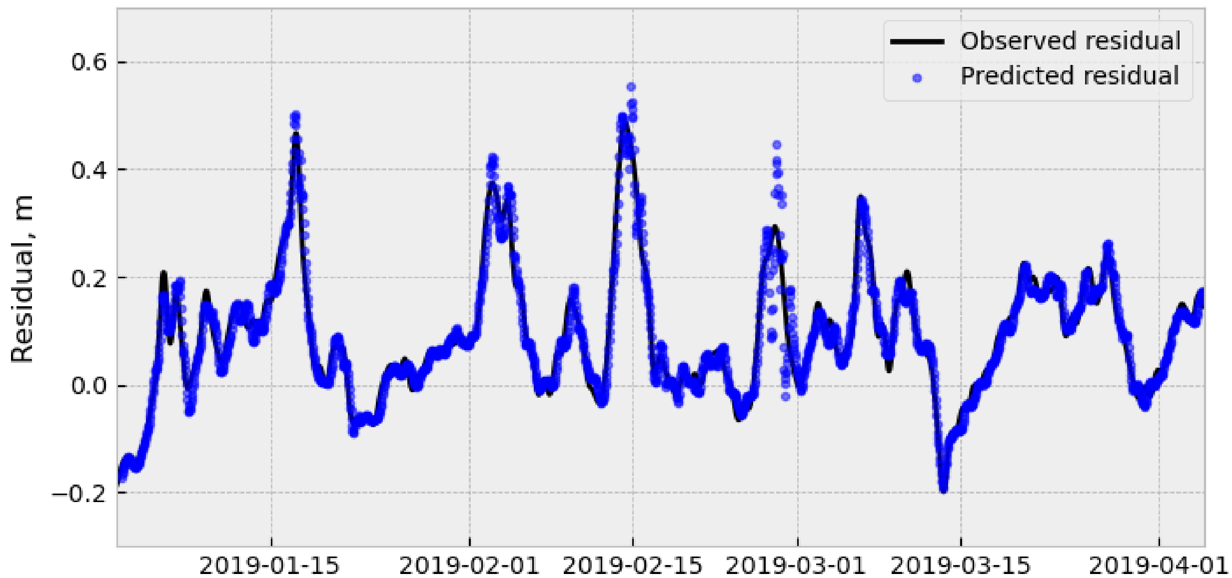

Figure 13. Observed and predicted residuals at Novato Mouth with predictions using a 3rd degree polynomial and including autoregressive error correction.

This autoregressive error correction uses the error from the previous day, which becomes less effective as one predicts forward more days. In predicting water level (tide plus residual) the final error thus increases as one predicts further into the future, with the autoregressive error correction showing no benefit for predictions 3 days or more in the future (Figure 14).

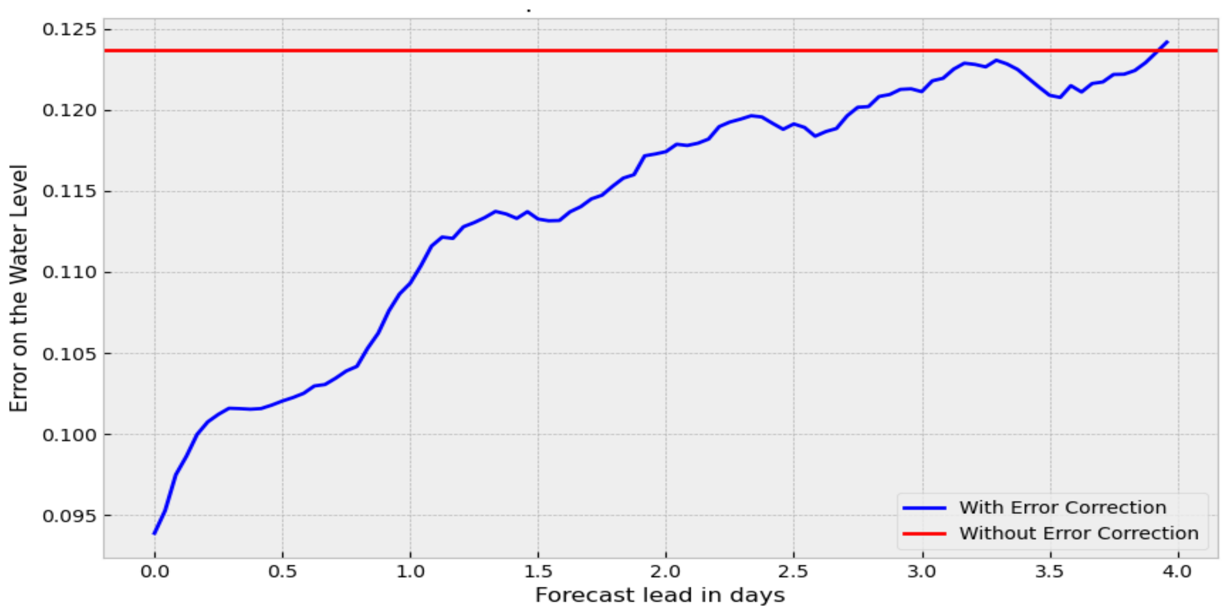

Figure 14. The Novato Mouth water level prediction exhibits a 95-percentile error of 12.4 cm without error correction, but error correction reduces error to less than 10 cm for predictions within a day and shows improved forecasts up to 3 days for this site.

3 Results

3.1 Model Predictions

We used the statistical model outlined above to produce 4-day forecasts of tidal residuals and combined that with tidal predictions to forecast water level at the three project sites: Novato Mouth, Rowland Bridge, and Petaluma River. The workflow illustrated in Figure 4 is executed automatically every 4 hours and the result is displayed on the web platform (as shown in Figure 14) https://coastalocean.ucdavis.edu/ocean-observing/hwy37. The entire model is retrained every 4 hours using all the data available up until that point, learning more every day.

