Supplemental Material

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A Water Balance–Based, Spatiotemporal Evaluation of Terrestrial Evapotranspiration Products across the Contiguous United States

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Supplemental Material for:

A water balance based, spatiotemporal evaluation of terrestrial evapotranspiration products across the contiguous United States

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Introduction

The figures and text contained in this document are intended to support the methods, results, and conclusions from Carter et al. (2018). Information enclosed includes Supplemental Text 1-3 and Supplemental Figures S1-S9.

Supplemental Text 1: Calculation of GRACE Total Water Storage (TWS)

In 2002, the Gravity Recovery and Climate Experiment (GRACE), a partnership between NASA and the German Aerospace Center, launched a pair of satellites to measure small-scale changes in Earth's gravitational field. Observations from the GRACE satellites have been used to estimate monthly TWS changes globally. Two methods for converting GRACE data into ΔTWS estimates were evaluated in this study: GRACE Tellus (Swenson 2012) and GRACE Mascon (Wiese 2016, Save et al. 2016).

> GRACE Tellus (ΔTWS_T): Three estimates of monthly total water storage estimates, independently derived from GRACE data by the Center for Space Research at University of Texas, Austin; the Jet Propulsion Laboratory; and the Geoforschungs Zentrum Potsdam, were downloaded from the JPL website (ftp://podaac-ftp.jpl.nasa.gov/allData/tellus/L3/land_mass/RL05/netcdf/), averaged, and then multiplied by the scaling grid as described in Landerer and Swenson (2012). Water year ΔTWS_T is approximated by taking the mean September and October TWS anomaly for year *t* in 2003-2015 and subtracting the mean September and October TWS anomaly for year *t* -1. The mean ΔTWS for each year was calculated for each basin. We note that many basins were smaller than the minimum spatial resolution of the GRACE Tellus product, and were assigned values for ΔTWS_T based on the grid cell in which they fell.

GRACE MASCON (ΔTWS_M): The Jet Propulsion Lab has developed a total water storage change anomaly product based on Mass Concentration block ("mascon") functions, instead of spherical harmonics. The GRACE Mascon approach allows for easy implementation of geophysical constraints to filter out noise in GRACE observations. ½ degree GRACE Mascon surface TWS anomaly grids with the Coastline Resolution Improvement filter were downloaded from the JPL website (ftp://podaac.jpl.nasa.gov/allData/tellus/L3/mascon/RL05/JPL/CRI/netcdf/). The provided ½ degree scaling grid was multiplied by the GRACE Mascon layers. ΔTWS_M was calculated from the monthly scaled GRACE Mascon grids as described for GRACE Tellus data. While GRACE Mascon data is at a higher spatial resolution than the GRACE Tellus data, we note that the majority of our basins were still below the minimum resolution for GRACE Mascon data, and were assigned ΔTWS values similarly to the Tellus data.

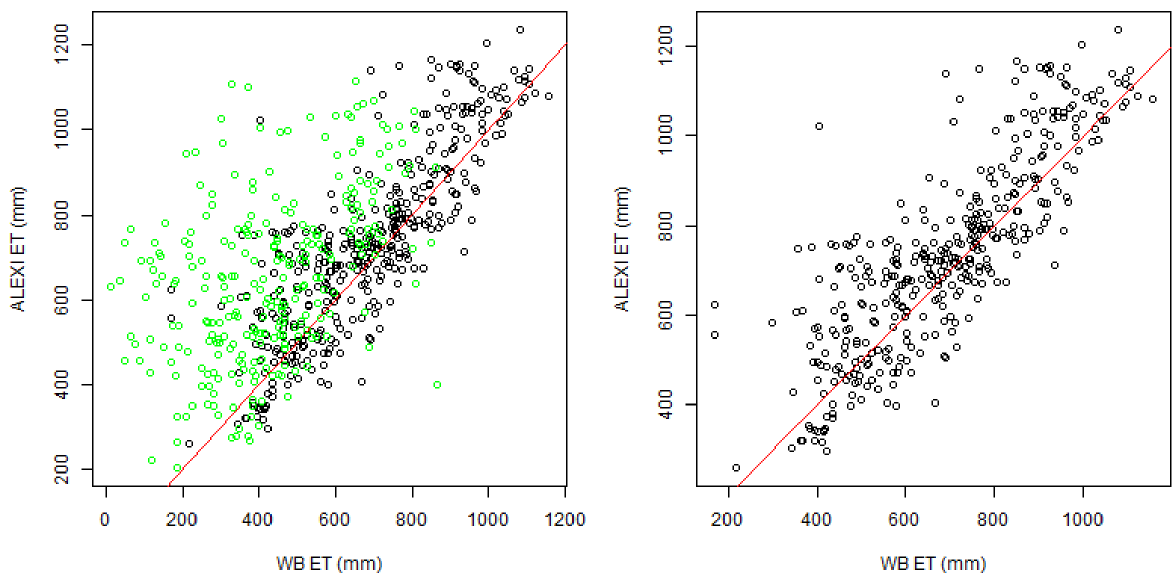

Figure S1: Scatterplot of $\overline{ET_{EB}^{ALEXI}}$ and $\overline{ET_{WB}}$ with a 1:1 relationship drawn in red. Left: basins with average slopes greater than 15% are highlighted in green. Right: basins with average slopes greater than 15% are removed from the scatter.

