Supplemental Information for: Spatial Data on U.S. Coastal Wetland Greenhouse Gas Inventory Uncertainty

These supplemental materials and methods are included for convenience and clarity. The supplemental methods for creating a probabilistic mean higher high water spring (MHHWS) elevation map were also included in the supplemental information for the associated journal article (Holmquist *et al* Provisionally Accepted). The section on mapping total and sector level fluxes is unique to this documentation.

1. Creating a Probabilistic Mean Higher High Water Spring Maps

To create a probabilistic coastal lands map we utilized digital elevation models archived and aggregated by the NOAA sea-level rise viewer (NOAA 2016) (Supplemental Table 1). Some data sources for the San Joaquin Delta (Wang and Ateljevich 2012), Maryland State (Eastern Shore Regional GIS Cooperative n.d.), and the Northern Gulf of Mexico Region (USGS 2014) were not archived through the NOAA portal, so we cite the original data sources (Supplemental Table 1). All DEMs were relative the NAVD88 datum. In the rare cases in which units were not in meters relative to NAVD88, they were converted to m in ArcGIS Pro (Esri Inc. 2017).

For the LiDAR maps we corrected for bias and propagated random error by calculating mean error and root mean square error from weighted averages from a literature review (Hladik *et al* 2013, Medeiros *et al* 2015, Buffington *et al* 2016, Holmquist *et al* in Prep). If a LiDAR pixel intersected a wetland as mapped by the Coastal Change Analysis Program (C-CAP) (NOAA 2013) we applied an average 17.3 cm offset.

To transform the NAVD88 datum of the LiDAR DEMs to a tidal datum, we used NOAA tide gauge data. For the NAVD88 to MHHW datum transformation, we used NOAA datums which had established MHHW relative to NAVD88 (NOAA 2017). To establish datum uncertainty we used NOAA's reported standard errors for tidal datum transformation (NOAA n.d., n.d., n.d.). This included 705 gauges. To transform MHHW to MHHWS we calculated MHHWS offsets at gauges using NOAA high-low tide data (NOAA CO-OPS n.d.) and astronomical records of full and new moons (USNO n.d.). We assumed that the spring tides occur twice monthly and can have occur between one day before to two days after a full or new moon. We queried NOAA servers for all of those gauges over the most recent datum period for the gauge and represented MHHWS relative to MHHW as the mean offset over those time periods. We represent uncertainty in the datum itself by estimating the standard error of the mean (Eq. 1). There was a notable and precipitous increase in standard error for gauges that had few observations of spring tides, which we detected using a piecewise linear regression (Sonderegger 2012). So we excluded tide gauges from the analysis that had fewer than 31 datapoints. 127 tide gauges were included in the MHHW to MHHWS transformation.

$$se = \frac{sd}{\sqrt{n}} \qquad 1.$$

In which:

se = standard error of the mean
sd = standard deviation
n = sample size

For the NAVD88 to MHHW transformation and MHHWS to MHHW offset we extrapolated point data to a 2-d surface using Empirical Bayesian Kriging (EBK) (Pilz and Spöck 2008, Krivoruchko 2012). We reduced the resolution of both datum transformation layers 300 x 300 m, with pixel edges snapped to C-CAP's dimensions.

Our goal in creating a probabilistic MHHWS layer was to reflect uncertainty in both the datums themselves (i.e. areas with lower-quality datums have greater uncertainty than areas with high-quality datums), as well as distance from gauges (areas further away from any gauge have greater uncertainty than those nearer). We calculated total propagated error for NAVD88 measurement, MHHW transformation and MHHWS transformation. For the NAVD88 surface we used the weighted mean RMSE for wetland surfaces from multiple studies (Supplemental Table 2). For tidal datum transformations we incorporated for two types of uncertainty: 1. uncertainty in the extrapolation process itself -- the standard error of prediction from the empirical bayesian kriging output -- and 2. uncertainty in the datums themselves (NOAA datum uncertainty report), also extrapolated from points to a 2-d surfaces using empirical bayesian kriging. EBKs were run in ArcGIS pro (Esri Inc. 2017) with a power semivariogram model, 100 maximum points for each local model, a local model area overlap factor of 1, 100 simulated semivariograms, a standard circular neighborhood with a radius of 15, and max and min neighbors of 15 and 10 respectively.

We calculated total propagated uncertainty in all of the transformations algebraically (Eq. 2). We resampled raster resolutions of the DEMs to 30 x 30 m to match C-CAP. At the pixel level we calculated a Z-score according to Eq. 3 (Schmid *et al* 2013). We used the function 'z2p' in Python's (Continuum Analytics, Inc 2017) NumPy package (NumPy Developers 2017) to calculate a 'p value' -- probability of a pixel being below MHHWS -- from the standard score.

$$se_{total(x,y)} = \sqrt{RMSE_{LiDAR}^2 + se_{MHHW(x,y)}^2 + se_{krig.1(x,y)}^2 + se_{MHHWS(x,y)}^2 + se_{krig.2\,(x,y)}^2} \qquad 2.$$

In which:

$se_{total(x,y)}$ = the total propagated uncertainty of the transformation for point x,y
$RMSE_{LiDAR}$ = the root-mean square error for LiDAR-based DEMs for marsh surfaces
se_{MHHW} and se_{MHHWS} = the standard errors of the datums at point x,y
$se_{krig.1}$ and $se_{krig.2}$ = the standard error of prediction resulting from the EBK process for MHHW and MHHWS respectively at point x,y

$$Z_{(x,y)} = \frac{(water\ surface_{(x,y)} - elevation_{(x,y)})}{se_{total\ (x,y)}} \qquad 3.$$

In which:

$Z_{(x,y)}$ = the standard score of point x,y
Water $surface_{(x,y)}$ = elevation of MHHWS relative to NAVD88 at point (x,y)
$elevation_{(x,y)}$ = elevation of the surface at point (x,y) relative to NAVD88

The number of palustrine stable and change 2006-2011 category, excluding changes to and from estuarine wetlands, totaled to 111. For each of these categories we extracted values from the probabilistic inundation map using ‘extract by mask’ in ArcGIS Pro (Esri Inc. 2017).

2. Creating Per-Pixel Total and Sector Fluxes, and Confidence Interval Maps

We mapped the modeled CO_2e fluxes for all relevant wetland pixels in the C-CAP data. For each C-CAP 2006 to 2011 land cover class we calculated the median of total flux at the scale of the entire contiguous United States by multiplying emissions factors by the estimated area at each iteration of a Monte Carlo analysis. We also separately calculated soil, biomass, and CH_4 contributions. We calculated the median, minimum (0.025 quantile) and maximum (0.975 quantile) confidence intervals and the confidence interval range (0.975 quantile - 0.025 quantile) for the total fluxes, as well as separate soil, biomass, and methane sectors. In order to visualize this data at the scale of the mapped pixel we divided total flux by mapped areas. A table with those results was joined to the subset of the C-CAP 2006 to 2011 layer in ArcGIS Pro (Esri Inc. 2017). This layer incorporated all land classes converting to and from wetlands that fell below a 97.5% likelihood of being below the MHHWS tidal elevation.

Works Cited

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