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Assessing Causal Drivers of Diurnal Streamflow Fluctuations Using Convergent Cross Mapping

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ABSTRACT

Variations in stream water quality are strongly linked to diurnal fluctuations in streamflow, which themselves have been observed across diverse climatic regions. In temperate regions, these fluctuations have mostly been attributed to changes in evapotranspiration, riparian soil moisture, and riparian water viscosity. Previous research mostly assumed causality and linearity among these drivers without explicitly testing these assumptions. However, studies showed that these drivers may be nonlinearly related and not directly causative in the riparian zone. Here, we apply convergent cross mapping (CCM), a causal detection method, (i) to quantify how causal effects (i.e., the influence of one driver on another) among evapotranspiration, riparian soil moisture, and viscosity induce diurnal streamflow fluctuations, and (ii) to assess whether causal effects vary between the dormant and growing seasons. Our study site is the Wüstebach headwater catchment, located in a temperate region in Germany. Despite deforestation in 2013, diurnal streamflow fluctuations persists at the site. CCM reveals for the first time that evapotranspiration, riparian soil moisture, and riparian water viscosity simultaneously affect diurnal streamflow fluctuations, though with different effect strengths. Riparian water viscosity had the strongest effect followed by evapotranspiration and riparian soil moisture. The weaker evapotranspiration effect likely reflects the long-term deforestation in the catchment. The strength of causal effects varied between dormant and growing seasons, reflecting seasonal differences in the regrowth of deep-rooted vegetation. We also observed some non-causal relationships among drivers, highlighting the necessity of explicitly assessing causality in hydrologic studies instead of assuming it. This explicit assessment is crucial to uncover complex ecohydrologic interactions in future research.

1 | Introduction

Diurnal streamflow fluctuations have been observed in headwaters across diverse climates (Kirchner et al. 2020; Wondzell et al. 2007; Lundquist and Cayan 2002). These fluctuations typically occur during baseflow recession and show streamflow maxima in the morning or afternoon. They are closely linked to changes in chemical constituents (Schwab et al. 2018; Tunaley et al. 2017) and to stream water temperature (Baker et al. 2018). Since environmental conditions (hereafter 'drivers') influence the physical mechanisms in

the riparian zone that cause diurnal streamflow fluctuations, understanding water chemistry changes depends on quantifying how these drivers alter fluctuations. Several drivers have been shown to induce streamflow fluctuations, including changes in streambed hydraulic conductivity (Lundquist and Cayan 2002; Freeze and Cherry 1979), fluctuations in water viscosity in the streambed (Constantz et al. 1994) and in the riparian zone (Schwab et al. 2016, 2018), freeze-thaw processes (Gribovszki et al. 2006), or diurnal precipitation events in tropical climates (Wain 1994). In temperate regions, water consumption by vegetation plays an important role in

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driving diurnal streamflow fluctuations by reducing riparian soil moisture and water flux to the stream (Blaney and Young 1930; Blaney et al. 1933). This water consumption is often considered the dominant control on diurnal streamflow fluctuations as its temporal patterns frequently match observed streamflow fluctuations (e.g., Wondzell et al. 2007). However, vegetation removal does not necessarily eliminate streamflow fluctuations (Bren 1997), showing that attributing fluctuations solely to water consumption by vegetation misses other riparian processes. Indeed, streamflow fluctuations often result from multiple strongly interrelated environmental processes in the riparian zone (Kirchner et al. 2020; Newcomb and Godsey 2023), and disentangling their individual effects remains a top priority in hydrologic research.

Several site-specific perceptual models have been developed to explain how different drivers within the riparian zone cause diurnal streamflow fluctuations. For example, Burt (1979) attributed this temporary streamflow reduction to a daytime decrease in unsaturated matrix potential in soils adjacent to the stream, which lowers the hydraulic gradient and decreases lateral downslope flux. Bond et al. (2002) proposed that higher transpiration rates reduce soil moisture, causing a temporary decline in water flux to the stream. Similarly, Bren (1997) suggested that riparian vegetation extracts water from lateral subsurface flow, which moves downhill from adjacent hillslopes, temporarily reducing streamflow. Although these concepts are physically plausible, they rely heavily on assumed cause-effect relationships, even though relationships among ecohydrologic drivers may not be causally linked (Goodwell et al. 2020). For instance, Newcomb and Godsey (2023) found evidence of causal linkages between water level, soil moisture, sap flow, and vapour pressure deficit affecting subsurface flux in the stream channel, persisting even during periods of surface flow cessation. Therefore, it is essential to critically reassess the causality assumption in studies of diurnal streamflow fluctuations. Such reassessment may help shift from site-specific perceptual models toward more generalizable conceptual frameworks that explain diurnal streamflow fluctuations across diverse environments.

Linear methods such as cross-correlation and Granger causality (Granger 1969) are frequently used in environmental research to study correlations. However, correlation alone does not confirm causality, and the absence of correlation does not imply the lack of causal effects. Recent advances in causal inference have improved the ability to explicitly test for causality in time series (Deyle and Sugihara 2011; Sugihara et al. 2012; Ye et al. 2015; Runge et al. 2019; Goodwell et al. 2020). Among these, convergent cross-mapping (CCM) has emerged as a prominent method in environmental research. CCM builds upon time-delay embedding and attractor reconstruction theory from time series (Takens' Theorem; Takens 1981) and is particularly suited for detecting causality and weak, nonlinear interactions (Sugihara et al. 2012; Ye et al. 2015). CCM can also identify time-delayed causality by determining lags between drivers and effects (Ye et al. 2015). In hydrologic research, CCM has been applied to assess causality between soil moisture and rainfall (Wang et al. 2018), groundwater and surface water levels (Bonotto et al. 2022), hydrologic connectivity in karst systems (Delforge et al. 2022), and stream intermittency (Newcomb and

Godsey 2023). These studies highlight the value of CCM in revealing causal relationships overlooked by conventional linear methods and challenge perceptual models developed without explicitly testing causality.

To date, no hydrologic study has explicitly examined whether different drivers in the riparian zone are causally linked in inducing diurnal streamflow fluctuations. This gap is surprising given the widespread perception that drivers, such as evapotranspiration, riparian water viscosity, and riparian soil moisture, are strongly interconnected and mutually dependent (e.g., Bond et al. 2002; Schwab et al. 2018; Moore et al. 2011). Understanding whether and how evapotranspiration, riparian water viscosity, and riparian soil moisture causally affect diurnal streamflow fluctuations could provide valuable insights into the physical mechanisms underlying these riparian-stream interactions. Such insights may also help develop a conceptual model transferable across different sites. Building on the work by Newcomb and Godsey (2023) who pioneered the use of CCM to analyse ecohydrologic interactions in the riparian zone, we expect that (i) applying CCM to time series of riparian soil moisture, riparian water viscosity, evapotranspiration, and streamflow will reveal the key drivers of diurnal streamflow fluctuations within the stream-riparian zone-vegetation continuum, and (ii) the presence and strength of causal relationships among these drivers will vary seasonally within the same study site. We test these expectations by addressing the following research questions:

1. How do interactions among riparian soil moisture, riparian water viscosity, and evapotranspiration affect diurnal streamflow fluctuations?
2. Do these interactions, and their effects on streamflow, change between the growing and dormant season?