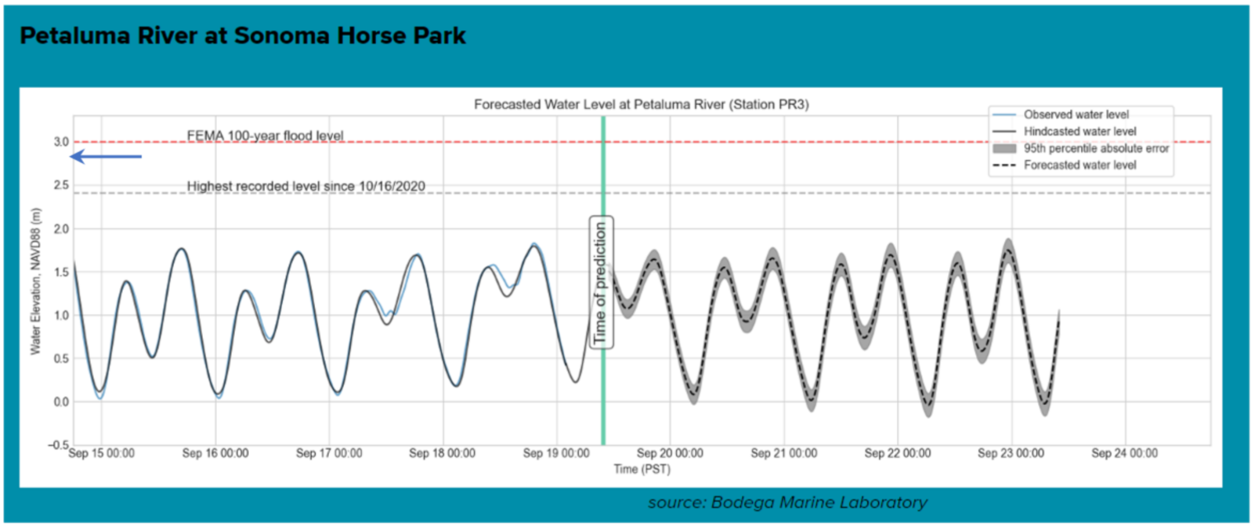

Figure 15. Observed water levels (blue line left of green bar) and predicted water levels (dashed line right of green bar) at Petaluma River site. For days in the past, the 1-day forecast value is also plotted as an illustration of model performance. For days in the future, the 95-percentile error is shaded gray. Horizontal dashed lines represent flood thresholds (Table 6) and the blue arrow represents the elevation of a low point in the levee close to this site (about 2.83 m NAVD88, Figure 2).

Table 6. Reference Water Levels (NAVD88)

	Novato Mouth	Petaluma River	Rowland Bridge
Highest recorded water level	2.42 m	2.54 m	4.13 m
Date of highest recorded level	2/14/2019	1/03/2022	2/14/2019
FEMA 100-Flood	2.99 m	2.99 m	N/A
Lowest point in the levee	N/A	2.83 m	N/A
Estimated Flood Stage	N/A	N/A	4.33 m

An illustration of web-page graphics for Novato Mouth is shown in Figure 16 and for Rowland Bridge in Figure 17. In each plot, the left side represents the past, showing both model predictions (with one-day error correction) and observations. The right side represents the future, showing predicted water levels for the next four days together with a band of uncertainty representing the 95-percentile error, which increases each day into the future. The left-side hindcast gives an idea of the model performance when meteorological and hydrological conditions are known, with peaks generally well estimated and larger errors generally at lower water levels or due to offset in timing of the tidal curve (this occurs because of interactions between residual water level and tidal propagation that is not included in this model which assumes linear superposition of tidal and non-tidal effects). The 95-percentile error estimate for water level predictions assumes perfect input data, thus it does not account for uncertainty in the predicted values for wind, flow, and pressure input data. This uncertainty is typically small for meteorological and hydrological forecasts over time horizons of 4 days or less, but it could be quantified in future collaborative work linking with meteorological and hydrological forecast models.

High-water thresholds are represented on each plot and listed in Table 6:

- For the Novato Mouth and Petaluma River sites, the red dashed line represents the elevation of the 100-year flood as listed in the new FEMA flood map as calculated by AECOM (2016).
- For the Rowland Bridge site, the red dashed line represents the flood stage, based on information from the USGS gauge upstream of this site.
- The gray dashed line is the highest level recorded to data at each station. This is a 2-year record at the new Petaluma River site that started in October 2020 and almost 5 years at Novato Mouth and Rowland Bridge (long enough to include high water extremes and highway flooding in early 2019).
- For the Petaluma River site, we surveyed the elevation of the levee crest (Figure 2) and the low point in this levee is represented by a blue arrow in Figure 15.

The web-based graphic for the Novato Mouth site does not show predictions for water levels below 0.75 m because we did not generate these predictions. The low-water portion of the tidal signal is highly influenced by frictional effects of a shoal offshore of the creek mouth (as discussed above and as evident in observed water levels that are plotted). The tidal analysis did not include these low-water values and predictions would not be well founded. Thus, given the interest in high-water values, the analysis, model, and predictions are only available for water levels above 0.75 m NAVD88 (Figure 16).

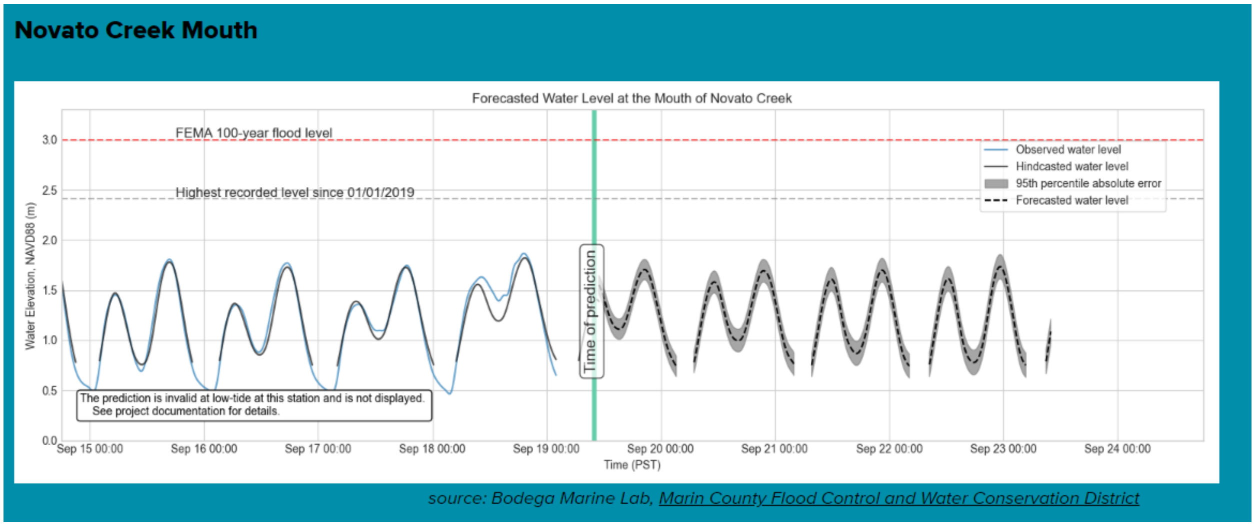

Figure 16. Observed water levels (blue line left of green bar) and predicted water levels (dashed line right of green bar) at Novato Mouth site. For days in the past, the 1-day forecast value is also plotted as an illustration of model performance. For days in the future, the 95-percentile error is shaded gray. Horizontal dashed lines represent flood thresholds (Table 6).