Supplemental Text 2: $\overline{ET_{WB}}$ calculated from multiple P datasets

In the main text , we argue that it would be unlikely that long-term error in orographically-adjusted basin-averaged P would be biased in the same direction across all 671 basins considered in this study, and if such systematic bias did exist, it would most likely be caused by one of two plausible reasons: 1) well-documented undercatch of gage precipitation linked to surface winds (Adam and Lettenmaier 2003, Yang et al. 2005), or 2) potential systematic errors in data processing. The first source of bias would lead to a systematic underestimation of true basin-averaged P, while the second source of bias could lead to either positive or negative systematic errors. If undercatch were the only source of systematic bias across all gages, then we can assume that accurate ET_{EB} products would produce long-term ET estimates near or slightly above ET_{WB} estimates on average. This conclusion requires that we eliminate the possibility of data processing errors as another source of systematic bias. To do this, $\overline{ET_{WB}}$ is re-calculated with several different precipitation datasets that would have different processing procedures: NLDAS-2 Secondary Forcing dataset P ($\overline{ET_{WB}^{NLDAS\_B}}$, Xia et al. 2012), Global Precipitation Climatology Centre (GPCC) P ($\overline{ET_{WB}^{GPCC}}$, Schneider et al. 2011), and P data for the 1/8 degree gridded observed meteorological dataset published by Maurer et al. (2002) and distributed at http://www.engr.scu.edu/~emaurer/data.shtml ($\overline{ET_{WB}^{Maurer}}$). These $\overline{ET_{WB}}$ estimates are compared to $\overline{ET_{EB}}$ products in Figure S2. While there are fundamental differences in how these respective P datasets were constructed, and therefore it is unlikely they would share similar processing errors, we note that there is significant overlap in rain gage data and/or radar data used in the datasets. Therefore, it cannot be assumed that the datasets have independent error due to issues like undercatch. The only exception is $\overline{ET_{WB}^{NLDAS\_B}}$, which is a reanalysis-based precipitation product and therefore would have its own unique set of systematic errors that differ from gage-based products.

When comparing the different $\overline{ET_{WB}}$ estimates to the different $\overline{ET_{EB}}$ products, similar relationships and systematic biases are seen for the gage-based NLDAS-2A, GPCC, and Maurer datasets, while a different set of systematic errors are seen for the reanalysis-based NLDAS-2B P data. This indicates that processing error in the NLDAS primary precipitation forcing data that is unique from the other gaged products is unlikely to contribute to the systematic biases seen with the different $\overline{ET_{EB}}$ estimates. Rather, any systematic bias in gaged-based $\overline{ET_{WB}}$ is likely linked to undercatch, which would explain the different bias seen for the NLDAS-2B reanalysis-based P dataset. Based on these results, we conclude that the NOAH $\overline{ET_{EB}}$ estimates likely exhibit a moderate negative bias compared to the true long-term ET across the CONUS.

