




## Resolving the dry period projection paradox: Treat 'Consecutiveness' as a nonlinearity

Title	Resolving the dry period projection paradox: Treat 'Consecutiveness' as a nonlinearity
Author(s)	O'Brien, Enda;Griffin, Seanie;Duffy, Catriona;Nolan, Paul
Publication Date	2024-12-30
Publisher	Wiley;Royal Meteorological Society
Repository DOI	<a href="https://doi.org/10.1002/joc.8745">https://doi.org/10.1002/joc.8745</a>

## RESEARCH ARTICLE OPEN ACCESS

# Resolving the Dry Period Projection Paradox: Treat ‘Consecutiveness’ as a Nonlinearity

Enda O'Brien<sup>1</sup>  | Seanie Griffin<sup>2</sup> | Catriona Duffy<sup>2</sup> | Paul Nolan<sup>1</sup><sup>1</sup>Irish Centre for High-End Computing, University of Galway, Galway, Ireland | <sup>2</sup>Met Éireann, Glasnevin, Dublin, Ireland**Correspondence:** Enda O'Brien (enda.obrien@ichec.ie)**Received:** 1 May 2024 | **Revised:** 18 December 2024 | **Accepted:** 20 December 2024**Funding:** This work was funded by Met Éireann as part of the TRANSLATE project, under grant number ROG1725 to the University of Galway.**Keywords:** bias correction | climate indices | climate projection | consecutive dry days | dry period | quantile mapping

## ABSTRACT

This paper provides a worked example of how the property of consecutiveness, or continuity, can be lost when computing climate indices such as consecutive dry days (CDD) or dry periods from model simulations of the future. That essential continuity property can easily be lost if such indices are computed from future projections of bias-corrected daily precipitation time series. A bias-correction algorithm such as quantile-mapping typically adjusts daily time series to remove overall precipitation bias, but takes no account of consecutiveness, and so can introduce occasional wet-day interruptions into otherwise dry periods. This can lead to inconsistencies between the raw and bias-corrected projections of such indices. To obtain consistent projections, CDD and related indices should be treated as independent parameters and bias-corrected directly in their own right. Such indices should be counted first, and bias-corrected later. In this sense, consecutiveness should be treated as a nonlinearity to be computed before performing any other mathematical operation such as bias correction. This paradox and its resolution are demonstrated using future climate projections from the TRANSLATE project, all of which are derived from global CMIP5 simulations as downscaled over Ireland by two separate regional model ensembles.

## 1 | Introduction

Consecutive Dry Days (CDD) is a standard climate index defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) as the largest number of consecutive days in a period (usually a year, or a season) with precipitation less than 1 mm (ETCCDI 2009). The CDD index can be very easily counted for any period and location, given a continuous time series of daily precipitation values at that place. Future projections of CDD are of interest because (among other reasons) they help to estimate future agricultural production (Duku and Groot 2020; Setiawan et al. 2021). Future projections of CDD over the globe are provided by Sillmann et al. (2013), based on CMIP5 simulations, and by Almazroui et al. (2021) based on CMIP6 projections. Almazroui et al. (2021) also provide separate CDD projections over 26 sub-continental-scale regions.

Van Oort (2014) reported that CDD values are projected to typically increase or remain broadly unchanged over several regions in the Hindu-Kush Himalayas under future projections under the representative concentration pathway (RCP) 4.5 and 8.5 scenarios using the Norwegian Earth System Model (NorESM) downscaled with the Weather Research and Forecasting (WRF) regional model. While Van Oort (2014) adjusted raw precipitation projections using a straightforward ‘delta change’ method (by which model changes were added to historical observations), his CDD estimates were based on the unadjusted changes between past and future model simulations.

Another index related to CDD (but not part of the standard ETCCDI set) is the number of ‘dry periods’ (DP) per year or season, where a ‘dry period’ is 6 or more consecutive dry days (and ‘dry’ again means less than 1 mm of precipitation). Thus,

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial](https://creativecommons.org/licenses/by-nc/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

© 2024 The Author(s). *International Journal of Climatology* published by John Wiley & Sons Ltd on behalf of Royal Meteorological Society.

when using the `eca_cdd` function in the Climate Data Operators (CDO) software package (<https://code.mpimet.mpg.de/projects/cdo>) to compute CDD, the number of dry periods is provided as a supplementary index in the output file. Yet another related index is the total number of dry period days (TDPD) per year or season. Unlike CDD, the DP and TDPD indices do not necessarily measure extreme or maximum values of any quantity, and so are perhaps more representative of the underlying climate of any given place and period. The three indices together, however, provide more insight than any one index alone into the nature of ‘consecutive dryness’ within the climate at any given place or time.

Nolan, O’Sullivan, and McGrath (2017), and Nolan and Flanagan (2020) provided future high-resolution projections of dry periods over Ireland using different RCP scenarios from an ensemble of CMIP5 global models which were in turn downscaled by both the COSMO-CLM and WRF regional climate models. Those projections provide the underlying data used in this study. Nolan (2024, section 3.13) provided further projections using different shared socioeconomic pathway (SSP) and RCP scenarios from an ensemble of CMIP6 global models, also downscaled to high resolution over Ireland by both COSMO-CLM and WRF. The consistent pattern that emerges from both sets of DP projections over Ireland is that the number of dry periods over a full year is expected to slightly increase as time progresses to the end of this century, especially for the stronger emission scenarios. The number of DPs is projected to increase more markedly during the summer months. DPs are also projected to increase for the other seasons, though these changes are more uncertain (especially for winter) due to weaker consensus among the model ensemble members.

Note that all those projected DP changes are relative to values obtained from simulations of a historical reference period, not relative to historical observations. Indeed, the *changes* projected by the models are probably more reliable than the projected *absolute values* of any variable, since both historical and future simulations have systematic errors or biases which are assumed to largely cancel out when computing the change fields.

The TRANSLATE project, in contrast, provides a small collection of future climate projections based on detrended, bias-corrected, and further statistically downscaled model simulations (O’Brien and Nolan 2023). TRANSLATE projections are of bias-corrected absolute values for each variable, along with changes relative to past observations. The bias-correction used is quantile delta mapping (Cannon, Sobie, and Murdock 2015). In TRANSLATE, the ‘raw’ primary variables as simulated by the high-resolution regional models (daily minimum, maximum and mean temperature, and daily precipitation) were detrended and bias-corrected into modified 30-year time series for each future scenario, and all indices (including CDD and DP) were then computed from the modified time series. Model biases that were measured against observations during the common reference period were used (on a quantile-by-quantile basis) to correct all future simulations by the same model. This adjustment process works very well for the daily temperature and precipitation

variables that are explicitly bias-corrected (for a full description see (O’Brien and Nolan 2023)). Our a priori assumption was that all ETCCDI (or other) indices could be computed in a straightforward manner from a bias-corrected temperature or precipitation time series. However, for those indices that depend on a ‘consecutiveness’ or ‘continuity’ property, the bias-correction process for *daily* precipitation or *daily* temperature is usually not aware of such a property and so can easily break it up or otherwise treat it inappropriately.

