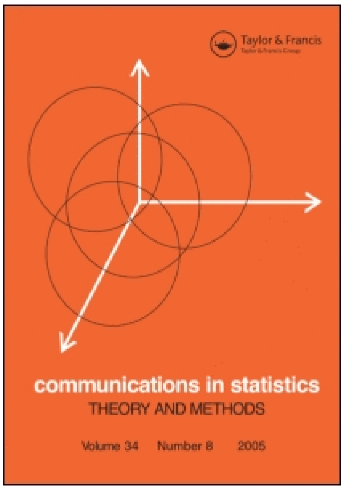

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Analysis of tidal data and datums: accessible examples of harmonic modeling with autocorrelation and imputation

F. Michael Speed [a]; William B. Smith [a]; Rong Chen [a]; F. Michael Speed Jr [a]
[a] Department of Statistics, Texas A & M University, Texas

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Analysis of Tidal Data and Datums: Accessible Examples of Harmonic Modeling with Autocorrelation and Imputation

F. Michael Speed, William B. Smith, Rong Chen,
and F. Michael Speed Jr.
Department of Statistics
Texas A&M University
College Station, Texas 77843-3143

Key Words: *Harmonic analysis, autocorrelation, imputation, water levels*

ABSTRACT

Tidal data have been deemed to serve many important purposes, including establishing maritime boundaries, dredging sites, and navigation. Recently, even some building codes are dependent upon these data. We explore the efficacy of using harmonic analysis to model changes in water levels both in ocean and in protected sea environments. Typically, these data are correlated and have 'not-completely at random' missing observations. Our new analyses account for the presence of autocorrelation and missingness.

1. INTRODUCTION

Most governmental jurisdictions have defined coastal boundaries in terms of water level, tide-gauge data based upon some average of daily water-level readings. These water-level data use mean water levels derived from a theory of homogeneous or astronomical tides (Schureman, 1988). However, tides in estuaries and bays are not homogeneous, often having both meteorological as well as seasonal components. Understanding the forces that produce changes in water levels in coastal waters is essential to proper application of datums; such as mean higher high water, mean low water etc. Thus, a procedure for determining marine boundaries based upon mean water-level data using homogenous tides is without solid foundation and produces results that are not physically sensible in the situation where the periodic changes in water levels may be caused by other variables, not strictly on "astronomical" tides. Inappropriate definition of extreme mean waters impacts legal boundary definition and regulatory jurisdiction for environmental permitting, as well as various legal, engineering, and scientific topics (Kenedy v Texas, 1993).

This paper reports on data analysis for water level measuring stations (tide gauges) that are located both on the east and west coasts of the United States, as well as on the Gulf of Mexico coast and in the inland waters of Texas. See Section 2.3 for the data source. The analyses included traditional harmonic analysis, harmonic analysis adjusted for autocorrelation, and time series methods for imputing missing observations.

Harmonic analysis for Mean Higher High Water (MHHW) and Mean High Water (MHW) was developed for coastal areas that had primarily deterministic type changes in water level and had a significant daily change in water level (one or two high tides a day). Our analyses will show that there are areas where the water levels do not follow the deterministic model, and thus the use of MHHW and MHW does not any practical physical meaning

2. METHODOLOGY

The underlying variable is a reported tide level as measured by water level gages. We note, in passing, that these measurements generally under-report the true height to the water. As an example, Fig. 1 shows how the *reported* water level

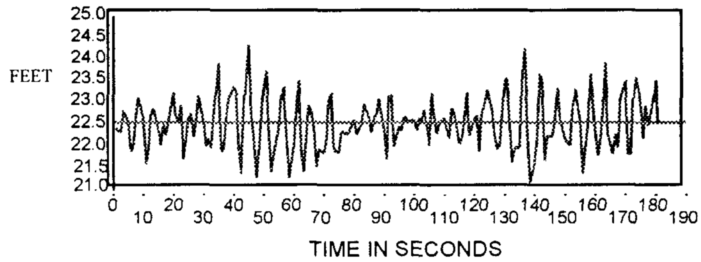

Figure 1 Typical Tide Gage Measures

(the solid line) underestimates the actual level of the water. The National Ocean Service (NOAA) advocates using an acoustical gage to measure water levels on six minute intervals. The reported measurement is the mean of 181 observations taken approximately 1 second apart. The reported readings are damped both mechanically and statistically, eliminating most short frequency waves and underestimating the true height of the water. The appropriateness of using this damped reading will depend upon its ultimate use.

