Text S1 Detailed vine copula construction, including mathematical notation: As described by Sklar (1959), the joint multivariate distribution (F) can be described as:

$$F(x) = C\{F_1(x_1), \ldots, F_d(x_d)\} \tag{1}$$

where $x_1, \ldots, x_d$ denotes a setting of d relevant variables, $F_1, \ldots, F_d$ the marginal distributions and C is a copula (itself a d-dimensional distribution function on $[0, 1]_d$ with uniform margins) (Erhardt and Czado, 2018).

Following the methodology of Erhardt and Czado (2018), the copula data that are obtained from the marginal models corresponding to d different drought variables can be described as:

$$u := (u_1, \ldots, u_d) \tag{2}$$

where $u_j = (u_j)$, $j = 1, \ldots, d$ and u_j are the copula data corresponding to variable j.

As noted by Aas *et al*. (2009), vine copulas can be used to model multivariate data acting on two variables at a time, offering a way in which to construct higher-dimension copulas. For a three variable example, the vine copula density c is given as:

$$c(u_1, u_2, u_3;\ \Theta) = c_{1,2}(u_1, u_2;\ \Theta_{1,2})c_{1,3}(u_1, u_3;\ \Theta_{1,3})c_{2,3;1}\{h_{2|1}(u_2, u_1;\ \Theta_{1,2}), h_{3|1}(u_3, u_1;\ \Theta_{1,2}); \Theta_{2,3;1}\} \tag{3}$$

where $c_{1,2}$, $c_{1,3}$ and $c_{2,3;1}$ are the pair copula densities corresponding to the copulas $C_{1,2}$, $C_{1,3}$ and $C_{2,3;1}$. The h-functions involved are defined as $h_{b|a}(u_b, u_a; \Theta) := C_{b|a}(u_b|u_a; \Theta)$, where $C_{b|a}$ denotes the conditional distribution function of U_b given U_a (Erhardt and Czado, 2018).

Having fitted the copula, the resultant copula data were transformed into independent data in the [0, 1] space using the Rosenblatt transformation (Rosenblatt, 1952). The Rosenblatt transform $v := (v_1, \ldots, v_d)$ on the basis of the selected vine copula C for the data $u = (u_1, \ldots, u_d)$ is defined as:

$$v_d := C_{d|1,\ldots,d-1}(u_d|u_1, \ldots, u_{d-1}) \tag{4}$$

where $C_{j|1,\ldots,j-1}$ is the conditional cumulative distribution function for variable j given the variables $1, \ldots, j-1$ for all $j = 2, \ldots, d$. In the Canonical Vine (C-Vine) context the order of the variables is determined by the selected order of root variables (Erhardt and Czado, 2018).

The elements from this multivariate probability integral transformation were transformed to the standard normal distribution p, using the inverse of the cumulative distribution function of a standard normal distribution:

$$p_j = \Phi^{-1}(v_j) \tag{5}$$

Finally, these uniform elements were then aggregated and standardised to the final Standardised Multivariate Index (SMI):

$$SMI = \frac{1}{\sqrt{d}} \sum_{j=1}^{d} p_j \tag{6}$$

Limits of -3/3 were also imposed (Stagge *et al.*, 2015). Index construction was performed using R software (R Core Team, 2017), and the following packages:

Standardised Indices:

SCI Package: Stagge *et al*. (2015)

fitdistrplus: Delignette-Mueller and Dutang (2015)

Copula:

copula: Hofert *et al*. (2020)

Vine Copula:

VineCopula: Nagler *et al*. (2022)

rvinecopulib: Nagler and Vatter (2021)

Text S2 Method Description:

The following provides a more specific description of the methodological procedure used in the construction of the Standardised Multivariate Index (SMI) and Standardised Bivariate Index (SBI), and aligns with the flowchart illustrated in Fig. S1.

Overview

Maximum temperature, precipitation and soil moisture were selected as the variables from which an extreme event index was constructed, using the European ReAnalysis 5th Generation Land Component (ERA5-Land) dataset (Muñoz-Sabater *et al*., 2021).