To address these questions, we apply CCM to time series of riparian soil moisture, soil water temperature (used as a proxy for riparian water viscosity), latent heat flux (as a proxy for evapotranspiration), and diurnal streamflow fluctuations during baseflow recession. Our study focuses on the Wüstebach, a headwater stream in North Rhine-Westphalia, Germany, where the riparian zone was deforested in 2013. Despite this disturbance, diurnal streamflow fluctuations continue to be observed.

2 | Materials and Methods

2.1 | Theoretical Background on Convergent Cross-Mapping (CCM)

2.1.1 | Attractor Manifolds

CCM is a nearest-neighbour forecasting approach based on the principle that nonlinear, dynamic systems are deterministic rather than stochastic (Lorenz 1963). In a hydrologic context, a nonlinear dynamic system might be a catchment (Kirchner 2009), with X and Y representing time series of surface water and groundwater levels (Bonotto et al. 2022). Such systems follow specific rules whereby variables transition from one state to another, exhibiting dynamic recurrence.

The system's states are solutions to equations describing its development and the interactions among variables over time. The temporal evolution of a dynamic system can be visualized as a trajectory in a state-space diagram, which originates from an unknown initial state (Ivancevic and Ivancevic 2008). This evolution produces trajectories that are recurrent and converge to an “attractor” region in state space (Figure S1). Attractors may be multi-dimensional and have a manifold geometry, denoted as the attractor manifold M_Y . According to Takens (1981), the attractor manifold can be reconstructed using only trajectory segments from a single time series:

$$M_Y = \{Y_t, Y_{t-\tau}, Y_{t-2\tau}\} \quad (1)$$

where Y represent the variables of the single time series, M is the system dimensionality and $Y_{t-\tau}$ $Y_{t-2\tau}$ are the lagged-coordinate embeddings. The dimensionality of the system is called the embedding dimension ‘ E ’. Reconstructing attractor manifolds from a single time series creates shadow manifolds that preserve the topological, geometric, and spatial relationships of the original attractor manifold M_Y . Thus, time series can be seen as a one-dimensional projection of the attractor manifold of a dynamic system (Deyle and Sugihara 2011). This means that information about the system's behaviour remains encoded in the state-space reconstruction of a single variable, even when the system involves multiple variables.

CCM tests whether the variables Y can predict the state of the variables X . To do this, the method first creates shadow manifolds for variables X and Y (denoted as M_X and M_Y , respectively) by embedding time-delayed vectors. The number of vectors used corresponds to the optimal embedding dimension for each variable. Variable X is considered to causally affect Y if M_Y can reliably predict the states of M_X . For this prediction, an exponentially weighted nearest neighbour algorithm is applied (Sugihara et al. 2012). Accurate prediction of M_X by M_Y indicates that X causally drives Y because X leaves an information signature on Y . The quality of this prediction is measured by the cross-map skill (ρ), calculated as the Pearson correlation coefficient between the predicted and actual values of the response variable derived from the reconstructed attractor manifold of the driving system.

2.1.2 | Identifying Causal Relationships From CCM Analyses

CCM can identify significant causal relationships between X and Y . These relationships emerge when the cross-map skill increases and converges as more data points are used to construct the attractor manifolds (Sugihara et al. 2012). This increase in data points is referred to as an increased library size. A larger library size improves the reconstruction of the manifold structure. Improved manifold reconstruction yields closer neighbours, which in turn increases the cross-map skill. This convergence behaviour is the defining criterion for causality in CCM. In the absence of a causal relationship, cross-map skill does not increase with library size. For a causal relationship to be significant, the cross-map skill at full library size must be significantly higher than the maximum linear cross-correlation coefficient between X and Y . CCM can detect both unidirectional and bidirectional causality by performing cross-mapping in both directions. Figure 1 illustrates these

interaction types using convergence and significance criteria. If Y can reliably estimate X and X can reliably estimate Y , then X and Y have a bidirectional causal relationship (Figure 1a). If X can estimate Y but Y cannot estimate X , then X drives Y unidirectionally (Figure 1b,c). No causal interaction exists if neither convergence nor significance criteria are met (Figure 1d). Hereafter, we refer to X as the driving variable and Y as the affected variable when X causally influences Y . The time lag between driving and affected variables indicates how long it takes for changes in X to propagate to Y (Ye et al. 2015).

2.2 | Study Site, Hydrologic and Hydrometeorological Data

We used CCM to identify causal relationships between drivers of diurnal streamflow fluctuations in the Wüstebach catchment (Figure 2). We focused on this catchment because it underwent deforestation in 2013. Deforestation led to decreased evapotranspiration, increased streamflow, and increased soil water storage locally in the deforested area (Wienkamp et al. 2016). Despite these changes, diurnal streamflow fluctuations continue to be observed. The Wüstebach catchment is located in North Rhine-Westphalia (Germany) and covers 38.5 ha. Elevations range from 595 to 631 m a.s.l., with an average slope of 3.6%. The geology consists of Devonian shales, overlain by a 1- to 2-m thick periglacial solifluction layer. Cambisols and Planosols dominate the hillslopes, while Gleysols and Histosols form in the valley due to groundwater influence. The soil has a silty clay loam texture. The mean annual precipitation is 1220 mm (Bogena et al. 2010). The primary vegetation is Norway spruce (*Picea abies*), planted in 1946. In late summer 2013, approximately 9 ha of trees near the main Wüstebach stream were removed to promote natural regeneration of beech (*Fagus sylvatica*) forests (see Figure S1; Bogena et al. 2025). The catchment is part of the TERENO network (Bogena et al. 2016; Bogena et al. 2018; Zacharias et al. 2024) and is monitored by a hydrologic system with streamflow stations, groundwater piezometers, meteorological towers, and soil measurement stations.

To identify causal relationships between drivers and diurnal streamflow fluctuations, we applied CCM to pairs of streamflow, latent heat flux (proxy for evapotranspiration), soil water temperature (proxy for riparian water viscosity), and riparian soil moisture (Figure 3). Based on previous studies, we assume that riparian soil moisture, evapotranspiration, and riparian water viscosity are the primary drivers for diurnal streamflow fluctuations, although other drivers not considered in this study may also induce such fluctuations. We used measurements of these variables from the existing measurement network of the Wüstebach headwater catchment (<https://ddp.tereno.net/ddp/>; Figure 2). Using these data, our objective was to assess whether and how the presence and strength of causal relationships among streamflow, evapotranspiration, riparian water viscosity, and riparian soil moisture vary with season. To this end, we screened the data for diurnal fluctuations in baseflow recession across different seasons within a single year, focusing on periods long enough to conduct CCM. We identified diurnal streamflow fluctuations across the available record in all years. However, most periods of diurnal fluctuations were also accompanied by additional smaller streamflow peaks caused by precipitation events. Since our study aimed to assess