However, in paper, we will analyze these damped water level measurements.

2.1 Harmonic Analysis of Water Level Data

The classical equation for analyzing tidal data that are recorded at a single measuring station is the deterministic harmonic analysis:

$$h(t) = h_o + \sum_{i=1}^{p} \{a_i \sin(s_i * t_i) + b_i \cos(s_i * t)\} \tag{1}$$

where *h(t)* is the water height (level in feet) at time t, h_o is mean sea level, $\sqrt{a_i^2 + b_i^2}$ is the amplitude of the ith harmonic constituent, and s_i is the speed of the ith harmonic constituent.

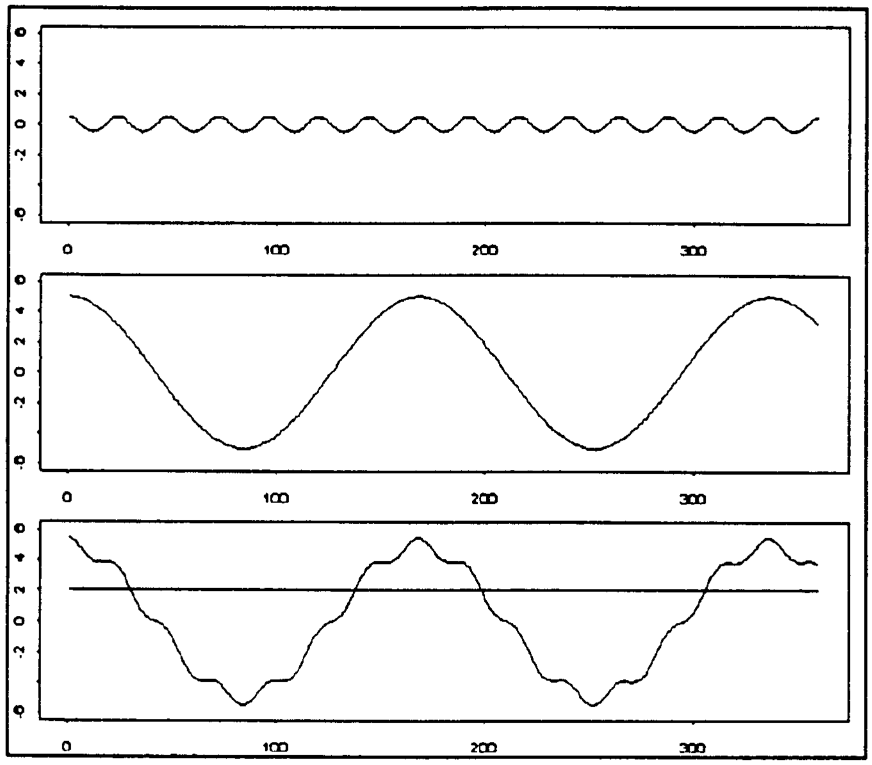

Figure 2 Theoretical Tidal Constituents and MHHW.

In the United States, p=3 pre-defined constituents of various known astronomical cycle lengths are used for equation (1) (Cole(1997)). See Table5. Some of the constituents (Sa, Ssa) are based upon long term periodicity and some are based upon short term periodicity (O1,M1,K1 etc). Figure 2. illustrates the concept of Harmonic Analysis (Cole (1997)). The top inset corresponds to a daily tidal cycle, the middle inset to a fortnightly tidal cycle, and the bottom inset is the sum of the two cycles. The straight line represents Mean Higher High Water (MHHW) illustrating the idea that these data under-estimate the true reach of the water.

In statistical reality, the harmonic model of equation (1) is stochastic. Including an error term, a regression model may be written as

$$\mathbf{Y} = \mathbf{Z}\,\beta + \varepsilon \tag{2}$$

where $\mathbf{Y} = (h(t))$, $h(t)$ being the water height at epoch t, $\mathbf{Z}$ represents the sines and cosines of the various harmonic (astronomical) gravitational forces at epoch t, β is the matrix of amplitude coefficients, and ε is the n-vector of errors. By using ordinary least squares (OLS), one can estimate the amplitudes associated with the constituents and draw inferences upon which constituents contribute the most to the variation of the water levels. Amplitude estimates close to zero relative to their variation indicate little or no contribution; those much greater than zero indicate some contribution.

