Runoff and evapotranspiration elasticities in the Western U.S.

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Key Points:

- The precipitation and potential evapotranspiration runoff elasticities over the Western U.S. are estimated from both statistical and modeling approach
- The behaviors of the elasticities and Dooge's complementary relationship are evaluated

Abstract

Many studies have examined how runoff (R) responds to long-term changes in precipitation (P) and temperature (T), but the effects of potential evapotranspiration (PET) have received less attention. We examine observational data sets for P, T, and R; and PET estimated from observations, to determine the extent to which derived P and PET runoff elasticities (ε_P and $\varepsilon_{PET,}$ the fractional changes in runoff associated with given fractional changes in precipitation and PET, respectively) meet Dooge's complementary relationship (under certain conditions, $\varepsilon_P + \varepsilon_{PET} = 1$). We apply three statistical methods and two hydrologic models to estimate ε_P and ε_{PET} in 84 headwater river basins in California, Oregon, and Washington. We find that while the estimates of ε_P are generally consistent across the three statistical estimators and the model-based estimators, the estimates of ε_{PET} using the statistical methods differ considerably (generally they are much more negative) from the model-based estimates and most appear to be implausible. The model-based estimates show better conformance to the complementary relationship (and in the median across sites, they sum to close to 1.0). We explore several factors that might explain the failure of the observation-based estimators, including interaction between P and PET and non-closure of the water budget at annual time scales.

1.0 Introduction

Water resources are crucial to human survival and well-being. Streamflow, often the most readily accessible water source, plays a particularly important role in agricultural and municipal water supply, industrial production, hydropower generation, and other beneficial uses of water. However, the hydrologic cycle is subject to change as climatic factors such as temperature and precipitation respond to a warming climate. These changes have been especially prominent in the Western U.S. (Karl et al., 2009). Ongoing warming can intensify drought risk and severity by increasing the probability of coincident anomalous temperature and precipitation events, even if mean precipitation and the likelihood of anomalously low-precipitation do not change (Diffenbaugh et al., 2014; AghaKouchak et al., 2014). Such changes would create challenges for water resource management, especially where water demand is high and where water resources are already heavily exploited (Zhang, et al., 2014). For example, reservoirs' ability to produce hydropower in summer might be impaired due to earlier runoff in California headwater streams resulting from earlier snowmelt (Null et al., 2010). In addition to the negative impacts of climate change on water resources, ecosystems are also likely to be affected by exacerbation of drought events. Elevated temperature stresses aquatic ecosystems, increases the number and severity of wildfires, and makes forests more vulnerable to moisture stress and insect infestations (Null et al., 2010; Cayan et al., 2010). All of these factors motivate a better understanding of how streamflow will respond to changes in climate.

Many past studies have used hydrologic models to simulate streamflow under different climate change scenarios by perturbing relevant input variables (e.g., Vicuna et al., 2007; Zhang et al., 2014; and Vano and Lettenmaier, 2014; among many others). These approaches usually evaluate streamflow change under different future scenarios in which precipitation (P) and temperature (T), and other variables change. Fu et al. (2007) extends the

runoff elasticity into a two-parameter index as a function of P and T. This approach has some drawbacks. One is that P and T usually change by different amounts at different times of year, so it is difficult to deconvolve the effects of their changes separately. Another shortcoming is that water balance changes in a river basin are governed by changes in precipitation and evaporative demand (and not temperature directly). On a physical basis, evaporative demand is driven by net radiation, vapor pressure deficit, wind speed, and temperature; the first two variables depend not only on temperature, but also on other variables such as net solar radiation and humidity. These attributes have been changing over time along with temperature, and they can have greater influence on evaporative demand than T (Vano et al., 2012), whereas they are often neglected in runoff sensitivity studies. Furthermore, if hydrologic models use T as an input and estimate potential evapotranspiration (PET) using temperature indexed PET algorithms such as Hamon (Hamon, 1961), Thornthwaite (Thornthwaite, 1948), Hargreaves (Hargreaves, 1975), and many others, they tend to overestimate changes in the water balance associated with general warming and cause inaccuracies in runoff sensitivity estimates (Milly and Dunne, 2011). In short, it is the variation of evaporative demand (PET) that drives hydrologic change whereas T is only an index embedded in PET (Vano and Lettenmaier, 2014), and it is important to understand not only how P change affects runoff in a warming climate, but also how runoff responds to PET change.

Given the above background, the question we address here is: What are the runoff sensitivities in the headwater streams of the Pacific States (California, Oregon, and Washington) to changes in precipitation and potential evapotranspiration? We conduct our analysis in the context of the complementary relationship demonstrated by Dooge (1992) that the (annual) P and PET elasticities of runoff sum to one. We discuss this relationship further in the following section.

2.0 Background

The runoff elasticities to P and PET (all quantities are long-term means) was formulated analytically by Dooge (1992). He showed, under two conditions, that these elasticities sum to one. The first condition is the long-term mean water balance, runoff = precipitation – evapotranspiration (with storage change assumed to be negligible). The second is the Budyko hypothesis, which has the form

$$\frac{AET}{PET} = \emptyset\left(\frac{P}{PET}\right) \quad (1)$$

where AET is actual evapotranspiration, and the ratio of P to PET is termed the humidity index. The Budyko hypothesis has been explored widely due to the increased focus on the effects of global change on water resources and has now been verified at thousands of natural watersheds around the globe (Sankarasubramanian and Vogel, 2002; Williams et al., 2012; Padrón et al., 2017). For a recent review of the application of the Budyko hypothesis in hydroclimatology see Wang et al. (2016a).

The Budyko hypothesis states that over the long term, the ratio of AET to PET can be expressed as a function of ratio of P to PET. From these two conditions, Kuhnel et al. (1991) and Dooge (1992) showed that the following runoff elasticity equation holds:

$$\frac{\Delta Q}{Q} = \varphi\frac{\Delta P}{P} + (1-\varphi)\frac{\Delta PET}{PET} \qquad (2)$$

where Q is runoff and φ is the precipitation elasticity (ε_P) of runoff (Schaake & Chunzhen, 1989). Using the same nomenclature, 1 - φ is the PET elasticity (ε_{PET}) of runoff, and ε_P and ε_{PET} add to unity, over the long term. Dooge (1992) then calculated the elasticities of runoff for different values of the humidity index based on different empirical expressions of the Budyko hypothesis, and showed that higher humidity ratios, indicating wetter climates, lead to smaller elasticities (less positive ε_P and less negative ε_{PET}), with a limiting condition where

ε_P approaches unity as the humidity index approaches infinity. This pattern has been evaluated and confirmed in many other studies (e.g., Sankarasubramanian et al. 2001; Chiew, 2006; Zheng et al., 2009; Wang and He, 2017); furthermore, Sankarasubramanian et al. (2001) showed that ε_P tends to decline as regional average snow depths increase.