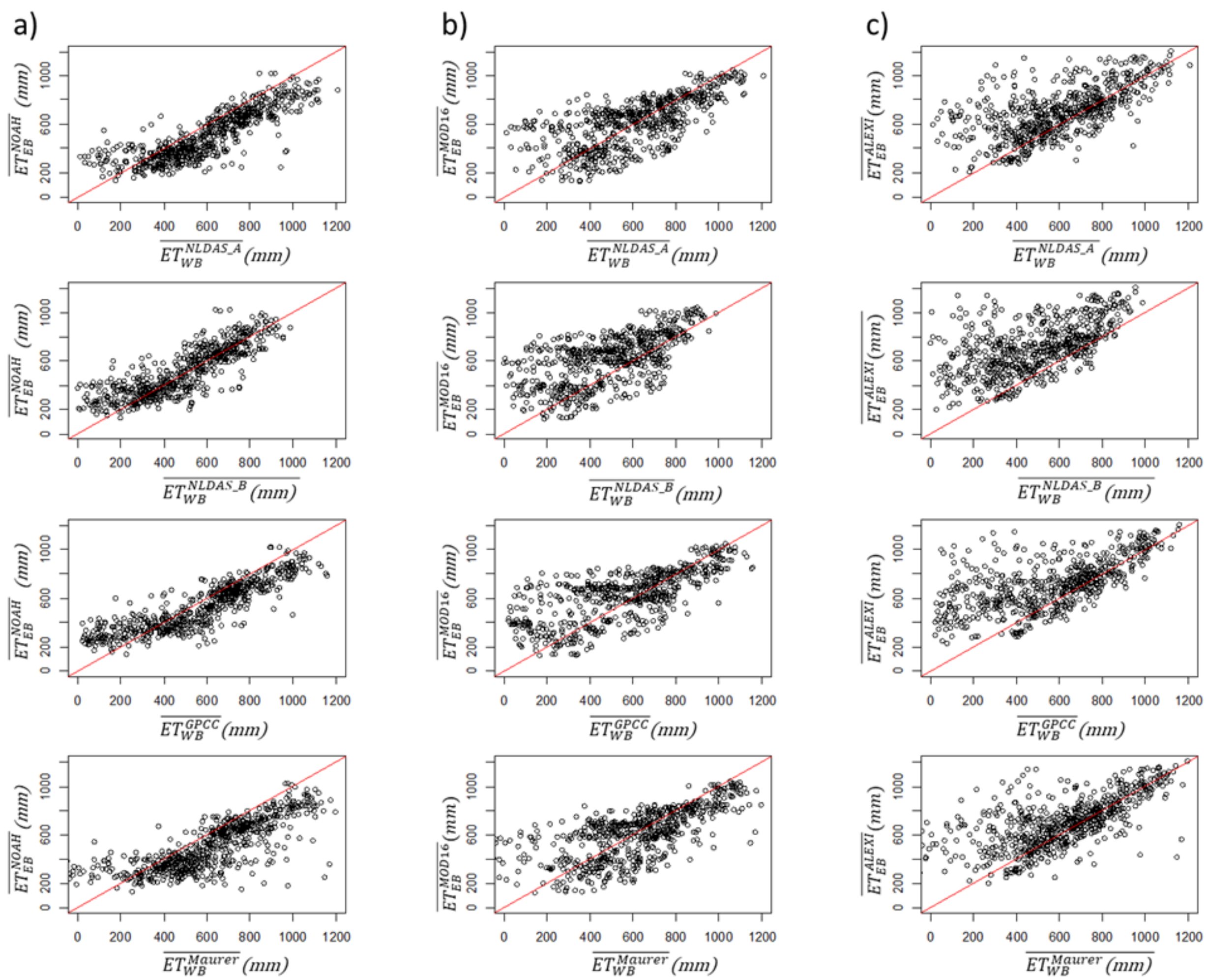

Figure S2: Scatterplot of a) $\overline{ET_{EB}^{NOAH}}$, b) $\overline{ET_{EB}^{MOD16}}$, c) $\overline{ET_{EB}^{ALEXI}}$ against $\overline{ET_{WB}^{NLDAS\_A}}$ (as is used in main text, first row), $\overline{ET_{WB}^{NLDAS\_B}}$ (second row), $\overline{ET_{WB}^{GPCC}}$ (third row), and $\overline{ET_{WB}^{Maurer}}$ (fourth row).

