Identifying Regime Shifts in the Arkansas River Near Larned, Kansas

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Abstract

Characterizing the drivers of flow in non-perennial streams is increasingly important for understanding the effects of variable flow regimes on local communities and ecosystems. Regime shift theory has been used to explain changes in other hydrologic systems, but the theory as it applies to non-perennial streams has yet to be fully explored. Here, we use the Arkansas River basin near Larned, Kansas, to determine whether changes between flow and no-flow conditions can be described using a regime shift framework. We combined hydrological, meteorological, and ecological time series data to test for the presence of statistical "hints" commonly associated with regime shifting systems and used a sequential t-test analysis of regime shifts (STARS) algorithm to test for regime shifts in the time series of weekly and monthly no-flow days. Although flow data exhibited hints such as critical slowing down and asymmetry of flow rates, evidence for increased variance and autocorrelation was weak. STARS identified at least five shifts between dry (predominantly no-flow conditions), intermediate (alternating flowing and no-flow conditions), and wet (predominantly flowing conditions) regimes in the river between 1998 and 2021. The intermediate regime appears to be a transitory phase between the stable wet and dry regimes observed at Larned. Regime shifts at the site are likely driven by a complex interaction between climate, pumping, and stream-aquifer interactions.

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1. Introduction

Non-perennial streams, which are streams that experience both flow and no-flow conditions and include intermittent rivers and ephemeral streams (Busch et al., 2020), make up approximately 51–60% of the world's streams and rivers (Messager et al., 2021).They provide a variety of ecosystem services and host a wide range of organisms that are suited to both aquatic and dryland environments (Datry et al., 2017; Kaletová et al., 2019). Non-perennial streams are essential in providing hydrologic connections between perennial river reaches or between the stream and aquifer (e.g., groundwater recharge) and in transporting biota, materials, nutrients, and water within the landscape for humans and other animals (Yeakley et al., 2016; Acuña et al., 2017; Boulton et al., 2017).

Just as they are robust in biodiversity, non-perennial streams are sensitive to changes in environmental and anthropogenic activity. No-flow conditions are becoming more prevalent, notably in the southern United States (Zipper et al., 2021) and much of Europe from community water use and increases in aridity (Tramblay et al., 2021). Because of their importance as an ecological niche and vital water source, characterizing physical mechanisms associated with flow and no-flow periods in non-perennial streams is essential to understand and anticipate future water availability.

Modeling changes between system states, or ***regime shifts,*** offers a potentially useful framework to investigate non-perennial streams. The Stockholm Resilience Centre's Regime Shifts Database (https://www.regimeshifts.org/) documents numerous studies that identify state changes in many earth systems, including oligotrophic and eutrophic aquatic systems, glacial fields, and biota food-web interactions (Andersen et al., 2009; Guttal et al., 2013; Chemello et al., 2018; Pedersen et al., 2020). However, the database does not include reference to non-perennial streams, and in the broader hydrologic literature, studies have investigated non-perennial streams using primarily linear and monotonic changes and trends in streamflow and intermittency in non-perennial streams (Zipper et al., 2021; Tramblay et al., 2021). As a result, nonlinear changes in non-perennial streams, particularly abrupt shifts, have not been thoroughly investigated.

To address this, we investigated the question, *is there evidence for regime shifting in a non-perennial section of the Arkansas River near Larned, Kansas?* To determine the applicability of regime shift frameworks and test quantitative evidence of regime shifting, we investigated historical Kansas Geological Survey (KGS) and U.S. Geological Survey (USGS) groundwater and surface water data from the KGS Larned Research Site in south-central Kansas. These data were used to address three objectives:

1. Quantitatively analyze and discuss indicators of regime shifting in surface water and groundwater time series data at the site.
2. Evaluate the ability of statistical models to detect the presence of regime shifting in historical stream intermittency data and identify potential drivers of regime shifts.
3. Design and discuss conceptual models for the observed regime shifts, including suggesting stabilizing ecohydrological feedback during both wet and dry regimes.