Roderick and Farquhar (2011) and Yang and Yang (2011) employed an analytical approach based on the Budyko hypothesis to calculate ε_P and ε_{PET}. Although approaches based on Eq. 2 can conveniently estimate the elasticity of runoff for different climatic regions once a Budyko formulation is determined, the results have three inherent sources of uncertainty. First the key result that ε_P and ε_{PET} sum to unity depends on the Budyko hypothesis as the starting point, so the accuracy of the result depends on how well the Budyko formulation represents reality. Second, the results are highly variable depending on the specific formulation of the Budyko hypothesis (that is, the form of $\emptyset(\frac{P}{PET})$ in equation (1)). A third source of uncertainty arrives from the assumption that in the long term, the water balance closes, i.e., there is no long-term storage change. We explore the implications of this assumption further below. These sources of uncertainty can be considerable, because while (1) and (2) are good first approximations to the long term hydroclimatoloy of a river basin, it is now well known that the evapotranspiration ratio (AET/PET) in (1) is a function of a number of variables in addition to the aridity index (P/PET), including the soil moisture holding capacity (Sankarasubramanian and Vogel, 2002), the number of precipitation events per year, and seasonality parameters (Milly 1994). For a review of the now myriad of approaches for estimation of ε_P and ε_{PET} see Table 1 in Wang et al. (2016b).

Eq. 2 depends on the long-term means of Q, P, and PET. Most studies that have estimated ε_P and ε_{PET} from observations (the predominant focus has been on ε_P) have used annual data. For example, Sankarasubramanian et al. (2001) and Zheng et al. (2009) tested several estimators of ε_P using annual Q, P, and PET (over the conterminous U.S. and the

Yellow River basin, respectively), and Risbey and Entekhabi (1995) used annual Q, P, and T data to estimate ε_P and the streamflow sensitivity to temperature in the Sacramento basin. Approaches based on annual data embed an implicit assumption that the annual quantities for each variable in each year are a surrogate for their long-term means, implying that different years are independent and that there is minimum carryover storage from one year to the next. This of course is not true for runoff, which typically has some interannual carryover effects (the assumption arguably is more defensible for P and PET). Furthermore, especially during extremely high and low precipitation and runoff years, carryover storage can be substantial, depending on the specifics of a given river basin with respect to runoff generation and the magnitude of effective subsurface storage capacity.

3.0 Data and Methods

We estimated ε_P and ε_{PET} for a set of headwater river basins along the U.S. West Coast using two general approaches. The first is statistical, with various estimators applied to annual Q, P, and PET. The second is model-based, in which we perturbed P and PET forcings to a hydrologic model and calculated the model-predicted changes in simulated runoff. The statistical methods require streamflow data for rivers that are minimally affected by anthropogenic activities upstream (e.g., reservoir impoundments and/or diversions) as well as climate data including precipitation and variables required to calculate PET (which is a derived, rather than observed variable). We discuss below the data sources for both methods.

3.1 Streamflow Data and Gauge Selection

We retrieved average daily streamflow data from USGS Water Data for the Nation (http://waterdata.usgs.gov/nwis/). The stream gauges we used are a subset of the GAGES-

II (Geospatial Attributes of Gages for Evaluating Streamflow) dataset (https://water.usgs.gov/GIS/metadata/usgswrd/XML/g agesII_Sept2011.xml), which includes 2057 reference sites across the conterminous U.S. that were selected (by USGS) to be minimally disturbed by human influences (Falcone et al., 2010). We selected gauges in the states of CA, OR, and WA from the reference sites based on the following criteria and procedures:

(1) We identified and removed gauges with any regulation or diversions upstream based on the USGS remarks files;

(2) We required all gauges to have at least 50 years of continuous data. We arbitrarily defined a year of continuous data (we used water years in all cases) as having no more than 30 days of missing data nor more than 15 days in any continuous gap. Any stations that did not meet these criteria were removed from our list of candidates;

(3) We excluded gauges where the streamflow data have visually unusual patterns or many discontinuities and zero values. Such cases included, for instance, sudden changes in streamflow patterns that could not be attributed to natural factors. We note that there is considerable (although not complete) overlap in our criteria and station list with those used by Cooper et al. (2017).

The screening process resulted in 84 gauges, 24 of which are in CA, 23 in OR, and 37 in WA (Figure 1). The drainage areas associated with these gauges mostly are relatively small; the largest is 2463 km^2, and the smallest is 21 km^2. About half of the river basins have drainage areas smaller than 250 km^2.

3.2 Climate Data

The climate data we used include gridded precipitation, temperature, net radiation, vapor pressure deficit, wind speed, and atmospheric pressure. Precipitation, temperature,

wind speed, and atmospheric pressure are from the University of Washington's Surface Water Monitor (SWM; Wood and Lettenmaier, 2006) data set archived at UCLA (http://www.hydro.ucla.edu/SurfaceWaterGroup/monitors.php). P and T values were gridded directly from observations using the same methods as are used to produce the SWM. Net radiation and vapor pressure deficit are output of the Variable Infiltration Capacity (VIC) macroscale hydrology model (Liang et al., 1994; Mao et al., 2015; Xiao et al., 2016) using the gridded P and T forcings, and other forcings derived using methods described by Bohn et al. (2013). All data are at 1/16-degree spatial resolution; precipitation and atmospheric pressure are at 3- hourly time step, and other variables are daily. We estimated PET as Penman-Monteith reference ET (ET_0), which uses the aforementioned variables as inputs. We followed Allen et al. (1998) in our estimation of ET_0. Wind speed is constant (although seasonally varying) for each grid cell. Livneh et al. (2013) evaluated the implications of this assumption which are modest when averaged over long time periods.

3.3 Statistical Methods

We used three alternative statistical methods to estimate ε_P and ε_{PET}: a nonparametric estimator, bivariate ordinary least squares (OLS) regression, and bivariate generalized least squares (GLS) regression. The nonparametric estimator was employed and evaluated by Sankarasubramanian et al. (2001), and was shown to be relatively robust and unbiased. It has the form

$$\varepsilon_X = median\left(\frac{\Delta Q * \bar{X}}{\bar{Q} * \Delta X}\right) \quad (3)$$

where X is P or PET, $\bar{Q}$ is average annual runoff, ΔQ is the difference between one year's runoff and $\bar{Q}$, $\bar{X}$ is average annual P or PET, and ΔX is the difference between one year's P or PET and $\bar{X}$.

Of the numerous statistical approaches to estimation of ε_P and ε_{PET} summarized in Table 1 of Wang et al. (2016) we chose the approaches based on bivariate OLS and GLS regression (Andreassian et al., 2016; Konapala & Mishra, 2016) which were introduced in the same year that Wang et al. (2016) performed their historical review. Andreassian et al. (2016) showed that both the OLS and GLS approaches performed better than the nonparametric estimator in (3). The elasticity estimator in (3) is termed a 'one-factor-at-a-time' (OAT) approach, and Saltelli and Annoni (2010) argue that while OAT approaches are popular for sensitivity analyses, they are generally ineffective and multivariate approaches are preferred. Due to the findings of Andreassian et al. (2016) and Saltelli and Annoni (2010) we do not consider the OAT estimator in (3). Even sensible use of multivariate statistical methods for sensitivity analysis can occasionally lead to nonsensical results, as was clearly shown by Wallis (1965), and which our results show as well.

The bivariate model has the form

$$\frac{\Delta Q}{\bar{Q}} = \varepsilon_P \frac{\Delta P}{\bar{P}} + \varepsilon_{PET} \frac{\Delta PET}{PET} + \omega \quad (4)$$

where ω is a residual.

The main differences between OLS and GLS regression are that OLS assumes homoscedasticity and no spatial correlation among the annual runoff values, whereas GLS attempts to account for both. OLS assumes homoscedasticity meaning that the variance of the error term (ω) is constant, while GLS allows the error term to have unequal variance. OLS also assumes the dependent variable is not a random variable, whereas GLS accounts for the spatial correlation of the dependent variable. For GLS, we followed the implementation outlined in Andreassian et al. (2016).