Standardised Indices

The extreme event index was constructed using copulas, after first constructing individual standardised indices: the Standardised Precipitation Index (SPI) (McKee *et al*., 1993) (precipitation), the Standardised Temperature Index (STI) (Zscheischler *et al*., 2014) (maximum temperature) and the Standardised Soil Moisture Index (SSMI) (Xu *et al*., 2018) (soil moisture). Gamma, Normal and Beta distributions were used to fit the SPI, STI and SSMI respectively across a 30-day accumulation period.

Pre-processing Work

Here, the pre-treatment guidelines proposed by Tootoonchi *et al.* (2022) are addressed (Fig. S1). The first step, an initial exploratory analysis, was performed in Bennet *et al*. (2023). Data ties, predominately within precipitation data (i.e. zero precipitation), are treated via the use of the Weibull plotting position for zero precipitation values (Stagge *et al.*, 2015) when constructing the SPI. Autocorrection is addressed by the approach of Kao and Govindaraju (2010) via the constructing of daily subsets in the time series, resulting in 365 individual time series for each index. Stationarity is not addressed, with the baseline period (1961-1990) used for the standardised indices generally considered free from non-stationarity (World Meteorological Organisation, 2017), and thus copula parameters are able be stabilised.

Vine Copula Structure

A Canonical Vine (C-Vine) is a sub-class of R-Vine (itself a nestled set of trees used for pair copula construction as building blocks; Erhardt and Czado (2018) and Bedford and Cooke (2002)), having a star like structure where a centre node is linked to all remaining nodes (Wu *et al.*, 2021). This star like structure allows the order of variables to be set to the order of importance, with the variable of highest importance being set as the root variable (Erhardt and Czado, 2018). In the current work, this C-Vine structure was selected, while testing (not shown; utilizing the algorithm of Dissmann *et al*. (2013)) revealed the conditional/root variable precipitation as the chosen optimal variable.

Parameter Estimation

A semi-parametric approach for the estimation of copula parameters is common in hydroclimatic studies (Pham *et al.*, 2016; Tootoonchi *et al.*, 2022), and is herein employed. The semi-parametric approach first establishes the individual marginal distributions based on their rank behaviour and by forming pseudo observations, before copula parameters are estimated by maximizing the pseudo likelihood function (Kim *et al*., 2007; Tootoonchi *et al*., 2022). The automatic fitting and model selection contained within the “rvinecopulib” and “VineCopula” packages of Nagler and Vatter (2021) and Nagler et al. (2022) provides for parameter estimation of semi-parametric models (i.e. after forming pseudo observations) using either maximum likelihood or the inversion of Kendall’s τ. Both parameter estimation methods were trialled by creating two copula models. Each model automatically selected the optimal copula families at each tree edge, for each calendar day and each grid cell (and for each accumulation period), using the “RVineCopSelect” function of Nagler et al. (2022), with the parameter estimation method being the only difference across the two models (either maximum likelihood or the inversion of Kendall’s τ). Parameter estimation using maximum likelihood was the best performing vine copula model, with 95.24% of grid cells having the best fit (log-likelihood) compared to the copula set.

Copula Families

Copula selection was from a family set made up of Clayton, Frank and Joe (no rotations), selected via Akaike Information Criterion (AIC). This process was performed for each calendar day, for each grid cell and for each accumulation period. The selection of only three copula families was made to reduce the overall spatial and temporal complexity associated with fitting highly unique copula families on the fine scales of this study (0.10 x 0.10 and daily resolution).

Goodness of Fit

To minimise computational load, goodness of fit tests were performed on the vine copula model fitted to the 15th day of each month, before aggregation of the test results. Testing was performed using Cramér-von Mises (CvM) and Kolmogorov-Smirnov (K-S) statistics. Results indicated strong agreement in the goodness of fit tests, with an overall good fitment of the copula model.

