West Virginia White

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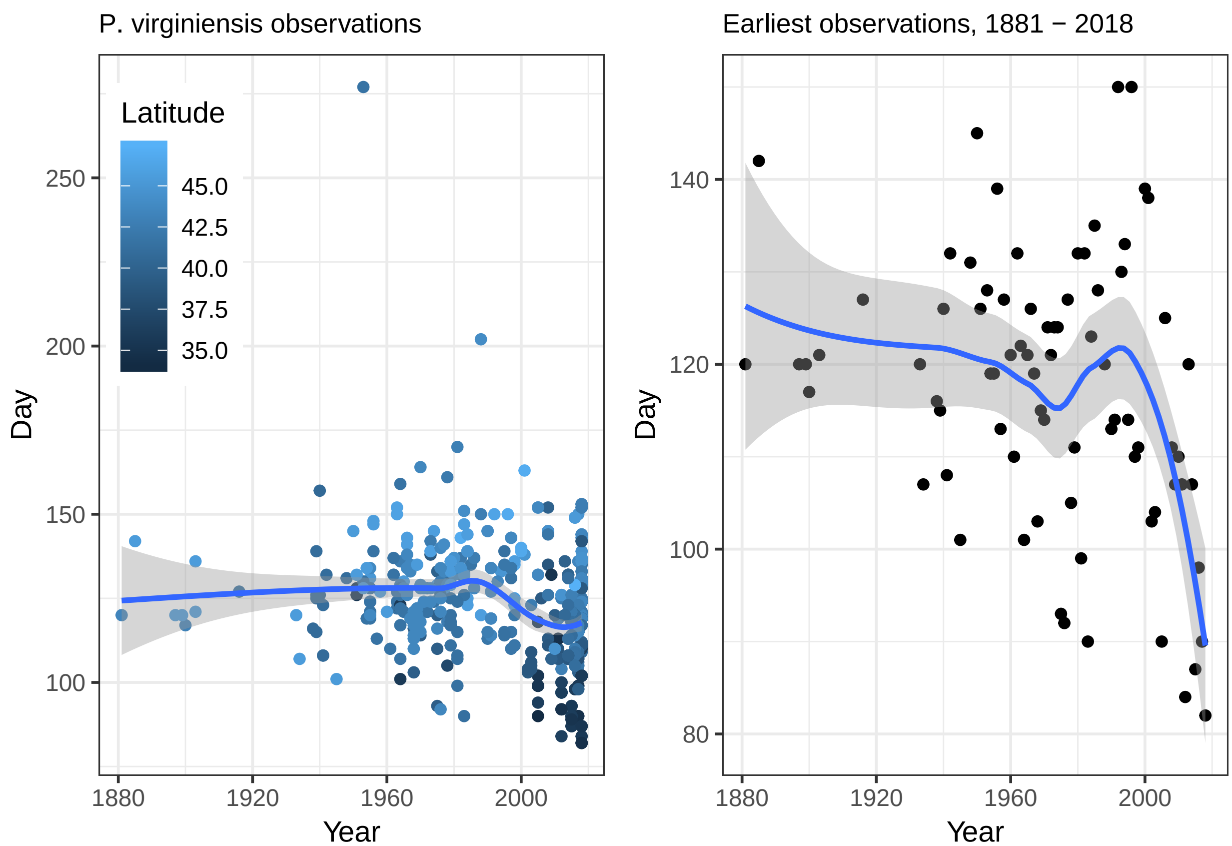
Preliminary analyses

“Preliminary”" does not do it justice. This is very, very back of the envelope. Data are from iNaturalist observations downloaded on 2 May 2019 and GBIF data downloaded on 17 May 2019.

After dropping some unrealistic GBIF observations (some from the Indian Ocean some from January 1) and those from 2019, there are 487 observations. If we plot these by year and day of year, it looks like recently there may have been a shift to earlier emergences.