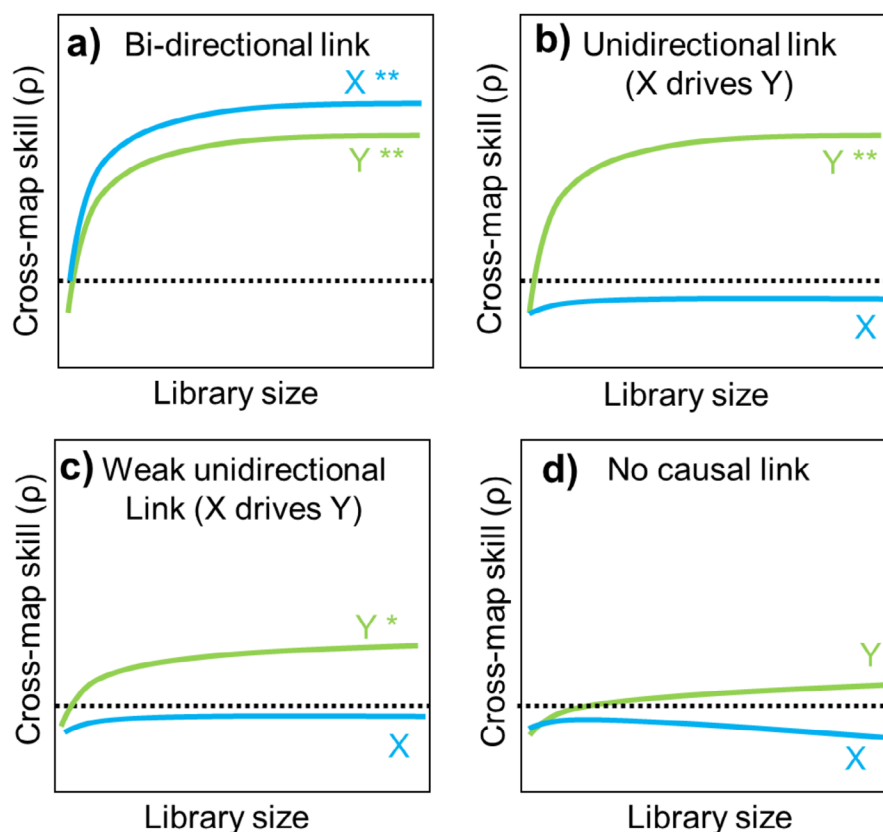


FIGURE 1 | Conceptual figure showing a strong bi-direction (a), a strong unidirectional (b), a weak unidirectional (c), and no causal relationship between two hypothetical variables X and Y. An increasing library size (more data points used in the time series) generates denser manifolds with closer nearest neighbours. An increased library size leads to a better reconstruction of the structure of the manifolds. A better reconstruction of the structure of the shadow manifolds results in closer neighbours, which in turn increases the cross-map skill (Pearson correlation coefficient between data of the predicted manifold against the actual manifold) and thus more precise cross-map estimates (adapted from Newcomb and Godsey 2023). The dashed line indicates the maximum linear cross-correlation coefficient and thus the significance threshold.

drivers of diurnal fluctuations rather than precipitation-driven peaks during baseflow recession, we excluded periods affected by such events. We therefore focused on the hydrologic year 2017, during which we identified three periods across different seasons and long enough to conduct CCM, without precipitation signals during baseflow recessions. In terms of precipitation and streamflow, 2017 was broadly representative of the long-term hydrometeorological conditions at the site. The first period (#1) occurred in April, during the dormant season. The other two periods (#2 and #3) fall within the growing season in May and June. Streamflow was measured at the catchment outlet every 10 min using a combination of Venturi and V-notch weirs (Figure 2, Bogena et al. 2021). April (period #1) was substantially wetter than May and June (periods #2 and #3), as reflected in higher streamflows. Therefore, we refer to April (period #1) as the “wet” period and May and June (periods #2 and #3) as the “dry” periods.

Latent heat flux data were obtained at 30-min resolution from an eddy-covariance station located in the deforested area of the upper catchment (Ney et al. 2019). Hereafter, we refer to latent heat flux measurements as ‘evapotranspiration,’ though no unit conversion was necessary for applying CCM. Latent heat flux data contained gaps (between 12% and 18%, depending on the study period). These gaps were linearly interpolated. Riparian soil moisture was measured at 20 cm

depth every 15 min using a SoilNet station located next to the stream (Bogena et al. 2022). We used soil water temperature at 20 cm depth, measured at 15-min intervals, as a proxy for riparian water viscosity. This depth was selected to avoid the influence of unsaturated conditions at shallower depths. The relationship between temperature and viscosity is described by the Vogel equation (Vogel 1921). In the context of using temperature as a proxy for riparian water viscosity, this equation is only applicable under saturated conditions, where the measured temperature corresponds to soil water temperature. We verified saturation by comparing the measured riparian soil moisture with the soil porosity. Measured riparian soil moisture fell within the uncertainty range of published porosity estimates for the study site (0.78 ± 0.07 for Gleysols and 0.78 ± 0.38 for Plansols; Wiekenkamp et al. 2016), confirming saturated conditions and supporting the use of soil temperature as a proxy for riparian water viscosity. To synchronize the datasets, we linearly interpolated the time series of streamflow, latent heat flux, soil water temperature, and riparian soil moisture to a common 10-min resolution and length.

2.3 | CCM Analyses

To apply CCM to pairs of streamflow, latent heat flux, soil water temperature, and riparian soil moisture, we first determined the

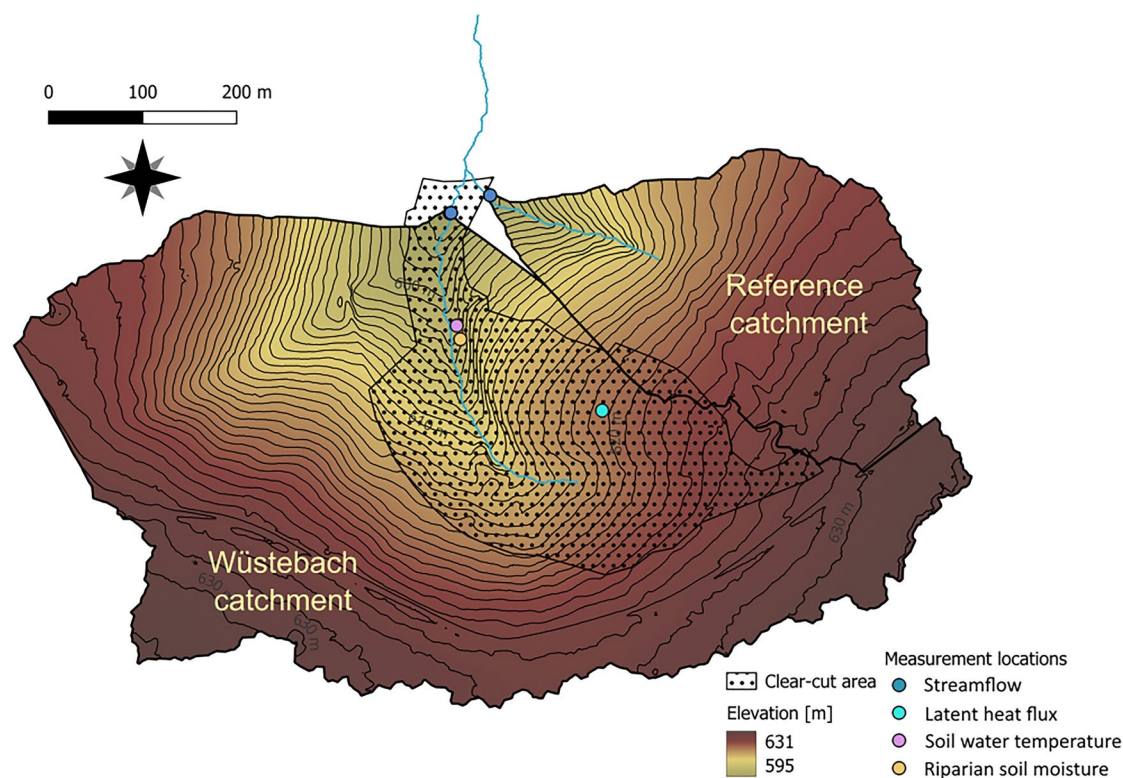


FIGURE 2 | Wüstebach and reference catchments. In the Wüstebach catchment, the measurement locations for streamflow (blue marker), riparian soil moisture (yellow marker), soil water temperature (pink marker), and latent heat flux (green marker) are highlighted. Elevation is shown by a colour gradient, ranging from brown (higher elevations) to green (lower elevations). The deforested area (clear-cut) is shown with a dotted overlay.

embedding dimension (E) for each variable by selecting the lowest value that gave the highest prediction accuracy (e.g., Wang et al. 2018). In our case, the system represents the stream–riparian zone–vegetation continuum, where E did not vary across the three periods. Next, CCM analyses were performed using the selected embedding dimensions. For the initial CCM run, we set the time lag to -1 (corresponding to 10 min) to test for convergence as the library size increased (Figure 1). The number of data points used to construct the manifolds was incremented by 10 at each step, up to a maximum of 1729, which corresponds to the length of our time series. At each increment, we drew 10 random nearest-neighbour samples without replacement.