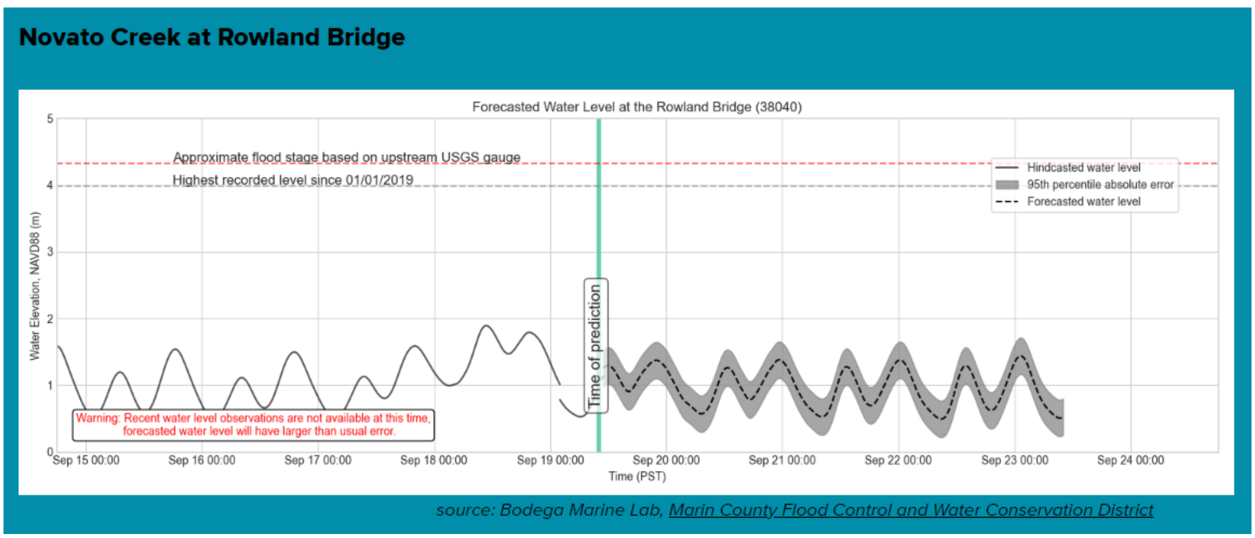

Figure 17. Predicted water levels (dashed line right of green bar) at Rowland Bridge site. For days in the past, the 1-day forecast value is plotted, and for days in the future, the 95-percentile error is shaded gray. At the time of writing the report, no real-time data were available. This contributes to the larger error in forecast data evident at this site. Horizontal dashed lines represent flood thresholds (Table 6).

At the time of writing this report the water-level sensor at the Rowland Bridge was out of service, resulting in the absence of observed values (blue line) in Figure 17. As the model is based on analysis of historical data, it can continue to produce useful predictions. However, in the absence of real-time data, the autoregressive error correction cannot be made and thus the 95-percentile error bar is larger—and will remain so until the real-time sensor comes back online. This section of the creek has levees on both sides and is disconnected from surrounding lands, hence there is no published 100-year flood level. In place of the FEMA level, the flood stage level was estimated from a USGS gauge located on the Creek about a mile upstream of Rowland Bridge (USGS 11459500).

3.2 Model Performance

The performance of the model was evaluated by comparing predicted water levels with observed water levels using historical data. Differences between observed and predicted values can be due to errors in the tidal prediction model, errors in the residual prediction model, errors related to the linear combination of models, or errors in the predicted factors that drive the residual model. Where errors are due to slowly varying effects (like seasonal fluctuations), the autoregressive error correction reduces error over multi-day forecast times, but where errors are due to higher frequency factors the autoregressive correction deteriorates over the time scale of these factors (i.e., over days). The error correction applied is the mean error of the previous 12 hours.

We assess the performance of the tidal residual prediction model developed in this project (Table 7) as well as the performance of the water-level prediction model (Table 8) that combines the residual prediction with tidal prediction and thus includes additional error related to the tidal model and the way in which the two predictions are combined.

Table 7. Performance of model predicting tidal residual with error correction (12-hour forecast).

Metric (meters)	**Novato Mouth**	**Rowland Bridge**	**Petaluma River**
Mean Average Error	0.0122	0.0340	0.0155
Mean Squared Error	0.0030	0.0033	0.0004
Root Mean Squared Error	0.0167	0.0575	0.0206
R2	0.9583	0.9639	0.9439
Maximum Error	0.1864	0.7942	0.1764
99 Percentile Error	0.0516	0.2481	0.0607
95 Percentile Error	0.0324	0.0983	0.0405

Table 8. Performance of model predicting water level with error correction (12-hour forecast).

Metrics (meters)	**Novato Mouth**	**Rowland Bridge**	**Petaluma River**
Mean Average Error	0.0344	0.0967	0.0420
Mean Squared Error	0.0021	0.0201	0.0030
Root Mean Squared Error	0.0462	0.1416	0.0544
R2	0.9730	0.8953	0.9915
Maximum Error	0.4355	1.1760	0.3284
99 Percentile Error	0.1422	0.5214	0.1563
95 Percentile Error	0.0936	0.2718	0.1091

Typical errors are small for the Novato Mouth and Petaluma sites, which are controlled primarily by Bay hydrodynamics (RMS error about 5 cm for water level predictions and about 2 cm for predictions of residual). However, errors are larger at Rowland Bridge, which at times is dominated by fluvial forcing that accounts for very large anomalies in water level (RMS error for water level is 14 cm and 6 cm for the residual). The differences in model performance are evident in scatter plots of predicted daily maximum water level versus observed daily maximum water level (Figure 18). Rowland Bridge scatter is notably greater for higher water levels that occur during rare high-flow events. Over time, as more high-flow events are captured in the water-level data, the model can be expected to improve for these fluvially dominated events and the scatter will narrow (i.e., RMS error will be reduced).