We conducted field significance tests (Livezey & Chen, 1983) to investigate whether the null hypothesis that the sum of elasticities equal to 1 is rejected at the 5%

significance level. Because the degrees of freedom (number of independent sites) cannot be clearly assessed, we used a Monte-Carlo approach. First, we generated 1000 sequences of annual data (P, PET and Q) that have the same statistical properties and spatial correlations as the observation data. Then we applied the OLS and GLS methods to estimate the elasticities, applied the statistical test, and counted the number of rejections. By constructing the distribution of the number of rejections of the 1000 tests, we determined the critical value (the 5% exceedance value). We constructed 95% confidence intervals for the sum of ε_P and ε_{PET} from the results for each site and counted the number of rejections.

3.4 Hydrologic Model Implementation

We implemented a physical-based hydrologic model: the USGS Thornthwaite Water Balance Model (McCabe & Markstrom, 2007) (which we refer to hereafter as the USGS model). The USGS model is a simplified bucket model, but represents the dominant processes in runoff generation, albeit at a monthly time step. (We also tested a more sophisticated, widely-used hydrological model (Sacramento; SAC (Burnash et al. 1973)) with results that were quite close to those obtained with the USGS model; therefore, we utilized the USGS monthly model as our primary tool for model-based analysis). We estimated runoff elasticity for the USGS model by uniformly changing P or PET, calculating the change in the simulated runoff, and then determining the elasticity. Our approach follows, for instance Vano and Lettenmaier (2014). For example, if P is increased by 1%, and leads to an average 2% increase in runoff, then our estimate of ε_P is 2.0.

The USGS model has six parameters with monthly total precipitation, monthly average potential evapotranspiration and monthly average temperature as inputs. The model

parameters are: (1) a runoff factor, which determines the percentage of "surplus water" that contributes to runoff at each (monthly) time step, the rest adds to the next month's "surplus water", (2) direct runoff factor, which represents the percentage of rainfall in a given month that goes directly to runoff, (3) rain temperature threshold, above which all precipitation occurs in the form of rainfall, (4) snow temperature threshold, below which all precipitation occurs in the form of snowfall, (5) maximum snowmelt rate, which determines the maximum percentage of snow storage that can melt during a month, (6) soil moisture storage capacity, and (7) latitude. The model computes PET given $ET_{0,}$ which we computed as described in section 3.2.

We calibrated the USGS model for each basin manually by testing alternative combinations of the parameters. We tested soil moisture storage capacities ranging from 50 to 200 mm at 50 mm intervals, runoff factor and maximum snowmelt rates ranging from 0.5 to 0.8 at 0.1 intervals, and several sets of temperature thresholds between -5 to 5 °C. We fixed the direct runoff factor at the default value (5%). We found that the parameters to which the model predictions were most sensitive were soil moisture storage capacity and snow temperature thresholds. The soil moisture storage capacity mainly affects low flows since precipitation has to fill the soil storage before runoff can be generated. Temperature thresholds affect the runoff seasonal cycle by determining how much and when snow melts. We selected parameter sets based on the Kling-Gupta efficiency (KGE) (Gupta, et al., 2009) of the resulting model streamflow predictions. We found that the simulated runoff in a number of basins was underestimated, but a good match could be obtained by shifting the hydrograph up. The reason is that precipitation was unrealistically small in most of those basins. We calculated the ratio of precipitation to runoff, and found that they likewise were small and were less than 1.0 in some basins,

which is clearly infeasible. For these basins, we upscaled the precipitation by factors that led to the highest KGE.

4.0 Results

Precipitation elasticities estimated by the three different methods are generally similar, except that ε_P estimated using the USGS model resulted in considerably larger values of ε_P compared with the OLS and GLS methods (Figure 2a). Similarly, many of the estimates of ε_{PET} are quite similar and negative, however, both GLS and OLS often led to positive values whereas all values were negative for the USGS model (Figure 2b). OLS and GLS produce similar results for ε_{PET} and thus the sum of ε_P and ε_{PET}. OLS and GLS methods produced a few large positive complementary sums (>2). The interquartile range of the complementary sum of ε_P and ε_{PET} corresponding to OLS and GLS was approximately [0.7-1.4] and the interquartile range for USGS was about [1.0-1.1]. Thus, the USGS model led to considerable improvements in reproduction of the complementary relationship relative to the OLS and GLS methods.

The results based on the USGS model led to precipitation elasticities that are all larger than 1.0. PET elasticities are all negative, and the sums of ε_P and ε_{PET} are all equal or greater than 1.0. For OLS and GLS, the medians of the sums of ε_P and ε_{PET} across sites are around 1.0 (but with larger ranges than corresponding to the USGS model). The USGS model results generally have sums that are closer to 1.0 than the statistical methods. The nonparametric estimator showed poor reproduction of the complementary relationship in our results and due to concerns raised by Andréassian et al. (2016) and Saltelli and Annoni (2010) we dropped the nonparametric estimator from our comparisons in Figure 2, and it is not included in further analysis or discussion.

In terms of field significance, the number of rejections (of the hypothesis that $\varepsilon_P + \varepsilon_{PET} = 1.0$) is 25 out of 84 basins (30%) for OLS and 23 (27%) for GLS. Thus, the OLS and GLS results indicate that complementary hypothesis holds at approximately 70% of the sites. According to our Monte Carlo approach, the critical value of the field significance test was 12 for OLS and 13 for GLS. Therefore, we must reject the overall null hypothesis that the sum of elasticities at all sites is 1.0 using an overall 5% field significance level. On the basis of these hypothesis tests there is considerable evidence that the statistical methods are unable to reproduce the complementary relationship across all sites, whereas, even though we were unable to perform an analogous field hypothesis test for the USGS results, Figures 2c and 2f indicate excellent reproduction of the complementary hypothesis corresponding to the USGS model..

5.0 Discussion

While ε_P values computed using the two statistical and model-based methods are roughly similar, the characteristics of ε_{PET} estimated using the statistical methods are peculiar. About 30% (26) of the basins have ε_{PET} estimated using OLS and GLS that are both positive, which is counter-intuitive and infeasible. One fundamental difference between hydrologic model-based and statistical estimates is that the change of climate variables is controllable in the models but not in observations. Another fundamental difference between the hydrologic model-based and statistical estimates is that the hydrologic model has built into it, a Budyko-like relationship, whereas the statistical models do not. We discuss both of these fundamental differences between the statistical and hydrological model based approaches below.

In the models, we changed P and PET uniformly and independently, whereas when implementing statistical methods, both the time of change (e.g. if all of an anomaly

in P occurs in one month or is spread throughout the year) and the change in magnitude (e.g. 1% increase or 10%) varies from year to year and are out of our control. In the analysis of climate elasticity of runoff by Dooge (1992) and other studies based on analytical approach and Budyko hypothesis, the climate is usually assumed to change uniformly from one long-term mean to another. Thus, some physical constraints exist. For instance, PET elasticity should always be negative since more water will be lost with higher evaporative demand. However, if a 1% total increase in PET is distributed as a 2% increase in a season when surface water is scarce and a 1% decrease in a season when surface water is abundant, the net result could be increased runoff and apparently positive ε_{PET}. By allocating the 1% change in P to the summer months in the USGS model, Figure 3 demonstrates the enormous impact that such a variation from a uniform to a seasonal change affects the resulting precipitation elasticities.