Note that observations from lower latitudes (darker points) are generally towards the bottom of the plot, and observations from more northern latitudes (lighter points) are nearer the top of the plot. No big surprise there.

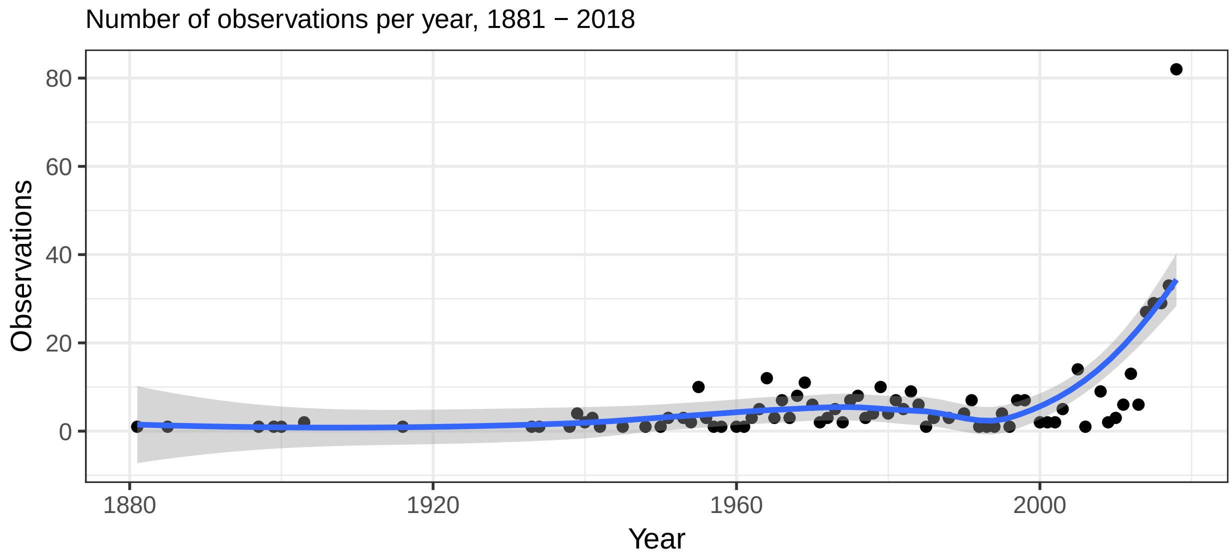
There *is* a trend towards earlier emergences in more recent years, so let’s consider a very crude linear model:

$$Earliest\ observation\ day_i = Year_i + \epsilon_i$$

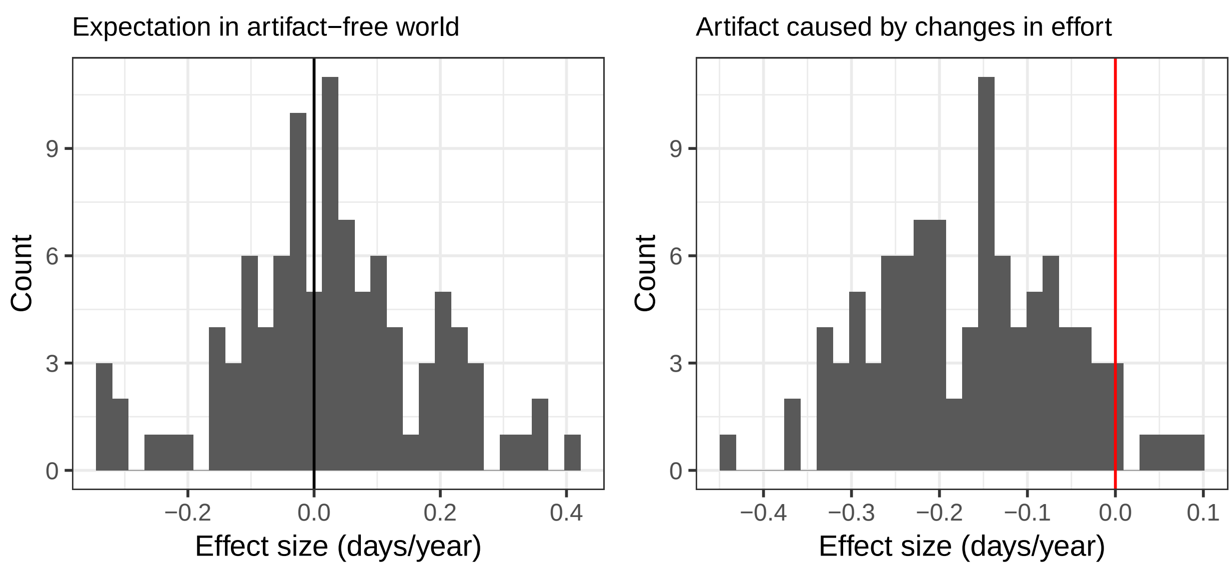
There is an effect of year on earliest observation date, with the first earliest observation occuring 0.14 days earlier each year (p = 0.0059). Cool!