Fitting equation (2) by ordinary least squares (OLS) methods ignores the autocorrelations between the elements of Y, but this use has been the traditional method of analyses of tidal data (NOAA (1995)). Absent of non-astronomical factors such as seasonality, prevailing wind direction and weather phenomena in the watershed area, the astronomical factors are known as the *structural portion* of the model.

The autocorrelation evident in water heights may be accounted for by using Yule-Walker equations on the residuals that remain from fitting the structural portion of the model (2). Ignoring the autocorrelations may produce different estimates of the structural relationship. Also, when prediction is the goal, then inclusion of the autoregressive approach is necessary.

As accessible examples of the effectiveness and necessity of accounting for the autocorrelations, we have chosen to report on modeling water level gauging stations of three types, namely, open ocean stations (such as Los Angeles, Boston, and San Fernandina, Florida), sampling locations in more protected bodies in the Gulf of Mexico (Galveston, Texas), and measurements from waters that are inland from barrier islands (known as Laguna Madre, Texas). Table 1 reports the results for 1992 measurements.

TABLE 1

1992 ANALYSES							
		STATIONS					
	Period	Open Ocean	Outer Stations			Inner	
Constituent	Days	Los Angeles	Galveston	B Hall	Port Isabel	Rincon	El Toro
SA	364.960						
SSA	182.700						
Mm	27.550						
MSF	14.770						
Mf	13.660						
2Q1	1.167			ns		ns	ns
Q1	1.120						ns
RHO1	1.113					ns	ns
O1	1.076						
M1	1.035					ns	ns
P1	1.003						
S1	1.000						
K1	0.997						
J1	0.962					ns	ns
OO1	0.929		ns			ns	ns
2N2	0.538		ns	ns		ns	ns
Nu2	0.536		ns		ns	ns	ns
MU2	0.536			ns	ns	ns	ns
N2	0.527					ns	ns
M2	0.518					ns	ns
LAM2	0.509		ns	ns	ns	ns	ns
L2	0.508		ns	ns	ns	ns	ns
T2	0.501		ns	ns	ns		ns
S2	0.500					ns	ns
R2	0.499		ns	ns	ns		ns
K2	0.499		ns	ns	ns	ns	ns
2Sm2	0.484	Ns	ns	ns	ns	ns	ns
2MK3	0.349	Ns	ns	ns	ns	ns	ns
M3	0.345		ns	ns	ns	ns	ns
MK3	0.341	Ns	ns	ns	ns	ns	ns
MN4	0.261	Ns	ns	ns	ns	ns	ns
M4	0.259				ns	ns	ns
MS4	0.254	Ns	ns	ns	ns	ns	ns
S4	0.250	Ns	ns	ns	ns	ns	ns
M6	0.173	Ns	ns	ns	ns	ns	ns
S6	0.167	Ns	ns	ns	ns	ns	ns
M8	0.091	Ns	ns			ns	ns
OLS R2		0.999	0.695	0.766	0.789	0.254	0.422
Lag12 R2 (Y-W)		0.995	0.839	0.905	0.916	0.424	0.872

2.2 Summary

The structural model (i.e., classical harmonic analysis) fits the water level data extremely and uniformly well for open ocean stations, supporting NOAA's use of a tide predictor machine (now algorithm) at these stations. However, equation (1) fits the Gulf of Mexico stations less well, leaving unexplained a substantial portion of water height variation. In addition, the use of only the structural portion/harmonic analysis fails on water heights measured inland of barrier islands. Only when the autocorrelations are included, does the model become adequate for estuarial stations.

The failure to adequately fit the estuarial stations without accounting for autocorrelation indicates that other influential, but unmeasured, variables are acting on the bodies of water. The other variables may include meteorological phenomena at the station (e.g., wind direction and intensity, barometric pressure). In these cases, the use of tidal datums based on equation (1) alone is not appropriate. We will discuss this in more detail later.

2.3 Large Data Sets

We note here that these large data sets (n = 8760) are readily accessible over the WEB. The URLs are: http://www.opsd.nos.noaa.gov/data_res.html or http://tcoon.cbi.tamucc.edu/pquery. These data sets can be used in a variety of statistics classes to illustrate a number of statistical concepts.

