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Ragno, E., Diakomopoulos, F., Hariharan Sudha, S., & De Michele, C. (2026). The Role of Structural and Transient Compoundness in Advancing Compound Event Characterization. *Earth's Future*, *14*(8), Article e2025EF007691. https://doi.org/10.1029/2025EF007691

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Earth's Future

RESEARCH ARTICLE
10.1029/2025EF007691

The Role of Structural and Transient Compoundness in Advancing Compound Event Characterization

Elisa Ragno[1], Faidon Diakomopoulos[1], Srividya Hariharan Sudha[1], and Carlo De Michele[2]

[1]Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands, [2]Civil and Environmental Engineering Department, Politecnico di Milano, Milano, Italy

Key Points:

- Structural Compoundness describes the average contribution of each driver in the generative mechanism of the compound variable
- Transient Compoundness reflects the relative role of the drivers in the individual realization of the compound variable
- Dependence and magnitude of underlying drivers play equally important roles in shaping the resulting compound event

Correspondence to:
E. Ragno,
e.ragno@tudelft.nl

Citation:
Ragno, E., Diakomopoulos, F., Hariharan Sudha, S., & De Michele, C. (2026). The role of structural and transient compoundness in advancing compound event characterization. *Earth's Future*, *14*, e2025EF007691. https://doi.org/10.1029/2025EF007691

Received 6 NOV 2025
Accepted 18 JUN 2026

Author Contributions:
Conceptualization: Elisa Ragno (lead), Carlo De Michele (lead)
Data curation: Faidon Diakomopoulos (lead), Srividya Hariharan Sudha (lead)
Formal analysis: Elisa Ragno (lead)
Methodology: Elisa Ragno (lead), Carlo De Michele (lead)
Writing – original draft: Elisa Ragno, Carlo De Michele
Writing – review & editing: Elisa Ragno (lead), Carlo De Michele (lead)

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Abstract Compound events, arising from the combinations of multiple interacting underlying physical drivers, have gained increasing attention over the past decade with a wide range of applications, including floods, droughts, and wildfires. This growing body of research has advanced both the conceptual understanding and statistical modeling of compound events, often emphasizing the role of dependence between underlying drivers. Building on this foundation, we recognize the need to further describe hydrological and climate phenomena not only through the overall tendency of contributing physical drivers to interact but also by considering the individual combinations of drivers leading to compound events, regardless of whether these drivers are statistically dependent. Here, we introduce the concepts of structural and transient compoundness as system properties of compound events. Structural compoundness quantifies the overall contribution of each driver to the generative mechanism of the compound variable, while transient compoundness captures the role of each driver in the individual realization of the compound variable. This will ultimately improve risk assessment and mitigation strategies. Indeed, by applying these concepts to two types of compound events, river discharge at confluences and hot and dry events, we show that structural and transient compoundness can inform modeling choices and enhance system understanding, with both the dependence and magnitude of the drivers playing critical roles in shaping compound events. Incorporating structural and transient compoundness enhances scientific modeling and, at the same time, improves risk assessment, guiding adaptation strategies for persistent (structural) and temporary (transient) risks.

Plain Language Summary Extreme events such as floods, droughts, and wildfires can be the result of several physical drivers occurring together. These are called compound events, and scientists have been studying them more and more in recent years. So far, most research has focused on finding ways to model how these drivers combine to better understand how often compound events happen and how severe they might be. Following up on the work done in the past, we suggest introducing two distinct properties when describing compound events, namely structural and transient compoundness. Structural compoundness quantifies how much each physical driver contributes on average to the compound event, while transient compoundness quantifies how much each driver contributes to a single realization of the event. We show these concepts by investigating two types of compound events: river flooding at confluences and hot and dry weather events. Our results show that both the strength of the dependence between physical drivers and their size matter when investigating the resulting compound events. These new concepts can help improve scientific models and also support better decision-making, preparing communities for long-term risks, which can be quantified via structural compoundness, and short-term extremes, quantified via transient compoundness.

1. Introduction

Extreme events, such as heavy rainfall, floods, and droughts, have been widely studied using extreme value theory (Coles, 2001; Salvadori et al., 2007), which provides a statistical framework for modeling occurrences of rare events. In this approach, the event, for example, a flood event, is described as the outcome of a random variable, for example, river discharge, following a probability distribution function fitted to available observations of the phenomenon of interest. In 1993, Klemes (1993) proposed a combinatorial approach to frequency analysis, arguing that meteorological and hydrological extremes result more from unusual combinations of multiple interacting factors than from extreme values of individual factors. This approach treats the variable of interest as a compound event and synthesizes its distribution function by enumerating all physically plausible combinations of its major components for which data are available rather than only those few that actually took place.

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Over the past decade, the concept of compound event, under a slightly different connotation than the one defined by Klemes (1993), has received a great deal of attention in hydrology and climate science. The IPCC Special Report on Extremes (SREX) published in 2012 (Seneviratne et al., 2012) first defined compound event as an event occurring when multiple extreme events happen together or in sequence, when extremes combine with underlying factors that amplify their impact, or when non-extreme events combine to create an extreme outcome, with the contributing events potentially being similar (clustered multiple events) or different types. SREX provided the example of floods and droughts being related to precipitation extremes and, simultaneously, influenced by other atmospheric and surface conditions. Leonard et al. (2014) refined SREX's definition by emphasizing that a compound event results from multiple and statistically dependent drivers causing an extreme impact, that is, events' drivers should have a causal relationship with the impact. Moreover, Leonard et al. (2014) argued that the statistical dependence of the drivers is key for evaluating the risk associated with compound events. Hao and Singh (2020) highlighted that statistical dependence between the drivers arises from the interaction of physical processes, system feedbacks, and preconditioning factors. On the other hand, Serinaldi et al. (2022) pointed out that compound events (events with great impacts) can also result from independent drivers. In addition, statistical correlation or dependence does not necessarily imply physical dependence since the former often depends on sample size.

Studies of compound events in the scientific literature include, for example, hot and dry events (AghaKouchak et al., 2014; Manning et al., 2019; Tabari & Willems, 2023; Tian et al., 2024), wildfires (Dulin et al., 2025; Richardson et al., 2022; Torres-Vázquez et al., 2025), and floods (Banfi & De Michele, 2022; Cazzaniga et al., 2025; Couasnon et al., 2020; Deidda et al., 2021; Green et al., 2025; Moftakhari et al., 2017; Rahimi et al., 2021; Wahl et al., 2015). Among these studies, many investigated the joint occurrence of their drivers regardless of the realized impact at different geographical scales (e.g., Xu et al., 2023); others adopted an impact-centric approach (e.g., Bevacqua et al., 2017; Ragno et al., 2023) which allows backtracking the relevant drivers from the observed impact to focus only on impactful combinations of drivers (Bevacqua et al., 2021; Zscheischler et al., 2018), reminding of the approach proposed by Klemes (1993). The common trait of these studies is the quantification of dependence between the drivers via statistical measures of dependence, for example, Kendall's tau (Kendall, 1938), and the subsequent modeling of their joint occurrence via probabilistic dependence models such as copula functions (Salvadori & De Michele, 2004; Salvadori et al., 2007; Zscheischler & Seneviratne, 2017).

Building on the compound event's formalization developed over the years, we emphasize the need to describe hydrological and climate phenomena not only through the overall tendency of contributing physical drivers to interact, but also by considering individual combinations of drivers leading to compound events, regardless of whether these drivers are statistically dependent. This distinction is important because it enables a more comprehensive characterization of compound events by separating two complementary levels of analysis: a system-level perspective, which captures the overall interaction structure, and an event-level perspective, which evaluates each realization individually to determine whether it constitutes a compound event. By integrating these two levels, the proposed framework advances the current formalization of compound analysis. Moreover, a clearer formalization will enable more effective strategies for risk assessment and management.