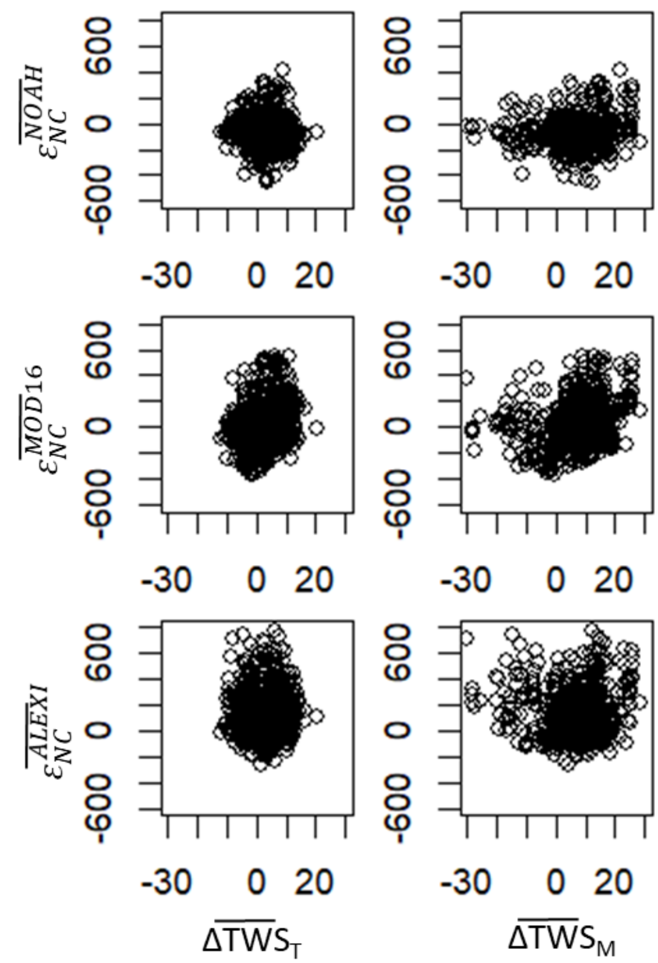

Figure S3: Scatterplot of $\overline{\varepsilon_{NC}^{NOAH}}$ (mm, top), $\overline{\varepsilon_{NC}^{MOD16}}$ (mm, center), and $\overline{\varepsilon_{NC}^{ALEXI}}$ (mm, bottom) against $\overline{\Delta TWS_T}$ (mm, left) and $\overline{\Delta TWS_M}$ (mm, right).

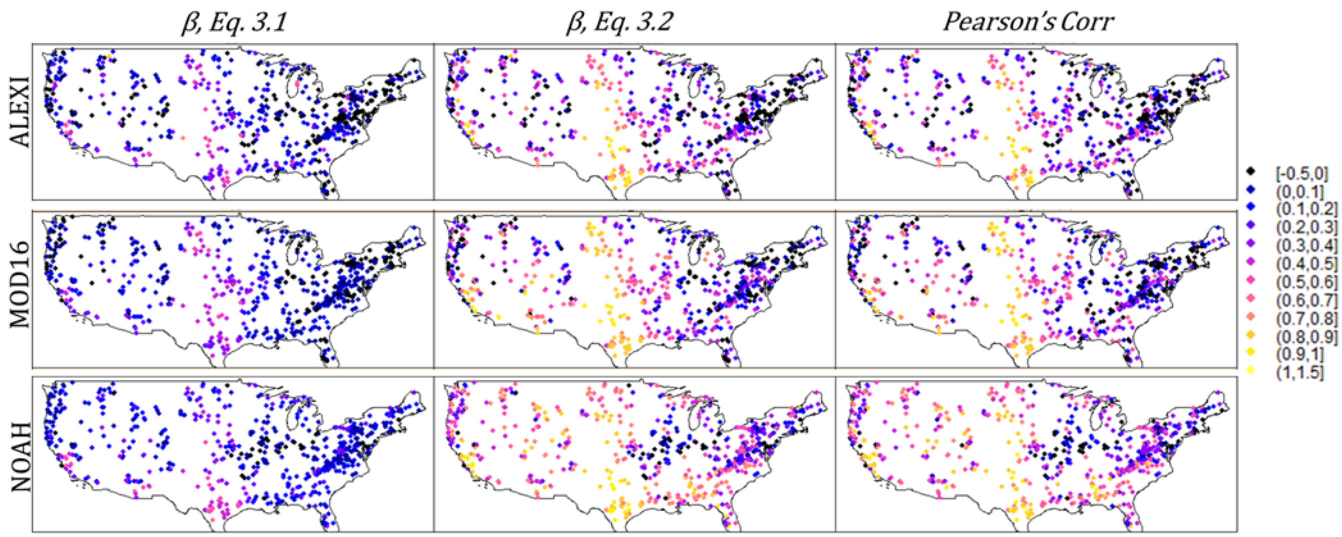

Figure S4: β values for Equation 3.1 calculated by basin (left column), β values for Equation 3.2 calculated by basin (center column), and Pearson's correlation coefficients relating ET_{EB} to ET_{WB} calculated at by basin (right column). Spatial patterns shown here confirm the results of the GWR coefficients in Figure 4.