Another complication is that in observations, P and PET change simultaneously instead of independently. This means that the statistical methods need to be able to separate the complex and interacting influences of P and PET on runoff. Two problems arise. One is that the independent variables P and PET exhibit weak multicollinearity, however this is not expected to be a problem for estimation of model coefficients using GLS and OLS regression as shown recently by Kroll and Song (2013). The other is that annual PET variations (as a fraction of, say, the mean) are usually smaller than for P, and P is the main driving factor in runoff generation with greater influence than PET. This complicates the task of statistical methods to segregate the two effects, and it may partially explain why estimates of ε_P by different methods are similar, whereas estimates of ε_{PET} by statistical methods often seem implausible.

Regarding the extent to which estimates of ε_P and ε_{PET} are complementary, our results show better conformance by hydrologic model-based than observation-based

estimates, and the analysis above suggests that one reason has to do with our use of observation-based estimates of ε_{PET}. Of course, another reason is due the fact that the USGS model (like most physically based hydrologic models) has a Budkyo-like hypothesis built into its model structure. Thus an obvious question is whether the lack of closure of the complementary hypothesis concerning ε_P and ε_{PET} is due to problems with the modeling approach (i.e. estimators), or with the hypothesis.

As we note in Section 2.0, complementarity comes about as a result of closure of the long-term water balance (in terms of the means of Q, P, and ET) and the Budyko hypothesis (in its general, rather than any specific, form). We note that because hydrologic models (including the USGS model) balance water by construct, and generally have Budyko-like behavior in their evapotranspiration parameterizations, it should not be surprising that the USGS model results generally reproduce the complementary relationship. There are no such physical constraints on the statistical methods, so we further explored the extent to which the long-term water balance is reproduced by the observations. Here we evaluate how ΔP/P, ΔPET/PET and ΔQ/Q correlated with ΔStorage/Storage by calculating the corresponding R^2. Out of the total 84 basins, only 8 basins have one or more variables highly correlated to storage changes (defined as at least one of the correlations greater than 0.3). This implies the influence of storage changes should not change our main findings and conclusions, which implies that the long-term water balance is nicely reproduced by the observations.

The degree to which the Budyko hypothesis holds for these basins is evaluated in Figure 4 which illustrates the relationship between AET/PET and P/PET (where AET is the output of USGS model. Figure 4 suggests that there does seem to be a Budyko-like form when taken across all 84 river basins. Red and green circles in Figure 4 indicate those basins in which the complementary hypothesis was rejected, or not, respectively, when

using the OLS and GLS estimators. The degree to which the complementary hypothesis is reproduced by the statistical estimators does not appear to be related to either the degree to which the Budyko hypothesis holds, or the hydroclimatology of the basins. Figure 4 illustrates a very broad range of hydro-climatologic regimes, because according to the climatic classification system introduced by Ponce et al. (2000, Table 1), the values of P/PET reported in Figure 4 range from approximately [0.1, 2.5] a range which corresponds to hydro-climatologic conditions ranging from arid and semi-arid, to subhumid and even humid conditions. It is important to note that neither AET nor PET are observed values, which might compromise inferences from Figure 4.

The multivariate statistical estimators perform poorly compared to the physical-based model approach in terms of their ability to reproduce the complementary relationship as was shown in Figure 2cf. This result should not be surprising given the warnings of Wallis (1965). In order to explore possible improvements of the statistical method, we imposed a constraint to ensure that the complementary relationship holds (i.e. $\varepsilon_P+\varepsilon_{PET}=1$) in the OLS method, which we denote OLS-CS method. The resulting distribution of the elasticities is shown in Figure 5. Distributions from other methods in Figure 2 are also plotted for comparison. The ranges of both ε_P and ε_{PET} are generally similar to USGS model results and importantly are more realistic than either the unconstrained OLS or GLS estimators. However, even when constrained to reproduce the complementary relationship, the OLS-CS method still produces some (albeit few) positive values of ε_{PET}. Importantly, estimates of both ε_P and ε_{PET} obtained from the constrained OLS-CS method are much less variable than those derived from the unconstrained OLS and GLS methods.

6.0 Conclusions

We applied three statistical methods and the USGS hydrologic model to estimate P and PET elasticities of runoff for 84 basins in CA, OR, and WA, and evaluated the degree to which those methods are able to reproduce the complementary relationship. We conclude that:

1. Complementarity is generally observed (at least in the central tendency of the distribution across the 84 basins) in the hydrologic model-based estimates, but only for a portion of the observation-based estimates based on the statistical methods.
2. The estimates of ε_P using different methods are generally consistent. Deviations from complementarity are mostly attributable to the ability to estimate ε_{PET}, and in particular to highly negative estimates for some of the basins. The problem appears to be a combination of (a) relatively smaller scales of variation in interannual variability of PET which is a reflection of PET being a weaker factor in runoff generation than P, and b) correlation between P and PET (both with an understanding that for most of the basins, P is winter dominant, and PET is summer dominant).
3. Hydrologic model-based relationships between AET/PET and P/PET displayed a typical Budyko form across a very broad range of hydroclimatic conditions ranging from arid to humid conditions. Although the OLS and GLS statistical methods led to strong deviations from the complementary relationship at some basins, we could not discern any significant departures from the Budyko hypothesis for those basins.
4. Estimates of P and PET elasticities derived from multivariate statistical methods such as the OLS and GLS approaches often led to questionable results, especially when compared to the results based on a hydrologic model. This result is consistent with the warnings given by Wallis (1965). However, our results indicate that the statistical approaches may be improved considerably by including the

reproduction of the complementary relationship as a constraint in the fitting process. Nonetheless, the most realistic estimates were generally obtained from a hydrologic model, which as we note above, has a general structure that meets the two key assumptions underlying complementarity – water balance closure, and a Budyko-like ET parameterization.

Acknowledgement

All the data used in this study is archived at: https://doi.org/10.6084/m9.figshare.10278089

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List of figures:

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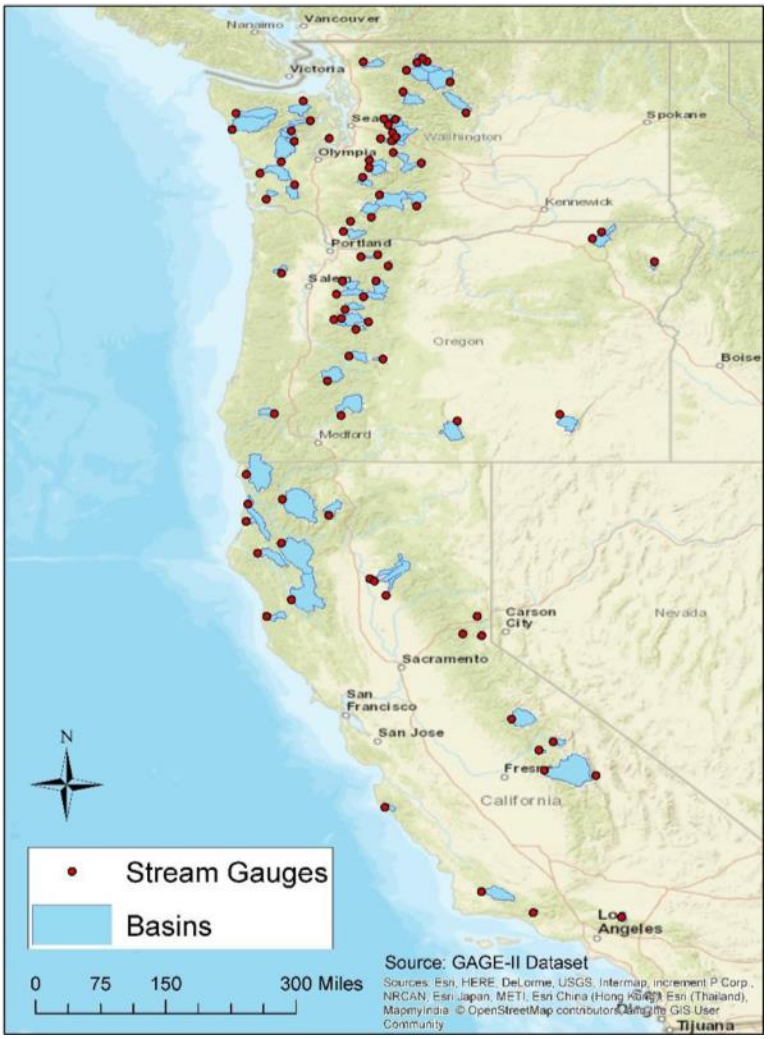
Figure 5: ε_P (a), ε_{PET} (b), and the sum (c) estimate by constrained linear regression method (OLS-CS). The other results are identical as in Figure 2 and shown for comparison here.



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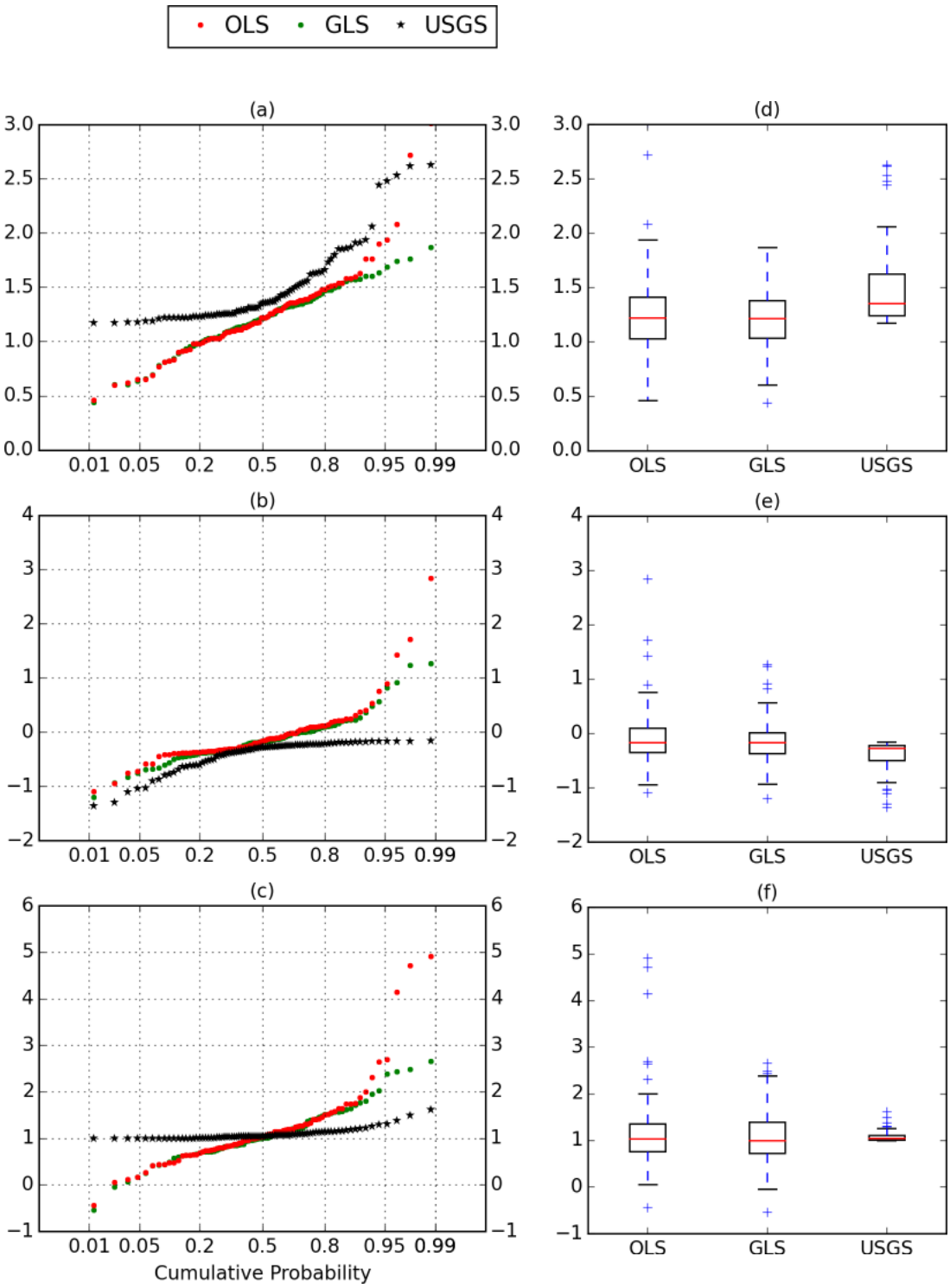

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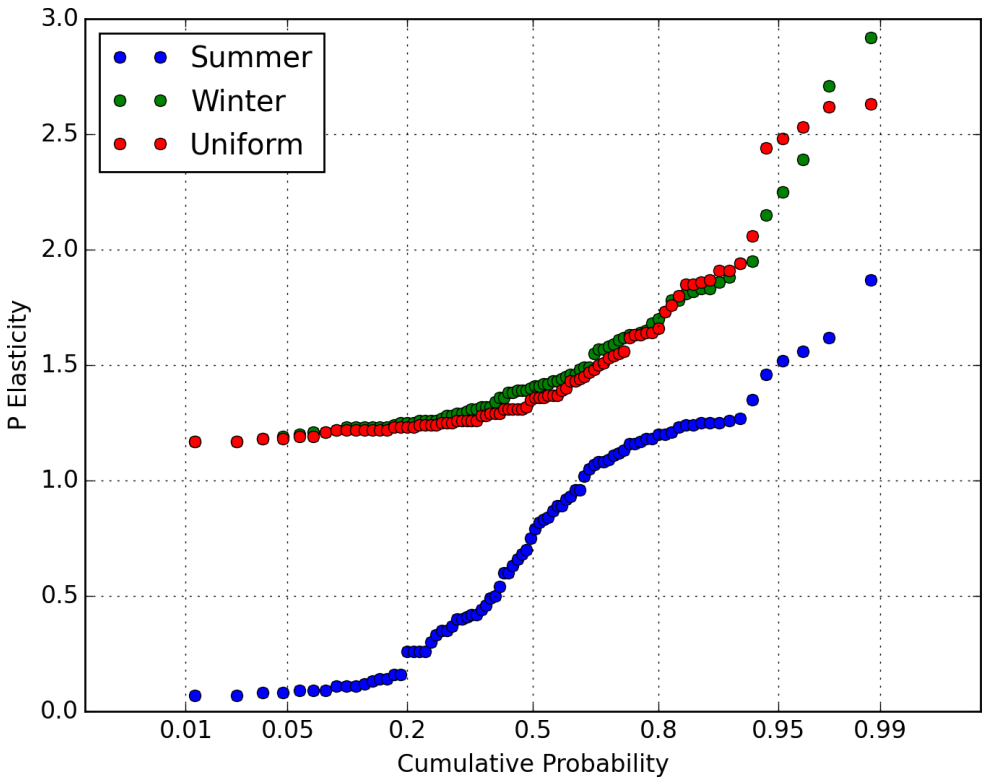