Hence, in this study, we introduce the concepts of structural and transient compoundness, as properties of a system providing a comprehensive description of compound events. Here, structural compoundness refers to the average contributions of the individual drivers, while transient compoundness captures the specific contributions of each driver in the realization of individual events. We argue that this distinction will enhance the understanding, prediction, and management of compound events, ultimately improving risk assessment and mitigation strategies. More specifically, by distinguishing between structural and transient compoundness, adaptation efforts can focus on strengthening infrastructure against persistent risk patterns (structural) while also preparing for extreme but temporary conditions (transient).

In the following, we formalize the concepts of structural and transient compoundness, with a more in depth focus on compound events that can be described as additive systems, adopting an impact-centric approach. Afterward, we apply these concepts to compound floods in confluences and to compound hot and dry events. Finally, we discuss the implications of this approach for advancing the study of compound events.

2. Transient and Structural Compoundness

The increasing availability of machine learning algorithms, which are readily accessible and easily implementable on large data sets, promotes the use of highly nonlinear and complex functions to improve event description and prediction. However, the complex interactions between the input variables and the model outputs make the interpretability of the results challenging.

In the context of compound events, complex models can be used to describe the interactions among physical drivers. However, their interpretability can be limited. To address this, such models can be approximated by simpler models (Štrumbelj & Kononenko, 2013). For example, additive feature attribution methods simplify complex functions via a linear model where the model output, that is, the compound event, is expressed as the sum of the contributions of each predictor. The contribution of each predictor can be computed based on principles of cooperative game theory, where predictors are treated as players, and their contributions are measured by how much they influence the outcome of the game. Lundberg and Lee (2017) proposed the SHapley Additive exPlanation (SHAP) value to quantify the contribution of each predictor to the model output.

In this study, we adopt the principles of additive feature attribution methods within a SHAP framework to describe the interaction between physical drivers generating a compound variable/event of interest.

Let Z be the compound variable such that $Z = f(\mathbf{X})$, where $\mathbf{X} = (X_1, X_2, \ldots, X_F)$ denotes the set of F physical drivers (more in general impact function predictors), and f is a generic model, that is, the impact function, modelling the relationship between them, which can be inferred from physical relationship or empirical evidence. The compound variable Z is generated by the interaction between the drivers (or physical drivers), and it becomes an event of interest, that is, a compound event, when $Z > z^*$, where z^* is a threshold above which the compound variable Z leads to damages, or an unsafe situation.

Within the additive SHAP framework, the impact function can be expressed as

$$f(\mathbf{X}) = \phi_0 + \sum_{i=1}^{F} \phi_i \tag{1}$$

where $\phi_0 = E[f(\mathbf{X})]$ is the base value, that is, the model output without considering the effect of the drivers, and ϕ_i (the SHAP value) is the contribution of the $i-th$ driver to the model output. The advantage of such method is that the contribution of each driver, ϕ_i, is computed considering all the possible subsets of drivers. For details about the methodology, the reader is referred to Appendix A.

From such decomposition, we can identify structural and transient compoundness, that is, the average contributions of the individual drivers, and the specific contributions of each driver in the realization of individual events, respectively.

The choice of defining the impact function $f(\mathbf{X})$ implies that there is always a structural relationship between the event and its underlying physical drivers. Hence, its expectation, that is, $\phi_0 = E[f(\mathbf{X})]$, serves as a quantitative measure of structural compoundness. On the other hand, ϕ_i is the event-specific contribution of the $i-th$ driver (X_i) to the output. Hence, we adopt it as the metric to quantify transient compoundness, that is, the contribution of the drivers to a single event of interest.

For the purpose of this study, we limit the analysis to $F = 2$ drivers, denoted by $X, Y \in \mathbb{R}$. Regardless of whether X and Y are statistically dependent, the compound variable is obtained as $Z = f(X,Y) = X + Y$. This type of impact function will be used to describe spatially connected physical variables. In a river network, the compound variable Z represents the river discharge generated downstream of a confluence, and it results from the interaction between the river (X) and its tributary (Y) upstream of the confluence. Similarly, the same impact function will be used to quantify the water deficit/surplus deriving from the balance between water fluxes, that is, evapotranspiration (water outflow, X) and precipitation (water inflow, $-Y$).

Let $(x_j, y_j, z_j)_{j=1}^{N}$ denote N realizations of the drivers and compound variable, with $z_j = f(x_j, y_j)$. According to Equation 1, the impact function can be approximated as

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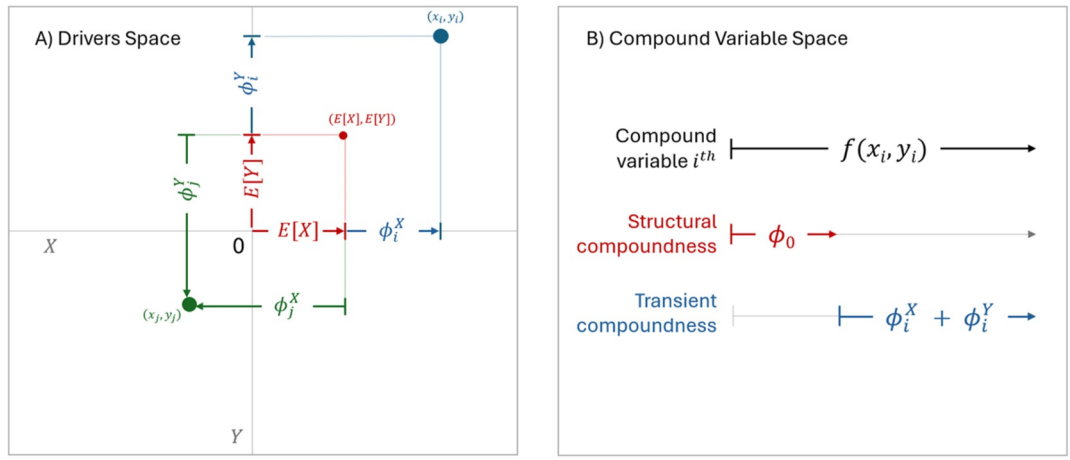


Figure 1. Conceptual description of structural and transient compoundness metrics in the domain of the physical drivers (panel a) and in the space of the compound variable (panel b) for the case of the $i - th$ compound variable with drivers x_i and y_i (blue dot panel a).

$$f(x_j, y_j) = \phi_0 + \phi_j^X + \phi_j^Y \tag{2}$$

where

$$\begin{aligned} \phi_0 &= E[f(X,Y)] \\ \phi_j^X &= x_j - E[X] \\ \phi_j^Y &= y_j - E[Y] \end{aligned} \tag{3}$$

ϕ_j^X and ϕ_j^Y represent the transient compoundness of the $j - th$ realization, while the base value ϕ_0, quantifies the structural compoundness, Figure 1.

To improve the interpretability of the proposed metrics, structural compoundness can be further analyzed based on the relative contribution of $E[X]$ and $E[Y]$ and the system under investigation, while transient compoundness, that is, the SHAP values of each realization, can be expressed relative to the expected value of the variable at hand. More specifically

$$\begin{aligned} \phi_j^X &= E[X]\frac{x_j - E[X]}{E[X]} = E[X]\bar{\phi}_j^X \\ \phi_j^Y &= E[Y]\frac{y_j - E[Y]}{E[Y]} = E[Y]\bar{\phi}_j^Y \end{aligned} \tag{4}$$

where $\bar{\phi}_j^X$ and $\bar{\phi}_j^Y$ denote the relative (percentage) deviations of x_j and y_j from their respective expected values. Thus, ϕ_j^X and ϕ_j^Y can be interpreted as the expected value multiplied by the corresponding relative deviation, making the magnitude of the effect easier to interpret.

