Modeling the linkages between transit time distributions and climate variability: Opportunities and challenges in the Chesapeake Bay Watershed

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Introduction

The watershed transit time distribution (TTD) describes the distribution of times that water travels along various pathways from entrance (e.g., rainfall) to exit (e.g., discharge) of a watershed. The TTD varies spatially and temporally according to local characteristics including catchment geometry, topography, soil type, and climatic conditions (McGuire & McDonnell 2006). Hydrologists have historically lacked adequate data and theory to characterize the time-varying nature of TTDs. Studies of environmental tracer data have instead tried to estimate a mean transit time (mTT) or a stationary TTD (McGuire & McDonnell 2006). These approximations have provided useful insight into the sensitivity of catchments to anthropogenic inputs and land-use changes (McDonnell et al. 2010). New theory and modeling tools are emerging, however, that characterize the dynamism of TTDs (hereafter referred to as dynamic TTDs or dTTDs). Multiple studies suggest that modeling the time-varying nature of dTTDs improves our understanding of watershed processes that inter alia control chemical transport (e.g., Rodhe et al. 1996; Heidbuechel et al. 2012; Harman 2015). Understanding dTTDs may be especially important to efforts to restore water quality in the Chesapeake Bay. Non-stationarity in the dTTD could alter the timing and quantity of sediment and nutrient loads transported from the Chesapeake Bay Watershed (CBW). Previous studies suggest that water quality in the Chesapeake Bay – the largest estuary in the United States – can be sensitive to relatively small upstream changes (Kemp et al. 2005). One phenomena with the potential to shift dTTDs across the CBW is anthropogenic climate change. Few studies, however, have explicitly quantified the association between climate and dTTDs and its implications under a changing climate (though see for example Capell, Tetzlaff, & Soulsby, 2013).

Objectives

We present ongoing work to understand the extent to which *shifts in climate* cause *shifts in watershed dTTDs* which cause *shifts in the quantity and timing of chemical transport* in the CBW and other watersheds. The specific questions examined are:

- How much of the variability in dTTD estimates across different watersheds can be explained by variability in climate? Which climate variables (e.g., precipitation, ET, temperature) explain the most variability?
- How much is already known about dTTDs as well as the potential extent of climate change within sub-catchments of the Chesapeake Bay Watershed?

Perceptual Model

Figure 1 shows a perceptual model of the phenomena under investigation. First, climatic shifts cause changes in watershed fluxes (e.g., rainfall, ET) and watershed structure (e.g., variable source areas) that change flow pathways and other hydrologic processes. Second, these changes manifest as non-stationarity in the dTTD of the watershed. Third, the new dTTD reflects a new regime for chemical transport due to changes in travel times and other time-dependent transport processes (e.g. radioactive decay).

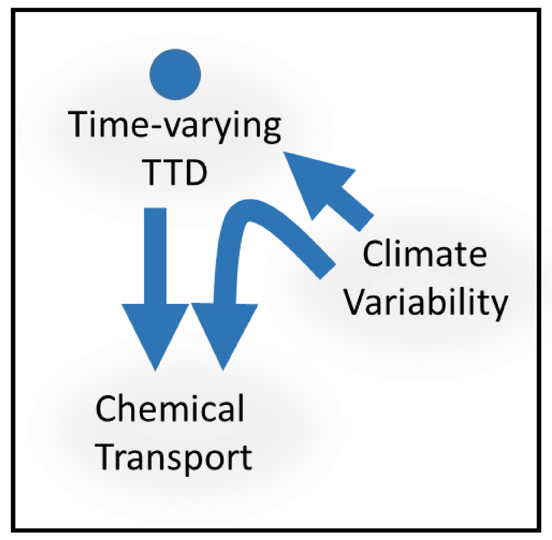
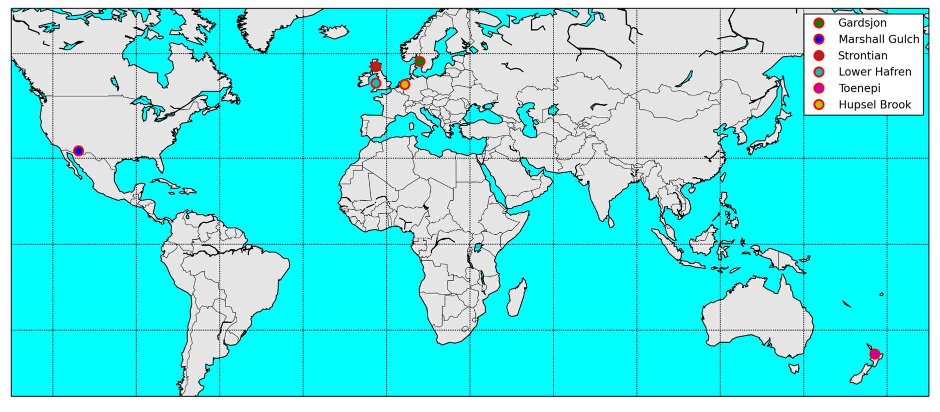