2. Study Site

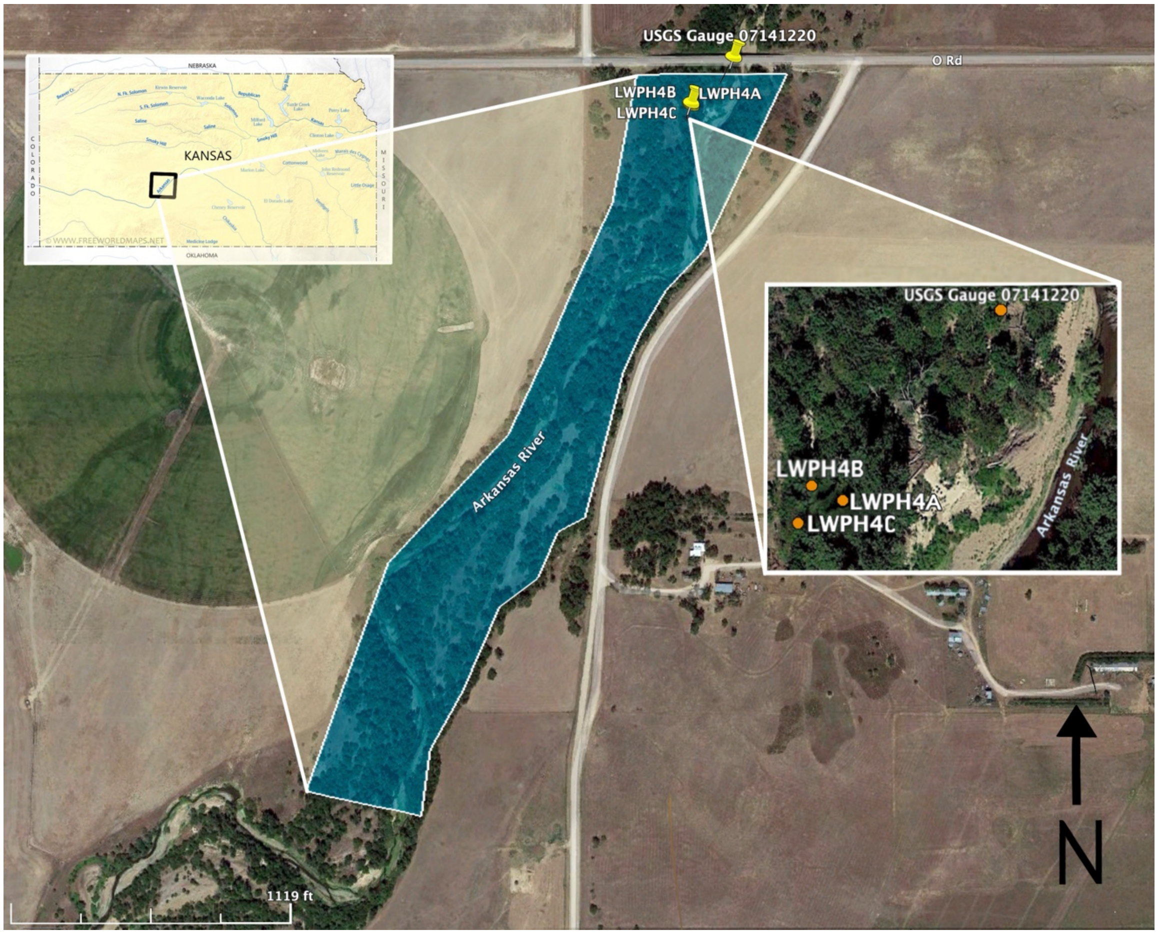

Figure 1. Map of Arkansas River stream reach in Larned, Kansas. The blue-shaded region defines the Kansas Geological Survey's study area. Active wells labeled LWPH4a and LWPH4b are used to measure groundwater levels of the alluvial aquifer, while well LWPHc measures groundwater levels in the High Plains aquifer. USGS stream gage 07141220 is slightly downstream of the KGS study area and has been collecting data since 1998.

The KGS Larned Research Site (fig. 1) is located approximately 10 kilometers northeast of Larned, Kansas, at a latitude of 38°12'13" N and longitude of 99°00'07" W, surrounded by rural farmlands consisting both of irrigated and non-irrigated agriculture. The site includes USGS gaging station 07141220, which has been active since 1998 (fig. 2). The KGS has conducted research at Larned since 2001, with past work focusing on hydrostratigraphic characterization (Healey et al., 2001; Loheide et al., 2005; Butler et al., 2007), evapotranspiration by phreatophytic vegetation (Loheide, 2005; Butler et al., 2007), and aquifer responses to barometric pressure variations (Butler et al., 2011). The primary hydrostratigraphic units at the site are, from top to bottom, a surficial alluvial aquifer, a leaky clay confining unit, and the High Plains aquifer. The research site contains 19 monitoring wells, and each of the three hydrostratigraphic units at the site has at least two wells screened in it. The alluvial aquifer is composed of mixed gravels and sands with occasional clay layers, extending to about 10 meters below the surface (Healey et al., 2001). The leaky confining unit is composed of clay and is several meters thick, with variability across the site (Healey et al., 2001). The leaky confining unit divides the local alluvial aquifer from the regional, heavily pumped High Plains aquifer. The High Plains aquifer is composed of sand and gravel. Bordering vegetation consists of cottonwood trees as well as woody and herbaceous riparian grasses.