To provide additional support to the structural compoundness, we assess the relative behavior of the pair of drivers, for example, if high values occur simultaneously or not, using the Jaccard Similarity Index (J). In contrast, we assess the relative behavior of the pair driver-event (i.e., their statistical dependence) via the Normalized Pointwise Mutual Information (I_{NPMI}). Both metrics quantify the association between pairs of variables. However, the J holds regardless of whether the variables are statistically dependent since the interaction between independent drivers can result in a compound event (Serinaldi et al., 2022). On the other hand, by definition of the impact function, the drivers and the resulting compound variable are dependent. For completeness, we also include the contribution of the drivers to the variance of the resulting compound variable

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Table 1
Summary of Metrics to Determine the Strength of Structural Compoundness

Aspect	Metric
Contribution driver-compound var.: magnitude	$\phi_0 = E[f(X,Y)]$
Contribution driver-compound var.: variability	$\sigma_{X,Z}/\sigma_Z^2$, $\sigma_{Y,Z}/\sigma_Z^2$
Relative behavior driver-compound var.	I_{NPMI}
Relative behavior driver-driver	J

based on the consideration that $\sigma_Z^2 = \sigma_{X,Z} + \sigma_{Y,Z}$. The metrics suggested to quantify the strength of structural compoundness are given in Table 1.

2.1. Dependence Between Drivers: Jaccard Similarity Index

Leonard et al. (2014) and later Zscheischler et al. (2018) highlighted statistical dependence between physical drivers as a key characteristic in defining compound events. Leonard et al. (2014) illustrated this with the example of coastal flooding, where ocean levels and rainfall are statistically independent. In such cases, flooding cannot be defined as a compound event because the risk calculation simplifies due to this independence. In addition to this, given the challenges in determining the impact's probability of occurrence, Leonard et al. (2014) considered the statistical dependence between contributing drivers necessary to determine those combinations of drivers physically possible to be used in scenario-based analysis from which the assessment of the impact's probability of occurrence can be derived. However, we argue that the statistical dependence between contributing drivers is unnecessary, since the joint occurrence of statistically independent variables can still be computed, and pairs of independent variables can still be physically possible combinations. In this context, it is important to distinguish the joint occurrence of drivers from cases of mutual exclusiveness (Serinaldi et al., 2022). For this, we quantify the similarities and dependencies between the occurrences of driver-driver pairs via the Jaccard Similarity Index (J). Given two sets with n binary attributes, that is, 0 absence of the attribute and 1 presence of the attribute, it is possible to define the matrix $M_{2\times 2}$ with elements m_{00} and m_{11} indicating the number of attributes not present and present, respectively, in both sets, while the elements m_{01} and m_{10} indicating the number of elements that are present in either one or the other set. The Jaccard Similarity Index is then given by:

$$J = \frac{m_{11}}{m_{01} + m_{10} + m_{11}} \tag{5}$$

It quantifies the similarity between two sets by calculating the ratio of the shared attributes and their union. It ranges from 0 (no overlap) to 1 (identical sets), providing a measure of shared elements relative to the total elements. In the context of compound events, the vectors of drivers and the resulting compound variable can be transformed to binary vectors where 0 indicates that the single realization is below its expected value, and 1 otherwise. The choice of the threshold is made to be consistent with the decomposition of the impact function given in Equation 2.

When discussing compound events, we are generally interested in potentially harmful events. Hence, we focus our attention on the relative behavior of the variables above a given (safety) threshold. In this context, a realization exceeding the expected value is considered to possess the attribute, and the corresponding element in the vector is assigned a value of 1. Let us now consider the vector of drivers X and Y transformed in binary vectors, X_{b} and Y_{b} respectively, based on whether the realization is below (0) or above (1) the mean. Values of J close to 1 indicate that the compound variable Z results mostly from drivers behaving similarly (e.g., both above their respective thresholds). Values of J close to 0 indicate that the compound variable is mostly defined by one of the two contributing drivers. The index J can also be seen as the ratio between *AND* and the *OR* scenario defined in Salvadori et al. (2016). In other words, $J = \Pr(X_{\mathrm{b}} = 1 \wedge Y_{\mathrm{b}} = 1)/\Pr(X_{\mathrm{b}} = 1 \vee Y_{\mathrm{b}} = 1)$. Values of J close to 1 indicate dependence between X_{b} and Y_{b}, that is, within the physical drivers domain all the pairs cluster in quadrant I of a cartesian plane, while values close to 0 indicate independence, the pairs evenly distributed in the quadrants I, II, and IV.

2.2. Dependence Between Drivers and Compound Variable: Normalized Pairwise Mutual Information

We quantify the similarities and dependencies between the occurrences of driver-compound variable pairs via the Normalized Pointwise Mutual information I_{NPMI} (Bouma, 2009) since, by definition, a dependence between the drivers X and Y and the compound variable Z always exists.

I_{NPMI} derives from the Pointwise Mutual information (I_{PMI}), introduced by Church and Hanks (1990), which is a measure of how much the actual probability of a particular co-occurrence of events differs from what we would expect under the assumption of independence between the events.

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$$I_{\mathrm{PMI}}(X_{\mathrm{b}}=1, Y_{\mathrm{b}}=1)=\log_2\left(\frac{\Pr(X_{\mathrm{b}}=1 \wedge Y_{\mathrm{b}}=1)}{\Pr(X_{\mathrm{b}}=1)\Pr(Y_{\mathrm{b}}=1)}\right) \tag{6}$$

Here, I_{PMI} can take negative (pairs not occurring together) or positive values (pairs occurring together), and $I_{\mathrm{PMI}}=0$ indicates completely uncorrelated pairs. However, I_{PMI} does not have meaningful bounds. To overcome this limitation, Bouma (2009) introduced the normalized version I_{NPMI}.

$$I_{\mathrm{NPMI}}=\frac{I_{\mathrm{PMI}}(X_{\mathrm{b}}=1, Y_{\mathrm{b}}=1)}{-\log_2 Pr(X_{\mathrm{b}}=1 \wedge Y_{\mathrm{b}}=1)} \tag{7}$$

Values of I_{NPMI} close to 1 indicate dependence between the pairs, while values close to -1 indicate mutual exclusiveness of the events, meaning that they do not occur together, rather than occurring together by chance. This indicator follows the rationale of the likelihood multiplication factor proposed by Zscheischler and Seneviratne (2017) and the interest factor proposed by Meroni and De Michele (2023), with the advantage of having meaningful boundaries.

3. Applying Structural and Transient Compoundness to River Confluences

In the following section, we explore the concept of structural and transient compoundness in river confluences. Confluences are key elements along a river network, requiring careful consideration when developing flood risk reduction strategies since the combination of discharges upstream generates the downstream discharge. We can then regard the downstream discharge as the compound variable Q_Z resulting from a linear combination of drivers Q_X and Q_Y:

$$Q_Z = Q_X + Q_Y \tag{8}$$

We can formulate Equation 8 in a SHAP framework to explicitly investigate structural and transient compoundness. More specifically, we have

$$Q_Z = \phi_0^{Q_X,Q_Y} + \phi_{Q_X} + \phi_{Q_Y} \tag{9}$$

where,

$$\begin{aligned} \phi_0^{Q_X,Q_Y} &= E[Q_X] + E[Q_Y] \\ \phi_{Q_X} &= Q_X - E[Q_X] \\ \phi_{Q_Y} &= Q_Y - E[Q_Y] \end{aligned} \tag{10}$$

We investigate river confluences as compound events in two confluences: the Mississippi-Missouri (Case A) and the Rhine-Nahe (Case B). For this specific application, if $E[Q_X] \ll E[Q_Y]$ or $E[Q_Y] \ll E[Q_X]$, the base value, the expected value of the impact function, can be approximated to the expectation of one variable, $E[Q_X]$ or $E[Q_Y]$, respectively. This implies that the structural compoundness is weak.