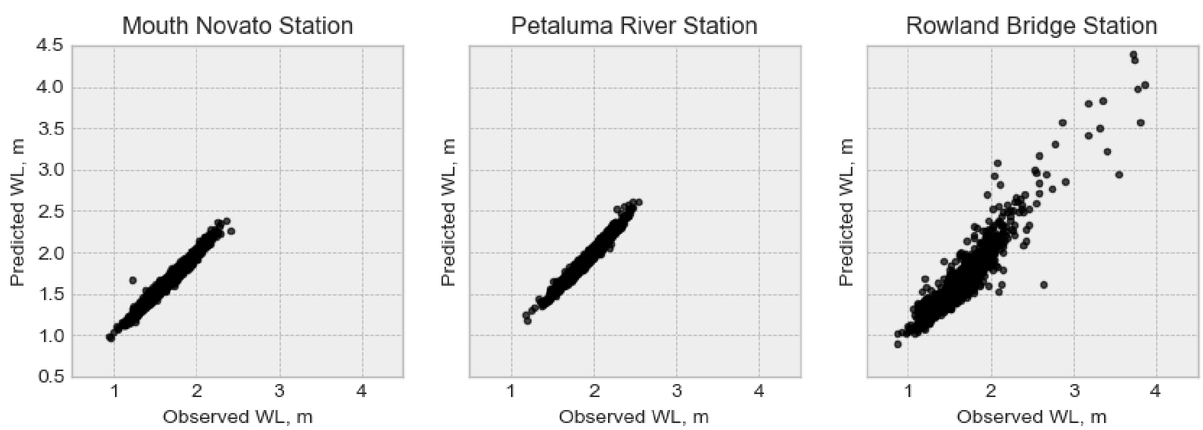

Figure 18. Scatter plot of model-predicted daily maximum water level versus observed daily maximum water level at each of the three sites.

The model generated from just 2 years of data performs well at sites primarily influenced by Bay and ocean factors, with RMS errors less than the error in land surface elevations. Our interest is in predictions of water level maxima, which is plotted in Figure 18, illustrating that predictions correlate well with observed water levels. This performance is also indexed by quantifying 99-percentile or 95-percentile errors (Table 8) for the bay-dominated sites, 99% of predictions are within about 15 cm of the observed value, and 95% are within about 10 cm—uncertainties comparable with or less than the uncertainty in the elevation of levee crests. Further, it is expected that these errors will be reduced as more years of observed water level become available (including more storm events) and as the error in model predictions of wind, atmospheric pressure and river flow are reduced. We obtain meteorological forecasts from NOAA for 3 hours to 4 days in the future, but uncertainties in those forecasts are not shared nor readily available.

In statistical modeling, it is common practice to evaluate the accuracy of the model using an independent set of data that were not used in model training. However, our data record is short and specifically lacks storm events. Clearly the model performs well for periods between storms, but without more data we cannot at this time assess the efficacy of the model in representing the largest future storms. Specifically at the Rowland Bridge site, fluvial effects dominate during runoff events and flood risk may be better represented by traditional river-flood models which already exist for Novato Creek.

To represent uncertainty in forecasted water level in the web-based graphics we have used the 95-percentile error, which increases with increasing time between the time when the model error is estimated and the time for which the forecast is given. For example, a forecast made 3 days ahead will be using the same error correction (the average error of the last 12 hours of observations) as one made one day ahead. However, that correction is less effective as illustrated in Figure 14. To quantify this loss of effectiveness over time, the 95-percentile error was calculated for different forecast horizons (1 day, 2 days, 3 days, and 4 days) and included in web-based graphics (Figure 15, Figure 16, and Figure 17).

3.3 Importance of Individual Forcing Factors

The four primary factors (local wind, ocean wind, river flow, atmospheric pressure) exhibit different influences on the tidal residual and thus on the water level. These relationships are quantified in the model predicting the residual at each site. Here we explore the relationship between an individual forcing parameter and the response in the residual by altering that parameter value while holding the other parameters constant. The range of values for each of the model parameters is summarized in Table 9 and the forcing-response curves are shown in Figure 19.

Table 9. Range of values for each of the model parameters.

Metric	Pressure *mBar*	Ocean SSW wind *m/s*	Local SE wind *m/s*	Napa flow *cfs*
Count	32,256	32,256	32,256	32,256
Mean	1017.4	-1.3	-0.6	120.1
Standard Deviation	4.7	3.3	1.9	656.4
Minimum value	996.2	-11.7	-7.7	0.0
25%	1014.3	-3.5	-1.8	0.0
50%	1017.0	-1.7	-0.4	4.7
75%	1020.4	0.7	0.8	32.5
Maximum value	1035.4	13.5	7.8	16,600.0

In the hypothetical scenario where only one factor is forcing the water level residual, one could estimate the relationship from physical principles. However, there are multiple factors varying in parallel and the statistical model only approximates a physical model because the aim of the statistical model is to account for as much of the variance in the observed water level residual as possible. At all sites the response of the water level residual to atmospheric pressure is close to the theoretical expectation that water level will drop 10 cm for each 10-mBar increase in atmospheric pressure. Likewise, one expects a similar relationship between ocean wind and water level residual at all sites as the effect of ocean wind is to raise the water level in the coastal ocean, which is common for all sites. While this response is similar, about 10 cm increase in water level for 10 m/s onshore wind, the quadratic response at Rowland Bridge is physically more realistic as wind forcing scales with a power between 2 and 3. Local wind exhibits similar relationships. The most complex response in water level residual is related to land runoff indexed by Napa River flow, which is not simply explained by an open-channel discharge curve. For the Novato Creek and Petaluma River sites increasing river flow explains an increase in water level residual up to a limit (3000 cfs at Novato Mouth; 1500 cfs at Petaluma River); however, for larger flow values this relationship changes and greater flows are associated with decreased water level residuals. While this relationship is based on limited flow events (Napa River flows only reach these higher values several times in the model training period), the fact that this statistical model doesn't match physical expectations does not invalidate it as many of the forcing factors are co-varying. During high flow events or immediately preceding it, it is common to also see strong onshore winds locally and over the ocean, as well as low atmospheric pressure (Figure 20)—in other words, all four factors contribute to high values of the water level residual. In addition, there are other compounding phenomena that may become important when water levels are high—for example, it is expected that runoff will spread out as a wider flow when high water levels allow flow to crest high points in the landscape. This may occur at water levels below flooding levels and account for the decrease in the response of water level to increased flow at all three sites. This occurs for flows above 2000, 1000, and 3000 cfs at Novato Mouth, Petaluma, and Rowland Bridge sites, respectively, when water levels are high, and may be related to differences in channel hypsometry at these sites.

