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US SEA LEVEL DATA: TIME TRENDS AND PERSISTENCE

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Abstract

This paper analyses US sea level data using long memory and fractional integration methods. All series appear to exhibit orders of integration in the range (0, 1), which implies long-range dependence; further, significant positive time trends are found in the case of 29 stations located on the East Coast and the Gulf of Mexico, and negative ones in the case 4 stations on the North West Coast, but none for the remaining 8 on the West Coast. The highest degree of persistence is found for the West Coast and the lowest for the East Coast.

Keywords: Sea level; time trends; fractional integration

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West coast the increase is around or below the GMSL rise of 1.7 mm year ¹. The highest regional sea levels increases have been observed in Louisiana, Eastern Texas and the stretch from Virginia to New Jersey, which can be explained by Gulf Stream variations, land subsidence and tectonic movements (Zervas, 2009; Sweet et al., 2017).

Future scenarios for the sea level rise are based on emissions and the associated risks. It is expected that GMSL will continue increasing during the 21st

methodology; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

2. Literature Review

processes appear to be the most appropriate for geophysical/climate time series, since these tend to exhibit long-run dependence (LRD) or temporal correlations (Beran, 1994; Percival et al., 2001; Gil-Alana, 2006; Ercan et al., 2013; Graves et al., 2017). Such models range from those proposed by Hurst (1951) in hydrology, and later by Mandelbrot (1967) and Mandelbrot and Van Ness (1968) for self-similarity and the fractal dimension, to the AutoRegressive Fractionally Integrated Moving Average (ARFIMA) model of Granger and Joyeux (1980), and its subsequent extensions.

Long-memory models have been widely used for climate variables such as temperature (Bloomfield, 1992; Caballero et al., 2002; Franzke, 2012; Gil-Alana, 2005, 2008, 2018), but less for sea level data. In particular, there is very limited evidence concerning US tide gauge records. Jiang and Plotnick (1998) were the first to carry out fractal analysis using US coastline data with a continental dimension; applying the

In another recent study, Dangendorf et al. (2014) investigated sea level changes using 60 monthly average tide gauge records around the world. Their results from the Detrended Fluctuation Analysis -DFA2- (Kantelhardt et al., 2001) show, for all records, a LRD up to 35 years, which suggests the importance of the internal behaviour to understand sea level changes. By contrast, Becker et al. (2014) concluded that global and regional sea level changes are strongly driven by anthropogenic forces, in particular in the case of New York, Baltimore and San Diego. Finally, Royston et al. (2018) addressed the issue of residual noise when estimating linear trends, and showed that it is coloured but non-AR(1) in the majority of cases, the AR(1) model being more appropriate for shorter series (Bos et al., 2014). The inclusion of climate indices in the regression does not affect the choice of noise model: for San Francisco and Seattle, the preferred noise models are ARFIMA specifications, with a trend coefficient (including climate indices) of 2.37 and 2.71, respectively, while for Honolulu, the preferred model is the Generalized Gauss Markov (GGM) noise model, with an estimated trend coefficient of 1.29. The study by Royston et al. (2018) is the closest to ours, since we also consider long-range dependence models based on fractional integration and estimate the time trend coefficients allowing the errors to be fractionally integrated.

3. Data and Methodology

The data examined concern 41 US stations covering most of the US coast. Table 1 reports the names of the stations and the percentage of coverage; we only consider series with a maximum of 10% missing data, and compute them as a simple arithmetic mean of the previous and following monthly value in the series. The data are available at https://www.psmsl.org/data/obtaining/.

TABLE 1 HERE

TABLE 4 AND FIGURE 1 HERE

All the estimated values of d are in the interval (0, 1) and range between 0.29 (Annapolis, Naval Academy) and 0.75 (La Jolla, Scripps Piers), which confirms that the series are fractionally integrated. The series can be divided into three categories according to their degree of persistence: those with values of d in the range (0, 0, 5), that is, covariance-stationary series; those with values around 0.5, on the boundary between stationarity and non-stationarity; a third group with values in the interval [0.5, 1), which implies non-stationary mean-reverting behaviour (see Table 5 and Figure 2)

TABLE 5 AND FIGURE 2 HERE

the West coast) there is evidence of non-stationary mean-reverting patterns

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Table 1: Time series examined and abbreviations

Series Name

% of observed data

Table 4: Classification based on the time trend coefficient

Significant negative

 Table 5: Classification based on persistence

0 < d < 0.5 Stationarity	0 < d < 1	0.5 d < 1 Non-stationarity	
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Figure 1: Time trend coefficients. Summary of data extracted from Table 4.

Sgnificant positive time trend; Insignificant time trend; Sgnificant negative time trend.

Figure 2: Degree of persistence. Summary of data extracted from Table 5.