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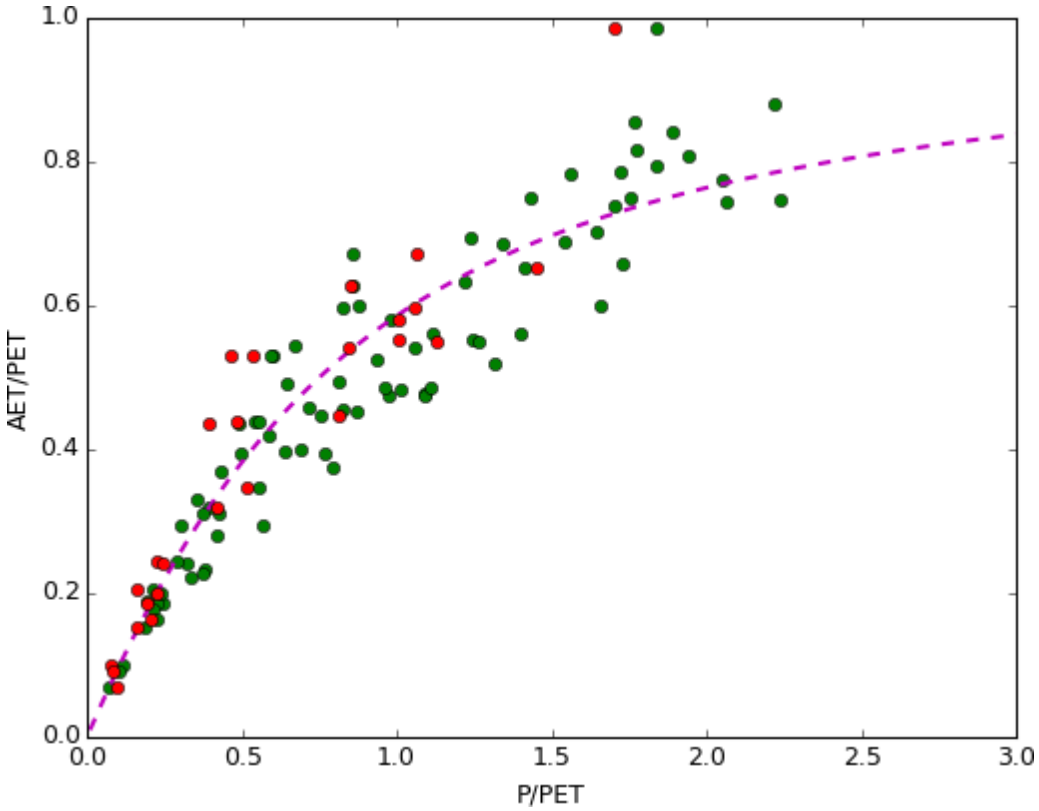

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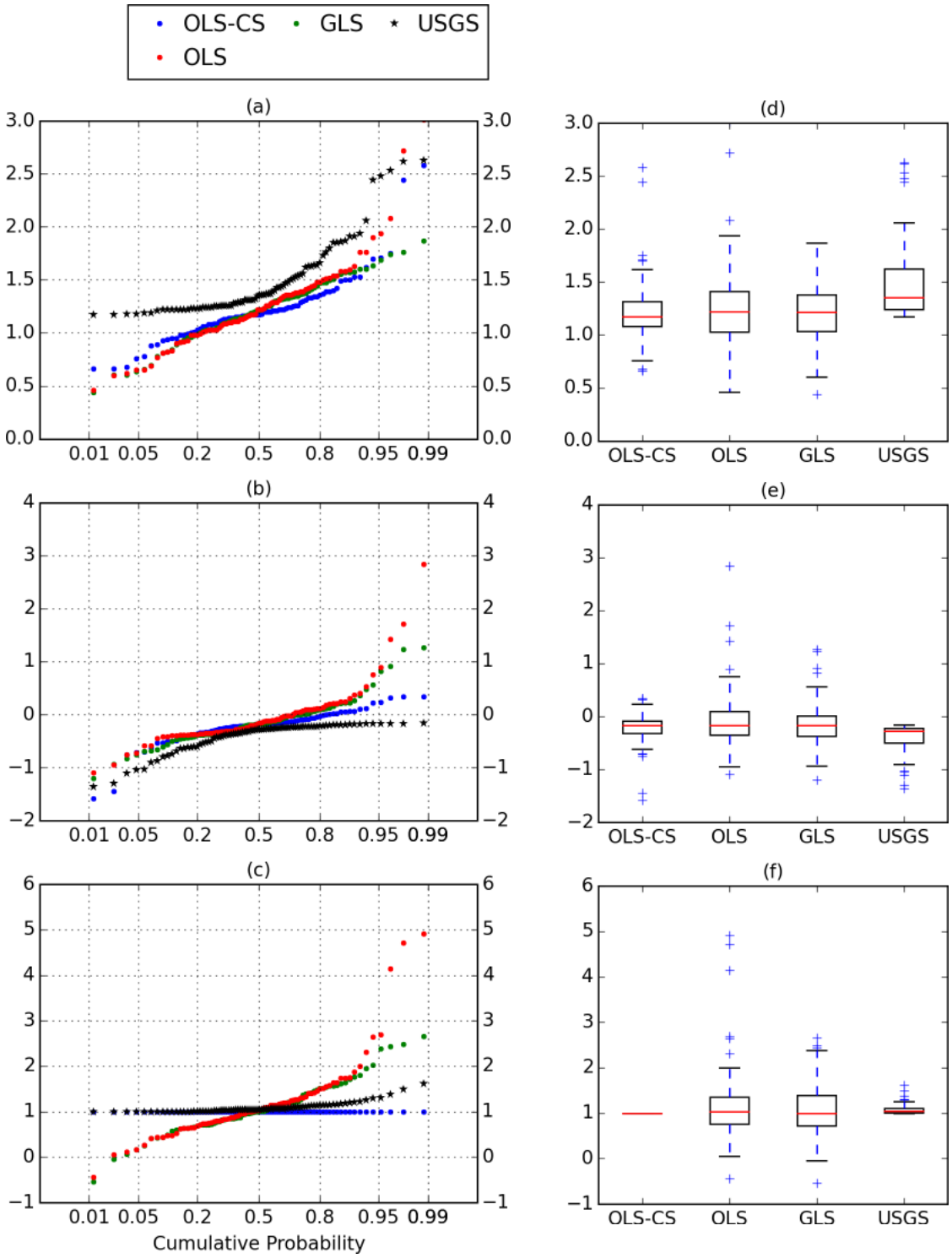