Figure 1 (above right). Perceptual model of the relationship under study between climate variability, dynamic transit time distributions, and chemical transport. **Figure 2 (below).** Map of identified watersheds with estimates of the time varying mTT



1. Climate and mTT variability across multiple watersheds

Methods: We reviewed the literature to identify modeling studies with time-series estimates of the mean (or median) transit time (mTT) of the dTTD. Plots of dTTD were digitized using Engauge Digitizer software (v4.1) for subsequent analysis in Pandas Python Data Analysis Library (v0.15.2), resampled into monthly averages, normalized to z scores, and log transformed. Monthly climate data (temperature (T), precipitation (P), and evapotranspiration (ET)) was acquired for the overlapping 1/8 degree resolution grid cell for each study watershed from the Global Land Data Assimilation System (GLDAS) (Rodell & Houser 2004) for the study period plus ten years prior. GLDAS soil moisture from depths of 1-10cm (S) was also examined. Monthly values of P, T, and ET were weighted exponentially backward using the decay parameter τ [month^{-1}] that resulted in the highest absolute rank correlation with dTTD. Climate values were also normalized. Five different predictive algorithms (stepwise GLM, lasso regression, random forest, MARS, and the mean) were compared in a 100-fold cross validation with 20% holdout in R software (v3.0.2). The top performing model based on mean square and absolute error was fit with all the data and examined for inference.

Results: We identified and digitized six studies with time-series estimates of mTTs from 3.4-6.1 years in duration for three different flow paths: groundwater, root zone, and all paths (see Figures 2-3 and Table 1). Figure 4 illustrates the relationship between mTT and the climate variables P (τ=5 months^{-1}), T (1 month^{-1}), ET (2 months^{-2}), as well as S (1 month^{-1}). The random forest (RF) model performed slightly but significantly better than the others with a mean absolute error of 0.64. Figure 3 shows that the RF simulations reproduced the general behavior of the observations, though some significant variability was missed. The RF partial dependence plots (Figure 5) shows that increases in P (T,ET) are associated with lower (higher) mTT. Measures of variable importance (not shown) indicate that P is most important to the accuracy of model estimates.