Recently, Compare et al. (2021) investigated potential historical drivers of flow at the Larned Research Site, including the roles of weather, groundwater pumping, and subsurface stratigraphy. They found that dry periods most frequently begin during the summer months, but switches between dry and wet conditions typically occur on annual or longer timescales and are coincident with long-term (greater than or equal to 12 month) precipitation anomalies. Although the interface between the stream and the alluvial aquifer is highly conductive, the leaky confining unit impedes water movement between the alluvial and the High Plains aquifers. The subsurface structure creates a delayed temporal relationship between the units, where alluvial aquifer head tends to increase before the High Plains aquifer during recharge events. While Compare et al. (2021) suggested that shifts between flowing and no-flow conditions were characteristic of wet and dry regimes, potential regime shifting has not been rigorously tested. This report extends this past work by investigating quantitative evidence for wet and dry regimes and developing a conceptual model to explain observed hydrologic dynamics.

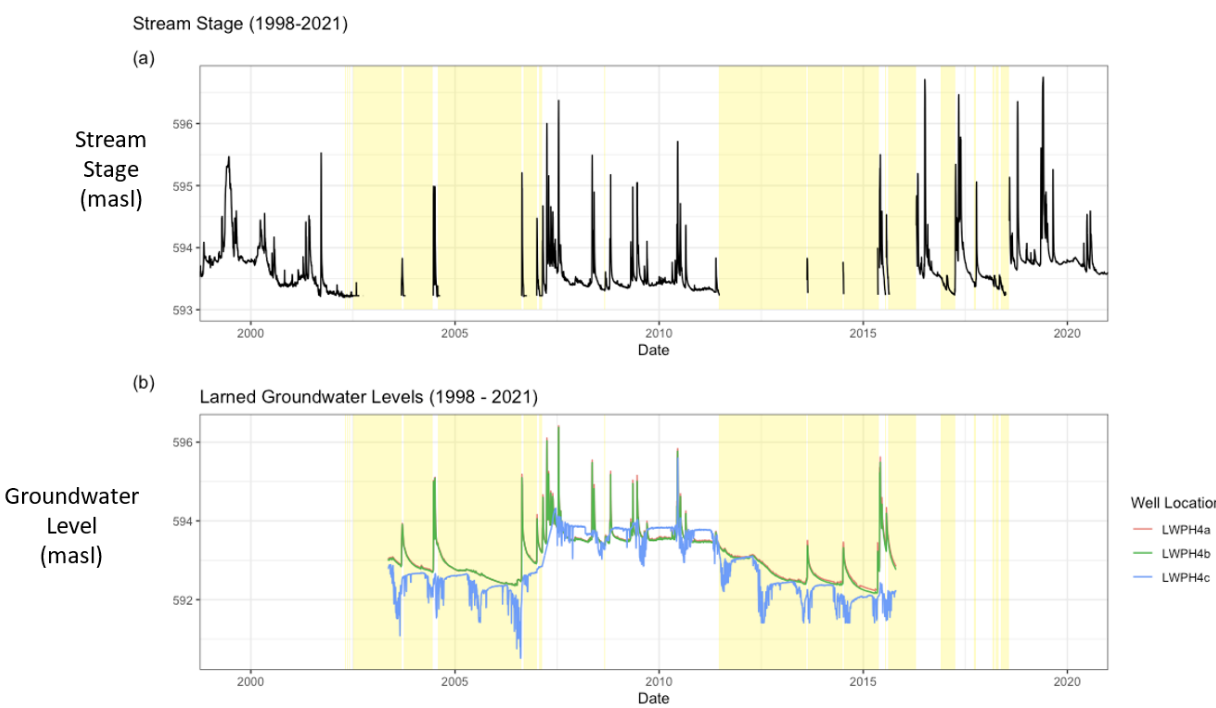

Figure 2. Time series graphs of stream stage (meters above sea level) and groundwater levels of wells located in the alluvial (labeled LWPH4a, LWPH4b) and High Plains (LWPH4c) aquifers in Larned, Kansas. Yellow shading indicates observed no-flow periods in the stream. For groundwater levels, well LWPH4a is obscured by well LWPH4b because both wells are screened in the alluvial aquifer and therefore their hydrographs are very similar.