3. Imputation

In this part of the paper, we describe two methods that are used for predicting missing observations in water level series observed at 7 monitoring stations along Texas coast. The stations Bob Hall Pier (BOB), Galveston (GAL) and Port Isabel (PTI) are classified as outer stations and the stations El Toro (ELT), Port Mansfield (PTM), Rincon Del San Jose (RIN) and Yarborough Pass (YAR) as inner stations. For detailed information of the monitoring stations and the data set, see Hart, Newton and Speed (1996). The station location plays an important role in modeling and prediction as the inner stations and outer stations have different geological features and water level changes behave quite differently. In fact, we will show empirically that the proposed prediction methods work differently for the two groups.

The first method we discuss (Section 3.1) is a standard prediction method for predicting the missing observation in univariate time series analysis. Some references can be found in Box and Jenkins (1976), Newton (1988) and Pourahmadi (1989).

The second method introduced (Section 3.2) is designed for geographic time series where related time series are observed over a network of monitoring stations in the same period. If those time series are correlated, it may be helpful to use the information from the other stations to improve the prediction of missing observations from one station. The approach we used here is a modified version of an approach first proposed in Carroll et al (1996).

In Section 3.3 we present some testing results to demonstrate and compare the performance of the procedures. A brief summary is also provided for some partial explanation of the testing results.

3.1 Method One: Univariate Time Series Missing Data Prediction

Hart, Newton and Speed (1996) have shown that the water level series can be adequately modeled using a harmonic regression model with autoregressive error (equation (2)). The error e_t is assumed to follow a Gaussian autoregressive (AR) model

$$e_t = \phi_1 e_{t-1} + \phi_2 e_{t-2} + \cdots + \phi_q e_{t-q} + \varepsilon_t \tag{3}$$

where ε_t are Gaussian white noise, the order q is to be determined by certain model selection criterion such as AICC. For detail discussion of the above model, see Hart, Newton and Speed (1996).

Here, we discuss a standard method to find the least square prediction of the missing observations based on the above model. Let T be the set of time index at which h(t) is observed. The following steps are used:

Step 1: Fit the harmonic regression with time series error model (3) using the series with missing data. The autoregressive order is determined by AICC and the coefficients of the models are estimated by ignoring all of the missing observations.
Step 2: Using the estimated harmonic regression model in step 1, we obtain the residual series

$$e_t = h(t) - \hat{h}_o - \sum_{i=1}^{p} \{\hat{a}_i \sin(s_i * t_i) + \hat{b}_i \cos(s_i * t)\} \quad (4)$$

for all the t that h(t) are observed.
Step 3: Treating the estimated coefficients of a_i and b_i as true and the observed estimated e_t as true, we use the estimated ϕ_i from Step 1 and the observed residual series $\hat{e}_t$ to predict e_t at missing time periods. Specifically, if h(t*) is missing, the least squares prediction of e_{t^*} is :

$$E[e_{t^*} \mid e_t, t \in T] = E[e_t \mid e_t, t \in T(t^*)] \quad (5)$$

where T(t*) is the set of time indices of the p nearest observed observation before t* and the p nearest observed observation after t*. The above equation is due to the Markov property of the AR(p) process. Under Gaussian assumption, the conditional expectation on the right hand side is a linear combination of the arguments in the condition and the coefficients can be obtained using the estimated AR coefficient ϕ_i from Step 1. Then the prediction of h(t*) can be obtained by combining the prediction of e_{t^*} and the estimated structural trend.

3.2 Method Two: Geographic Time Series Missing Data Prediction

In this section we describe a method that uses observations from a geometric time series to predict a missing observation. The following assumptions are made.

1. The univariate time series h(t,i) observed at the ith monitoring station has a structural harmonic trend

$$h(t,i)) = h_{i,o} + \sum_{j=1}^{p} \{a_{i,j} \sin(s_j * t) + b_{i,j} \cos(s_j * t)\} + e_{i,t} \tag{6}$$

Note that the coefficients for each monitoring stations are different.

2. Let

$$e_{i,t} = h(i,t) - h_{i,o} - \sum_{j=1}^{p} \{a_{i,j} \sin(s_j * t) + b_{i,j} \cos(s_j * t)\} \tag{7}$$

We assume the errors $e_{i,t}$ from different stations form a finite order multivariate autoregressive Gaussian process.

3. Although the error process is correlated, we will estimate the coefficients in the harmonic trend assuming the errors are independent. We do this for the only imputation process. This is partially justified since the least square estimator is consistent, even the true errors are correlated, and that the sample size is large in our case (8760 per year). In addition, we will treat the estimated coefficients as true when we form the Gaussian error process and when we predict the missing observation.