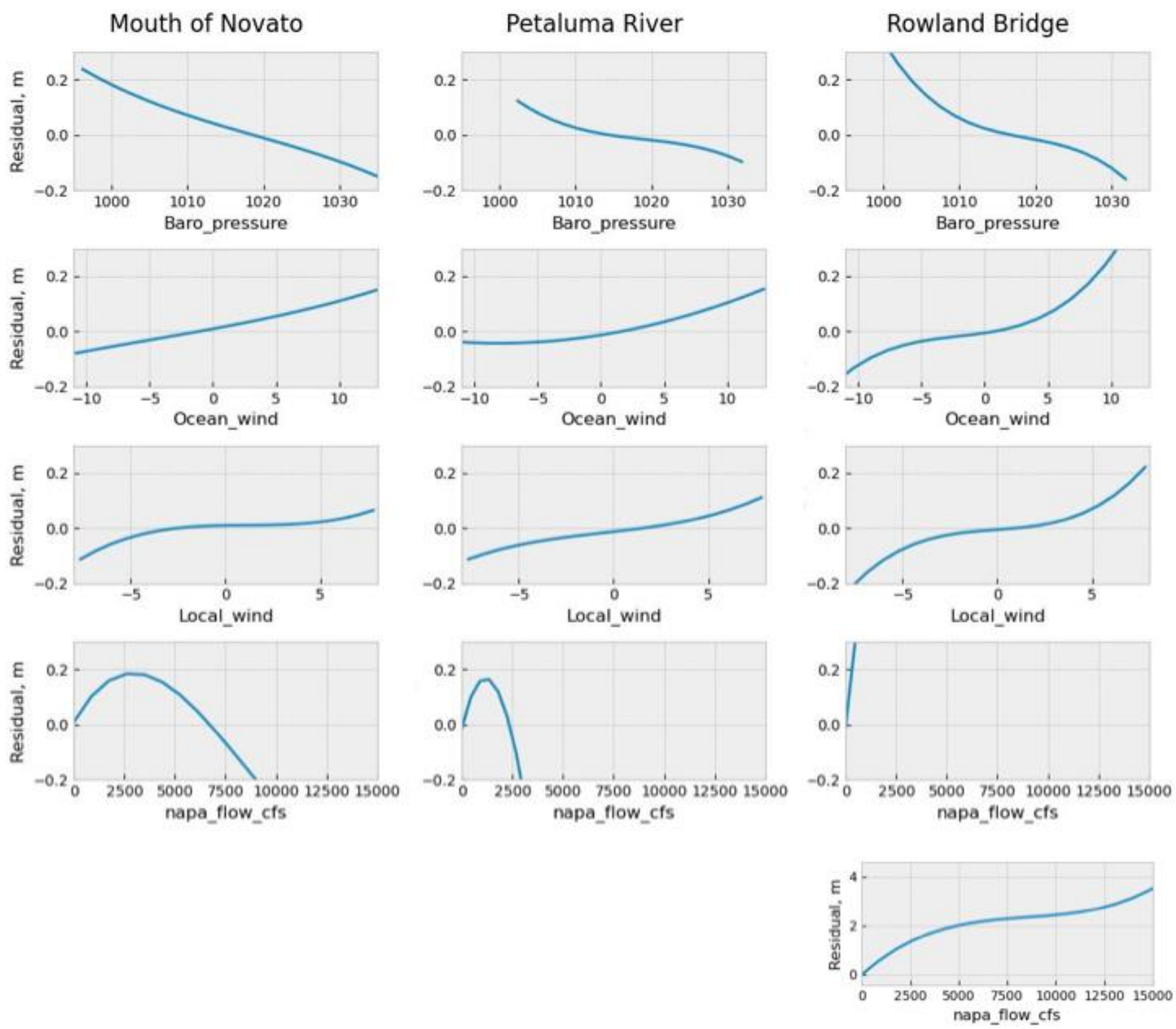

Figure 19. Statistical relationships between each forcing parameter and response in water level residual for each field site: Novato Mouth (left column), Petaluma River (middle column), Rowland Bridge (right column). Parameters are atmospheric pressure (top row), ocean wind (second row), local wind (third row), river flow (fourth row). An additional panel is inserted for the extreme response of water level residual to flow at the Rowland Bridge site (over 3 m).

Further insight into extreme water level residuals is obtained from inspection of individual events, such as those that occurred during the storms in early 2019 (Figure 20). For the largest flow event (27 February), the residual at Novato Mouth is not large as the atmospheric pressure was not very low—however, the residual is indeed the highest at Rowland Bridge where fluvial effects dominate. At Novato Mouth the highest residuals were observed during the 17 January and 14 February storms associated with strong winds and very low pressure, respectively. While our statistical model effectively resolves these peaks in water level residual, only time will allow an assessment of the robustness of this statistical model for a larger number of diverse storm events.