We used Fisher's Z test to determine whether the cross-map skill differed significantly from the cross-correlation coefficient of the pairs of time series (Bonotto et al. 2022; Newcomb and Godsey 2023). The cross-correlation coefficient was calculated by applying Pearson correlation to pairs of streamflow, latent heat flux, soil water temperature, and riparian soil moisture. Pearson correlation assesses the linear relationship between two synchronized time series without time lags. Pearson correlation was performed in MATLAB (The MathWorks Inc. 2021). A cross-map skill that is significantly higher than the cross-correlation coefficient indicates that CCM is suitable to infer causality. We considered p -values of 0.05 or less from Fisher's Z test as indicative of strong causality, while p -values between 0.05 and 0.15 indicated weak causality (Figure 1c).

We estimated lag by running CCM with time lags between ± 12 h to quantify the propagation time of changes from the driver to the response. We selected this maximum time lag based

on previous studies showing that time shifts between evapotranspiration and streamflow typically peak between 4 and 8 h (Graham et al. 2013; Kirchner et al. 2020). A (negative) lag between the driving and affected variable quantifies the propagation time of changes from the driver to the response. All CCM analyses were conducted in RStudio (R Core Team 2022) using the rEDM 1.13.1 package (Park et al. 2016).

2.4 | Additional Analyses

We visually examined the daily maxima and minima of time series for streamflow, latent heat flux, riparian soil moisture, and soil water temperature to contextualize the findings of the CCM analysis. Before plotting, we applied a smoothing algorithm ('smooth' in Matlab 2021) to enhance visualization of these extrema. Additionally, we conducted the same visual examination for a tributary of the Wüstebach that joins the main stream just downstream of the study site (Figure 1). This reference stream has a catchment area of 11 ha and is part of the TERENO monitoring network, which provides a long-term data record. Unlike the Wüstebach catchment, the catchment of the reference stream has not undergone deforestation. This contrast allows a direct comparison of maxima and minima fluctuations between a deforested and a forested catchment in close proximity. To complement the visual examination with a quantitative assessment, we calculated the mean daily relative amplitude for both streams (i.e., the daily range divided by the daily mean streamflow), the mean hour of the daily maximum, and the mean offset in the timing of daily maxima between the two streams.

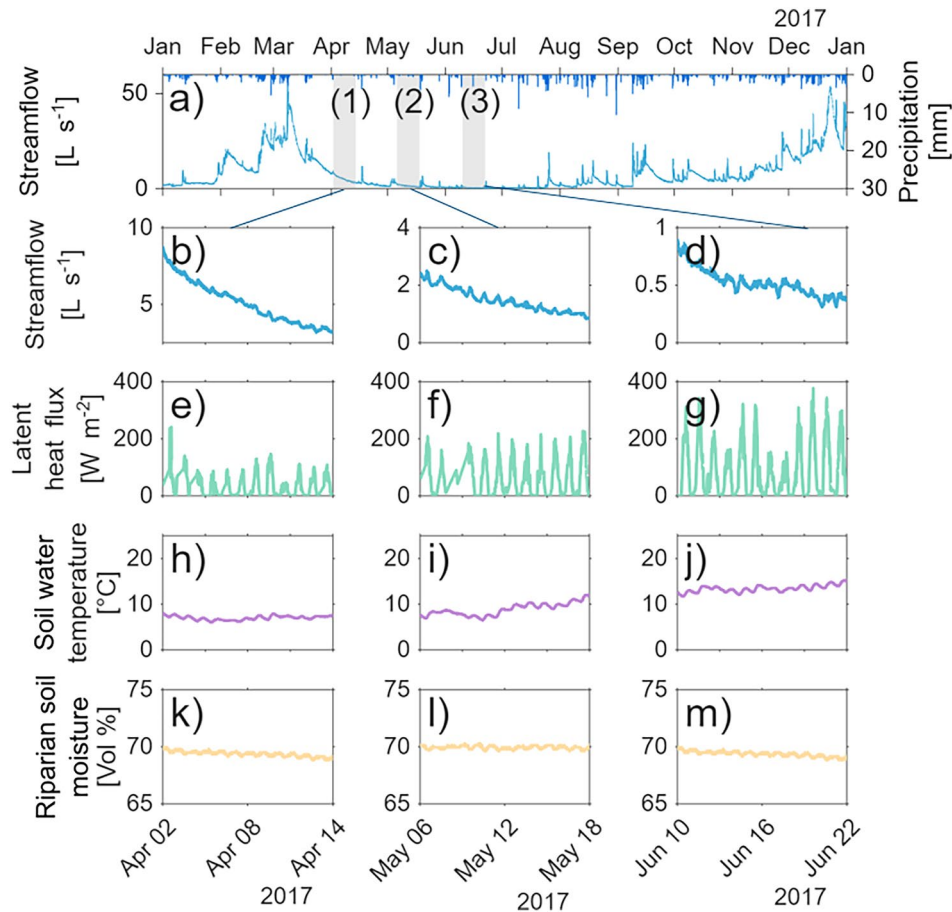


FIGURE 3 | (a) Hydrograph of the Wüstebach headwater stream for 2017, with the three study periods used for CCM (April, May, and June) highlighted in grey. Time series are shown for streamflow (b–d) [L s^{-1}], latent heat flux as a proxy for evapotranspiration (e–g) [W m^{-2}], soil water temperature as a proxy for viscosity (h–j) [$^{\circ}\text{C}$], and riparian soil moisture (k–m) [Vol %].

3 | Results

3.1 | Both Causal and Non-Causal Relationships Exist in the Stream-Riparian Zone-Vegetation Continuum

We found both causal and non-causal relationships among latent heat flux, streamflow, soil water temperature, and riparian soil moisture. Causality is inferred when the cross-map skill (ρ) exceeds cross-correlation at maximum library size, as exemplified for study period #1 (Figure 4a–d). Non-causal relationships are defined as those in which the cross-map skill does not exceed cross-correlation at maximum library size. The key difference among study periods was that no causal relationship was detected between soil water temperature and streamflow in study period #3 (Figures S2 and S3). Additionally, riparian soil moisture and latent heat flux showed causal effects exclusively in study period #1, with riparian soil moisture driving streamflow and latent heat flux driving riparian soil moisture.

The strength of causal relationships, measured by maximum cross-map skill, varied substantially among pairs of drivers (Figure 5). Riparian soil moisture and soil water temperature had the strongest effects on streamflow, with temperature controlling diurnal fluctuations through changes in water viscosity. Riparian soil moisture showed only weak causality. Notably,

streamflow drove soil water temperature, riparian soil moisture, and latent heat flux across periods #1 and #2.