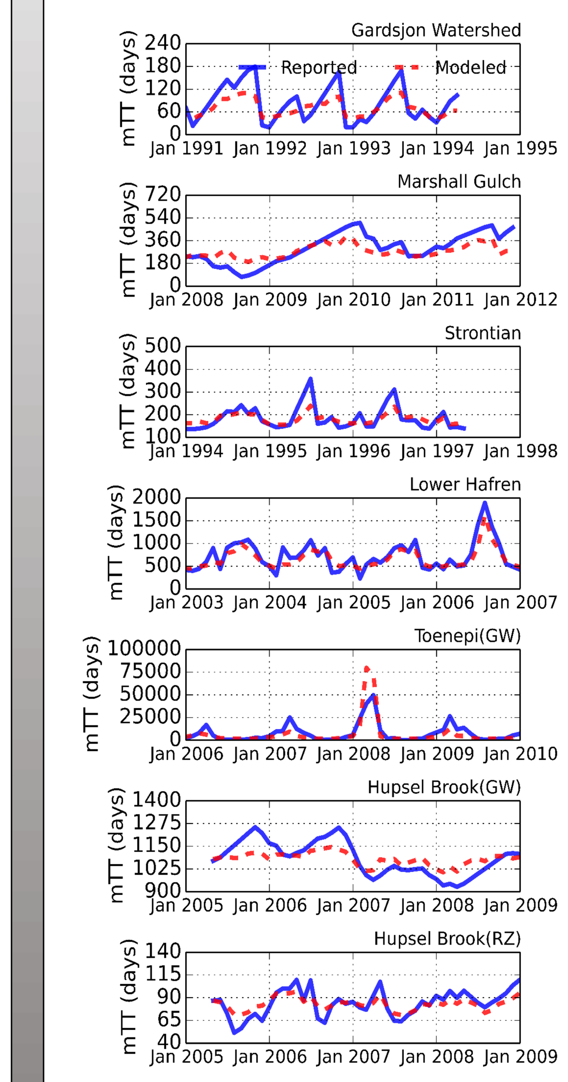
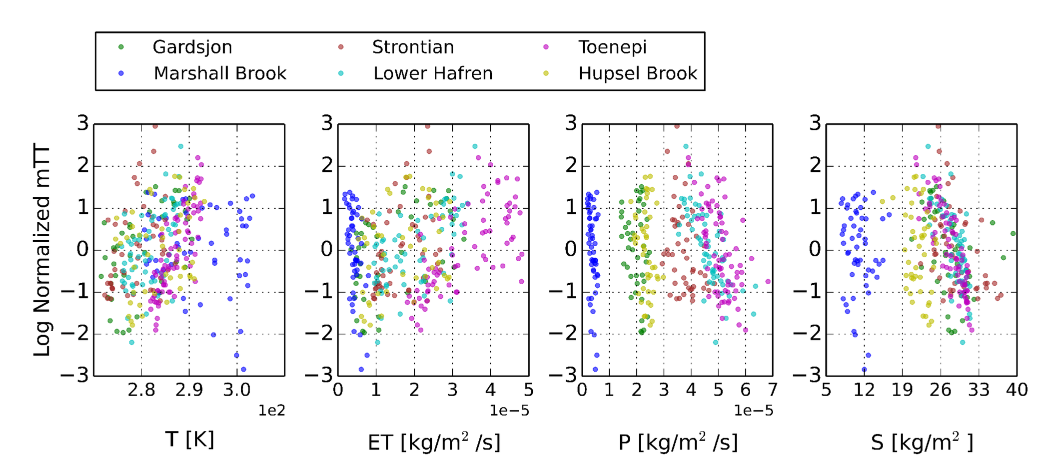


Figure 3. Plots of the time varying mTT for the six watersheds included in our study (blue line) and simulated mTT given by the random forest model with local climate as predictors (red dashed line). Raw data was digitized from the papers identified in Table 1.



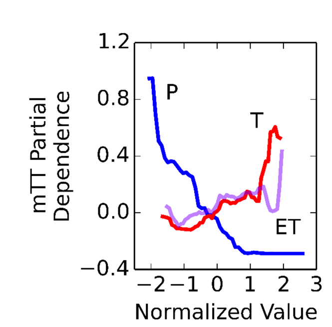


Figure 4 (above). Scatterplot of mean monthly GLDAS climate parameters (plus soil moisture) against log normalized mTT in the six watersheds studied. Note slight slopes can be observed, particularly for P and S. **Figure 5 (right).** Partial dependence of climate variables on mTT as given by the random forest model. Low P and high ET and T are associated with high mTT. **Table 1 (below).** Description of the six watersheds included in this study including mean GLDAS climate data. [1] mTT values reported in Harman (2015) are medians, not means.

Reference	Site	Basin Area [km^2]	Tracer	mTT Data: Flow Paths	mTT Data: n [Years]	mTT Data: Mean [days]	mTT Data: CV [-]	GLDAS Climate Data: T [K^o]	GLDAS Climate Data: ET [mg/m^2/s]	GLDAS Climate Data: P [mg/m^2/s]	GLDAS Climate Data: S [kg/m^2]	Methods Highlights
Rodhe et al. (1996)	Gardsjon	0.0063	^{18}O	All	3.4	82	0.6	280	14.1	19.0	27.7	Convolution with flow-weighted time.
Heidbuchel et al. (2012)	Marshall Gulch	1.54	^{18}O, ^{2}H	All	4.4	292	0.4	292	4.3	3.9	11.0	Mixing model with dynamic storage.
Hrachowitz et al. (2010)	Strontian	8	Cl$^-$	All	4.0	185	0.3	279	16.3	37.1	29.0	Time varying transfer function.
Harman (2015)	Lower Hafren	3.5	Cl$^-$	All	5.0	681[1]	0.5	282	20.2	47.1	28.5	Age ranked storge selection function.
Morganstern et al. (2010)	Toenapi	15.1	^{3}H	GW	6.1	6810	1.4	287	33.4	50.5	27.9	Exponential-piston flow model.
Benettin et al. (2013)	Hupsel Brook	6.5	Cl$^-$	GW	3.8	1084	0.1	284	16.7	23.3	21.8	Two reservoirs with random sampling.
				RZ	3.8	84	0.2	284	16.7	23.3	21.8	