But...

Given the increase in butterfly watching, this change in observations could be entirely due to sampling artifacts than biological reality. Consider the number of observations of *P. virginiensis* through time:



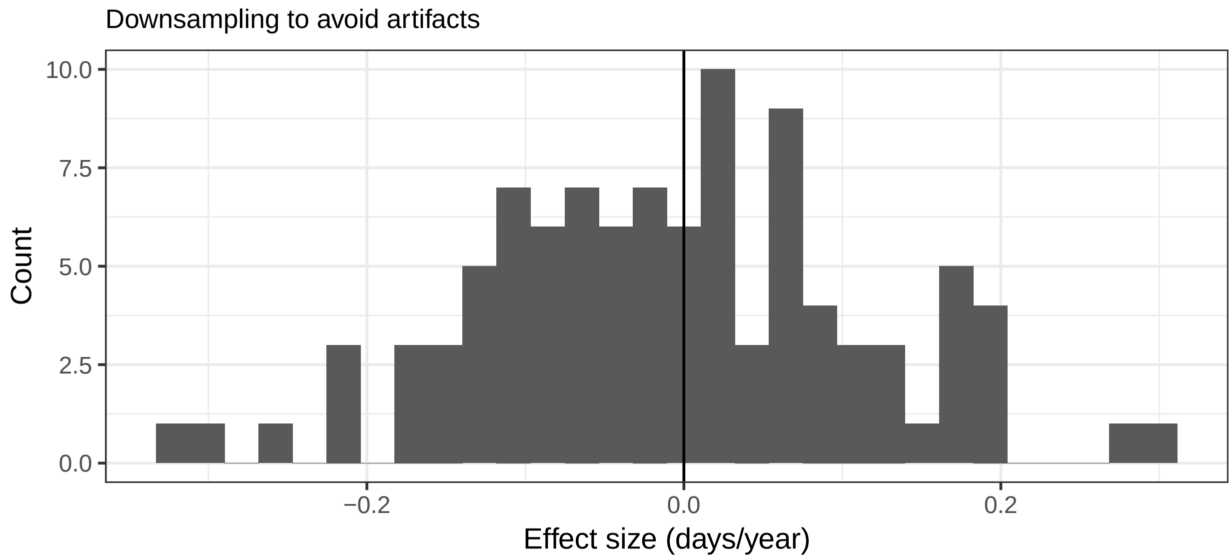
Pretty clearly increasing. So this means that by chance, recent years are more likely to "catch" earlier observations, just because there are more opportunities. To see this in action, consider a thought experiment where we make up data. Well, bootstrapping data, but it's nearly the same thing. If we create a data set that mimics the observation efforts for the observed data (i.e. 1 in 1881, 2 in 1974, 82 in 2018, etc.), but instead of actual observations, sample only from the most recent year of observations (2018). We then use those data to run the linear regression again and see if there is an effect. Ideally, if there is *no* artifact of sampling, we should see, on average, no effect of year on earliest observation (this is because, for these data, *all* days of observation are being drawn from the "real" data for 2018 alone).