3. Regime shift concepts

Natural systems often center on predictable trends or averages that are characteristic of system stability (Scheffer et al., 2009). However, there are instances where regime shifts can occur between two or more alternative stable states (table 1), characterized by abrupt changes in system behavior or dynamics. Regime shifts have been widely recognized in many ecosystems, and the Regime Shifts DataBase (https://www.regimeshifts.org/) compiles a body of literature showing regime shifts that include bivalve collapse, freshwater eutrophication, and bush encroachment (Hammond et al., 2012; Rocha et al., 2017; Luvuno et al., 2018), among other studies. The regime shift framework can even be used in non-earth system disciplines, such as in healthcare studies that attempt to predict episodes of epilepsy and asthma (Scheffer et al., 2009).

Table 1. Definitions of terms that frequently occur in regime shift literature (from Mac Nally et al., 2014; Capon et al., 2015). Some terms have interchangeable synonyms.

Term	Definition
Ecological Response	A time series of values of an individual component of ecosystem state, such as the abundance of a taxon or a rate of an ecological process (e.g., primary production).
Regime	A numerical description of an ecosystem that includes one or more ecological responses. This definition does not imply that the ecosystem state is equilibrial or stationary; rather, the ecosystem state is a vector of ecological responses that varies with time. Multiple regimes — also known as *alternative stable states* — can exist in a system.
Driver	A spatially and temporally large source of change, usually anthropogenic, that may create multiple pressures. For example, anthropogenic climate change produces multiple pressures, such as increasing global temperature and exacerbating droughts.
Tipping Point	A value of an ecological variable that acts as a threshold of change. Beyond this threshold, a previous ecosystem state cannot be recovered, even when pressure is released, and restoration actions are applied. Synonymous with *critical point.*
Regime Shift	Movement from one regime to another when drivers overcome a tipping point.

The movement of a system between alternative stable states can be visualized using a ball-and-hill diagram (fig. 3). In a trough, the ball (which represents the system) is stabilized in its current state based on a combination of the environmental or external drivers and pressures creating negative feedback mechanisms. The crest between regimes represents a tipping point beyond which feedback keeping the system in the current state is broken and the system moves into a new stable state or ***regime.*** The system can move between states when pressures and drivers become sufficient to push the system past the tipping point. In some cases, this transition can be irreversible. For the purposes of clarity, “regime” will be the preferred term for the rest of this report.

Only systems that have stability-inducing negative feedback exhibit regime shifting behavior, and identifying the presence of alternate regimes is challenging. Certain common “hints,” reviewed in Scheffer et al. (2009), have been identified in a wide class of regime-shifting systems as they approach a critical point between state changes. These hints include critical slowing down, asymmetry of the state distribution, and flickering of state changes. Critical slowing down manifests as increasingly slow recovery from perturbations when the system approaches a critical point as well as an increase in autocorrelation (Scheffer et al., 2009). Asymmetry of state distribution is often characterized by skewness, caused by the tendency of the system to remain near the unstable regime for increasingly longer periods of time before the system crosses the tipping point to its other regime. Flickering is also seen near the tipping point when the system moves between two states’ basins of attraction at a rapid speed. Evidence for flickering includes bimodality and an increase in the variance of ecosystem states and their relevant variables.

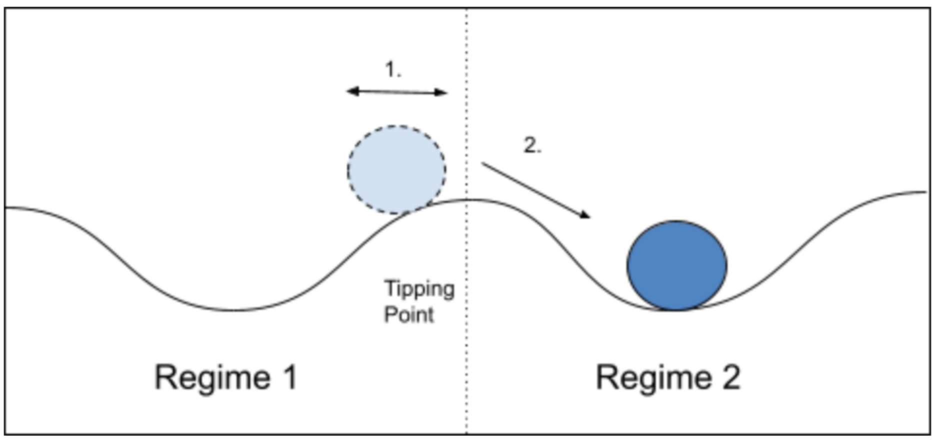

Figure 3. Ball-and-hill diagram commonly used in regime shift studies. At step 1, the system (ball) is within the basin of attraction for regime 1, but system drivers and pressures have pushed it toward the tipping point. If these pressures are sufficiently strong, the system can undergo a regime shift at step 2 into regime 2, overcoming the tipping point.