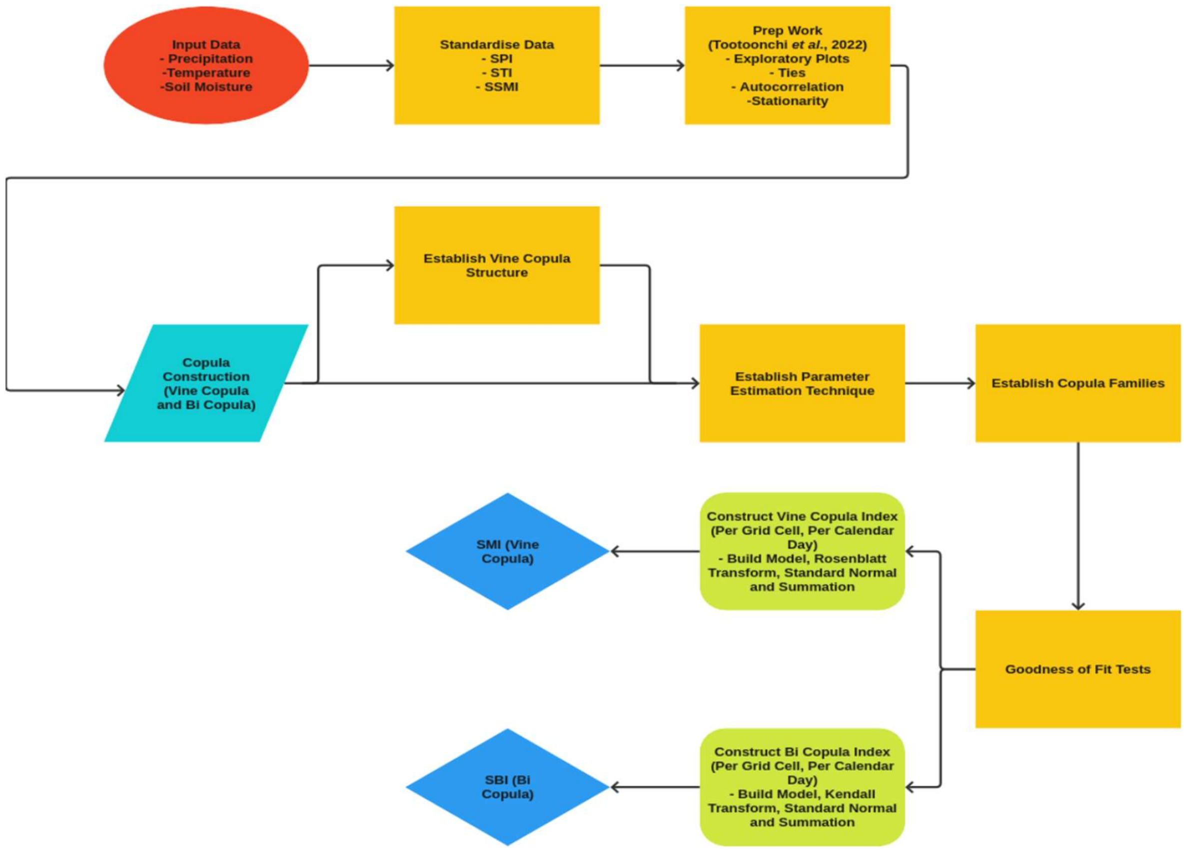

Fig. S1 Flowchart illustrating the methodological procedure and steps performed in the current work to construct the multivariate index using both bi (Standardised Bo-Copula Index; SBI) and vine (Standardised Multivariate Index; SMI) copula methods.