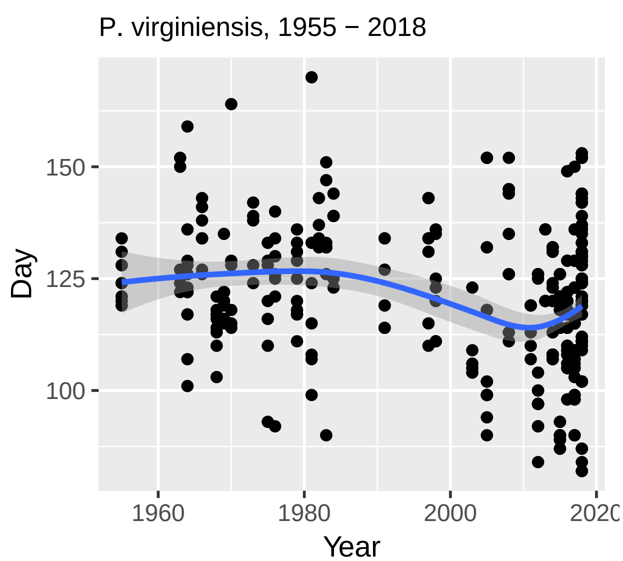
Repeating this process 100 times should result, on average, of an effect size of 0 (left panel). However, when we do the bootstrapping experiment, it looks like there is considerable potential for an artifact (right panel). The mean effect size from the right is -0.17, which we would take to mean that the first observation is getting earlier by 0.17 days per year. We know this is an artifact because all the data are based on 2018.

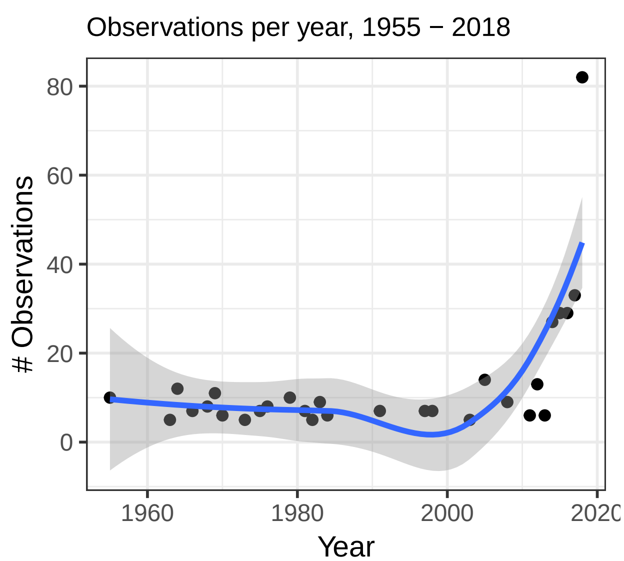
Back to the bootstrap

However, we can use bootstrapping to down-sample observations to make effort across years consistent. That is, for each year, we randomly sample a subset of observations so we only have a certain number of observations per year. For that "certain number", we'll a minimum of 5 observations per year. Let's test this first by doing the same process we ran before, basing everying on data from 2018 alone, but now only drawing 5 samples for each year. Ideally, we should see no effect of year on earliest observation (i.e. an effect size of 0).



Woo-hoo! So now we have a way to avoid artifacts due to variation in effort. Let's try it for real, downsampling each years' data to only 5 per year. Before we try that, what effect does this restriction of 5 observations per year have on the size of our data set? We had 487 observations, but if we restrict it to only those years with at least 5 observations, we have 390 total observations, spanning 1955 through 2018. Taking a look at these data:





There is still an increase in number of observations per year (right panel), so we need apply the downsampling approach to avoid the artifact described above. Downsampling to include only 5 samples from each year is going to vary each time we do a bootstrapping event. To see this in action, the plots below show three iterations, with different points being sampled at each iteration.