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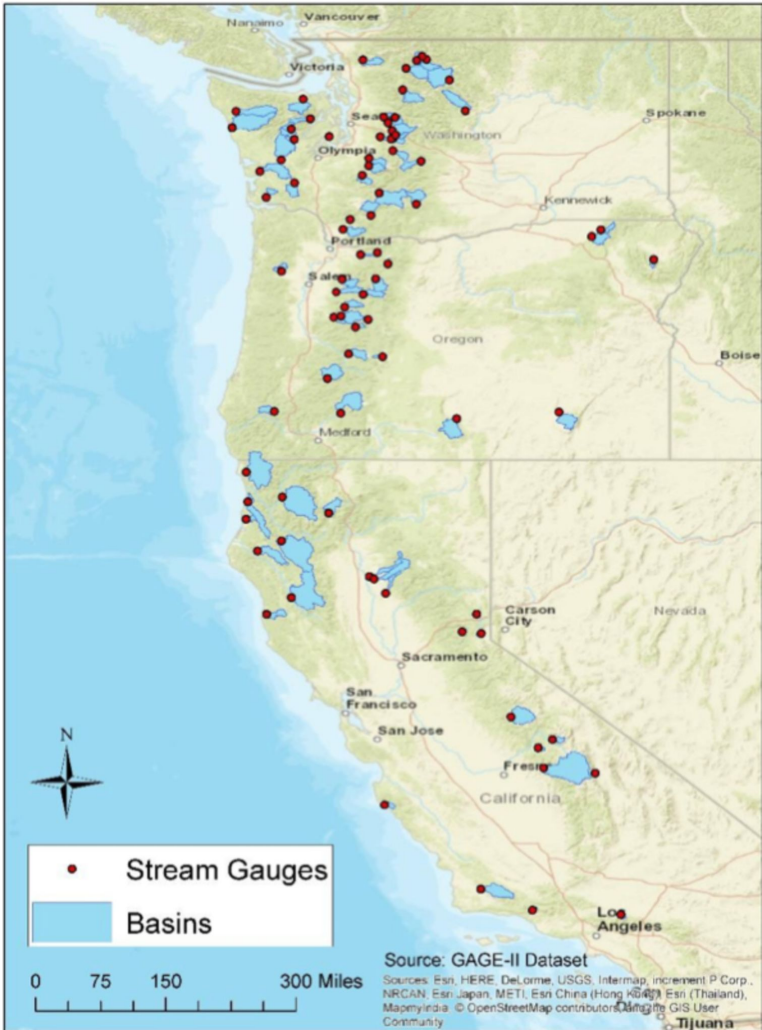
Figure1.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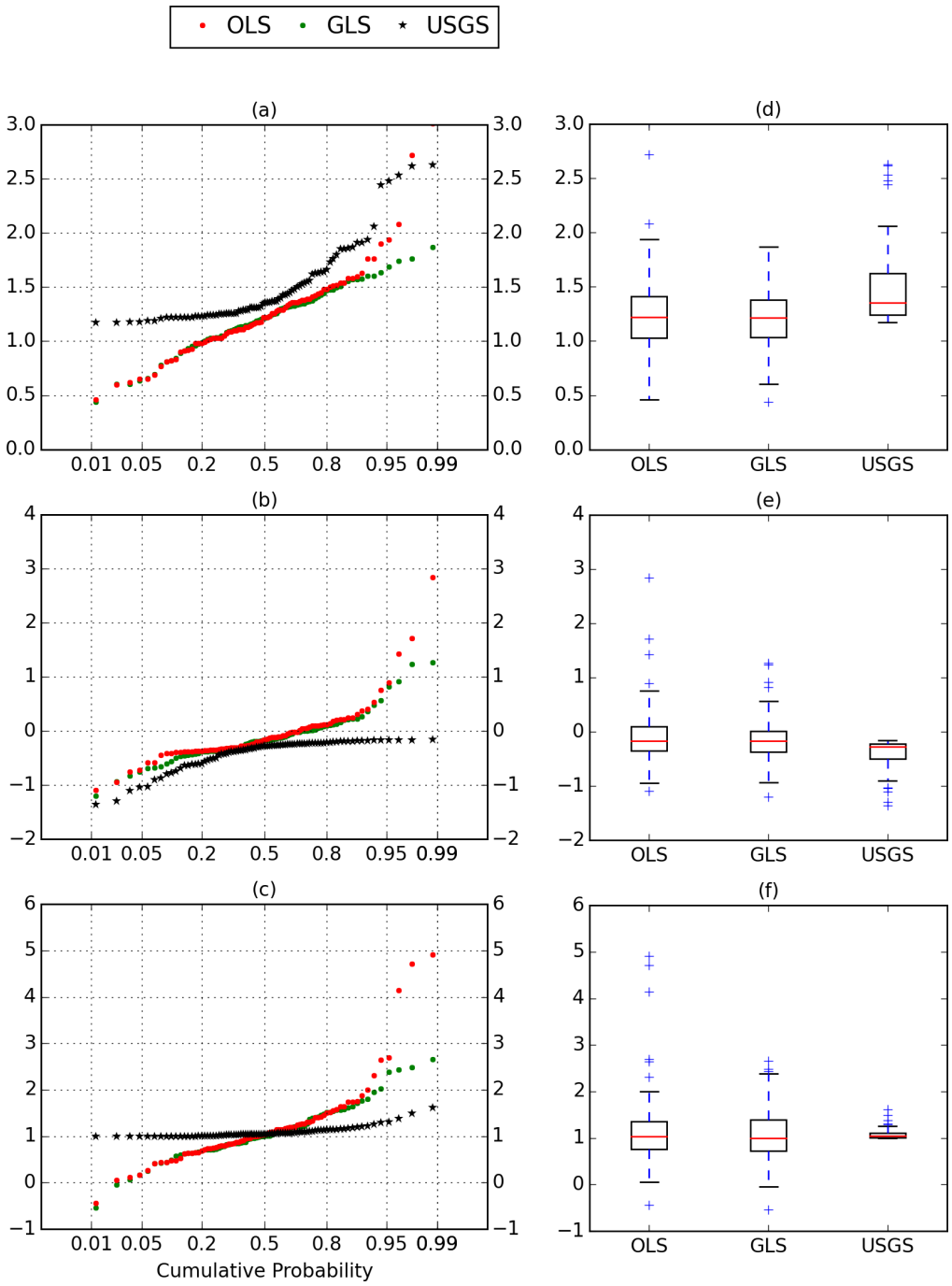
Source: GAGE-II Dataset
Sources: Esri, HERE, DeLorme, USGS, Intermap, increment P Corp., NRCAN, Esri Japan, METI, Esri China (Hong Kong), Esri (Thailand), MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

Figure2.