3.1. Structural Compoundness: Mississippi-Missouri

For case A, we collect upstream daily discharge observations (Q_X and Q_Y respectively) from the United States Geological Survey (USGS) archive of station gauges: the Missouri River at St. Charles (ID: 06935965) and the Mississippi River at Grafton (ID: 05587450). Observations for Missouri and the Mississippi River are available for a period of 24 years (2000–2023) and 91 years (1933–2023), respectively. For this, in the following analyses, we consider data only during overlapping years between 2000 and 2023. Over this period of time, the average (arithmetic mean) discharge and the maximum discharge recorded are 2661.57 m^3/s and 14300 m^3/s, respectively, for the Missouri River; while they are 3920.23 m^3/s and 14781.39 m^3/s, respectively, for the Mississippi River, Figure 2. For the purpose of the analysis, we select annual maxima downstream discharges. The expecteed values of the annual maxima are $E[Q_X] = 8987.06$ m^3/s and $E[Q_Y] = 7817.81$ m^3/s.

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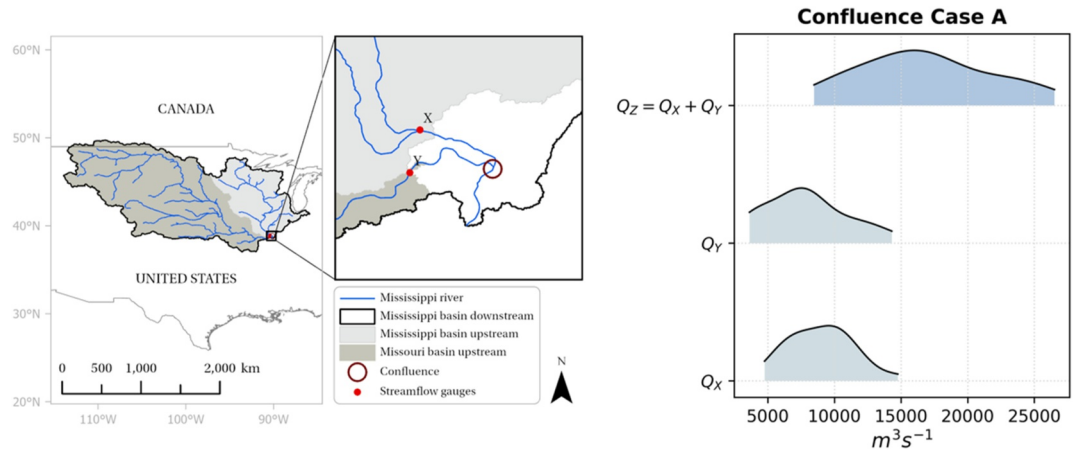


Figure 2. Mississippi-Missouri Confluence. The left panel shows the catchments associated with the discharge gauges. The right panel shows the probability density functions of river discharges. Q_X and Q_Y are observed values, while Q_Z, the compound variable, results from the sum of the observed discharges, and it is assumed to be an approximation of the discharge downstream of the confluence.

We first investigate the degree of structural compoundness following the metrics in Table 1. We observe that in the case of the Mississippi-Missouri confluence, the base value is $E[Q_Z] = 16804.87$ m^3/s and the two drivers contribute on average almost equally, Table 2. In terms of contribution to the variance of Q_Z, Q_Y contributes slightly more than Q_X. These results suggest that the Mississippi-Missouri confluence is structurally prone to compound events since the two drivers play an equally important role in the overall generation of downstream discharge. Based on this, we can conclude that even moderate events upstream can lead to extreme events downstream. We further investigate J and I_{NPMI} to understand the relative behavior of driver-driver and driver-compound variable. We obtain a value of J close to 0.5 for the pair (Q_X, Q_Y). This means that if one of the drivers is high, that is, above its mean value, the other driver also takes high values. We obtain values of $I_{\text{NPMI}}(1,1)$ of 0.78 and 0.43 for the pair driver-compound variable (Q_X, Q_Z) and (Q_Y, Q_Z), respectively, meaning that when a single driver is high, also the compound variable is high. The discrepancy between the two values indicates that Q_X contributes more to Q_Z than Q_Y.

3.2. Structural Compoundness: Rhine-Nahe

For the Rhine-Nahe confluence (case B), we considered upstream daily discharge observations (Q_X and Q_Y) from the Global Runoff Data Centre: the Grolsheim station (Nahe River - ID: 6335115) between 1935 and 2016 and the Mainz station (Rhine River - ID:6335150) between 1930 and 2022. For the following analyses, we used data in the overlapping years between 1935 and 2016. Over this time, the average (arithmetic mean) discharge and the maximum discharge recorded are 29.23 m^3/s and 803.00 m^3/s, respectively, for the Nahe River; while they are 1618.90 m^3/s and 6920.00 m^3/s for the Rhine River, Figure 3. Similarly to the previous case, we analyze annual maxima where $E[Q_x] = 4135.58$ m^3/s and $E[Q_Y] = 107.36$ m^3/s. The difference between the two upstream

Table 2
Strength of Structural Compoundness for the Mississippi-Missouri Confluence (Case A)

Metric	(Q_X, Q_Y)	(Q_X, Q_Z)	(Q_Y, Q_Z)
Contribution driver-compound var.: magnitude	–	0.53	0.47
Contribution driver-compound var.: variability	–	0.43	0.57
Relative behavior driver-compound var.: I_{NPMI}	–	0.78	0.43
Relative behavior driver-driver: J	0.47	–	–

Note. The magnitude of contribution of the driver-compound is given by $E[Q_X]/\phi_0^{Q_X,Q_Y}$ and $E[Q_Y]/\phi_0^{Q_X,Q_Y}$. I_{NPMI} represents the case in which both the driver and the compound variable are above their threshold (here their respective mean value).

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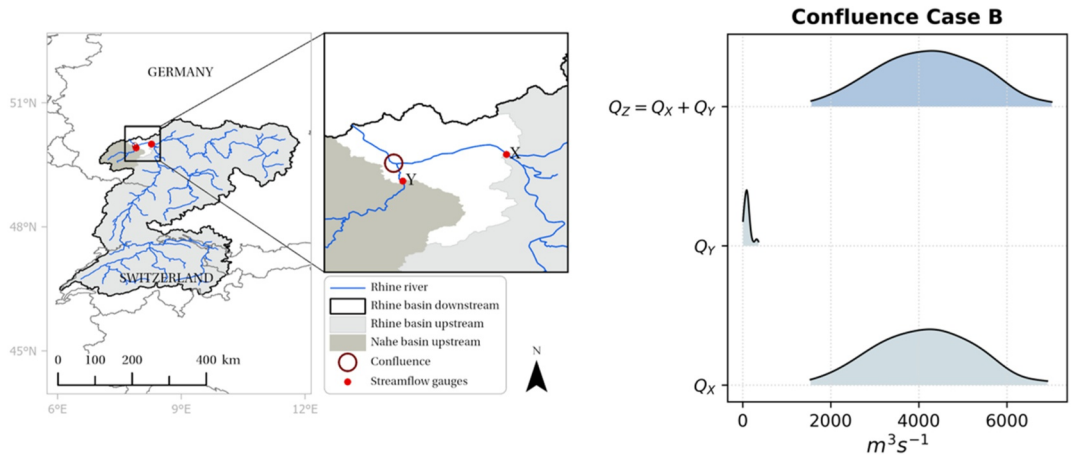


Figure 3. Rhine-Nahe Confluence. The left panel shows the catchments associated with the discharge gauges. The right panel shows the probability density functions of river discharges. Q_X and Q_Y are observed values, while Q_Z is the compound variable and results from the sum of the observed discharges.

branches is already clear. The base value $E[Q_Z] = 4242.94$ m^3/s is very close to $E[Q_X]$, indicating a low propensity to structural compoundness. Thus, the expected average prediction is that the system behaves similarly to the univariate case in which Q_X governs. However, individual realizations may still exhibit substantial departures from the baseline, which can be investigated by considering the event-specific contributions quantified via the SHAP values, that is, via transient compoundness. Also in terms of contribution to the variability of Q_Z, Q_X dominates over the contribution of Q_Y, see Table 3.