In particular, computing CDD, DP, and TDPD indices from bias-corrected daily precipitation time series can very easily produce inconsistent and erroneous results. As mentioned above for the van Oort (2014), Nolan (2024) and Nolan and Flanagan (2020) studies, and as demonstrated in the following sections, computing CDD and DP from the raw output of model projections typically showed future *increases* relative to historical *simulations*. However, computing CDD and DP from the bias-corrected output of model projections typically showed future *decreases* relative to historical *observations*. This is the ‘dry period projection paradox’ of the title. It was anticipated by Addor and Seibert (2014), who wrote that ‘It is *a priori* unclear whether [bias-] correcting the daily values would also lead to a correction of the multiday characteristics’. The answer, as reported both here and by Addor and Seibert, is that it does not.

The paradox was resolved by realising that the quantile-mapping process was unaware of and did not make any effort to conserve the ‘consecutiveness’ property of consecutive dry days or dry periods as they occurred in the original raw model output. The resolution was to first compute the CDD, DP and TDPD indices in the raw (i.e., biased) projections as well as in the historical simulations and in the observations for the same historical reference period, and then use quantile-mapping to bias-correct those indices directly. This method treats the property of consecutiveness as an intrinsic part of the variable that is bias-corrected, rather than just an incidental property of daily precipitation time series. This conclusion is supported by empirical evidence that when CDD, DP and TDPD are bias-corrected in this way, their future projections show changes (or trends) relative to past observations that are consistent with the raw changes (or trends) produced by the models. This resolution to the ‘dry period projection paradox’ is supported elsewhere by Grenier et al. (2019), wherein the importance of correctly ordering the calculation of climate indices and bias correction was highlighted.

The approach recommended here for the treatment of any index with a consecutiveness property is closely analogous to the principle that when computing the mean of any nonlinear quantity from fundamental variables, the nonlinear terms should be calculated before any linear operations are performed. A common example is that mean windspeed is not computed from the means of the vector components, but from a linear combination of all the nonlinear terms. For the purposes of this paper, ‘consecutiveness’ may be thought of as a nonlinearity that also should be computed before any further operations (like bias-correction) are performed.

The aim of this paper is to demonstrate how the dry period paradox can occur, and to explain how it can be resolved. Future

climate projections by the TRANSLATE project are used to provide specific illustrative examples.

## 2 | Data

The data used in this study are taken from the TRANSLATE project O'Brien and Nolan (2023). The purpose of TRANSLATE is to make standardised climate projections over Ireland. So far it has done this by taking two separate ensembles of regional climate models, one by Nolan and Flanagan (2020) with 6 ensemble members, the other the EURO-CORDEX (<https://www.euro-cordex.net/>) ensemble with approximately 30 members (depending on the scenario and variable of interest). Both ensembles used regional climate models to dynamically downscale the simulations of multiple CMIP5 global models under different emission scenarios, out to the end of the 21st century.

The future projections were condensed into 3 future time-periods, each 30-years long (2021–2050, 2041–2070, 2071–2100), for each of three representative concentration pathways (RCPs), namely RCP2.6, RCP4.5, and RCP8.5. The period 1976–2005 was used as a historical reference period, since both model simulations and high-resolution observations over Ireland (approx. 1 km grid spacing) were available for that period, at least for daily temperature and precipitation.

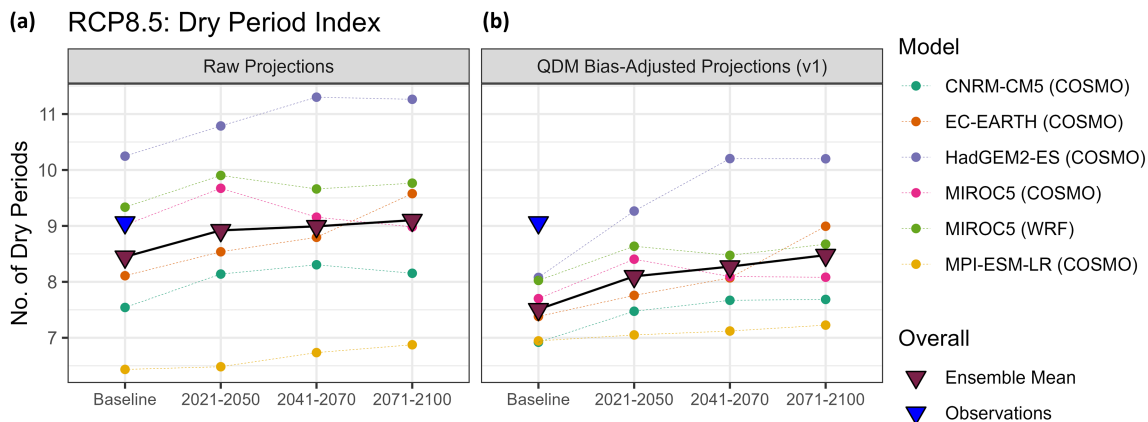
For each variable from each simulation, the daily output for each 30-year time series was detrended, bias-corrected, and further downscaled to the approx. 1 km grid spacing of the observations. For each grid-point, this process produced a reconstructed 30-year time series (almost 11,000 days) of daily precipitation. While the full TRANSLATE dataset is the combination of Nolan and Flanagan (2020) and EURO-CORDEX ensembles, data from only the Nolan and Flanagan (2020) subset of the ensemble are used in this paper for illustrative purposes. As mentioned in the Introduction, this reconstructed time series was then used to compute several ETCCDI indices of interest, such as Rx1day, Rx5days, CDD, DP, and TDPD. Following Grenier et al. (2019), we will refer to this method of index-counting using bias-corrected daily precipitation (or temperature) time series as 'BC-first'.

## 3 | The Problem

The problem that can occur when using this original (BC-first) method is illustrated by Figure 1, which compares the raw future projections (Figure 1a) with the bias-corrected ones (Figure 1b). The values shown are the mean number of DPs per year, averaged over the island of Ireland, obtained from several different 30-year time series, including the historical observations (blue triangles) on both panels. Figure 1a shows the raw historical and (raw) future projections for each of the 6 members of the Nolan and Flanagan (2020) ensemble (coloured circles), along with their ensemble mean (brown triangles). Figure 1b then shows the number of projected dry periods as computed from the bias-corrected daily precipitation time series for each of the same ensemble members (and ensemble mean).