3.2 | Time-Lags Differ Between Different Study Periods

Introducing time lags between the driving and affected variables led to both positive and negative lags (Figure 6). During period #1, we found negative lags for: latent heat flux affecting riparian soil moisture; soil water temperature affecting latent heat flux, riparian soil moisture, and streamflow; and streamflow affecting the remaining drivers. The response times ranged from 0.7 to 11.7 h.

3.3 | Fluctuations of Streamflow, Latent Heat Flux, and Stream Temperature

Streamflow, latent heat flux, and stream temperature in the Wüstebach exhibited different timing of daily maxima compared to the reference stream (Figures 7, S4 and S5). Streamflow maxima in the Wüstebach occurred at ~12:30 (Figure 7), coinciding with maxima in latent heat flux by several hours. In contrast, streamflow maxima in the reference stream occurred 4.3 h later at ~16:45 (Figure 7). In the Wüstebach, streamflow maxima

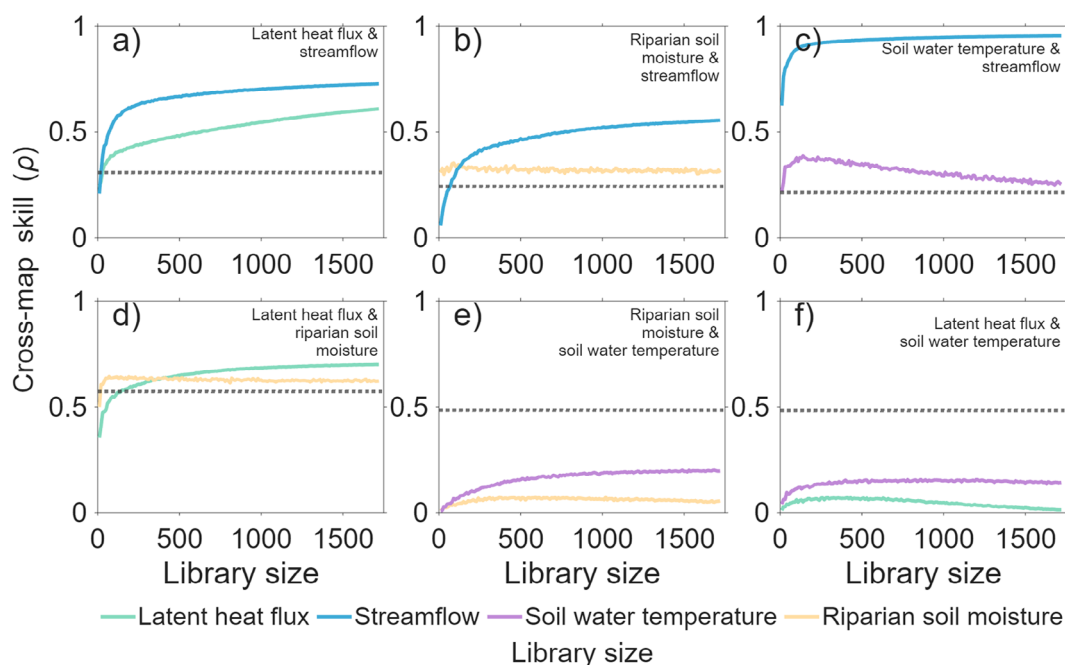


FIGURE 4 | Results of the convergent cross mapping analysis for period #1. Each plot shows library size (x-axis) versus cross-map skill (p) for different variable pairs. Subplots (a–f) represent different variable pairs, with line colours indicating the driving variable and the affected variable being the other in the pair. The grey dashed line represents the maximum cross-correlation coefficient.

also preceded those of stream temperature by several hours. This temporal offset between the two catchments likely reflects their contrasting land cover, partly deforested in the Wüstebach and fully forested in the reference catchment. Relative amplitudes also differed between the two streams, with the reference stream showing a greater relative amplitude (1.1 ± 0.5) than the Wüstebach (0.2 ± 0.05), despite the latter having higher absolute streamflow.

4 | Discussion

4.1 | Effects of Viscosity, Evapotranspiration, and Riparian Soil Moisture on Diurnal Streamflow Fluctuations

This study is to our knowledge the first to quantify the simultaneous effects of riparian soil moisture, soil water temperature, and latent heat flux on diurnal streamflow fluctuations. This is notable as these drivers have long been recognized as drivers of such fluctuations in temperate climates (e.g., Sarwar et al. 2022; Schwab et al. 2016). Among them, soil water temperature had one of the strongest effects on diurnal streamflow fluctuations (Figures 4 and 5), underscoring the importance of riparian water viscosity as a control on diurnal streamflow fluctuations. This result aligns with findings in the Weierbach catchment in Luxembourg where Schwab et al. (2016) demonstrated the pivotal role of viscosity in controlling diurnal streamflow fluctuations. Notably, both streams show afternoon streamflow maxima (Figure 7), unlike many headwater streams where maxima typically occur in the morning (e.g., Wondzell et al. 2007; Mutzner et al. 2015; Deutscher et al. 2016). Viscosity-driven afternoon streamflow maxima require several conditions (Schwab et al. 2016): (i) a prolonged dry spell; (ii) occurrence

during the dormant season to avoid evapotranspiration interference; (iii) high daily subsurface temperature variation; (iv) absence of snow cover; (v) lack of daily freeze–thaw cycles; (vi) a gaining stream; and (vii) significant inflow from riparian zones experiencing diel temperature fluctuations. While all apply to the Weierbach catchment, the Wüstebach shows afternoon streamflow maxima outside the dormant season. This observation suggests that the dormant season is not necessary for viscosity-driven fluctuations in the Wüstebach. We attribute this difference between the two catchments to the 2013 deforestation in the Wüstebach, which reduced riparian tree cover and lowered water consumption by vegetation compared to fully forested catchments like the Weierbach (Sarwar et al. 2022; Figure 7). The resulting reduction in evapotranspiration likely lessens its interference year-round, allowing viscosity-driven fluctuations to persist beyond the dormant period. Although Schwab et al. (2016) also noted that the viscosity-driven effect persists beyond the dormant season, the authors highlighted that effects become less obvious at the Weierbach due to competing processes.

We found causal effects of latent heat flux and thus evapotranspiration on diurnal streamflow fluctuations despite the 2013 deforestation, which likely reduced vegetation water use in the catchment. This effect could result from either transpiration by deep-rooted vegetation that has regrown since deforestation or direct stream evaporation. The latter would cause streamflow minima to coincide with peaks in stream temperature, as warmer water evaporates more readily. However, our results show that streamflow highs align with temperature peaks rather than dips (Figures 7 and S6), suggesting that transpiration by regrown vegetation underlies the causal link between evapotranspiration and streamflow. Regrown deep-rooted vegetation accesses deeper soil moisture (Mitchell