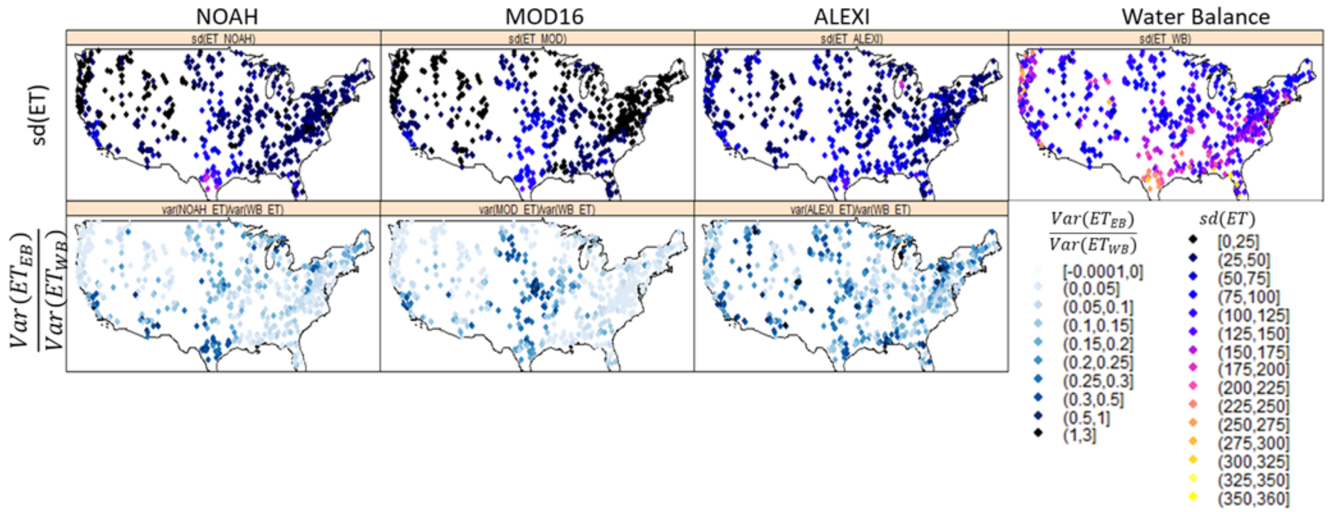

Figure S5: Standard deviations (top) of basin-level annual ET estimates from NOAH, MOD16, ALEXI, and WB. Variance ratios (bottom) between ET_{EB} and ET_{WB}.

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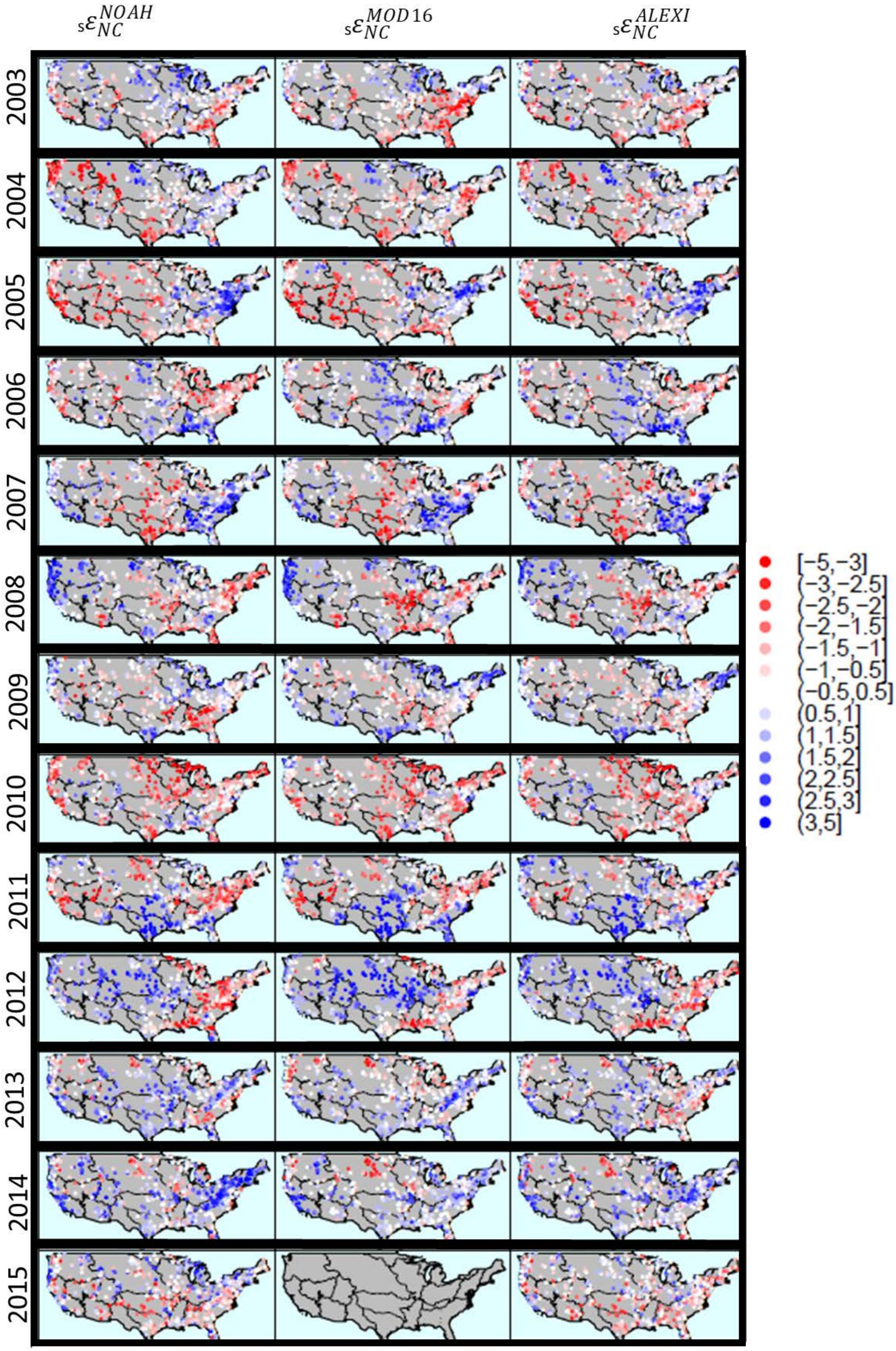