Following the metrics in Table 1, the similarity index J between the drivers (Q_X, Q_Y) is 0.54, meaning that they have the same behavior above their respective thresholds. The I_{NPMI} between (Q_X, Q_Z) and (Q_Y, Q_Z) are respectively 0.97 and 0.42. This indicates that the compound event, that is, $Q_Z \geq q_Z$, is mostly determined by extremes in Q_X, while the contribution of extremes in Q_Y is limited.

3.3. Transient Compoundness in Confluences

Transient compoundness describes single compound events and their generative drivers. A compound event is defined in the literature as an event generated by multiple drivers that leads to a greater impact than the case in which the drivers act individually. Hence, given the compound variable Z and its (safety) threshold z^*, a compound event is defined when $Z > z^*$. In the context of river confluences, we consider $Q_Z > q_Z^*$, where $q_Z^* = \phi_0^{Q_X,Q_Y}$. Although this threshold is arbitrary, it enables us to focus on events that deviate from the expected conditions, that is, events characterized by a positive sum of their SHAP values.

To improve interpretability, individual SHAP contributions are expressed as percentage changes. Specifically, the drivers are represented by the normalized SHAP values, $\bar{\phi}^X$ and $\bar{\phi}^Y$ in Equation 4. Pairs of SHAP values with a positive sum indicate drivers of compound events $\left(Q_Z > q_Z^*\right)$, as their combined contribution increases the

Table 3
Strength of Structural Compoundness for the Rhine-Nahe Confluence (Case B)

Metric	(Q_X, Q_Y)	(Q_X, Q_Z)	(Q_Y, Q_Z)
Contribution driver-compound var.: magnitude	–	0.97	0.03
Contribution driver-compound var.: variability	–	0.96	0.04
Relative behavior driver-compound var.: I_{NPMI}	–	0.97	0.42
Relative behavior driver-driver: J	0.54	–	–

Note. The magnitude of contribution of the driver-compound is given by $E[Q_X]/\phi_0^{Q_X,Q_Y}$ and $E[Q_Y]/\phi_0^{Q_X,Q_Y}$. I_{NPMI} represents the case in which both the driver and the compound variable are above their threshold (here their respective mean value).

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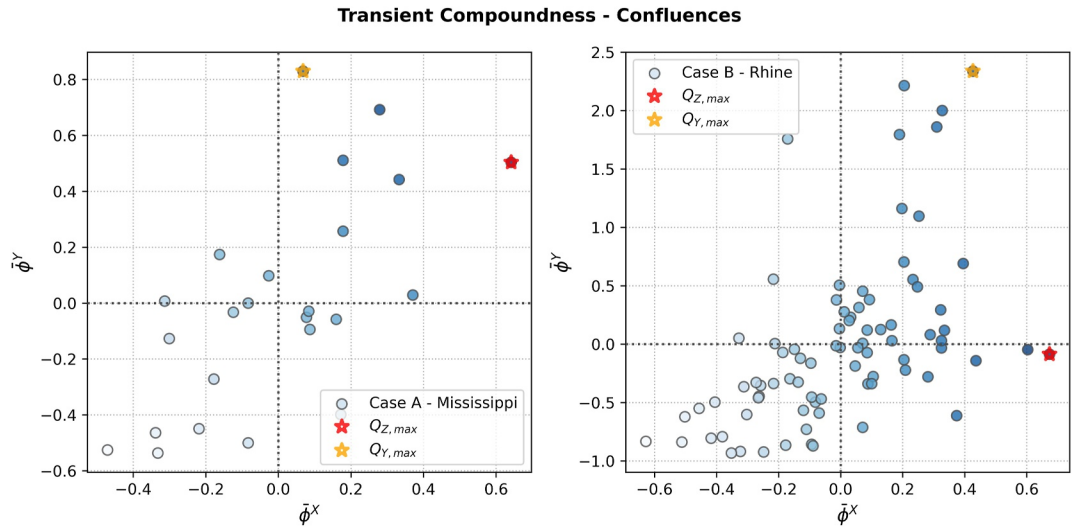


Figure 4. Scatter plot of event-specific contributions for the Mississippi-Missouri confluence (Case A–left panel) and Rhine-Nahe confluence (Case B–right panel). The blue color shades indicate the intensity of the compound variable. Darker blue indicates compound variables with greater magnitude. A red star indicates an event where the compound variable is the maximum observed; an orange star represents events where the discharge in the tributary is the highest recorded. Here, $\bar{\phi}^{Q_X} = \frac{Q_X - E[Q_X]}{E[Q_X]}$ and $\bar{\phi}^{Q_Y} = \frac{Q_Y - E[Q_Y]}{E[Q_Y]}$.

magnitude of the compound variable relative to its baseline, $\phi_0^{Q_X,Q_Y}$. Conversely, a negative sum indicates that the compound variable remains below its expected value.

Figure 4 presents the SHAP values normalized by their respective means (i.e., variable thresholds), which facilitates comparison across events and helps identify both the severity of individual events and differences in their underlying generative processes. We observe how the drivers in the Mississippi-Missouri confluence contribute almost equally to downstream discharge (drivers are aligned along the identity line and darker colors cluster toward the upper right corner of the left panel in Figure 4). This behavior differs from the Rhine-Nahe confluence, in which Q_X contributes the most to Q_Z (dots of darker blue shades are parallel to the y-axis). To better understand the individual events, we focus on two extreme cases: when the compound variable, or better the compound event since $Q_Z > E[Q_Z]$, is the maximum recorded (red stars in Figure 4) and when Q_Y, that is, the smaller river or tributary, is the maximum recorded (orange stars in Figure 4). In the case of the Mississippi-Missouri confluence, the two events are similar in magnitude and relative behavior of the upstream discharges. The resulting compound event is 26504.57 m^3/s and 23899.42 m^3/s, where the contribution of the tributary river (Q_Y) to the discharge downstream (Q_Z) was 0.44 and 0.60, respectively. This indicates that Q_Y can be the main contributor to a compound event even though, from a structural perspective, the dominant driver in the process is Q_X, see Table 2. On the other hand, in the case of the Rhine-Nahe confluence, we immediately see that the Nahe River (Q_Y) has a larger variability compared to the Rhine River, Figure 4. We then expect the associated compound event to be intense. However, the associated compound event, (Q_Z) is 6259.27 m^3/s (Figure 4 right panel, orange star), which is less than 90% of the highest maximum event recorded (Figure 4 right panel, red star) and the relative contribution of Q_Y is around 6%. The contribution of Q_Y to the maximum compound event is minimal, around 1%. In general, we see that the downstream river has a low sensitivity to the Nahe River. Even though in both cases the downstream discharge is above average, it does not reflect the uneven distribution of the discharges upstream of the confluence and their respective contributions.

4. Applying Structural and Transient Compoundness to Extreme Hot and Dry Events

We then explore the concept of structural and transient compoundness in the case of extreme hot and dry events, from the perspective of water availability, being a pressing issue given shifts in precipitation patterns and increasing temperatures. Water availability can be quantified in terms of precipitation deficit (P_D), being the balance between water inflow, that is, precipitation (P), and water outflow, that is, evapotranspiration (E_T), Equation 12.

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$$P_D = E_T - P \tag{11}$$

Similarly to the case of river confluences, we can reformulate Equation 11 based on Equation 2. More specifically,

$$P_D = \phi_0^{E_T,P} + \phi_{E_T} - \phi_P \tag{12}$$

where

$$\begin{aligned} \phi_0^{E_T,P} &= E[E_T] - E[P] \\ \phi_{E_T} &= E_T - E[E_T] \\ \phi_P &= P - E[P] \end{aligned} \tag{13}$$

Negative values of P_D indicate water surplus, while positive values indicate water deficit. The base value $\phi_0^{E_T,P}$ is an indication of the structural compoundness. Low to high positive values of this metric indicate that the system is generally dry, while low to negative values indicate that the system is generally wet. However, in contrast with the case of river confluences, large differences in $\phi_0^{E_T,P}$ components, that is, $E[E_T]$ and $E[P]$, show a system prone to hot and dry events. Indeed, dry conditions, for example, low precipitation inflow, are intensified by high evapotranspiration outflow. While similar values of the fluxes ensure a balanced system.