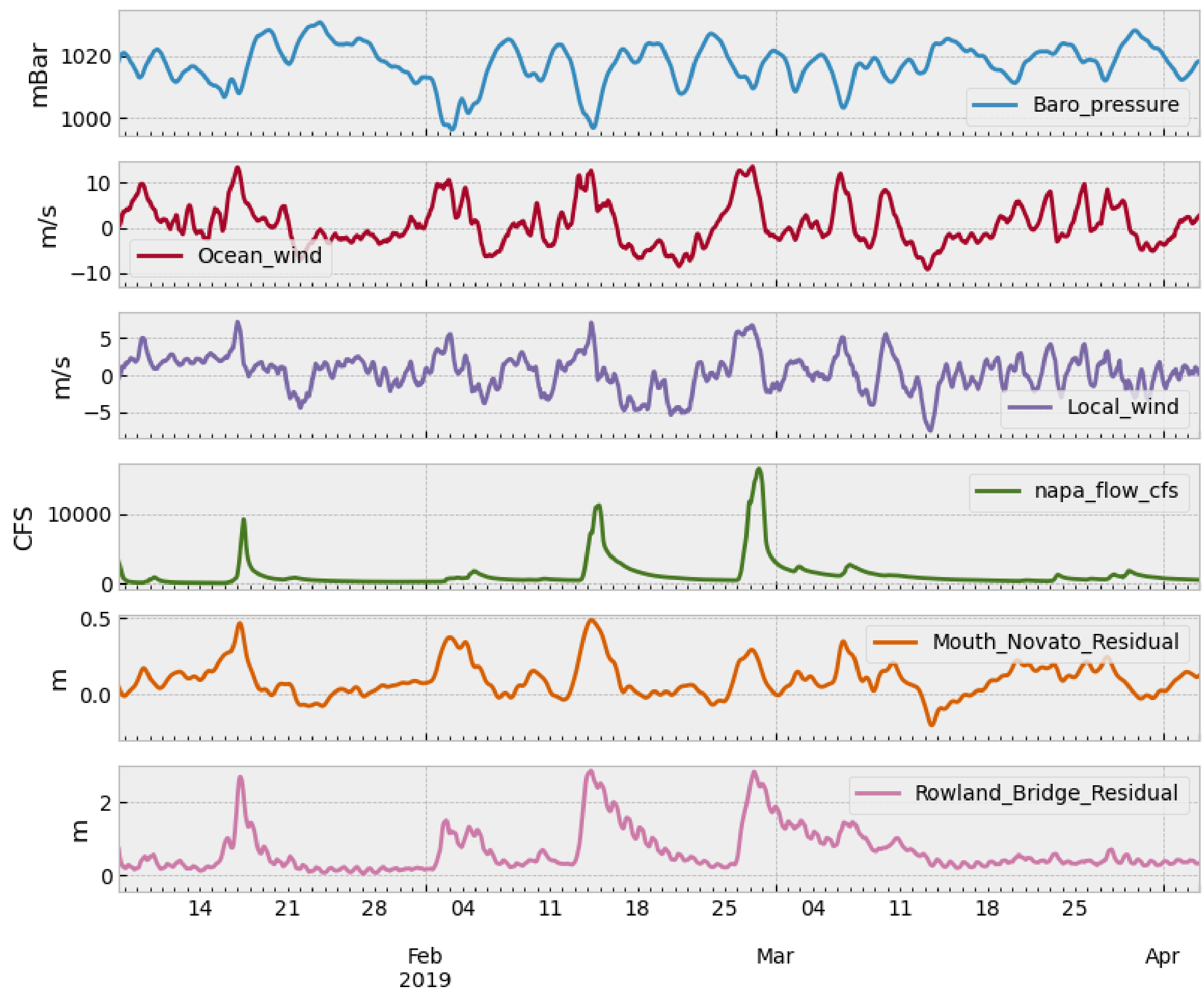

Figure 20. Fluctuations in water level residuals at Novato Mouth and Rowland Bridge during the passage of strong storms through the project area in February and March 2019. Notable storms and high-water-level events occurred on 17 January as well as 2, 14 and 27 February.

3.4 Effects of Sea Level Rise

The focus of this project is on the short-term forecast of water level, motivated by the need for operational information prior to flooding events. These long-term records of observed water level at specific sites also allow quantification of the probability of a threshold being exceeded under contemporary conditions. While the probability of high water levels may change as wind, atmospheric pressure and rain changes with climate change, that is difficult to project because local-scale predictions of wind, pressure and rain are poor. In contrast, the effect of sea-level rise can be assessed more readily because there are reliable long-term forecasts of the rising trend in sea level (NRC 2012; Griggs et al 2017). The primary effect of sea-level rise is to elevate the base level for all other processes, including tides and non-tidal forcing of residuals.

With sea-level rise, the distribution of water levels observed at each site can be expected to shift to higher values by the same amount. While several other sea-level-rise effects may alter this projection (e.g., inducing changes in morphology following Thorne et al 2018, or changes in tidal propagation following Holleman and Stacey 2014), it is expected that the simple elevation of the water-level distribution will be the dominant effect of sea-level rise. Thus, as sea level rises, we expect a greater number of flood events that occur when water levels at exceed critical thresholds, e.g., higher probability that water levels in Novato Creek or Petaluma River will overtop levees, resulting in flooding of Highway-37 and surrounding lands.

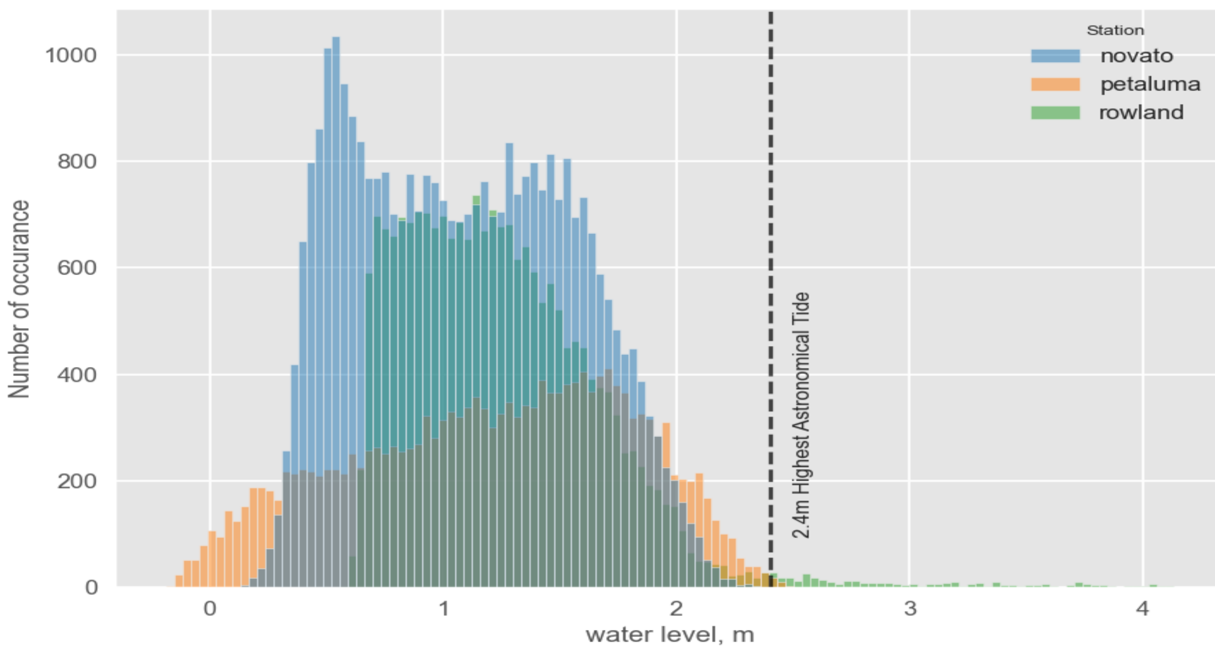

Figure 21. Distribution of hourly observed water level values at the three project sites: Novato Mouth (blue), Petaluma River (orange), and Rowland Bridge (green). The dashed vertical line at 2.4 m demarcates the historical highest astronomical tide for these sites.

The distribution of water levels observed at each site (Figure 21) illustrates differences between sites, e.g., Novato Mouth has a peak at 0.5 m, corresponding to the low-tide asymptote effect, whereas Petaluma River shows the broadest distribution of values (larger tidal range). At all stations, water levels rarely exceed the highest astronomical tide (HAT ~2.4 m NAVD88), which is the highest water level ever expected if residuals were always zero. However, water levels do exceed this occasionally at the Petaluma River site and more often at the Rowland Bridge site where water levels may exceed HAT by a meter or more due to backing up of creek flow.

While this HAT threshold was not exceeded in the five years of data from Novato Mouth, it was exceeded a few times at the Petaluma River site and several times at the Rowland Bridge site (Figure 22). If nothing else changes (i.e., the statistical distributions of water level remain the same), then as sea level rises this threshold will be exceeded more often. It is most marked at Petaluma River where this threshold will be exceeded 12 days each year with 0.25 m sea-level rise (expected within next 20-30 years, Figure 23 and Griggs et al 2017).