Figure S6: Maps of ${}_{s}\varepsilon_{NC}^{NOAH}$ (left), ${}_{s}\varepsilon_{NC}^{MOD16}$ (middle), ${}_{s}\varepsilon_{NC}^{ALEXI}$ (right) for each water year between 2003-2015. Spatial clustering of annual ${}_{s}\varepsilon_{NC}$, specifically in the Eastern US and Pacific Northwest, are consistent with what would be expected if weather/circulation anomalies were driving discrepancies between energy balance and terrestrial water balance models.

Supplemental Text 3: GW Regression of ε_{NC} and GRACE ΔTWS_M

Figure S7 demonstrates that ε_{NC} shows a weak, direct relationship to both ΔTWS_{Tellus} (left) and ΔTWS_{Mascon} (right), with a slightly stronger relationship to the Mascon data. If ΔTWS_{Tellus} or ΔTWS_{Mascon} are included directly into the water balance estimate of ET and scaled non-closure errors re-examined (Figure S8 and Figure S9), improvements can be seen in some regions and years, but errors can actually get larger in other areas or years. A similar result is seen if the errors are unscaled (not shown), and is not surprising giving the weak relationship in Figure S7. However, this approach of directly including GRACE ΔTWS into the water balance calculation may reduce the information content of the ΔTWS data, particularly if there is any variance bias in the GRACE ΔTWS estimates. If this were the case, then directly including ΔTWS as a term in the water balance could lead to additional error in the estimate of ET_{WB}, masking the importance of the true ΔTWS to the true ET_{WB}. This problem might be compounded if there were also variance bias in basin-averaged P. Therefore, to control for the potential variance biases in both ΔTWS and basin-averaged P, we prefer a to examine the correlations between ΔTWS and the scaled non-closure errors, as shown in Figure 6 of the main text.