We investigate compound hot and dry events in two different basins: Tagus River Basin (Portugal) and the Meuse River Basin (Netherlands).

4.1. Computing Precipitation Deficit

We compute P_D from the E-OBS ensemble data set (https://surfobs.climate.copernicus.eu/), which includes daily gridded observational data for precipitation, mean temperature, sea level pressure, and global radiation across Europe. The ensemble data is based on the station data collected by the European Climate Assessment & Data set (ECA&D) initiative, see Cornes et al. (2018). We use version 26.0e of the data set with a spatial resolution of 0.1 ° (~11.1 km at the equator) available from 1950 to 2022. E_T is then estimated by applying the Makkink formula (Hooghart & Lablans, 1988) to the mean temperature, sea level pressure, and global radiation data sets. Daily Makkink E_T for grass that has no shortage is given by Equation 14

$$E_T = \frac{1}{L_v}\left(0.65\frac{s}{s+\gamma}K^{\downarrow}\right) \tag{14}$$

where $K^{\downarrow}$ is the incoming solar radiation, s is the slope of the saturation water vapor-temperature curve at air temperature, γ is the psychometric constant, and L_v is the latent heat of vaporization.

Catchment boundaries for the Tagus Basin and the Meuse Basin are used to extract the precipitation and potential evapotranspiration timeseries within each basin. They are retrieved from the HydroBASINS database (https://www.hydrosheds.org/), which provides polygons of sub-basin boundaries at a global scale (Lehner & Grill, 2013). To obtain daily timeseries of P and E_T, weighted means are calculated using the relative area of the E-OBS grids that lie within the catchment boundary as weights.

The daily timeseries of P, E_T, and P_D are then summed over each month to obtain monthly timeseries. This is because the system takes time to show signs of stress in response to dry conditions, and short-term fluctuations from daily data may hinder the cumulative effects of prolonged dryness, while cumulative monthly data provide a more stable sign of the state of the system. We then consider only the months of July and August, being the hottest months for both cases.

4.2. Structural Compoundness: Tagus River Basin (Portugal)

We investigate P_D between 1950 and 2020, due to missing records of global radiation required for E_T calculation between 2020 and 2022. The average (arithmetic mean) monthly precipitation is 61.94 mm/month, and monthly

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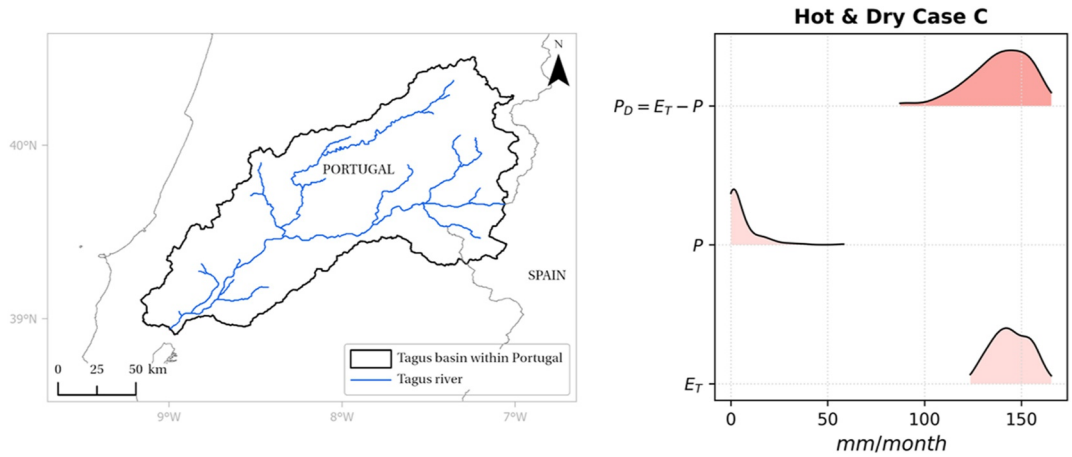


Figure 5. The left panel shows the extent of the Tagus River in Portugal over which gridded precipitation has been averaged. The right panel shows the probability density functions of the climate variables considered: accumulated monthly precipitation P, potential evapotranspiration (E_T), and precipitation deficit (P_D) for the months of July and August.

evapotranspiration is 82.28 mm/month. The expected values change when restricting the analysis to the months of July and August. Specifically, $E[E_T] = 144.45$ mm/month and $E[P] = 5.69$ mm/month, Figure 5. The highest E_T is 165.4 mm/month in July, which is also the highest P_D.

We investigate the strength of structural compoundness following the metrics proposed in Table 1. In contrast with the case of confluences, here the compound variable P_D can take negative values. Negative values indicate that, on average, the basin receives more water from precipitation than the amount lost from evapotranspiration. On the contrary, positive values indicate a system receiving less water from precipitation compared to the water lost via evapotranspiration (positive $E[P_D]$). In the case of the Tagus River, $\phi_0^{E_T,P} = 138.76$ mm/month. This value is very close to the expectation of evapotranspiration, meaning that the system is primarily driven by hot conditions, for which precipitation is not able to alleviate. As a matter of fact, if we look at how $\phi_0^{E_T,P}$ is composed, the expected precipitation is about 3% of the expected evapotranspiration. This indicates that the basin is prone to experiencing hot and dry events. Moreover, we observe that the variability of the compound variable is explained almost equally by the variability of evapotranspiration and precipitation.

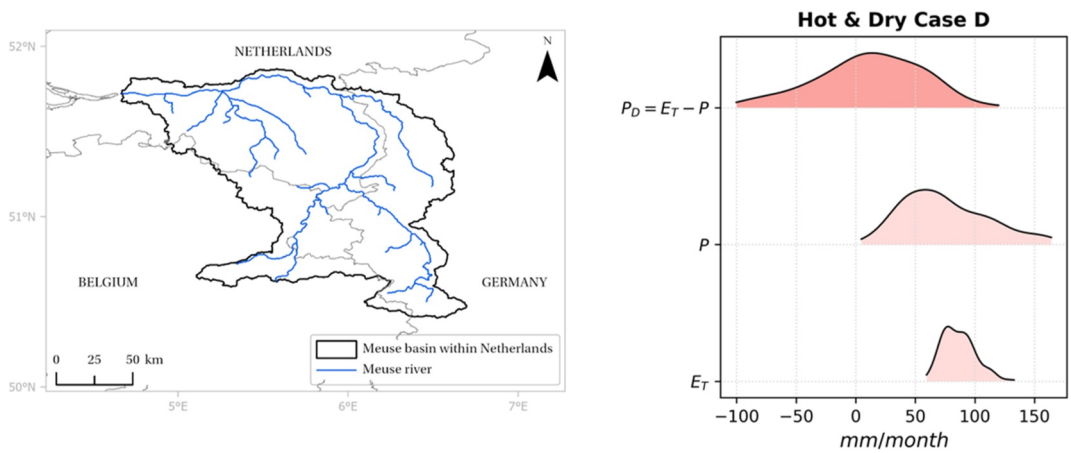


Figure 6. The left panel shows the extent of the Meuse River in the Netherlands over which gridded precipitation has been averaged. The right panel shows the probability density functions of the climate variables considered: accumulated monthly precipitation P, potential evapotranspiration (E_T), and precipitation deficit (P_D) for the months of July and August.