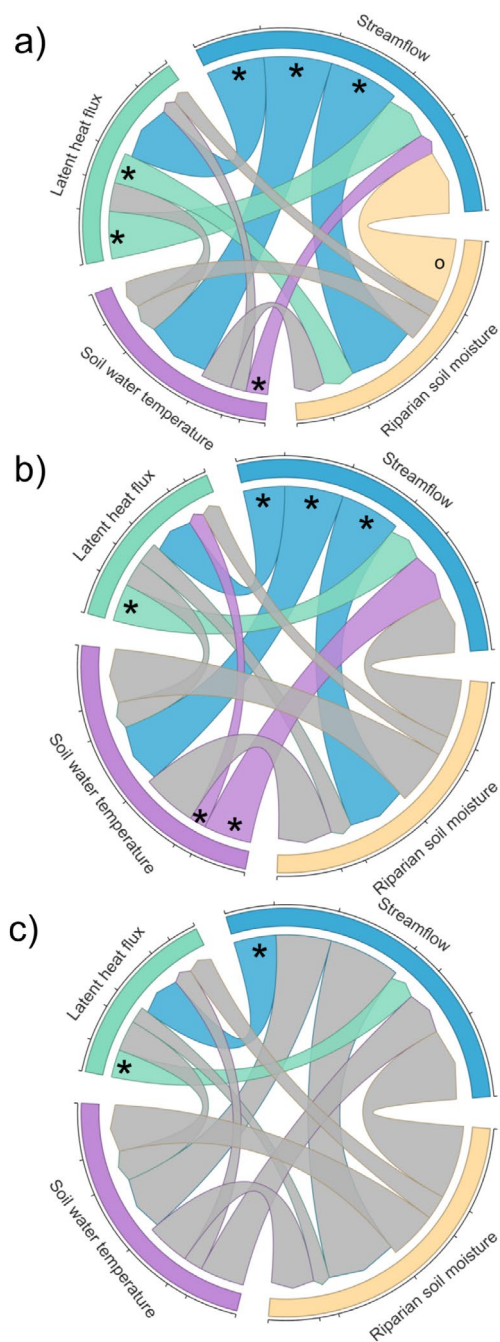


FIGURE 5 | Sankey diagrams showing causal relationships between streamflow, riparian soil moisture, soil water temperature, and latent heat flux across the three study periods: (a) period #1, (b) period #2, (c) period #3. Non-causal relationships are shown in grey. Causal relationships are colour-coded: Blue (streamflow), yellow (riparian soil moisture), pink (soil water temperature), and green (latent heat flux). Arrow width represents maximum cross-map skill at full library size (see Figure 4). Broader arrows show higher values. Arrows point from the driving to the affected variable. Asterisks denote strong causal relationships between the predicted and actual attractor manifold (Pearson correlation coefficient; $p < 0.05$). Black circles show weak causal relationships.

et al. 2015) and transpires water, thereby reducing soil moisture and water flux to the stream. This process may also explain the absence of a causal link between evapotranspiration and shallow riparian soil moisture for period #2 and #3 (Figure 5).

The effect of riparian soil moisture on diurnal streamflow fluctuations is expected given that variations in soil moisture directly reflect the draining behaviour of saturated and unsaturated water storages during recession (Bart and Hope 2014; Shaw 2016; Tashie et al. 2020). Indeed, drivers controlling base-flow recession are expected to affect diurnal fluctuations in a CCM analysis, since CCM reconstructs the entire time series, including the recession period. Notably, the effect of riparian soil moisture was most pronounced during wetter periods, suggesting that our CCM results directly inform the debate on the relative contributions of riparian zones versus hillslopes to streamflow under dry and wet conditions (e.g., Jencso et al. 2009; Detty and McGuire 2010). Specifically, these findings underscore the critical role of riparian zone water in sustaining streamflow during wetter periods.

4.2 | Causal Interactions in the Riparian Zone and Their Temporal Variability

The causal relationships identified in our study support a perceptual model (Figure 8) in which riparian soil moisture, soil water temperature (viscosity), and latent heat flux (evapotranspiration) interact within the stream–riparian zone–vegetation continuum, collectively driving observed diurnal streamflow fluctuations. This model recognizes that CCM does not distinguish between direct and indirect causal effects. Instead, observed causal relationships may arise from both direct and indirect effects along a chain of interactions (Ye et al. 2015). Due to this limitation, previous research emphasizes interpreting CCM results within established physical hydrologic principles rather than relying solely on CCM to infer physical mechanisms (Runge et al. 2019).

In our perceptual model for the Wüstebach, streamflow influences riparian soil moisture, evapotranspiration, and soil water temperature, indicating a water flux from the stream into the riparian zone. Although the Wüstebach catchment is predominantly a gaining stream, slug tracer tests (own data, unpublished) indicate that such a (gross) water flux to the subsurface also occurs in some stream sections. This bidirectional flux may influence soil conditions in multiple ways. First, riparian soil moisture increases when drier soil is rewetted by a water flux from the stream to the subsurface. Second, soil water temperature changes when a temperature gradient exists between lateral water and surrounding soil, leading to heat exchange. Finally, variations in soil water temperature indirectly affect evapotranspiration by altering water availability for vegetation uptake and influencing energy fluxes at the land–atmosphere interface. Together, these physical mechanisms illustrate how riparian soil moisture, soil water temperature, and evapotranspiration interact, supporting the perceptual model derived from CCM analysis.

The lack of causality between riparian soil moisture and streamflow during study periods #2 and #3 (the drier, growing season) compared to study periods #1 suggests that mechanisms in the riparian zone driving streamflow fluctuations differ between seasons. One possible explanation is that different water sources contribute to streamflow depending on catchment wetness (Stockinger et al. 2014; Bogen et al. 2013). However, Stockinger

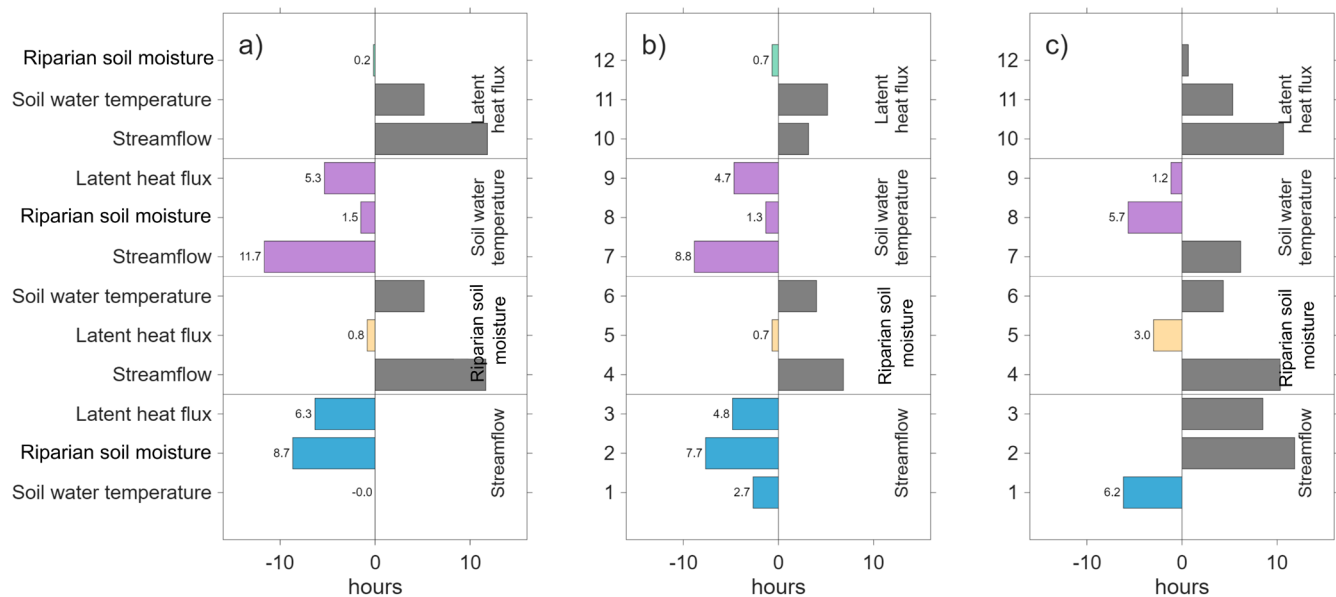


FIGURE 6 | Time lag at which maximum cross-map skill occurs for the three study periods: (a) period #1, (b) period #2, (c) period #3. The time lag was determined using lagged CCM analysis, where the affected variable was used to reconstruct the driving variable. The driving variable is labelled vertically in each panel, while the affected variable is listed on the left. The lag between the driving and affected variables provides insight into how long changes in the driving variable take to propagate to the affected variable. Larger (more negative) values show longer propagation times.