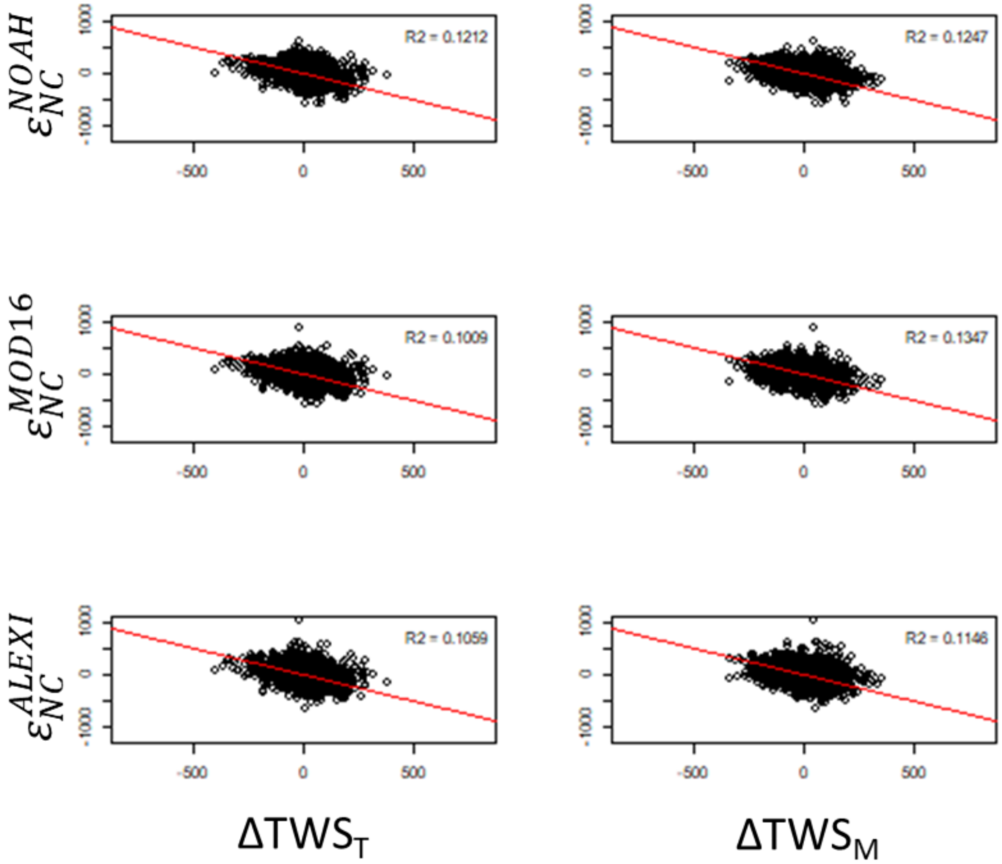

Figure S7: Scatterplot of annual non-closure error (ε_{NC}, in mm) for NOAH (top), MOD16 (middle), and ALEXI (bottom) compared to ΔTWS_T (left, in mm) and ΔTWS_M (right, in mm). Each point in the scatter represents a station/year. As ΔTWS_M showed slightly higher R^2 in comparison to ΔTWS_T, and as ΔTWS_M demonstrated an inter-annual range closer to the inter-annual ranges of ε_{NC}, it was selected for analysis

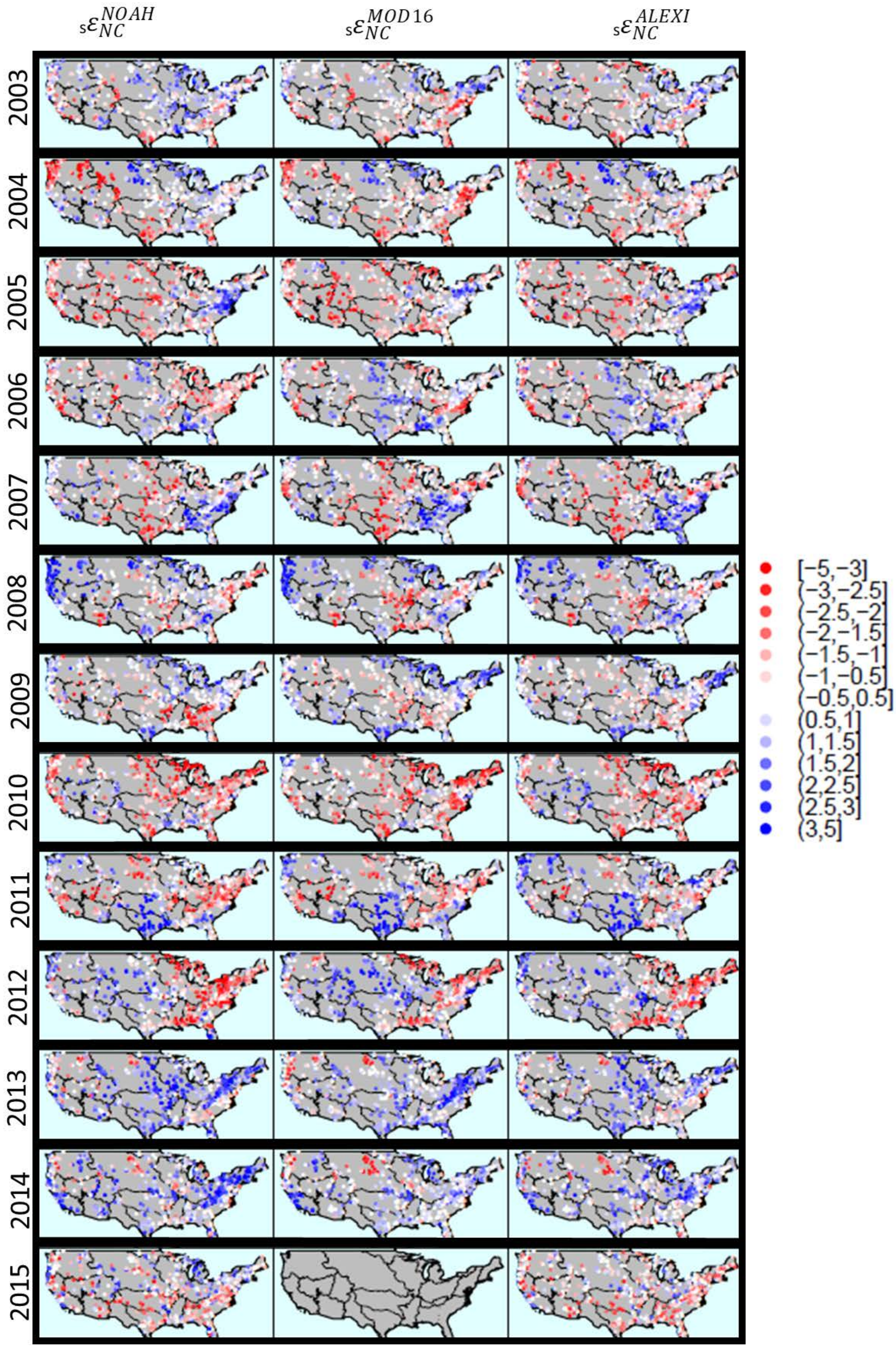

Figure S8: As in Figure S6, where ${}_{s}\varepsilon_{NC}$ is calculated from $ET_{WB} - \Delta TWS_{Tellus}$.