4. We will not model the Gaussian process. Instead, for simplicity, we will use the sample correlation in our prediction procedure.

Under the above assumptions, the following steps are carried out to predict a missing observation. Let T_i be the set of time indices of observed data in ith station.

Step 1: For each monitoring stations, estimate the coefficients in the harmonic trend using the method of least squares, assuming the errors are independent.

Step 2: For each station i, using the estimated harmonic regression model in step 1,

$$\hat{e}_{i,t} = h(i,t) - \hat{h}_{i,o} - \sum_{j=1}^{p} \{\hat{a}_{i,j} \sin(s_j * t) + \hat{b}_{i,j} \cos(s_j * t)\} \tag{8}$$

for all the t that h(i,t) are observed.

Step 3: Estimate the autocorrelation and cross correlation of the Gaussian process $e_{i,t}$.

Step 4: Select the maximum lag p to be used in prediction procedure. This corresponds to the AR order for the Gaussian process.

Step 5: Predict each missing observation. Specifically, if h(i*,t*) is missing, we predict e_{i^*,t^*} using

$$E[e_{i^*,t^*} \mid e_{i,t}, i = 1, \cdots d, t \in T_i] = E[e_{i^*,t^*} \mid e_{i,t}, (i,t) \in T_i(t^*), i = 1, \cdots d] \tag{9}$$

where $T_i(t^*)$ is the set of time indices of the p nearest observed observation before t* and the p nearest observed observation after t* in ith station. The above equation is due to the Markov property of the AR(p) process. The conditional expectation on the right hand side is a linear combination of the arguments in the conditional and the coefficients can be obtained from the sample autocorrelation and cross-correlation obtained in step 4.

3.3 Results

Several tests were conducted to ensure the quality of the procedure and to investigate the properties of the procedures.

3.3.1 The performance of univariate time series prediction

The 1994 series from the seven stations are used to test the performance of the procedure using univariate time series setting. Segments of different length (5, 10, 15, ... 95) are first removed at different starting locations (150, 200, 250, ... 5100). Then the univariate time series prediction method described in Section 3.1 is used to predict those segments. he autoregressive order used is five. The prediction is then compared with the true value and the MSE for each missing length are computed and presented in Table 2.

3.3.2 The performance of geographic time series prediction

Again, the 1994 series are used to test the performance of prediction using

Table 2

MSE's For The Univariate Procedure

	Outer Stations			Inner Stations			
Length	BOB	GAL	PTI	ELT	PTM	RIN	YAR
5	0.0085	0.0247	0.0035	0.0024	0.0024	0.0049	0.0033
10	0.0173	0.0334	0.0058	0.0035	0.0038	0.0109	0.0067
15	0.0198	0.0365	0.0070	0.0048	0.0044	0.0147	0.0081
20	0.0223	0.0442	0.0108	0.0059	0.0062	0.0230	0.0129
25	0.0244	0.0492	0.0115	0.0060	0.0073	0.0265	0.0142
30	0.0268	0.0562	0.0137	0.0062	0.0071	0.0328	0.0145
35	0.0291	0.0620	0.0164	0.0078	0.0069	0.0404	0.0163
40	0.0301	0.0698	0.0198	0.0085	0.0099	0.0513	0.0209
45	0.0331	0.0801	0.0225	0.0104	0.0085	0.0644	0.0217
50	0.0362	0.1010	0.0257	0.0112	0.0105	0.0623	0.0226
55	0.0367	0.0942	0.0260	0.0118	0.0108	0.0687	0.0244
60	0.0411	0.0966	0.0287	0.0129	0.0126	0.0809	0.0276
65	0.0398	0.1003	0.0297	0.0133	0.0112	0.0814	0.0282
70	0.0423	0.1023	0.0312	0.0138	0.0128	0.0833	0.0325
75	0.0452	0.1066	0.0314	0.0140	0.0134	0.0840	0.0355
80	0.0476	0.1064	0.0315	0.0134	0.0130	0.0850	0.0356
85	0.0482	0.1117	0.0324	0.0137	0.0135	0.0832	0.0345
90	0.0480	0.1115	0.0339	0.0137	0.0168	0.0842	0.0370
95	0.0485	0.1121	0.0342	0.0149	0.0148	0.0881	0.0346

the geographic time series setting. Since the inner stations and outer stations behave differently, we group the stations accordingly and use only the stations within each group to help prediction. Specifically, if a missing observation of an inner station is to be predicted, only the series from the four inner stations are used in the prediction procedure.