While there is some variation among the ensemble members, the overall pattern of Figure 1a (as represented by the brown triangles of the ensemble means) shows the number of DPs increasing slowly into the future relative to the 1976–2005 baseline period. The ensemble mean for that historical period is slightly lower than was observed (i.e., the blue triangle), reflecting a small overall negative bias within the models. Assuming that future simulations have a similar bias—or at least a bias of the same sign—we would expect a bias-correction of raw future results to adjust the mean upwards (even if some ensemble members are adjusted downwards).

As shown by Figure 1b, however, this is not what happens. The original bias-correction procedure leads to reduced ensemble mean numbers of DPs relative to the observations for both the baseline period and all future time periods, even while showing an overall increase from 2021 to 2050 onwards. All the brown triangles are adjusted downwards relative to the raw projections in Figure 1a. Among the individual ensemble members, only the HadGEM2-ES model behaves with the expected consistency, although it starts with a relatively large positive bias during the historical period. Only the MPI-ESM-LR model (with the lowest raw value mustard dots) has its raw DP projections adjusted upward by the bias-correction; all other models are adjusted downwards (as also reflected in the mean adjustments). Not surprisingly, bias correction does reduce the 'spread' among the ensemble members (as it



**FIGURE 1** | (a) Mean annual number of dry periods, averaged over the island of Ireland, computed from 30 years of daily precipitation values from observations (blue triangles), historical model simulations and raw future projections. (b) Shows the past and projected numbers of dry periods computed from bias-corrected daily precipitation values. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

is broadly designed to do). However, the overall adjustment of both past and future DP numbers relative to the observations remains inconsistent with the changes projected by the raw simulations. Specifically, EC-EARTH (brown), CNRM-CM5 (green) and MIROC5-COSMO (pink) are all adjusted downwards by the bias-correction in ways that don't seem justified by their baseline values.

Figure 1 highlights several issues. The negative bias in the raw baseline simulations indicates that the corrective adjustment should be positive, so why does the correction procedure for even this baseline period produce a negative adjustment instead? Why don't all the symbols on the baseline column of Figure 1b coincide with the observations (blue triangle)—as happens for other variables such as daily precipitation and temperature? If the baseline bias corrections are wrong, are the corrections for the future periods wrong too? The projected DP drops from the observed period (1976–2005) to 2021–2050, and then increases again, while changes to other variables (temperature, daily precipitation) and indices are typically monotonic in response to monotonic increases in forcing (see, e.g., Figures 7, 10, 11, of O'Brien and Nolan 2023, or Figures 3.7 to 3.10 and Figures 4.8 to 4.10 of Noone et al. 2023). So why is the projected change in dry periods not monotonic too (relative to the observations, at least)?

To take a more forensic look at what was going on, we compared multi-year time series of daily precipitation at single grid-points from single model simulations (e.g., MIROC5 downscaled with COSMO), both before and after bias-correction using the BC-first method. We also compared similar time series using a binary classification of each day as either a 'dry period' day or a 'non-dry period' day.

Comparing the day-by-day values in both time series at single grid points, it appears that any extra dry periods in the raw time series (or reduced number of dry periods in the bias-corrected time series) are due to occasional 'wet day interruptions' in the bias-corrected set. Inspection of 1000-day long sequences at a single grid point shows that typically, the number of dry-period days changes from approx. 120 in raw model output to 110 or so after bias-correction. Occasionally, however, at a few other points and time-sequences, bias-correction may similarly

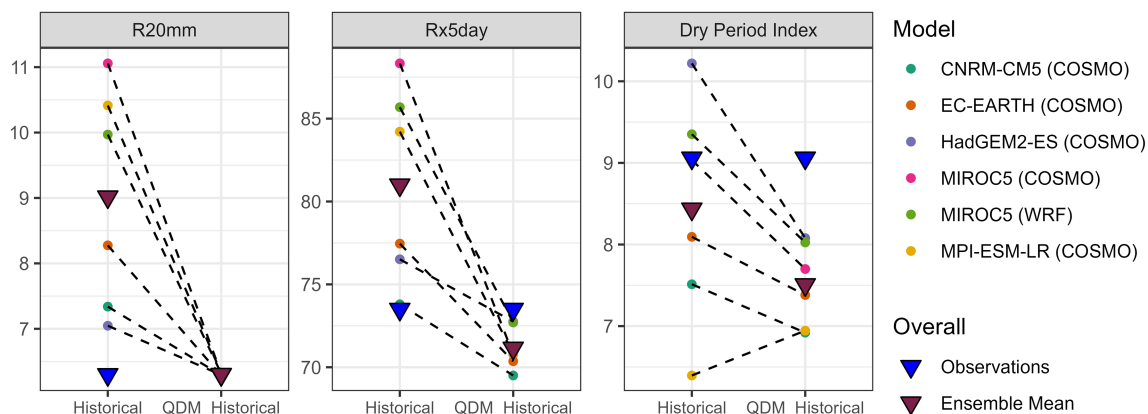
increase the count. Just as the quantile-mapping process of bias correction may either raise or lower the peaks in daily precipitation, it can similarly raise (or lower) the troughs or turn relatively dry days ( $< 1\text{ mm}$ ) into marginally wet ones ( $\geq 1\text{ mm}$ ). Note, that to avoid numerical singularities in the bias-correction computations, the driest value allowed in the precipitation timeseries is  $0.05\text{ mm}$ , so the  $1\text{ mm}$  threshold separating dry days from wet ones in the CDD and DP indices is 20 times that amount. Thus, it is relatively easy for any algorithm to adjust a raw value of, say,  $0.95\text{ mm}$  up to a bias-corrected value of  $1.05\text{ mm}$ , and so change that day from 'dry' to 'wet' according to the CDD and DP classification. When such adjustments occur during a raw dry period, it effectively eliminates the dry period in the adjusted series, reducing the overall dry period count.

However, Figure 1 shows too few dry periods in the raw baseline ensemble mean time series, so why doesn't bias correction increase them instead of reducing them?

An illustration of the disparity in behaviour of the quantile delta mapping (QDM) methodology for different indices is shown in Figure 2. The QDM bias correction method was applied to historical (rather than projected) model data at all grid-points over the island of Ireland separately. The R20mm, R $\times$ 5day, and Dry Period indices were calculated, and field means of these were computed. QDM applied the appropriate correction to the data for R20mm and the resulting bias-corrected historical data corresponded to the observed values (i.e., the blue and brown triangles overlap for the QDM historical values in the left panel of Figure 2). The corresponding bias correction of R $\times$ 5day (middle panel) is not perfect, but the magnitude of the original mean bias is reduced by approx. 80%. Meanwhile for dry periods (right panel) the biases persisted, and in some cases even became worse after QDM—as did the ensemble mean. This is another manifestation of the unusual behaviour in Figure 1b, but also partially explains it.