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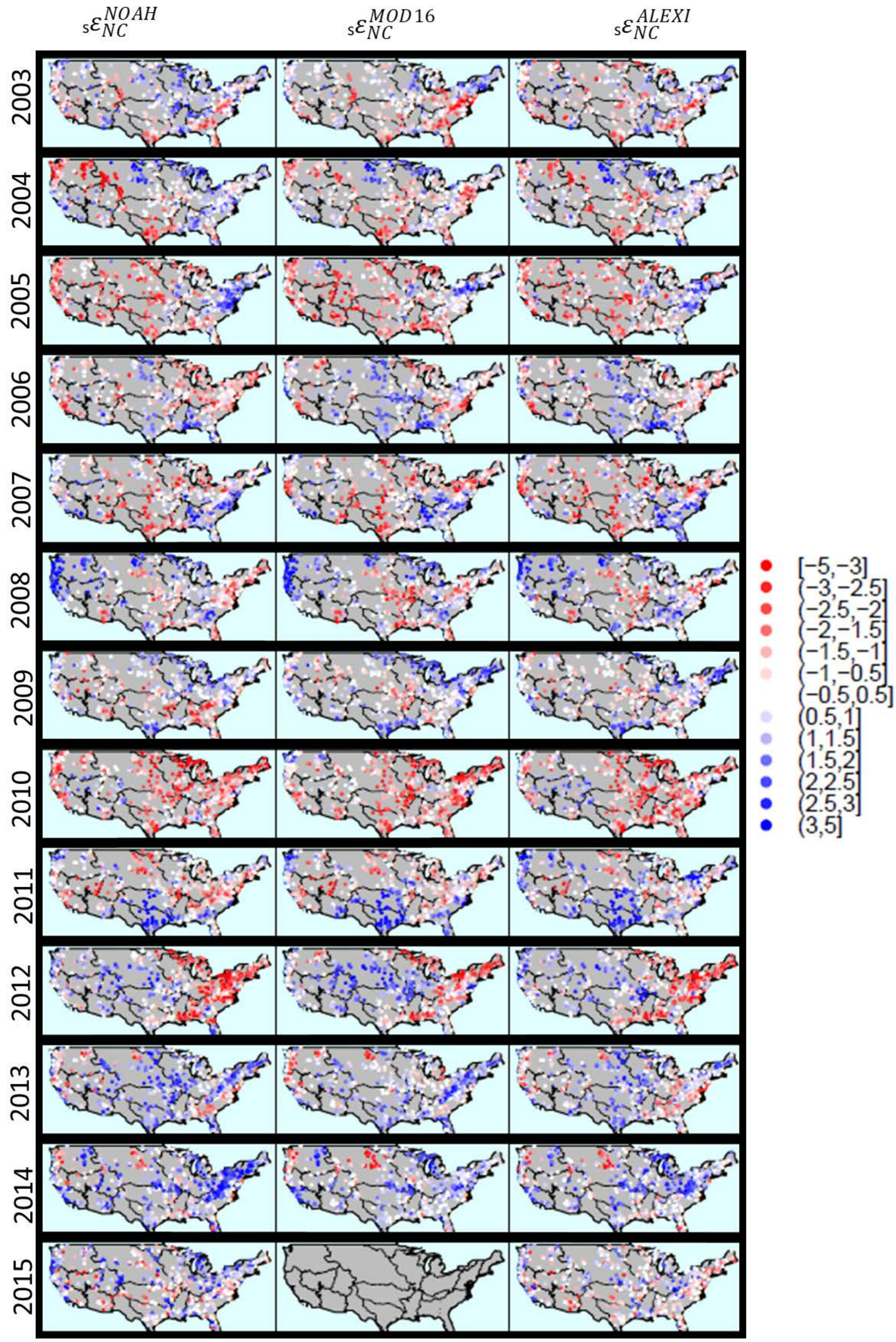

Figure S9: As in Figure S6, where $_{s}\varepsilon_{NC}$ is calculated from $ET_{WB} - \Delta TWS_{Mascon}$

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