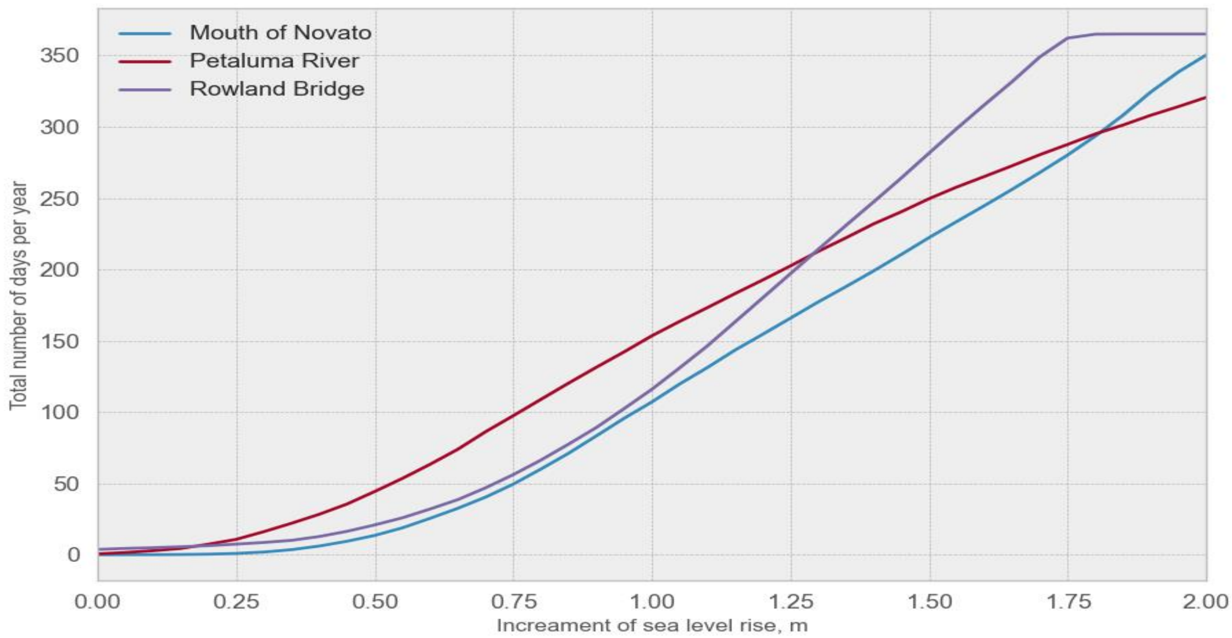

Figure 22. The probability of water level being higher than the present-day HAT threshold increases with a rise in sea level. Probabilities are calculated from observed distributions of water level values at each site (Figure 20).

However, there is little change in the probability of exceedances at Novato Mouth or Rowland Bridge until sea level rises more. With 0.5 m sea-level rise (expected before the year 2100, Figure 23 and Griggs et al 2017), the present-day HAT threshold will be exceeded 45 days each year at the Petaluma River site and 10-20 days a year at Novato Mouth or Rowland Bridge sites.

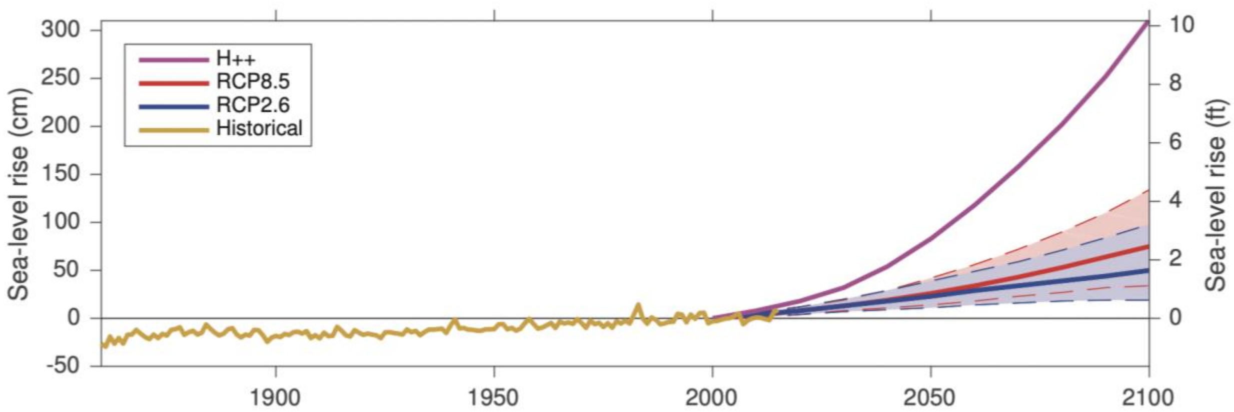

Figure 23. Observations of past and projections of future relative sea level rise for San Francisco, California from Griggs et al (2017).

4 Summary

Predicting coastal flooding days in advance is critical to protecting human life, economic productivity, and low-lying infrastructure—such as Highway-37 that runs across the wetlands along the northern shore of San Francisco Bay. We have developed an empirical model for short-term forecasts of water level at specific sites adjacent to low points in the highway, based on 2-3 years of water level observations at these sites. This demonstrates the feasibility of implementing a site-specific, hyper-local flood prediction and warning system if there are also precise, high-resolution data on low points in the landscape, i.e., water-level thresholds. The same approach can be implemented at multiple sites across the Bay, scaling up to a regional system. While water-level records exist at some sites, it will be necessary to deploy sensors at other priority sites that telemeter data in real-time, which can be done affordably as done here for the Petaluma River site. In addition to delivering operational forecasts of water level extremes, this network would provide real-time data on water levels as they occur at these high-priority sites. This approach provides lead time to transportation and emergency management agencies in planning for protection of people, property, and livelihood.

This data-based forecast system is built on a continuously updated model fed by a stream of new water level data from the field site. In terms of near-term, site-specific forecasts, the accuracy and confidence of these water level predictions outperform any other method (e.g., bay-wide simulation models, e.g., Barnard et al 2014) and model performance will continue to improve as additional years of data are collected. The incremental site-specific cost of this approach is about $2,000 for installation of a water-level sensor, about 5 days for initial model training and to develop site-specific forecasts and, following that, about 5 days per annum for visiting the site and monitoring/updating model output for the site. Even including many sites and core operations, the cost of such a system is dwarfed by the future cost of flood damages that can be pre-empted or mitigated (Hanak et al 2011; PPIC 2017 brief). Further, this model is built on open-source and publicly available software, facilitating implementation not only across San Francisco Bay but also in other bays.

In this project we developed the model and a 4-day forecast tool for two sites on Novato Creek and one on Petaluma River—sites that are critical for anticipating flooding of State Highway 37 and low-lying lands in the vicinity of Novato, California. The approach works well for sites dominated by bay hydrodynamic processes (i.e., Petaluma River and Novato Mouth), where errors are typically less than 10 cm (~4 inches). The approach does not work as well for sites at the head of the tide, where fluvial hydrodynamics dominate during high-flow events that are poorly predicted (i.e., Rowland Bridge). At all sites, the forecast error will be reduced as meteorological and hydrological forecasts improve and error is reduced in predictions for winds, atmospheric pressure, and rain as well as creek flow and stage.