## 4 | The Explanation

Given the evidence provided below, we conclude that the answer to the questions raised by Figures 1 and 2 lies in the fact that DP



**FIGURE 2** | Test case of bias correcting historical model data using QDM for R20mm (left), R $\times$ 5day (middle) and Dry Periods (right) indices. Ensemble members are represented by coloured circles, the ensemble mean by brown triangles and the observations by blue triangles. The data represent the field mean of all grid-points over the island of Ireland. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

bias correction operates on time series of daily precipitation, not time series of raw DP values. If the bias between the modelled and observed dry periods during the baseline period was used to adjust future dry periods, they would certainly be increased instead of reduced, by explicit design of the mapping process. However, since bias correction operates on daily precipitation in isolation, the process is not explicitly aware of dry periods. The relationship (i.e., the bias) between the models and observations for 1-day precipitation (or equivalently, dry periods of just 1 day or more) may not persist for dry periods of 6 or more consecutive dry days.

To check this, ‘dry periods’ were computed as a function of dry period length, from both observations and historical simulations during the baseline period, and from individual model projections under the RCP8.5 scenario for the 2071–2100 period (as in Figure 1).

In order to connect with the daily precipitation values used as the basis for the BC-first bias-correction, Figure 3 shows the total number of dry period days or TDPD (as distinct from number of dry periods) from the CNRM-CM5 model (left panel) and EC-EARTH (right panel). Values are shown over the full 30-year time series, rather than as means of 30 separate annual values.

For dry periods lasting just 1 day, the historical simulations produce too many dry periods (or days). Consequently, just as the historical (dashed blue) curve is reduced to the observed (solid blue) curve for 1-day dry periods, so too the raw projected (dashed red) curve is reduced to the Quantile Delta Mapped (QDM) or bias-corrected (solid red) curve. Once this ‘reduction’ pattern is set by bias correction of daily precipitation, it remains even as the defined length of a dry periods increases: the dashed red curves remain above the solid red ones in both panels of Figure 3.

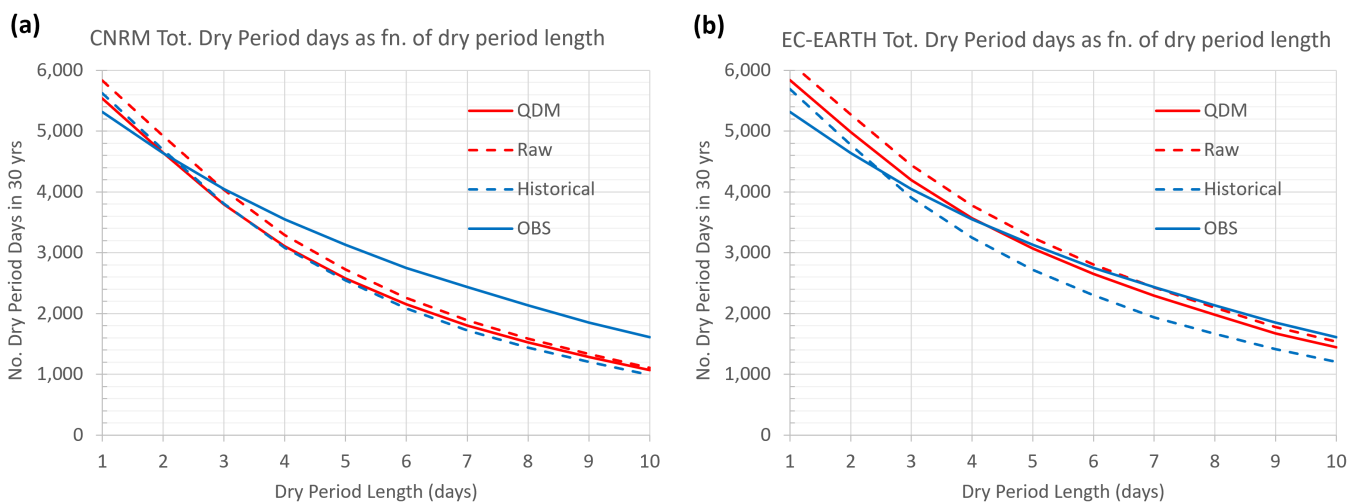
In contrast, the bias between the historical simulations and the observations reverses in both models as dry period length increases from 2 to 3 days—and remains reversed up to dry period

lengths of 10 days. This reversed relationship between historical and observed baseline values (with historical simulations now producing too few dry periods) for even some of the ensemble member models is reflected in the blue triangle (observations) placement above the brown one (ensemble mean) on the left panel of Figure 1. However, BC-first bias correction of CDD, DP and TDPD is unable to capture it because the correction is based on the relationship between the observed and historical values for dry periods of just 1-day duration.

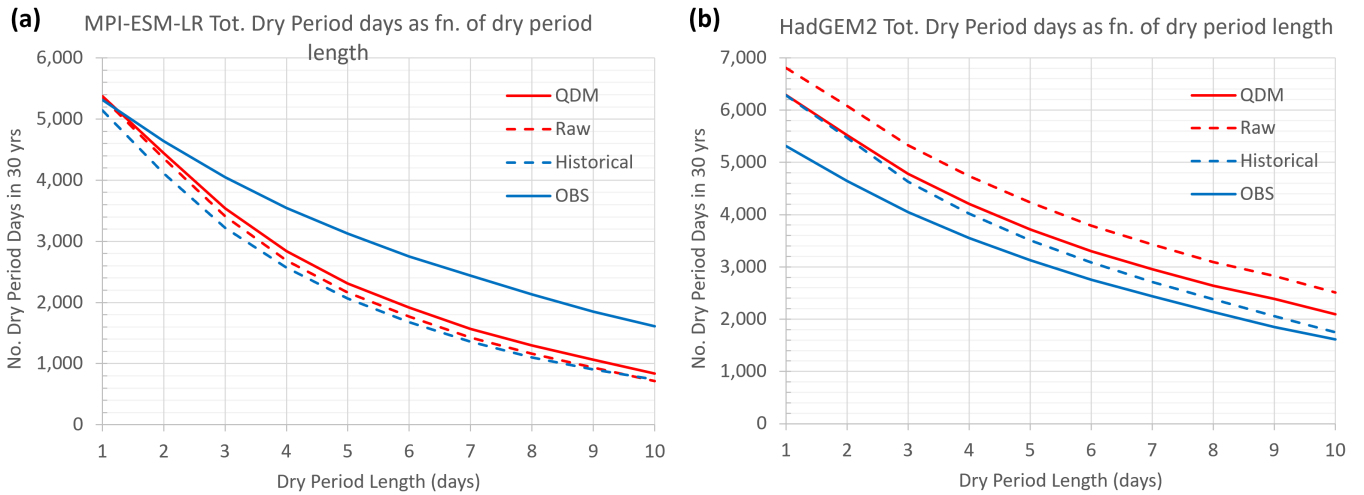
Meanwhile, there is no such bias-reversal in either the MPI-ESM-LR or HadGEM2 models (Figure 4), and so the bias correction based on 1-day dry periods remains valid (at least in the sign of the correction) for periods of 5-day duration as well—all consistent with the results shown in Figure 1. Together, Figures 3 and 4 illustrate that the sign of the bias in any model as a function of dry period length is highly contingent and can vary from model to model. The bias in daily precipitation may (or may not) be useful in correcting the biases over 5 or more consecutive days. Rajczak, Kotlarski, and Schar (2016) obtained results (e.g., in their Figure 3b,d) that are more analogous to Figure 4 here than to Figure 3, although at least one of their models behaves analogously to Figure 3 in showing a change in sign of bias as dry period length increases. The point is simply that we cannot assume that the bias that occurs over 1-day periods has the same sign over longer periods.