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Table 4
Strength of Structural Compoundness for the Tagus River Basin (Case C)

Metric	(E_T, P)	(E_T, P_D)	(P, P_D)
Contribution driver-compound var.: magnitude	0.03	–	–
Contribution driver-compound var.: variability	–	0.54	0.46[a]
Relative behavior driver-compound var.: I_{NPMI}		0.62	0.53
Relative behavior driver-driver: J	0.57	–	–

Note. The contribution of driver-compound in terms of magnitude is given by $E[P]/E[E_T]$. $I_{NPMI}(1,1)$ represents the case in which the compound variable is greater than the base value $\phi_0^{E_T,P}$ and the driver is above/below its threshold if the driver is E_T/P. [a]indicates that the absolute value is taken because σ_{P,P_D} has a negative sign.

Afterward, we analyze the relative behavior of driver-driver (J) and driver-compound variable (I_{NPMI}), Table 4. Here, we identify (safety) thresholds for the drivers and the compound variable so that we can capture their relative behavior in extreme (high/low) occurrences. Similar to the case of confluences, and in accordance with the SHAP framework, we select their expected values as a threshold for the drivers. However, in this specific case, we are interested in events with high E_T, that is, hot events with E_T greater than its expected value (positive ϕ_{E_T}), and events with low P, that is, dry events with P below its expected value (negative ϕ_P). Then, we define a compound event as one for which $P_D > p_D^*$, where p_D^* is equal to $E[P_D]$.

The metric J between E_T and P is around 0.6, meaning that the two drivers are fairly in agreement: higher evaporative demand is associated with a period of low precipitation. This is a reflection of the dry period during the summer months. The two $I_{NPMI}(1,1)$ between driver/compound event indicate that E_T contributes slightly more to P_D, which can be an indication of hot conditions exacerbating already dry conditions.

4.3. Structural Compoundness: Meuse River Basin (Netherlands)

Following the case of the Tagus River, we investigate P_D between 1950 and 2022. This same timeseries has been previously used by Sudha et al. (2024) to study historical wet and dry meteorological conditions in the Netherlands.

The average precipitation $E[P]$ is 65.3 mm/month, and the average potential evapotranspiration $E[E_T]$ is 46.2 mm/month. These values change when restricting the analysis to the months of July and August. Specifically, $E[P]$ is 86.43 mm/month and $E[E_T]$ is 75.08 mm/month, Figure 6, while the base value is $\phi_0^{E_T,P} = 11.35$ mm/month. In contrast with the previous case, structural compoundness is weaker since the fluxes balance each other, making the system less prone to compound hot and dry events. Overall, in the Meuse River 87 % of the evaporation is offset by precipitation received. The maximum potential evapotranspiration is 132.76 mm/month over the month of July. Precipitation seems to dominate evapotranspiration in the variability of precipitation deficit. Indeed, the contribution of P to the variance of P_D is around 0.78. Moreover, $I_{NPMI}(1,1)$ is 0.71 for the pair (P, P_D) in contrast with 0.37 for the pair (E_T, P_D), Table 5. This means that the catchment is less prone to the occurrence of hot and dry events.

Table 5
Strength of Structural Compoundness for the Meuse River Basin (Case D)

Metric	(E_T, P)	(E_T, P_D)	(P, P_D)
Contribution driver-compound var.: magnitude	0.87	–	–
Contribution driver-compound var.: variability	–	0.22	0.78[a]
Relative behavior driver-compound var.:$I_{NPMI}(1,1)$	–	0.37	0.71
Relative behavior driver-driver: J	0.46	–	–

Note. The contribution of the two variables to the baseline $\phi_0^{E_T,P}$ is expressed in terms of the ratio between precipitation and evapotranspiration. $I_{NPMI}(1,1)$ represents the case in which the compound variable is greater than $\phi_0^{E_T,P}$ and the driver is above/below its threshold if the driver is E_T/P. [a]indicates that the absolute value is taken because σ_{P,P_D} has a negative sign.

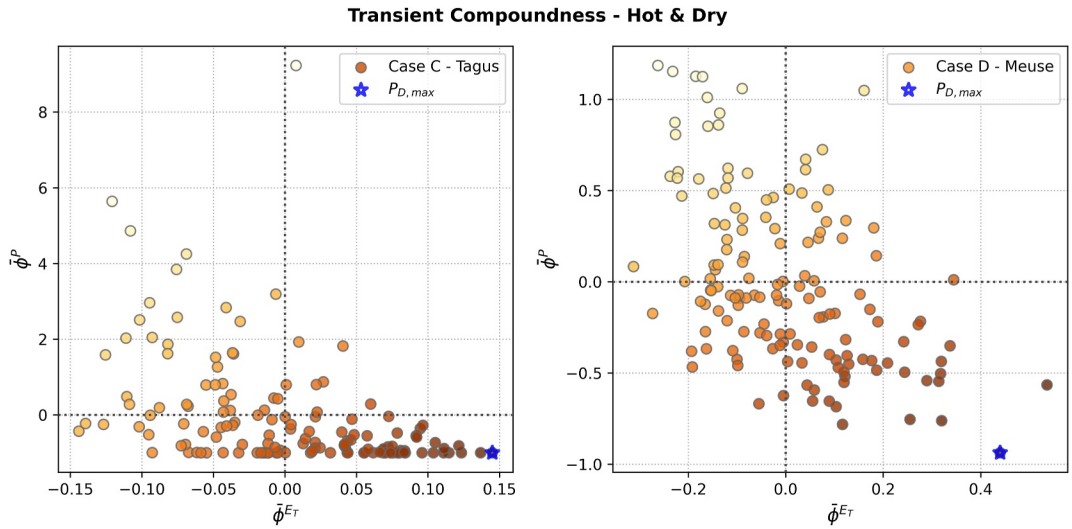


Figure 7. Scatter plot of event-specific contributions, for the Tagus River basin (Case C–left panel) and Meuse River basin (Case D–right panel). Color shades indicate the intensity of the compound variable, here P_D. Light shades indicate low to negative values of P_D while darker shades indicate high to positive values of P_D. A blue star indicates an event where the compound variable is the maximum observed. In the case of the Tagus River basin, it coincides with the condition of extreme E_T since $P = 0$. Here, $\tilde{\phi}^{E_T} = \frac{E_T - E[E_T]}{E[E_T]}$ and $\tilde{\phi}^{P} = \frac{P - E[P]}{E[P]}$.

4.4. Transient Compoundness in Hot and Dry Events

We further investigate hot and dry events in terms of transient compoundness. Similarly to the case of the confluence, a hot and dry compound event occurs when P_D is greater than its base value $\phi_0^{ET,P}$. This condition is realized when the interaction between $\phi_i^{E_T}$ takes positive values (values higher than expected) while ϕ_i^P takes negative values (values lower than expected). In the case of the Tagus River basin, we observe a clear association between high E_T–low P and low E_T–high P (Figure 7 left panel). This indicates that periods of low precipitation occur mainly during the summer months, when E_T is high. This is evident in the Tagus River basin, where the compound variable clusters in the bottom-right corner. The blue star indicates the event with the highest P_D, which in this specific case coincides with $P = 0$. In contrast, the Meuse River basin exhibits a compound variable that is more widely scattered across the space of the drivers, even though the drivers show a clear alignment along the identity line with slope -1. It is interesting to notice that the compound variable does not cluster in the bottom right corner. This results from the large variability in monthly precipitation compared to the variability of precipitation in the Tagus basin. However, hot and dry events are possible. The event with the highest P_D is the event in which E_T and P are the second highest and lowest, respectively. This implies that a combined effect of high temperature and low precipitation is still possible, even if the system is on average balanced (Figure 7 right panel).

In the case of the Meuse River, it is worth noticing that this event occurred during the summer of 2018, which is considered one of the most intense drought events in the Netherlands. The agricultural sector, mainly located in the eastern part of the country, suffered from the combination of low precipitation and high temperatures (Philip et al., 2020).

5. Discussion

We introduced the concepts of structural and transient compoundness to distinguish between compoundness arising from the event's generative mechanism (structural) and that resulting from a specific realization of drivers (transient).