For each of the stations, segments of different length (5, 10, 15, ... 95) are first removed at different starting locations (150, 200, 250, ... 5100) while the other stations within the group unchanged (no missing observation). Then the geographic time series prediction procedure described in Section 3.2 is used to predict those segments within the group. The autoregressive order used is five.

Table 3

MSE's For the Geographic time Series Method

	Outer Stations			Inner Stations			
Length	BOB	GAL	PTI	ELT	PTM	RIN	YAR
5	0.0014	0.0033	0.0097	0.0020	0.0300	0.0606	0.0645
10	0.0030	0.0078	0.0164	0.0038	0.0386	0.0746	0.0847
15	0.0040	0.0113	0.0206	0.0049	0.0421	0.0886	0.0949
20	0.0057	0.0114	0.0256	0.0064	0.0438	0.1014	0.0978
25	0.0058	0.0120	0.0286	0.0073	0.0452	0.1118	0.1007
30	0.0065	0.0126	0.0323	0.0084	0.0473	0.1170	0.1027
35	0.0067	0.0123	0.0331	0.0097	0.0486	0.1191	0.1043
40	0.0077	0.0126	0.0358	0.0105	0.0497	0.1204	0.1053
45	0.0082	0.0124	0.0390	0.0117	0.0512	0.1220	0.1059
50	0.0088	0.0123	0.0443	0.0132	0.0518	0.1241	0.1065
55	0.0090	0.0124	0.0423	0.0138	0.0523	0.1239	0.1077
60	0.0094	0.0135	0.0429	0.0147	0.0525	0.1220	0.1087
65	0.0093	0.0136	0.0446	0.0150	0.0525	0.1212	0.1098
70	0.0094	0.0136	0.0457	0.0152	0.0523	0.1210	0.1098
75	0.0092	0.0138	0.0460	0.0162	0.0520	0.1224	0.1099
80	0.0092	0.0140	0.0464	0.0161	0.0522	0.1231	0.1099
85	0.0091	0.0139	0.0456	0.0167	0.0521	0.1233	0.1100
90	0.0094	0.0139	0.0460	0.0167	0.0521	0.1234	0.1099
95	0.0283	0.0368	0.0513	0.0173	0.0525	0.1238	0.1097

The prediction is then compared with the true value and the MSE for each missing length are computed and presented in Table 3.

3.3.3 The effect of AR order in univariate time series prediction

The 1994 series from Bob Hall Pier were used to test the effect of different AR order in method one. Segments of different length (5, 10, 15, ... 95) are first removed at different starting locations (150, 200, 250, ... 5100). Then method one is used to predict those segments with different AR order. Table 4 shows that there is no effect for the different AR orders.

Table 4

The Effect of AR Order in Method One using 1994 Bob Hall Pier Series

	AR Order		
Length	5	10	20
5	0.0090	0.0080	0.0080
10	0.0170	0.0180	0.0170
15	0.0200	0.0190	0.0180
20	0.0220	0.0210	0.0210
25	0.0240	0.0240	0.0240
30	0.0270	0.0260	0.0260
35	0.0290	0.0290	0.0290
40	0.0300	0.0300	0.0300
45	0.0330	0.0330	0.0330
50	0.0360	0.0360	0.0360
55	0.0370	0.0370	0.0370
60	0.0410	0.0420	0.0420
65	0.0400	0.0390	0.0390
70	0.0420	0.0410	0.0410
75	0.0450	0.0450	0.0450
80	0.0480	0.0470	0.0470
85	0.0480	0.0480	0.0480
90	0.0480	0.0480	0.0480
95	0.0490	0.0490	0.0480
100	0.0510	0.0510	0.0510

3.4 Summary

Comparing Tables 2 and 3, we can see that the method under geographic time series setting performs better for the outer stations while the univariate time series prediction is better for the inner stations. This is primarily due to the fact that the outer stations have similar geographic features and behave similarly hence the information from the other stations does help in prediction. The inner stations have many differences. The inclusion of the other stations in the prediction procedure only introduces extra variation without much contribution to the prediction.

4. Practical Issues Related to Tidal Datums

In this section, we briefly discuss the implications of using datums, which are based upon the changes in water levels being primarily "astronomical" in nature, when in reality the periodic changes in the water level are based on other factors; i.e. Sa, Saa etc. These practical issues are discussed in greater detail in Speed Et. al. (1996).