The TDPDs as shown in Figures 3 and 4 are not the same as ‘number of dry periods’. For example, a TDPD of 12 dry period days could reflect either 1 DP that is 12 days long, or 2 DPs that are each 6 days long. Larger TDPD values permit even more DP permutations. For completeness, Figure 5 shows the number of dry periods as a function of dry-period length for the CNRM and EC-EARTH models and is analogous to Figure 3. Again, there is a sign reversal in the bias between the historical and observed metrics which shows up between 4 and 5-day dry-period lengths in Figure 5.

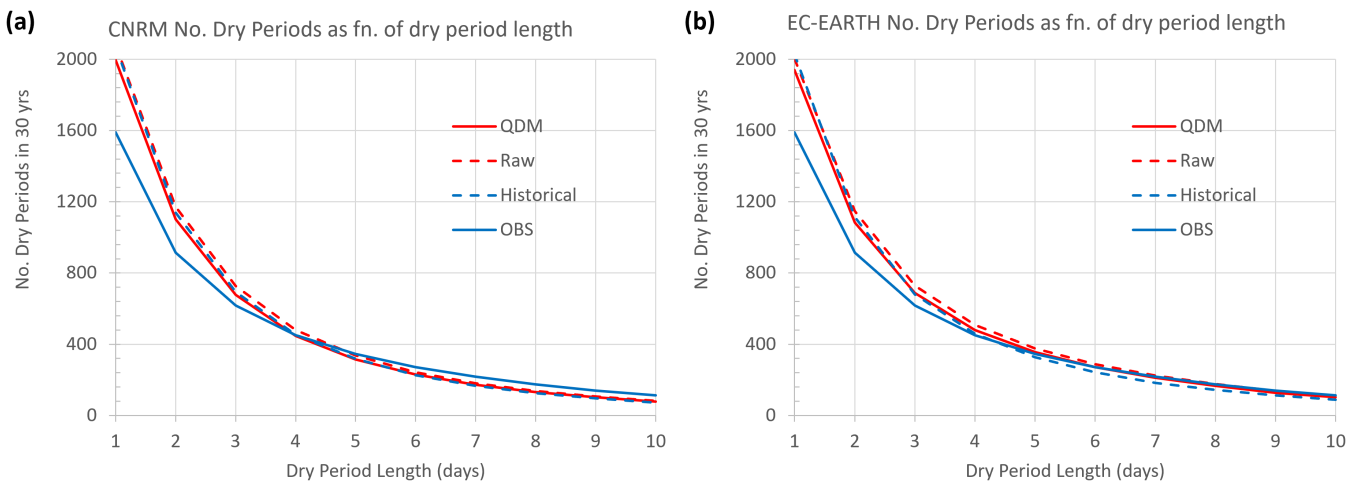
As a further experiment, the number of dry periods were also plotted as functions of the ‘dry day threshold’, which has a



**FIGURE 3** | Total number of dry period days over 30 years, averaged over the island of Ireland, from (a) the CNRM-CM5-based simulation, and (b) the EC-EARTH-based simulation, as functions of dry period length. Solid blue curves are from the historical observations during 1976–2005; dashed-blue curves are from the historical model simulation over the same period; dashed red curves are from raw future projections, while solid red curves are from the bias-corrected future projections (using BC-first index-counting, i.e., counting indices from bias-corrected daily precipitation time series). Future projections are for the period 2071–2100 under the RCP8.5 scenario. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]



**FIGURE 4** | As in Figure 3, but for (a) the MPI-ESM-LR-based simulation and (b) the HadGEM2-ES-based simulation. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]



**FIGURE 5** | As in Figure 3 but showing number of dry periods (rather than total dry period days) over each 30-year time-series for (a) the CNRM-CM5-based simulation, and (b) the EC-EARTH-based simulation. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

standard value of 1 mm in the ETCCDI indices. Results for the CNRM-CM5 model (again under RCP8.5 for 2071–2100) are shown in Figure 6, for thresholds ranging from 0.05 mm (the lower bound of precipitation values in TRANSLATE for QDM bias correction), up to 4 mm.

As in Figures 3 and 5, Figure 6 shows a bias reversal at a threshold value of approx. 1.7 mm, where the solid and dashed blue curves cross each other. There is even a reversal in the sign of the bias correction of the future projections (dashed red to solid red curves) at the low threshold value of 0.1 mm. There is nothing particularly strange about that, since the bias correction works quantile by quantile with 1 percentile granularity, and it is entirely possible that 0.05 mm falls into a different quantile than 0.2 mm.