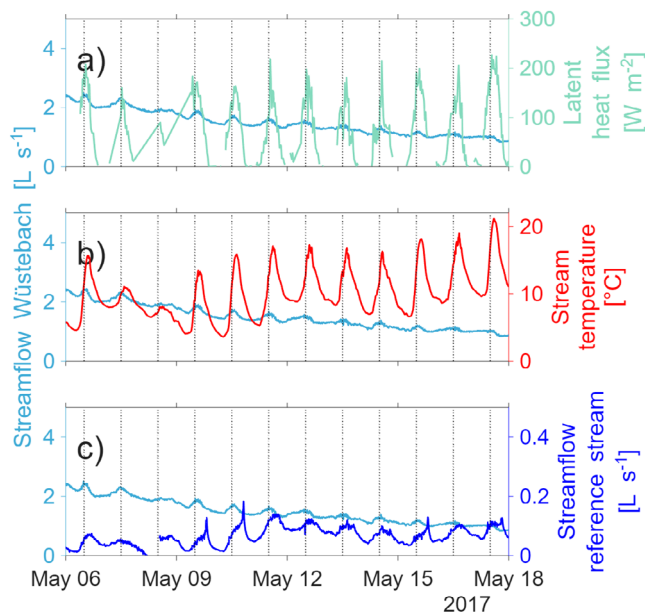


FIGURE 7 | Fluctuations of (a) streamflow in the Wüstebach and latent heat flux, (b) streamflow in the Wüstebach and stream temperature, and (c) streamflow in the Wüstebach and in the reference stream for May (study period #2). Noon is indicated by a dashed vertical line. Streamflow maxima in the Wüstebach and maxima in latent heat flux, a proxy for evapotranspiration, occur slightly after noon. Streamflow maxima in the reference stream occur delayed compared to the maxima in the Wüstebach.

et al. (2014) demonstrated that streamflow at the Wüstebach derives from riparian zones rather than hillslopes, even under dry conditions. This finding contradicts our CCM results, implying that mechanisms beyond shifting water sources explain the absence of riparian soil moisture–streamflow causality in periods

#2 and #3. Another possible explanation involves seasonal variation in vegetation water use, as documented in the Weierbach catchment (Schwab et al. 2016). This variation likely reduces water consumption by vegetation and riparian soil moisture during the dormant season (period #1). However, this effect is likely minor at our study site due to deforestation in 2013, compared to forested catchments like the Weierbach. Nevertheless, this seasonal difference in vegetation water use between the dormant and growing seasons may explain the varying strength of causal effects between evapotranspiration and streamflow across study periods (Figure 5), reflecting the regrowth of deep-rooted vegetation after deforestation.

The lack of causality between riparian soil moisture and streamflow during study periods #2 and #3 may also reflect methodological limitations of CCM. CCM can produce false negatives (Delforge et al. 2022; Ombadi et al. 2020) because this method cannot fully disentangle confounding factors or when a dominant forcing causes variables to appear mutually causal despite unidirectional relationships (“synchrony”; Ye et al. 2015). Because physical mechanisms alone do not explain the lack of causality during study periods #2 and #3, this absence is likely due to a false-negative CCM result during these periods. Further research is needed to clarify whether methodological limitations or seasonal differences in physical mechanisms account for variation in the strength and presence of causal relationships. To assess the effect of a common seasonal signal on causal relationships, previous studies have generated replicate datasets that retain the mean seasonal trend while shuffling the residuals of each variable (e.g., Park et al. 2022; Newcomb and Godsey 2023). These replicates have been used to test the hypothesis that a common seasonal signal drives causal relationships. However, the time series must be sufficiently long to cover multiple seasons for this approach to be applicable. Specifically, periods of diurnal streamflow fluctuations uninterrupted by

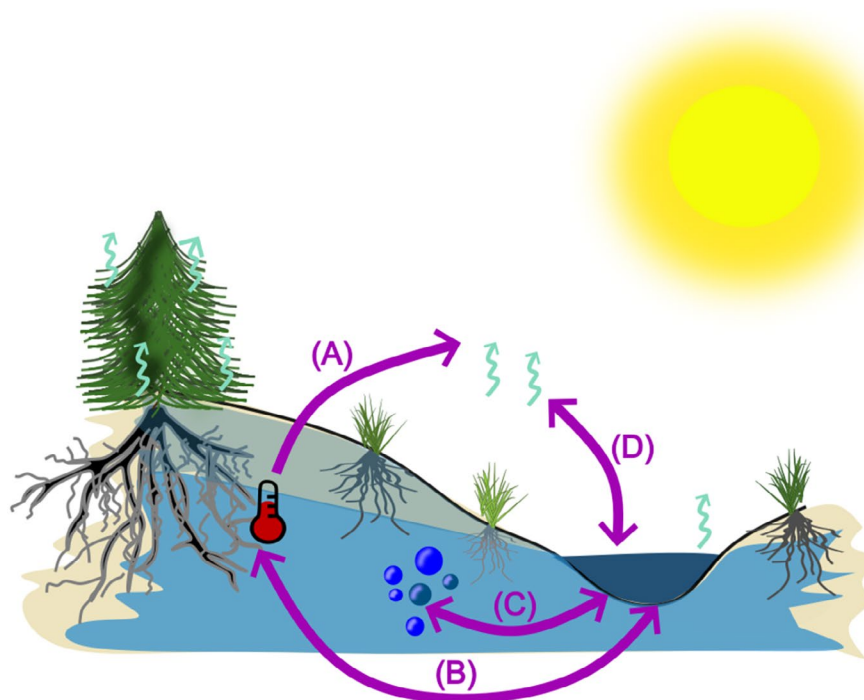


FIGURE 8 | Perceptual model showing interactions among riparian soil moisture (blue circles), viscosity (red thermometer), streamflow (dark blue stream area), and evapotranspiration (turquoise curved arrow) at the Wüstebach catchment. Observed causal interactions (pink arrows) include viscosity with evapotranspiration (A), viscosity with streamflow (B), riparian soil moisture with streamflow (C), and evapotranspiration with streamflow (D).

precipitation-driven peaks, as observed for example in semi-arid catchments in Idaho, USA (Newcomb and Godsey 2023), would allow assessment of whether such fluctuations can be explained by a common seasonal signal. In the temperate Wüstebach catchment, diurnal streamflow fluctuations are observed only over shorter periods, allowing us to compare periods from different seasons rather than formally identifying the effect of a common seasonal signal on causal relationships. Nevertheless, differences between study periods from our CCM analysis emphasize the importance of assessing diurnal streamflow fluctuations within the context of prevailing hydrologic (wet versus dry) and ecohydrologic (dormant versus growing) conditions, rather than focusing solely on individual baseflow recession events.