OLS
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(c)
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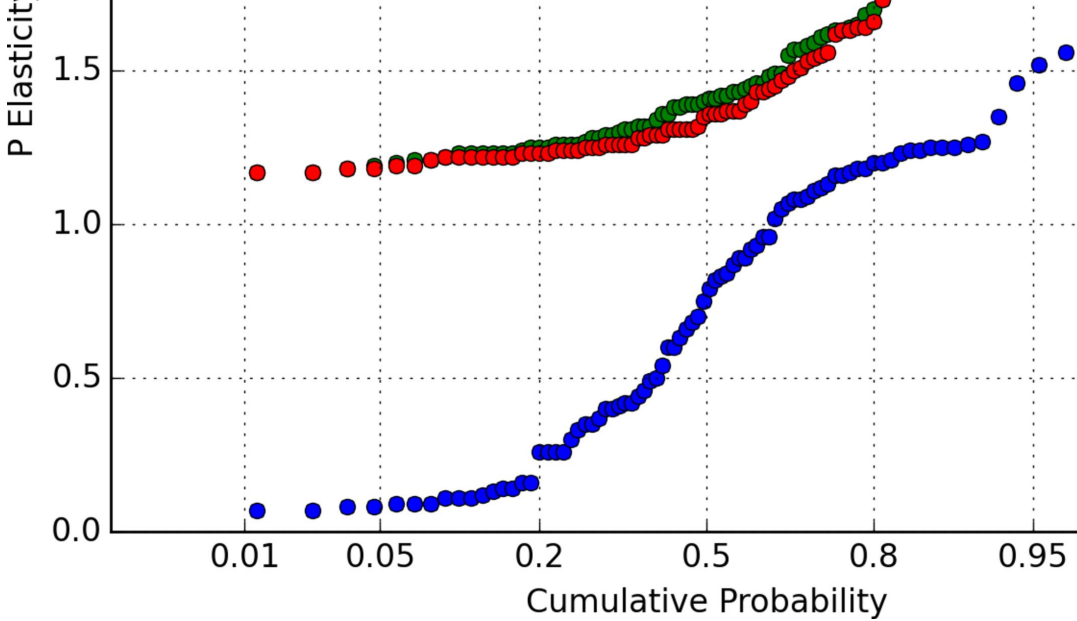
Cumulative Probability
OLS
GLS
USGS

Figure3.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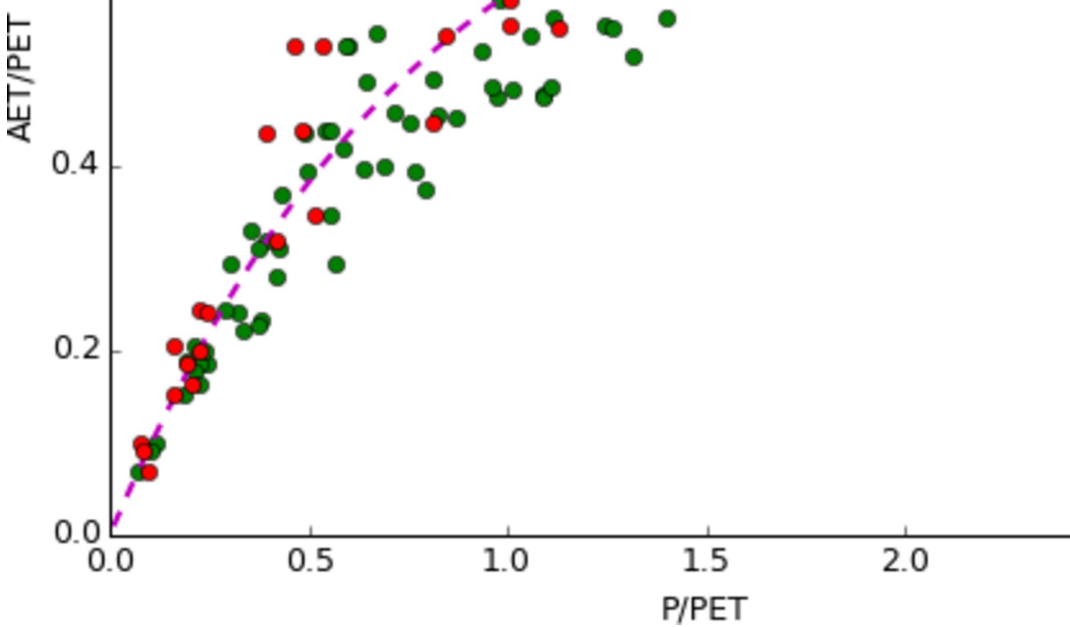
Cumulative Probability

Figure4.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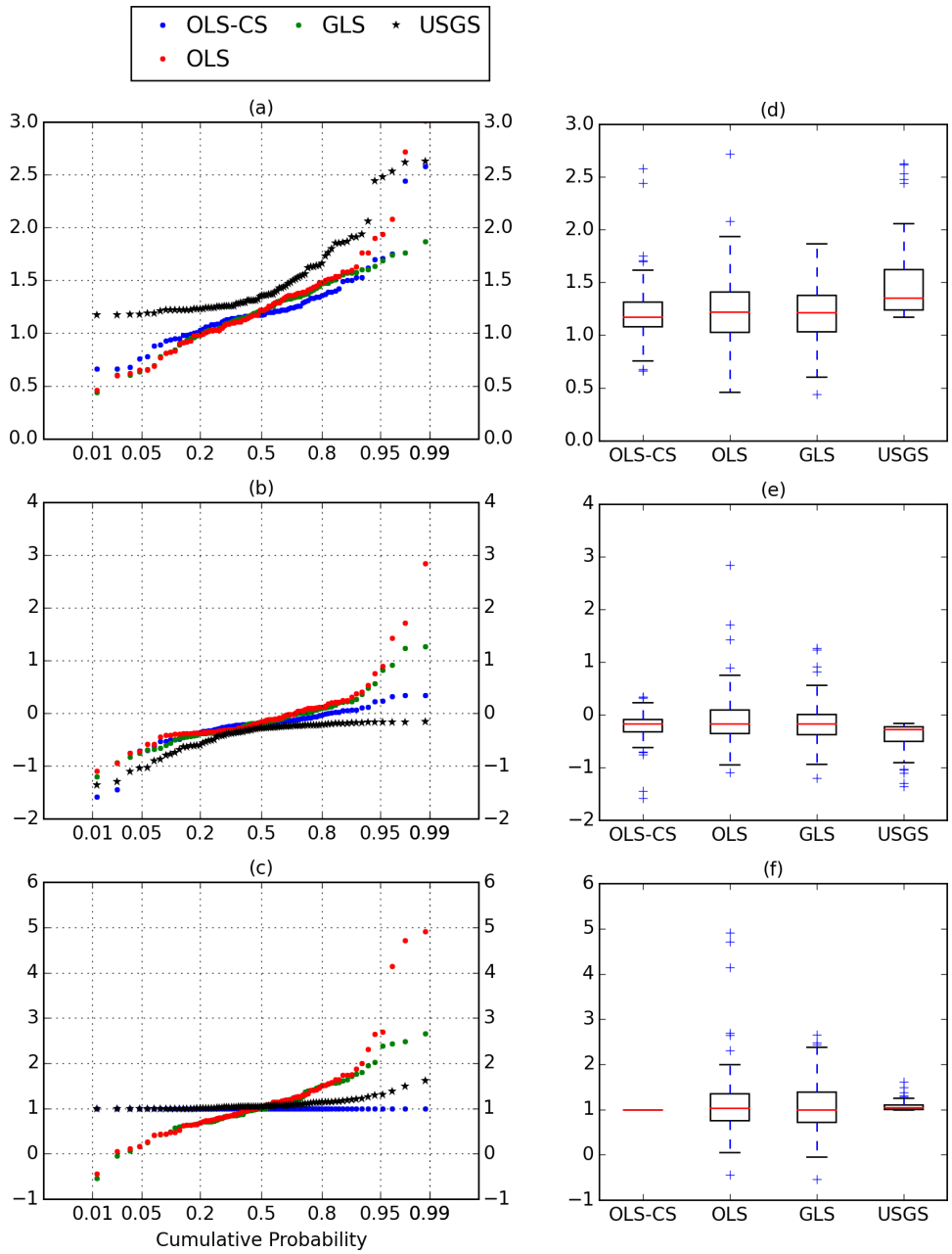
P/PET

Figure5.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Cumulative Probability
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