## 5 | The Solution

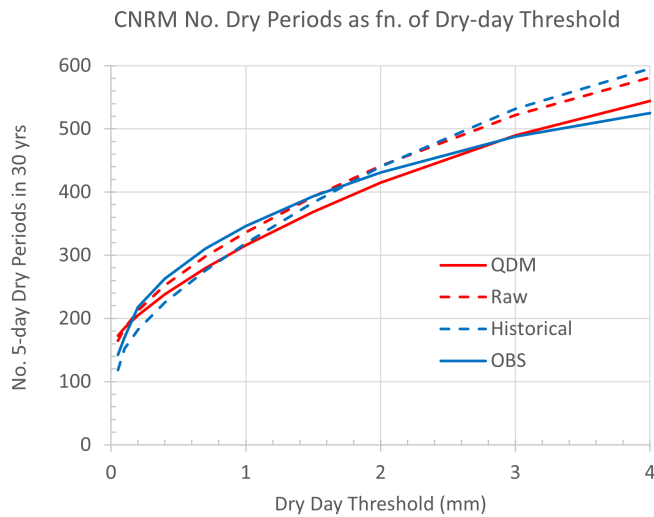
The inconsistencies shown in Figures 1 and 2 arise because for most models in the ensemble, the bias (between historical

simulations and observations) changes sign as the number of days in a dry period increases from 1 day (effectively used as the basis for BC-first bias correction) to 6 days (the standard dry period duration). Such inconsistencies can be avoided by a modified (‘BC-after’) bias correction, which involves first counting the CDD, DP, and TDPD indices directly in each of the 30 years of the observed, simulated historical, and (raw) future projection time series. Quantile-mapping bias correction is then applied directly to those dry-period indices (i.e., just 30 annual—or seasonal—samples in each case) to obtain a (BC-after) bias-corrected future projection.

Some results using this BC-after method are summarised in Figure 7, which shows the annual mean number of dry periods from various 30-year time series, averaged over the island of Ireland, as in Figure 1. Note that the vertical scale in Figure 7 is different to Figure 1, in order to highlight the variability among the values shown. The blue triangle in Figure 7 represents the observed dry period count during the 1976–2005 baseline period, as also shown by the blue triangles in Figure 1. The dry periods counted in the raw future projections (again, under

RCP8.5) are represented by the orange circles in Figure 7 and have the same values as the brown triangles representing the ensemble means in Figure 1a. Similarly, the black triangles in Figure 7 are dry period numbers, as projected after using BC-first bias correction, as also shown by the brown triangles in Figure 1b: the argument of this paper is that these are the inconsistent or erroneous projected values.

Finally, the green squares and triangles in Figure 7 are the projected values using the BC-after method. The green squares are the values obtained by using ‘multiplicative’ quantile mapping, which is the appropriate method to use for ‘ratio’ variables like precipitation that can take on values of zero, while the green triangles are the values obtained by using ‘additive’ quantile mapping, normally considered appropriate for ‘interval’ variables like temperature. See Cannon, Sobie, and Murdock (2015) for a discussion of the difference between the multiplicative and additive variants of quantile mapping.

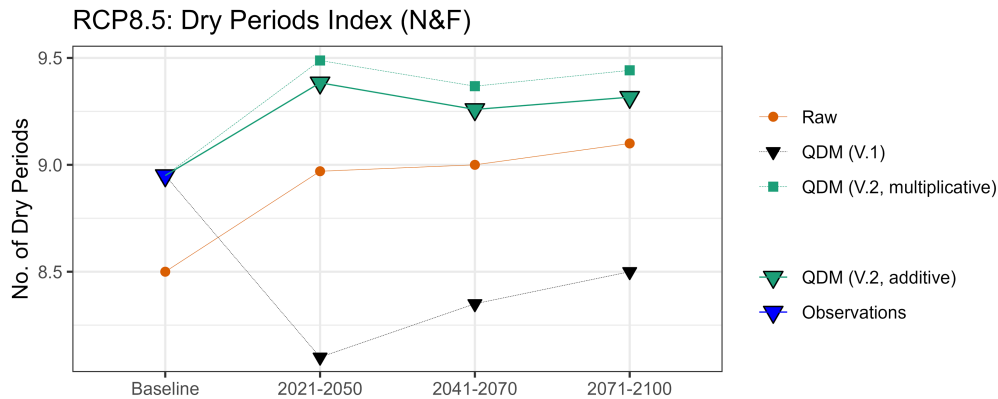


**FIGURE 6** | Number of dry periods over 30-year time series as a function of dry/wet day precipitation threshold, from the historical observations (OBS) and CNRM-CM5-based simulations (as in Figure 3a). [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

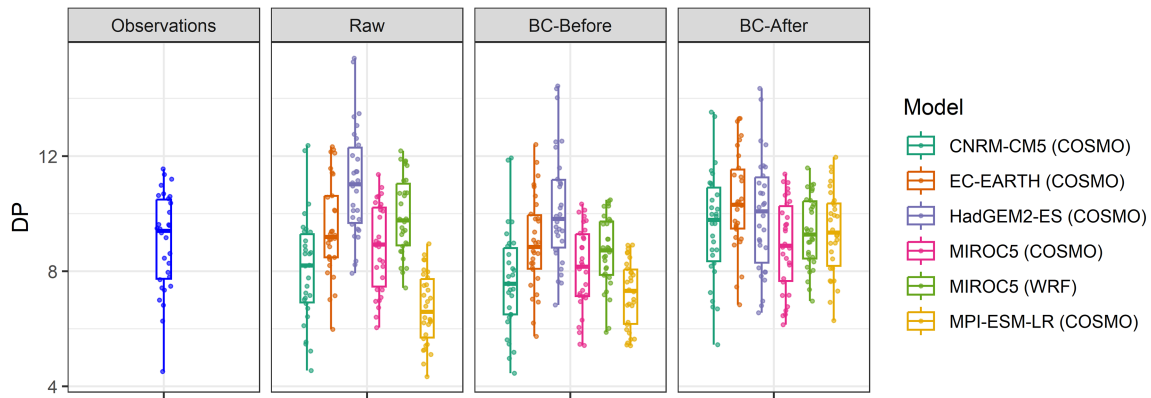
Figure 7 suggests that there is not a lot of difference between the DP projections made using the multiplicative and additive quantile mapping. From looking at the final maps of DP projections, however, it is immediately apparent that both methods agree almost perfectly over most of the country, but that the ‘multiplicative’ method generates small, scattered regions of anomalously large DP numbers, which in turn provide the positive bias to the green squares in Figure 7 over the green triangles. Those small anomalous regions correspond to places which have very few or even zero DPs in some years in either the observed, simulated historical, or raw projected time series. Those very small values (or zeros) in turn can lead to excessive and unphysical numerical sensitivity in the bias adjustment process, even if outright singularities are avoided. This type of phenomenon will be relatively familiar to users of climate model output for particularly arid regions, where projections of changes in precipitation are commonly anomalously high due to relatively small absolute changes in the variable. In the case of the DPs discussed here, all such anomalous regions vanish, however, once the ‘additive’ adjustment is used instead of the ‘multiplicative’ one. In principle, the scattered regions with very few or zero dry periods in the raw simulations could potentially be adjusted to unphysical negative values by the bias-correction algorithm, but in practice such small values seem to be (as far as we can tell) all adjusted upwards instead.