4.3 | Implications for Future Studies

To the best of our knowledge, the perceptual model identified in this study is the first to demonstrate the complex interactions in the riparian zone that drive diurnal streamflow fluctuations. These interactions likely occur in temperate catchments worldwide, suggesting that the model is broadly transferable across sites. The observed, simultaneous effect of multiple drivers challenges the prevailing hydrologic paradigm that evapotranspiration alone controls streamflow fluctuations in temperate regions. This insight encourages future research to account for multiple environmental drivers rather than focusing on a single one, as in much early work (e.g., Bren 1997; Burt 1979; Bond et al. 2002). Nevertheless, we acknowledge that the study of complex interactions among multiple drivers is limited by the lack of detailed data in many catchments (Smits et al. 2025). The Wüstebach catchment is highly instrumented and provides

exceptionally dense data (Bogena et al. 2010), making it especially well-suited for CCM analysis.

Future studies could use our perceptual model as a working hypothesis to evaluate how different catchment characteristics influence the strength of causal effects and the relevance of underlying physical processes. Starting from this broader perceptual perspective, the model can be applied to explain the causes of differences in finer-scale processes observed across catchments. Such an approach would advance hydrology by identifying common drivers across catchments, rather than extrapolating site-specific phenomena that emphasize localized heterogeneities (Sivapalan 2003; McDonnell and Woods 2004). For example, researchers might investigate how increased transpiration both reduces soil moisture and streamflow locally (Bond et al. 2002) and affects water uptake by riparian vegetation receiving flow from adjacent hillslopes (Bren 1997), by linking catchment topography to CCM results. Moreover, future work could explore how the strength of these causal relationships relates to stream chemical concentrations, directly assessing how diurnal streamflow fluctuations influence water chemistry in headwaters.

While ecological dynamics in the Wüstebach catchment motivate future research, broader methodological challenges also require attention to optimize the use of CCM in hydrology. First, hydrology currently lacks clear guidance on the minimum time series resolution needed for CCM analysis. Existing studies suggest causality can be inferred when cross-mapping skill exceeds the cross-correlation coefficient at full library size. However, this criterion alone may be insufficient. Interpolating data points artificially inflates library size without necessarily improving causal inference quality. Therefore, systematic

investigations on how interpolation influences CCM results are needed. Second, we observed mainly positive time lags and only some negative lags (Figure 6), despite CCM without time-lagging identifying causal relationships. Positive lags have been interpreted as lagged causality (Ye et al. 2015) or remain unexplained (Newcomb and Godsey 2023). We currently lack a clear physical explanation for the positive lags but speculate they may result from high similarity in the temporal patterns of the tested time series. This is supported by additional CCM analyses testing longer time lags than the original 12-h lag. These analyses produced highly periodic patterns in the cross-correlation coefficient (Figure S7), complicating identification of a single lag with the highest cross-mapping skill. Complementary methods like information flow analysis (Nichita et al. 2025) may help verify peak cross-correlation for time-lagged CCM. Finally, we note limitations in using Pearson's correlation coefficient to assess causality, despite its widespread use (e.g., Bonotto et al. 2022; Sugihara et al. 2012; Newcomb and Godsey 2023). The statistical significance of this coefficient depends on normally distributed data, which often does not hold in nonlinear, dynamic systems. An alternative is surrogate testing (Schreiber and Schmitz 2000), previously applied in CCM studies to assess significance and detect shared periodic forcing. Addressing these methodological challenges will be crucial to fully unlock the potential of CCM for advancing hydrologic research.

5 | Conclusions

The goal of this study was to apply convergent cross mapping (CCM) to time series of riparian soil moisture, soil water temperature as a proxy for viscosity in the riparian zone, latent heat flux as a proxy for evapotranspiration, and streamflow to identify how these drivers control diurnal streamflow fluctuations. We also assessed whether the presence and strength of causal relationships among these drivers varied between the dormant and growing seasons at the same site. Our results show that both evapotranspiration and riparian water viscosity contribute to diurnal streamflow fluctuations, but with differing effect strengths. Riparian water viscosity exerted the strongest effect on streamflow, followed by evapotranspiration and then riparian soil moisture. The strength of these causal effects varied between dormant and growing seasons, potentially influenced by vegetation regrowth since the 2013 deforestation. We propose a perceptual model which can be used as a working hypothesis to evaluate how common drivers across catchments affect diurnal streamflow fluctuations, rather than extrapolating site-specific observations that emphasize localized heterogeneities.

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Data Availability Statement

The data that support the findings of this study are openly available in Tereno measurement network at <https://ddp.tereno.net/ddp/>.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** (a) Attractor manifold of the original system (M). (b) Shadow manifold M_X constructed from variable X and its lagged values. (c) Shadow manifold M_Y constructed from variable Y and its lagged values. The attractor manifold in this example is based on the Lorenz system with three embedding dimensions (X, Y, Z). Shadow manifolds are reconstructed using lagged-coordinate embeddings (τ). Points that are close on M_X (e.g., black circle) correspond temporally to nearby points on M_Y (e.g., black circle) if X and Y are dynamically coupled. In this case, the black points of M_X and M_Y have the same time indices (values for t). These shared time indices enable estimating states across manifolds using nearest neighbours. As the time series length (library size) increases, shadow manifolds become denser, improving cross-map estimates (adapted from Deyle and Sugihara 2011). **Figure S2:** Results of the convergent cross mapping analysis for period #2. Each plot shows library size (x -axis) versus cross-map skill (p) for different variable pairs. Subplots (a–f) represent different variable pairs, with line colours indicating the driving variable and the affected variable being the other in the pair. The grey dashed line represents the maximum cross-correlation coefficient. **Figure S3:** Results of the convergent cross mapping analysis for period #3. Each plot shows library size (x -axis) versus cross-map skill (p) for different variable pairs. Subplots (a–f) represent different variable pairs, with line colours indicating the driving variable and the affected variable being the other in the pair. The grey dashed line represents the maximum cross-correlation coefficient. **Figure S4:** Fluctuations of (a) streamflow in the Wüstebach and evapotranspiration, (b) streamflow in the Wüstebach and stream water temperature, and (c) streamflow in the Wüstebach and in the reference stream for June (study period #3). Noon is indicated by a dashed vertical line. Streamflow maxima in the Wüstebach and maxima in latent heat flux, a proxy for evapotranspiration, occur slightly after noon. Streamflow maxima in the reference stream occur delayed compared to the maxima in the Wüstebach. **Figure S5:** Fluctuations of (a) streamflow in the Wüstebach and evapotranspiration, (b) streamflow in the Wüstebach and stream water temperature, and (c) streamflow in the Wüstebach and in the reference stream for June (study period #1). Noon is indicated by a dashed vertical line. Streamflow maxima in the Wüstebach and maxima in latent heat flux, a proxy for evapotranspiration, occur slightly after noon. Streamflow maxima in the reference stream occur delayed compared to the maxima in the Wüstebach. **Figure S6:** Soil water temperature [$^{\circ}\text{C}$] and latent heat flux [W m^{-2}] in the Wüstebach catchment during June. Peaks in soil water temperature do not coincide with peaks in latent heat flux. **Figure S7:** Cross-map skill as a function of lag, computed with a maximum lag of $\pm 18\text{ h}$ to identify the time lag of causal relationships. The peak cross-map skill indicates the most likely time lag; however, the highly periodic patterns in the cross-map skill complicate the identification of a single unambiguous lag.