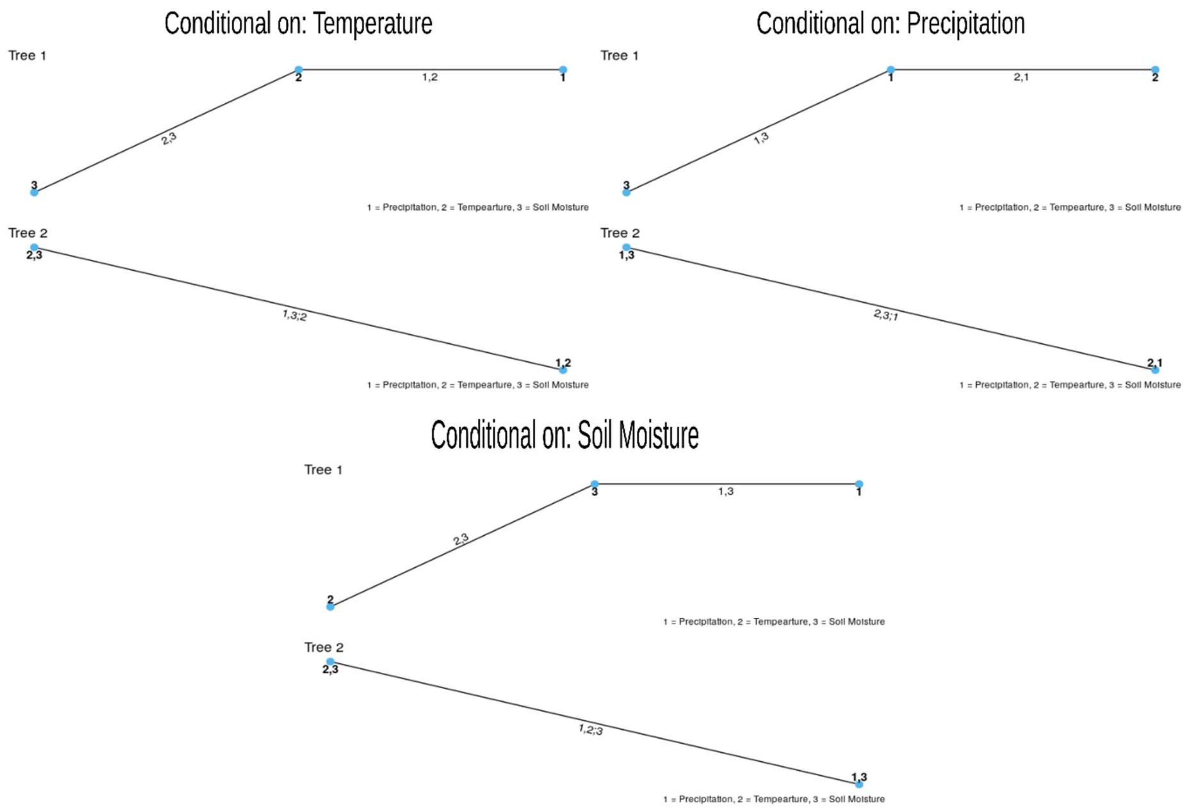

Fig. S2 Tree structure of optimal variables orders detected using the Dissmann *et al.* (2013) algorithm, applied across the entirety of New Zealand. Headings refer to the root/conditional variable: temperature (top left), precipitation (top right) and soil moisture (bottom).