2. Climate and mTT variability in the Chesapeake Bay Watershed

Methods: To begin to understand potential future climate variability in the CBW, we acquired all CMIP5 downscaled monthly climate projections under the RCP8.5 scenario available for download at the "Bias Corrected and Downscaled WCRP CMIP5 Climate Projections" archive as of 3/19/2015 (70 total) at 1/8 degree resolution (Maurer & Brekke 2007). The RCP8.5 scenario has the highest greenhouse gas emissions providing a "worst case" for initial analysis. The monthly estimates were averaged over three sub-catchments of the CBW (i.e., Susquehanna, Potomac, and James Rivers) for baseline years (1985-2005) and future years (2075-2095) and the difference calculated over all time and each season. To begin to understand the dTTD of the CBW, we assembled and geocoded known published estimates of mean groundwater age across the CBW and plotted them over the three catchments considered. The age of multiple estimates from the same location were averaged. Note that no explicit estimates of dTTDs within the CBW were found.

Results: Figure 6 shows the downscaled simulations of the effect of climate change across the three watersheds of the Chesapeake Bay Watershed. There is considerable spread across the different models. The median temperature increase ranges roughly between 3-7^{o}C with the largest increases in the summer and little variation across the watershed. The median precipitation increases although some models predict a decrease. The seasonal trends are generally consistent across basins, with relatively higher precipitation in winter and lower precipitation in summer. Figure 7 shows the spatial distribution of 212 separate estimates of groundwater age across the watershed from two USGS-authored publications (Lindsey et al. 2003; Sanford & Pope 2013). There is significant heterogeneity in the mTT across the watershed, even at close distances, as has been reported previously (Lindsey et al. 2003).

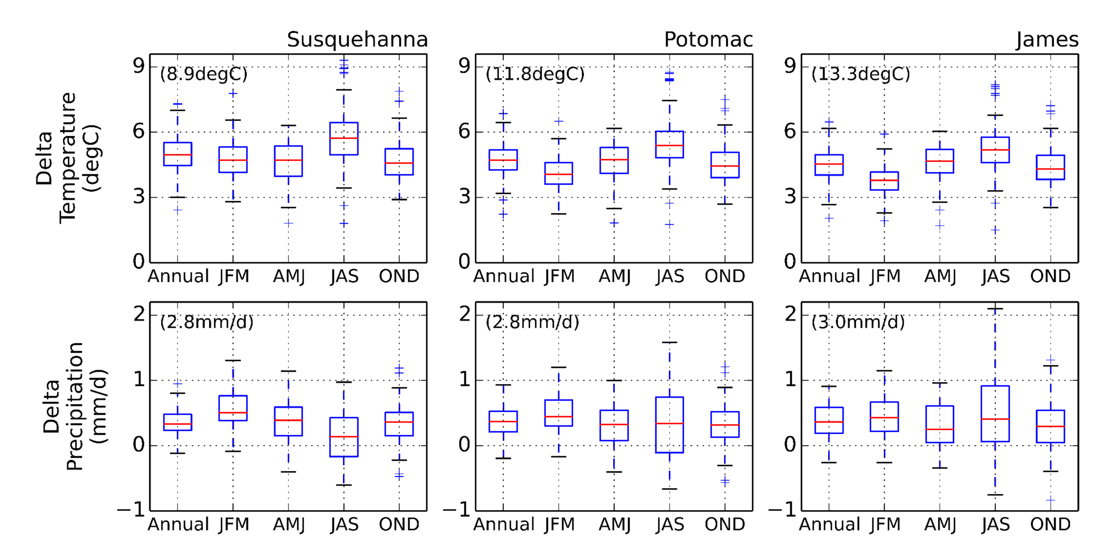


Figure 6. The downscaled CMIP5 simulations of the change in temperature (top) and precipitation (bottom) of climate change across three watersheds of the Chesapeake Bay Watershed shown in Figure 6. Delta values are the difference between monthly average values in the future scenario (2075-2095) and the baseline (1985-2005). Box and whiskers plots show the spread of 70 different downscaled GCMs under the RCP8.5 high emissions scenario (red line: median, box bottom/top: 25/75% percentile, line bottom/top: data extent excluding outliers). Delta values considering the full year and seasons are shown.