The compound variables were defined following the impact-centric approach proposed in the literature (Bevacqua et al., 2021; Raymond et al., 2020; Zscheischler et al., 2018). This implies that a structural compoundness always exists. However, this does not necessarily mean that a more complex model (i.e., a multivariate model) able to capture the interaction between the drivers is needed. On the contrary, its strength provides a solid basis for making a specific modeling choice.

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We proposed a compound event analysis within a more general framework that combines principles from additive feature attribution models and SHAP values. This framework is widely used in combination with machine learning methods to derive measures of feature importance. Consequently, even highly nonlinear impact functions can be examined within the proposed framework. For such complex functions, the base value ϕ_0 already incorporates interactions among the physical drivers. However, its decomposition may become challenging when the number of variables is large, as this can make it difficult to clearly identify the contribution of each individual driver. In such cases, structural compoundness cannot be explicitly quantified and is instead implicitly assumed through the structure of the impact function itself. In contrast, transient compoundness, that is captured by the individual SHAP values, allows us to assess the system's propensity for compound events at the level of individual events.

Here, we applied the framework to a linear impact function. This, at first, might appear overly simplified. However, it was instrumental to decompose the compound variables and identify the main contributors, that is, drivers and their interaction. The latter is particularly important in the context of compound event analysis, as the correlation between drivers has often been considered a necessary feature for defining events as compound in the literature. In an additive system, the relationship between drivers and the compound variable becomes particularly transparent. By this decomposition, we better see that the dependence between the drivers (here quantified via the covariance) directly affects the variance of the compound variable. When the drivers are correlated, this not only increases the variance of the compound variable but also strengthens the correlation between each individual driver and the compound variable. As a result, more information becomes available about what is likely to happen, enhancing predictability. At the same time, though, the magnitude of the drivers plays an equal, even if not more significant, role than the correlation. If one driver dominates over the other, a simpler model, for example, a univariate model, can work well, regardless of correlation. This was particularly evident in Case B of the confluence Rhine - Nahe. Indeed, even though correlation informs on whether the two drivers reach high values at the same time (assuming the correlation is positive), the (high) magnitude of one variable can be negligible when evaluating the magnitude of the compound variable/event. Hence, the impact of a compound event is shaped by both the dependence and the intensity of the drivers.

The impact function used is not only instrumental for decomposing contributions, as demonstrated earlier, but is also broadly applicable to other compound events that have received significant attention in the scientific literature. For example, it can be used to model river discharge for rivers fed by both rainfall and snowmelt. This means that river discharge is determined by the sum of discharge generated by rainfall and discharge generated by snowmelt. Depending on the season, drivers might co-occur, requiring a multivariate model, or one driver might prevail over the other, requiring a simpler, univariate model. Similarly, it can be used to model compound flooding in estuary regions, which is probably so far the most-studied compound event. The phenomenon here develops when the hydraulic head at the river mouth reduces due to higher sea levels, preventing the normal discharge of the river and causing backwater effects. An approximation of the extension of the backwater effect is given by the ratio between the bankfull flow depth and the water surface slope (Wu et al., 2023). In such a condition, as long as the hydraulic head (i.e., the difference between river depth and sea level) is lower than the bankfull flow depth, the resulting flood event can be considered compound. Hence, from a modeling perspective, a more complex, multivariate model is needed. Conversely, if the flood event is dominated by sea level, a simpler univariate model is sufficient.

In the current literature, studies typically focus either on the statistical dependence between drivers, for example, through copula-based approaches, or on the resulting impacts using physically based models driven by multiple input variables (i.e., the physical drivers). The proposed framework encompasses these approaches by explicitly linking the characteristics of the physical drivers and their interactions to the generation of the compound variable. At the same time, the framework allows the contribution of each driver to be quantified for a single realization of a compound event, providing information that may not be apparent from analyses of the overall behavior of the compound variable. Hence, we believe that the proposed framework provides a unifying perspective that helps identify the mechanisms that are most relevant for the compound event under consideration.

6. Conclusion

In this study, we introduced the concepts of structural and transient compoundness as system properties offering a more comprehensive framework for describing hydrological and climate phenomena. They provide a

quantification of the overall tendency of contributing physical drivers to interact (structural), and how specific combinations of drivers lead to compound events (transient), regardless of their statistical dependence. We introduced a generalized framework that combines additive feature attribution methods and SHAP values to define the impact function, enabling the quantification of both structural and transient compoundness. We investigated these concepts in events defined by impact functions modeled as additive systems: river discharge at confluences and concurrent hot and dry events. We showed that structural and transient compoundness can inform modeling choices and improve system understanding, highlighting that both the dependence and the magnitude of drivers play critical roles in shaping compound events. We also showed the broad applicability of these seemingly simple impact functions. Ultimately, incorporating structural and transient compoundness enhances scientific modeling and, at the same time, improves risk assessment, guiding adaptation strategies for persistent (structural) and temporary (transient) risks.

Appendix A: Additive Feature Attribution in SHAP Framework

Additive feature attribution methods approximate the output of a model $f(\mathbf{X})$ using a simplified explanation function $g(\mathbf{X})$ defined as the sum of feature attributions:

$$g(\mathbf{X}) = \phi_0 + \sum_{k=1}^{F} \phi_i, \tag{A1}$$

where F is the number of features, ϕ_0 is the base value, and ϕ_i for $i = 1, \ldots, F$ represents the contribution of feature i. Under this formulation, the model prediction for a specific instance x can be expressed as the baseline expectation plus the sum of the feature contributions. In other words, the prediction $f(\mathbf{X})$ is decomposed into how much each feature shifts the model output away from its base value, ϕ_0.

The most common approach to quantify the contribution of ϕ_i of each feature is based on cooperative game theory. The Shapley regression value, introduced for linear models in the presence of collinearity, measures feature importance by evaluating how each feature contributes to predictions across all possible feature subsets $S \subseteq F$. For each subset S, the model f is retrained with $\left(f_{S\cup\{i\}}(x_{S\cup\{i\}})\right)$ and without $\left(f_S(x_S)\right)$ the feature i, and the weighted average of the resulting prediction differences quantifies the contribution of the $i - th$ feature:

$$\phi_i = \sum_{S\subseteq F\setminus\{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!}\left[f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)\right] \tag{A2}$$

Lundberg and Lee (2017) proposed an unified measure for quantifying feature importance, named the SHapley Additive exPlanation (SHAP) value, in which for each subset S, f_S and $f_{S\cup\{i\}}(x_{S\cup\{i\}})$ are quantified as expectation values conditioned on unknown features, that is, not present in the subset S. The base value ϕ_0 in Equation A1 is the expectation of the original model when all the features are unknown ($E[f(\mathbf{X})]$). In other words, each SHAP value quantifies how much a feature contributes to shifting the prediction from the baseline value (expected value) to the current model output. It is important to notice that SHAP values satisfy three desirable properties: local accuracy (explanation model matching the original model, i.e., $g(\mathbf{X}) = f(\mathbf{X})$), missingness (no impact of missing features), and consistency (input attribution does not decrease if simplified input increases or stays the same regardless of other inputs).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The data used in this study have been retrieved from public repositories. Specifically, discharge data were obtained from the United States Geological Survey (USGS, 2021) and the Global Runoff Data Center (https://grdc.bafg.de/). Station IDs are mentioned in the text. Precipitation and evapotranspiration are obtained from E-OBS ensemble data set (Cornes et al., 2018).

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Acknowledgments
C.D.M. was supported by the RETURN project (Multi-risk science for resilient communities under a changing climate) with Extended Partnership, which received funding from the European Union Next-GenerationEU, National Recovery and Resilience Plan—NRRP, Mission 4, Component 2, Investment 1.3—D.D. 1243 2/8/2022, PE0000005. The authors thank the reviewers and the editor for their insightful comments and constructive suggestions, which greatly improved the manuscript.

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