This report serves as a reference document for the web-based prediction tool and for developing a dialog with stakeholders and first responders in the region. It is expected that feedback from this will allow tailoring of model predictions and development of longer-term prognoses for this region. While short-term forecasts are more deterministic, decadal projections are necessarily probabilistic and rely on projections of changes in non-tidal forcing under climate change. Over the 2 to 3-year period for which water level data are available at the three project sites, each of the non-tidal factors accounts for residuals with a range of about ¾ m (Figure 17), which is about 10% of spring tide range. With more extreme winds, pressure or runoff, these non-tidal residuals may be larger. Further, over time there is a growing prospect that these factors will align perfectly at a specific site, yielding an unprecedented non-tidal residual. Given that the highest water levels observed over the 2 to 3-year project were within ½ m of 100-year FEMA levels at Petaluma and Novato Mouth sites and within ¼ m of USGS-estimated flood stage at Rowland Bridge, there is significant likelihood of a flood occurring under present-day sea levels and increasing likelihood of a flood as the mean sea level rises (Figure 21).

5 Future Directions and Needs

Our successful demonstration of near-term, site-specific forecasts of water level has been implemented at three sites and it is immediately useful there. Looking forward, there are several pathways, each yielding additional value:

- Apply to diverse sites, to test or confirm the broad applicability of the approach.
- Implement at multiple sites, developing a network.
- Work with stakeholders and users of forecasts to fine tune available information.
- Combine water level forecasts with high-precision elevation data for flood warnings.
- Explore synergy between this site-specific model and bay-scale simulation models.
- Leverage site-specific insight to improve climate-change projections.

In this project, high-quality forecasts have been demonstrated for Petaluma River and outer Novato Creek. By implementing at other sites, the general applicability of this model can be tested. It is expected that it will perform well in sheltered waters (i.e., not exposed to high wave energy) and at sites that are not dominated by fluvial during high-flow events. The skill of this approach also rests on the availability of high-confidence, high-precision predictions for wind, pressure and runoff proximal to each site. These input predictions can be expected to improve over future years if ongoing data collection is prioritized as an essential part of the prediction model and warning system.

The primary value of this method is to obtain water level predictions at high-priority sites, i.e., low-lying infrastructure vulnerable to flooding. However, a network of sites may offer additional benefits, including the ability to track flood risk at multiple vulnerable sites at the same time. This is specifically valuable for transportation networks where flood risk at one location interacts with flood risk at another location. In the event of road closures, it will be invaluable to have real-time water level data as well as near-term forecasts of imminent flooding and closure of an alternate route. This would help local/state managers and officials to respond in a timely manner to flood impacts—and it would provide advance warning of sudden catastrophic flooding that could overwhelm local resources, requiring evacuation.

Going forward, the value of this model will be enhanced by dialog with stakeholders and specifically with people who will directly use model output. There are many ways model output can be delivered, in real-time or aggregate form as well as through retrospective assessment. Through dialog with stakeholders high-value indices can be identified and evaluated. And additional sites can be implemented affordably at new critical locations. However, as stakeholder interest can wax and wane with hydrological cycles, this dialog may not get immediate stakeholder interest and it would benefit from ongoing attention from local and regional government.

Building on the above, a critical challenge is to leverage this site-specific water level forecast into a flooding forecast and early warning system. Forecast of flooding requires high-precision data on the elevation of low points in the landscape, both infrastructure that can be flooded and flooding routes past levees and embankments. For example, while a low point in the levee near the Petaluma River site is within a foot of the water level maximum observed since 2020, the precise elevation is not well known and there are few data on other low points and flood routes through which water would flow from the bay to flood low-lying land and infrastructure. A precise digital elevation model is needed to predict how water will flow from the bay into these low-lying areas.

This site-specific, statistical approach yields information that is different to that provided by bay-wide simulation models like CoSMoS (Barnard et al 2014). These two approaches are complementary both in the information provided as well as in the cross-model comparisons that will lead to improvements in each approach. By combining approaches, improved short-term forecasts and long-term projections can be provided.

While the strength of this statistical model is in providing water level forecasts at specific sites and during specific events, it also has promise in improving projections of water level at longer time scales relevant to climate change and sea-level rise. The data analysis underlying this model provides insight to the hydrodynamic processes that account for water level extremes at specific sites. Not only can these data and understanding of processes be used to improved climate-change projections from bay-wide simulation models, but it can be used to analyze the potential interaction of processes that will likely become more non-linear as sea level rises (e.g., Holleman and Stacey 2015). The probability of extreme water levels depends most strongly on mean sea level (e.g., Figure 22), but it also depends on the probability of extreme winds, pressure, and runoff. A key question in the probability of non-tidal extremes is the likelihood that extreme wind, pressure, and runoff effects occur at the same time. Given the association of each with winter storms, these statistical distributions are not independent, and the probability of concurrent extremes is higher than one would expect from independence. Meteorological analyses can shed light on the likelihood of concurrence and how this may change with climate change (as well as across diverse sites in one bay).

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Data Summary

Products of Research

The primary dataset consists of the three water-level sites (both observations and predictions) and time series of the four parameters that are used to train the model. This includes hourly observed meteorological data such as wind, atmospheric pressure, and flow for the period of 2019-01-01 to 2022-09-27. The dataset consists of four fields: Ocean Wind, Local Wind, Atmospheric Pressure and River flow. The raw data were collected from publicly available sources as outlined on the DRYAD site (https://doi.org/10.25338/B8WS8H). The data was downloaded and resampled to hourly time intervals. Small data gaps were filled by linear interpolation. The wind data were transformed from a polar coordinate system of wind speed and direction to principal component x-y vectors. The principal components were oriented so that the alongshore (y-component) is oriented at 60 degrees North for the wind at Gnoss Field and 100 degrees north for the wind at the NDBC buoy. The listed onshore wind is the shore-normal component for each location.

Data Format and Content

Data format and type are described in detail on DRYAD site https://doi.org/10.25338/B8WS8H

Data Access and Sharing

Operational data are shown in real-time on the water level forecast website https://coastalocean.ucdavis.edu/ocean-observing/hwy37 and the primary access to data files is via the DRYAD site.

Reuse and Redistribution

Data are available for download, but we request that users of these data keep us informed of their use and we caution against widespread use of the forecast data until we have had the chance to submit a manuscript outlining the model to a peer-reviewed journal.

General public can access water level observations and predictions at the public website https://coastalocean.ucdavis.edu/ocean-observing/hwy37