The overriding conclusion from Figure 7, however, is that the BC-after method of making future bias-corrected projections of dry periods is now consistent both with the historical observations and with the changes projected by the raw future simulations. BC-after or direct bias-correction of dry periods displays none of the problems generated by the BC-first method as illustrated in Figure 1 and is clearly superior to it.

Figure 8 provides a more fine-grained view of the data underlying some of the mean values shown in Figures 1 and 7. It shows the interannual spread of annual DP values for each 30-year timeseries from the observations, as well as for each of the 6 Nolan and Flanagan (2020) model ensemble members (2071–2100), as projected under RCP 8.5 by the raw (un-corrected) model output, the BC-first method, and finally using the BC-after



**FIGURE 7** | Mean annual number of dry periods, averaged over the island of Ireland, computed from 30-years of annual dry period values from observations (blue triangle), raw historical and future model simulations (orange circles), bias-corrected dry periods as calculated using BC-first method (black triangles, as in Figure 1b), and as calculated using BC-after methods (green squares and triangles). All model data-points are ensemble medians. See text for further explanation. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]



**FIGURE 8** | Interannual spreads of DP index values over 30 years from observations (left panel) and from simulations using each of the 6 model ensemble members, for the raw projections and for each of the BC-before and BC-after adjustment methods used. All projections are for the 2071–2100 period under RCP8.5. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

method. The interannual spread is relatively large in all cases, much as it is for the observations too. Since Figure 1a shows the baseline bias of the CNRM and EC-EARTH models to be negative, we should expect a reasonable bias correction method to adjust the projections of those models upwards. Figure 8, however, shows the BC-first method adjusting the mean DP values of those model downwards instead. Meanwhile, the BC-after method does adjust them upwards, and so that adjustment at least has the correct sign. Of the other 4 models, they are adjusted either consistently up or consistently down by both BC-first and BC-after methods. Overall, however, (as highlighted in Figures 1 and 7) the BC-first method adjusts the ensemble mean DP count downwards, which is inconsistent with the raw baseline biases shown in Figure 1a. The BC-after method removes this inconsistency, as demonstrated and explained in this paper.

## 6 | Conclusions

The ‘dry period projection paradox’ is so called, because in trying to project how past climates evolve into the future, the signal from the number of ‘dry periods’ (i.e., periods of at least 6 consecutive dry days, where ‘dry’ means precipitation < 1 mm) can appear to be inconsistent between the ‘raw’ and ‘bias-corrected’ projections. When (raw) future projections are compared with (raw) historical *simulations*, models show the number of dry periods increasing into the future. However, when bias-corrected future projections of daily precipitation are compared with historical *observations*, the numbers of dry periods are projected to be fewer than in the past, under all scenarios and for all future time-periods considered.

Some general conclusions can be drawn from the results shown above:

1. The quantile mapping bias correction used by TRANSLATE does a good job in adjusting future projections of daily precipitation, but it cannot be relied upon to preserve the property of consecutiveness or continuity, since each day is adjusted according to its quantile value only, without any explicit reference to the days immediately preceding or succeeding it.
2. Consequently, the counting of projected future CDDs, DPs, and TDPDs from bias-corrected future daily precipitation (the BC-first method) is unreliable and leads to inconsistencies relative to raw projections (Figures 1 and 2).
3. When using the BC-first method, model bias in the simulation of dry periods may (or may not) change sign as the duration of a ‘dry period’ increases from 1 day to 6 days (the minimum duration of a canonical dry period), as shown in Figures 3–5. Three of the six models in the Nolan and Flanagan (2020) ensemble have negative biases for short 1- or 2-day ‘dry periods’ but positive biases for dry periods longer than about 4 days. However, it is the bias (and associated corrections) for dry periods of just 1 day length that propagates into adjusting numbers of future dry periods of the standard 6 days length. Those adjustments have the wrong sign for half the models considered.
4. The BC-after method of first counting CDD and DP numbers in all historical and future simulations and then directly bias-correcting these by quantile mapping produces much more consistent and plausible projections of these indices (Figure 7). Using this method, the property of consecutiveness is integrated into the bias-correction process.
5. Since this BC-after method has consecutiveness integrated from the beginning, it is analogous to the principle of computing all nonlinear terms before doing any (linear) averaging. As in this analogy, the ordering of operations is extremely important and the consequences of incorrectly sequencing the processing steps can lead to incongruous results. The results presented here serve to highlight the caution required when calculating indices from bias-corrected climate projections. Indeed, any index like CDD that relies on the sequencing of an underlying daily variable (e.g., precipitation), as well as its magnitude should be tested using the approach outlined here to ensure the robustness of resulting indices.
6. Other ETCCDI indices that rely on consecutiveness include RX5day (maximum consecutive 5-day precipitation),

WSDI and CSDI (warm and cold spell duration indices, which are the equivalent of TDPD for spells with daily maximum temperature above the 90th percentile, and for daily minimum temperature below the 10th percentile, respectively), and GSL (growing season length). Whether by luck or by some property of the weather circulations that lead to prolonged intense rainfall and prolonged warm or cold spells, no comparable inconsistency (or paradox) was noted when computing these indices from the bias-corrected precipitation and temperature time series. However, given our experience reported below with CDD and DP calculations, we suggest that it is safer and more reliable for all indices that depend on consecutiveness to be first computed from raw model output, and then bias-corrected directly (as opposed to being computed from bias-corrected precipitation or temperature fields). While this is a good rule of thumb, it is not an absolutely rigid one. As discussed by Grenier et al. (2019), there can be circumstances in which the BC-after approach is not appropriate, such as for threshold-based temperature indices where the threshold is not reached at all unless the underlying temperature is first bias-corrected using the BC-first method. Each problem needs to be considered in its own context.

All those conclusions are supported by very fine-grained analysis at one extreme (e.g., the investigation of raw and bias-corrected dry period indices at a single grid point from a single model simulation) and very integrated analysis at the other (e.g., the combination of the Nolan and Flanagan (2020) and EURO-CORDEX ensembles into future projections over a range of future time periods, emission scenarios and model sensitivities).

This work provides further evidence of the unphysical artefacts that can occur when bias correction is used in an overly rigid and uncritical way, as described by Maraun et al. (2017). The resolution presented here is also very much in the spirit of Maraun et al. (2017), who advocated the development of ‘rigorous standards for evaluating bias correction methods’.