4.1. Application to Boundary Determination

Based on the above discussion of the nature of water level changes in Texas coastal waters, it should be clear that the use of MHHW to determine boundaries is ill-suited. At some places along the inland waters, the "shore" as defined by MHHW and MLLW is no more than a meter wide; and yet the actual periodic covering and uncovering of land by waters of the sea extends more than six kilometers. Yet, there are definite periodic changes in water level that occur year after year at approximately the same time and which are related to Sa and Saa.

4.2 Regulatory Mandates of Tidal Datums

Environmental regulatory authority of the Federal government derives from the Clean Water Act (CWA) [9] of 1972, which encompasses the "Waters of the United States," a concept that includes oceans, rivers, estuaries, and lakes among other water bodies. 0.5 acre. The regulatory permit process administered by the Corps under Section 10 concerns possible obstruction of navigation and navigation works. Restricting the jurisdiction of the Corps to MHW will greatly reduce the areas covered under Section 10.

Another example of the use of water-level datums, the "chart datum" on navigation charts issued by NOS has been implemented as MLLW since 1989. The Corps, which is responsible for maintaining the navigability of the nation's federally authorized channels and waterways, has converted to MLLW in its dredging practice. The National Tidal Datum Convention of 1980 established this (MLLW) chart datum and changed the name of the former Gulf Coast Low Water

Table 5

Principal tidal constituents

Symbol	Description
S_a	Solar annual
S_{sa}	Solar semiannual
M_m	Lunar monthly
M_{sf}	Lunisolar synodic—semifortnightly
M_f	Lunar fortnightly
$(2Q)_1$	Second-order elliptical lunar
Q_1	Larger elliptical lunar
ρ_1	Larger evectional
O_1	Principal lunar
M_1	Smaller elliptical lunar
P_1	Principal solar
S_1	Radiational
K_1	Principal lunar-solar
J_1	Elliptical lunar
$(OO)_1$	Second-order lunar
$(2N)_2$	Second-order elliptical lunar
μ_2	Variational
N_2	Larger elliptical lunar
ν_2	Larger evectional
M_2	Principal lunar
λ_2	Smaller evectional
L_2	Smaller elliptical lunar
T_2	Larger elliptical solar
S_2	Principal solar
R_2	Smaller elliptical solar
K_2	Declinational lunar-solar
$(2SM)_2$	Shallow-water semidiurnal
$(2MK)_3$	Shallow-water third-diurnal
M_3	Lunar parallax
$(MK)_3$	Shallow-water third-dirunal
$(MN)_4$	Shallow-water fourth-diurnal
M_4	Shallow-water overtide
$(MS)_4$	Shallow-water fourth-diurnal
S_4	Shallow-water overtide
M_6	Shallow-water overtide
S_6	Shallow-water overtide
M_8	Shallow-water overtide

Datum to MLLW. As an average, the concept of MLLW implies that there are times when the water surface and, therefore, water under the keel, is less than that indicated on a navigation chart. This property of MLLW is a concern for promoting safe navigation in Texas's coastal waters. Since in Texas, MLLW suffers from the same problems of MHHW (specifically that MLLW does not account for the long term periodicity in water levels), the line of MLLW is dry 30% to 50% of the time, thus possibly posing a threat to safe navigation.

4.3. Building Codes

Since MHHW underestimates the actual reach of the water, it can not be used to set minimum heights for buildings for some coastal waters. For example, piers in Los Angeles, in order to comply with the requirements of the American with Disabilities Act (ADA), must correct MHHW by adding a component for wave height. In Texas, not only would this correction be necessary, but also a major correction would be necessary to reflect the actual recurring annual high waters.

5. Conclusions

The use of tidal datums based upon changes of water levels is useful and effective when the changes of water level are primarily deterministic or structural. In cases where there are significant errors and these errors are correlated, the classical method of Ordinarily Least Squares (OLS) is not an appropriate technique of analyses. The use of autocorrelation techniques and methods of imputation based on correlated errors help the researcher understand the nature of the changes of the water levels. We have found that unlike the water levels changes along the east and west coast, where there are major "daily" tides, the water level changes along the Texas coast and inland waters have periodic changes which are predominantly semi-annual or annual. Thus, the use of a datum based on a daily tide, such as Mean Higher High Water, is incorrect.

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