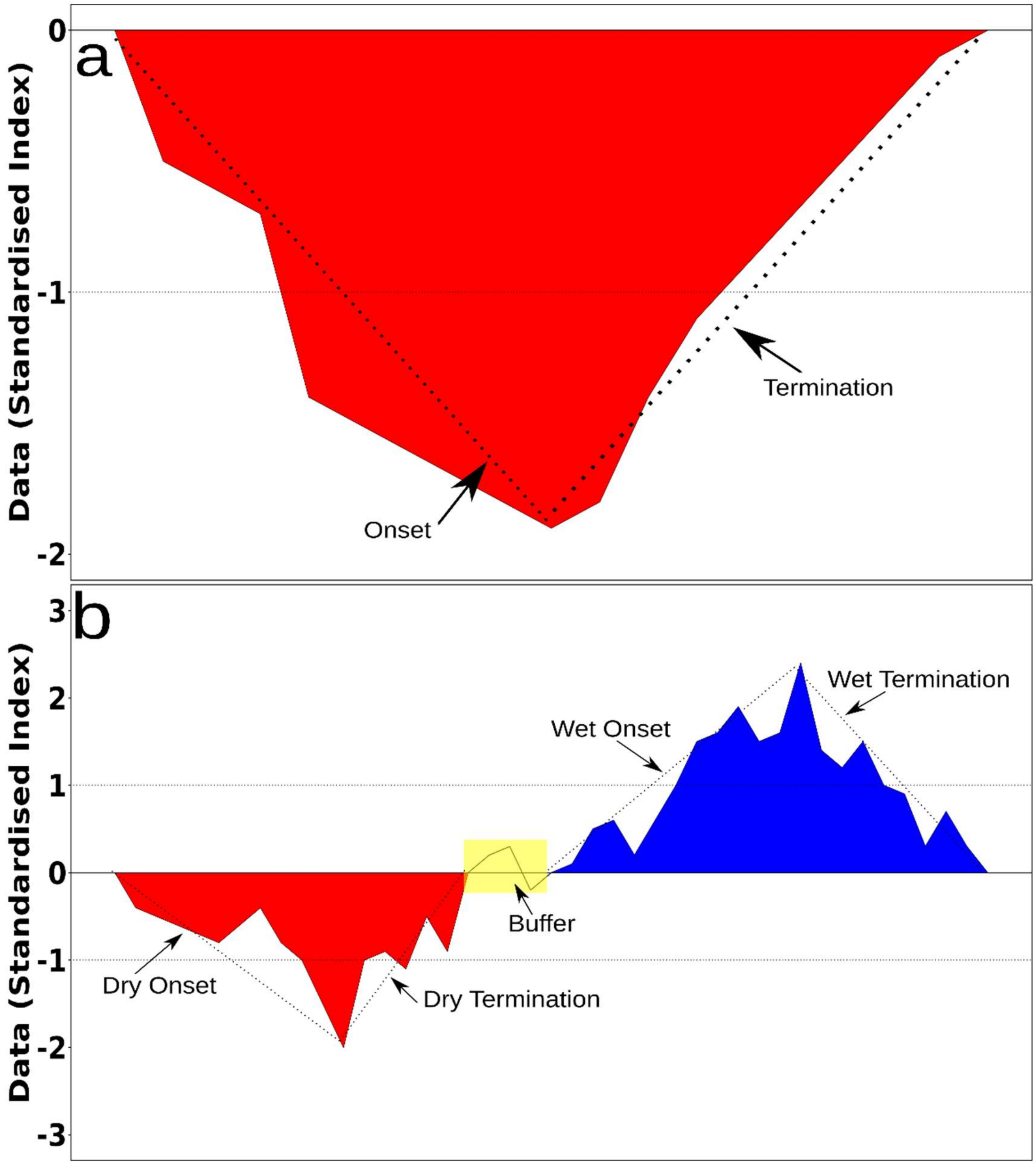

Fig. S3 Example of compound (a) and seesaw (b) events, adapted from Rashid and Wahl (2022). In the present work, the buffer within a seesaw event refers to a 30-day period, to ensure adequate sample size of events. Event characteristics are noted in the figure; for seesaw events representing onset rates of dry and wet phases, as well as termination rates of dry and wet phases, while for compound events representing onset and termination rates.

Table S1 Optimal bivariate copula family for each season (DJF, MAM etc.), identified as the most common copula family (i.e. most days) for each season from either Frank, Clayton or Joe copulas, for all grid cells. Identification of optimal copula is performed using AIC selection criteria.

Distribution	Precipitation-Soil Moisture Copula				Precipitation-Temperature Copula				Temperature-Soil Moisture Copula			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
30-Day	Frank	Frank	Frank	Frank	Clayton	Clayton	Frank	Clayton	Clayton	Frank	Frank	Frank