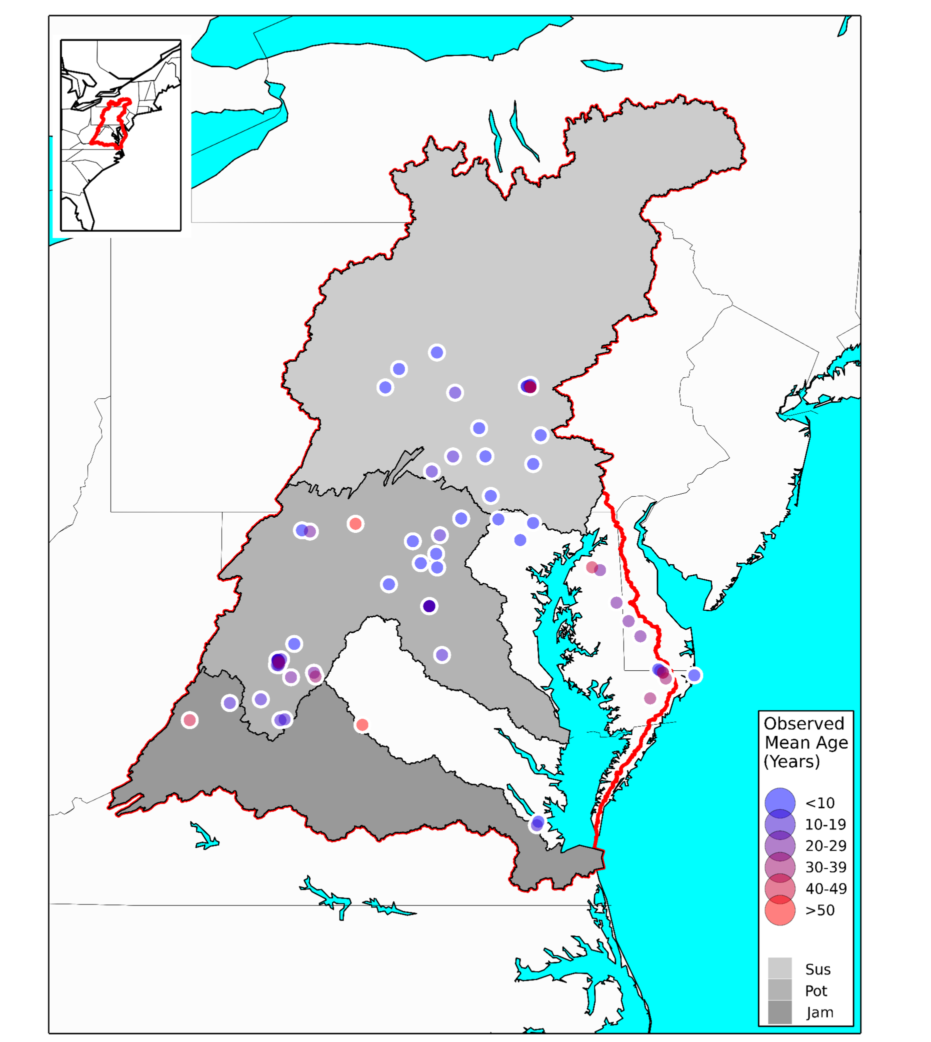


Figure 7. Map showing estimates of mean groundwater age across the Chesapeake Bay. Climate projections were tabulated for the three shaded watersheds: the Susquehanna (Sus), Potomac (Pot), and James (Jam) rivers. All age data from Lindsey et al. (2003) and Ward and Pope (2013).

Discussion and Conclusions

- Regional climate data explained a significant portion of the variability in time-varying mTT estimations across six different study sites. A random forest model found that increases in P (T, ET) are associated with decreases (increases) in mTT.
- Median GCM projections for 2075-2095 under a relatively high greenhouse gas emission scenario show increased temperatures (especially in the summer, higher certainty) and precipitation (especially in the winter, lower certainty) throughout the CBW.
- Our study of multiple watersheds suggests that the median projected changes in temperature and precipitation in the CBW under a changing climate would drive the mTT in opposite directions.
- Observed spatial heterogeneity of mean groundwater ages across the CBW is high. This could complicate the application of existing dTTD theory for simulation of chemical transport to the bay.

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