One ramification of using the BC-after method in the current context is that the sample size available for the quantile-mapping algorithm was reduced from almost 11,000 (days) to just 30 (years). However, no changes were required to the algorithm to account for this. Even though the number of centiles exceeded the number of samples, this just meant that not all centiles were truly independent, much as interpolating a physical field from a low-resolution grid to a high-resolution one spreads the data over more points without really introducing any new information. Meanwhile, the spread in the BC-after columns in Figure 8 suggests that interannual variability was well-preserved. Since the continuity property of DPs was preserved by design, however, the raw DP bias was adjusted correctly, which was the main objective.

As discussed by Rocheta, Evans, and Sharma (2014), quantile mapping does not enforce dynamical consistency between different fields (e.g., temperature and precipitation), so any such consistency can easily be lost if the fields are bias corrected separately. By the same token, and given the results presented here, multivariate quantities (such as evapotranspiration) should be computed first from their individual constituent variables and

any bias-correction should only be done afterwards. Again, a simple principle applies for the ordering of mathematical operations: compute any nonlinear, compound, or multivariate quantities first, and only then perform whatever bias-correction is required.

The broader value of the work presented here is not so much in its final results, but in its illustration of the principle that when combining a bias-correction algorithm with the counting of any climate index that has a consecutiveness property, the index should be calculated prior to the bias-correction.

---

### Author Contributions

**Enda O'Brien:** writing – original draft, funding acquisition, investigation, writing – review and editing, visualization, conceptualization, validation, software, data curation, methodology, formal analysis. **Seanie Griffin:** investigation, writing – review and editing, visualization, conceptualization, validation, data curation, software, methodology, formal analysis, resources. **Catriona Duffy:** visualization, conceptualization, writing – review and editing, investigation, methodology, validation, software, formal analysis. **Paul Nolan:** funding acquisition, writing – review and editing, project administration, conceptualization, supervision, resources.

### Acknowledgements

This work was funded by Met Éireann as part of the TRANSLATE project, under grant number ROG1725 to the University of Galway.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### References

- Addor, N., and J. Seibert. 2014. “Bias Correction for Hydrological Impact Studies—Beyond the Daily Perspective.” *Hydrological Processes* 28: 4823–4828. <https://doi.org/10.1002/hyp.10238>.
- Almazroui, M., F. Saeed, S. Saeed, et al. 2021. “Projected Changes in Climate Extremes Using CMIP6 Simulations Over SREX Regions.” *Earth Systems and Environment* 5: 481–497. <https://doi.org/10.1007/s41748-021-00250-5>.
- Cannon, A., S. Sobie, and T. Murdock. 2015. “Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes?” *Journal of Climate* 28: 6938–6959. <https://journals.ametsoc.org/view/journals/clim/28/17/jcli-d-14-00754.1.xml>.
- Duku, C., and A. Groot. 2020. “Climate Change Risks and Opportunities in Potato Production in Tanzania. CRAFT Technical Report.” <https://doi.org/10.13140/RG.2.2.11663.41121>.
- ETCCDI. 2009. “ETCCDI Climate Change Indices.” [http://etccdi.pacificclimate.org/list\\_27\\_indices.shtml](http://etccdi.pacificclimate.org/list_27_indices.shtml).
- Grenier, P., A. Firlej, A. Blondot, T. Logan, and M. P. Ricard. 2019. “The Issue of Properly Ordering Climate Indices Calculation and Bias Correction Before Identifying Spatial Analogs for Agricultural Applications.” *Climate Services* 16: 100122. <https://www.sciencedirect.com/science/article/pii/S2405880719300639?via%3Dihub>.

- Maraun, D., T. G. Shepherd, M. Widmann, et al. 2017. "Towards Process-Informed Bias Correction of Climate Change Simulations." *Nature Climate Change* 7: 764–773. <https://www.nature.com/articles/nclimate3418>.
- Nolan, P. 2024. *Updated High-Resolution Climate Projections for Ireland*. Wexford, Ireland: Environmental Protection Agency, in press.
- Nolan, P., and J. Flanagan. 2020. "High-Resolution Climate Projections for Ireland—A Multi-Model Ensemble Approach." In *EPA Research Report*. Johnstown Castle: Ireland. <https://www.epa.ie/publications/research/climate-change/research-339-high-resolution-climate-projections-for-ireland-php>.
- Nolan, P., J. O'Sullivan, and R. McGrath. 2017. "Impacts of Climate Change on Mid-Twenty-First-Century Rainfall in Ireland: A High-Resolution Regional Climate Model Ensemble Approach." *International Journal of Climatology* 37, no. 12: 4347–4363. <https://doi.org/10.1002/joc.5091>.
- Noone, C., D. McClean, D. Gallagher, J. McElwain, and P. Thorne. 2023. "Ireland's Climate Change Assessment Volume 1: Climate Science—Ireland in a Changing World, Environmental Protection Agency, Ireland, 228 pp." <https://www.epa.ie/publications/monitoring-assessment/climate-change/irelands-climate-change-assessment-volume-1.php>.
- O'Brien, E., and P. Nolan. 2023. "TRANSLATE: Standardized Climate Projections for Ireland." *Frontiers in Climate* 5: 1166828. <https://doi.org/10.3389/fclim.2023.1166828>.
- Rajczak, J., S. Kotlarski, and C. Schar. 2016. "Does Quantile Mapping of Simulated Precipitation Correct for Biases in Transition Probabilities and Spell Lengths?" *Journal of Climate* 29: 1605–1615. <https://journals.ametsoc.org/view/journals/clim/29/5/jcli-d-15-0162.1.xml>.
- Rocheta, E., J. P. Evans, and A. Sharma. 2014. "Assessing Atmospheric Bias Correction for Dynamical Consistency Using Potential Vorticity." *Environmental Research Letters* 9: 124010. <https://doi.org/10.1088/1748-9326/9/12/124010>.
- Setiawan, A. M., Y. Koesmaryono, A. Faqih, and D. Gunawan. 2021. "Application of Consecutive Dry Days (CDD) Multi-Model Ensemble (MME) Prediction to Support Agricultural Sector in South Sulawesi Rice." *IOP Conference Series: Earth and Environmental Science* 893: 012081. <https://doi.org/10.1088/1755-1315/893/1/012081>.
- Sillmann, J., Y. V. Kharin, F. W. Zwiers, X. Zhang, and D. Bronaugh. 2013. "Climate Extremes Indices in the CMIP5 Multimodel Ensemble: Part 2. Future Climate Projections." *Journal of Geophysical Research-Atmospheres* 118: 2473–2493. <https://doi.org/10.1002/jgrd.50188>.
- Van Oort, B. 2014. "Climate Projections for Local Adaptation in the Hindu-Kush Himalayas. CICERO Report 2014:01." <https://doi.org/10.13140/RG.2.2.26149.50405>.