4. Methods

In this section, we investigate whether the hints identified by Scheffer et al. (2009) and other regime shift literature (Dakos, Scheffer et al., 2008; Dakos van Nes et al., 2012, 2013; Dakos, Carpenter et al., 2015) are present in the non-perennial stream and groundwater system at the Larned Research Site. All analyses were conducted using the R statistical software (R Core Team, 2020) in RStudio (R Studio Team, 2020), with visualization primarily using the ggplot2 package (Wickham, 2016). Other packages and tools used are cited where further discussed in the text.

4.1. Investigation of Regime Shift Hints

4.1.1 Critical Slowing Down

Time series that exhibit critical slowing down can be used to identify when a system is approaching a shift near a tipping point (Scheffer et al., 2009). The first hint most directly relating to critical slowing down in regime-shifting systems is the physical slowing down of recovery rates as a state approaches a tipping point. In a hydrologic time series, we hypothesize that slowing down can be observed when the drying curve takes longer to recover to the average stream stage.

To evaluate critical slowing down at the Larned Research Site, we compared streamflow recession rates between wet periods and dry periods. We did this by plotting discharge since the day that streamflow dropped below 20 cubic meters per second (cms) for recession events that reached no flow eventually and for those that did not dry completely but reached a discharge of less than 5 cms. For these recession events, the discharge rate for each period was graphed from the time flow dropped below 20 cms until (1) discharge started to rise without an immediate recession, (2) streamflow reached 0 cms (no flow event), or (3) 130 days had passed since the flow dropped below 20 cms.

4.1.2 Increase in Autocorrelation of Groundwater Levels

Increases in autocorrelation are another hint that a system is undergoing a regime shift (Scheffer et al., 2009). Because rates of change slowly decrease as the system approaches a regime shift, future rates become increasingly similar to the past. Near a threshold, the system's memory for perturbations is longer (Scheffer et al., 2009) and as a consequence, there is a stronger (auto)correlation between subsequent system conditions.

We calculated rolling 28-day autocorrelation — AR(28) — for groundwater levels in well LWPH4a between 2003 and 2016 using the "roll" package (Foster, 2020). We used groundwater stage, rather than stream stage, for this analysis since stream stage data are not available during no-flow periods. We then compared the distribution of autocorrelation between wet and dry states in the system, temporally divided based on the system regime state (wet or dry) that was identified using the STARS analysis described in section 4.2.

4.1.3 Increase in Variance of Stream Stage and Groundwater Levels

An increase in variance in the system can be evidence for a regime shift change as the system nears a tipping point. Increases in variance occur because the system is more unstable and changes more rapidly near regime shift conditions. Variance fluctuations also can develop well before regime tipping points, making it more difficult to differentiate true signals of regime shifts from normal levels of variance (Scheffer et al., 2009).

To compare surface water and shallow groundwater variations, we calculated rolling weekly (seven day) variance using the "roll" package (Foster, 2020) for both surface water stage and groundwater stage from well LWPH4a. We then evaluated the variance time series between 1998 and 2021 to determine whether changes in variance accompanied shifts between wet and dry regimes.

4.1.4 Asymmetry, Skewness of No-Flow Distribution

Asymmetry in a system's state distribution, much like variance, can be an indicator of a system with alternate stable regimes. As the system approaches a regime shift, it will remain in the current regime until it is forced past the system's tipping point, which will translate as either an asymmetric skewed or bimodal distribution of system states.

We assessed skewness for the percent of no-flow days per month and per year using a histogram and the Pearson skewness coefficient (Skp) (Meyer et al., 2021). To test for multimodality, we used histograms of the percent of no-flow days in each month and year. The presence of at least two modes between 0% and 100% no-flow days would indicate multiple stable states are present in the Larned system.

4.2 Testing for Regime Shifting with Sequential T-test Analysis of Regime Shifts (STARS)

Many regime shift detection techniques have been created and evaluated in regime shift literature (Rodionov, 2005). Methods that focus on shifting variable means are commonly used and have the most robust selection of developed work to choose from, as opposed to shifts in variance or frequency (Rodionov, 2005). The sequential t-test analysis of regime shifts (STARS) developed by Rodionov (2004) is best suited for the hydrologic data available at Larned because it is well suited for accurately estimating regime shifts at the tail end of time series (Rodionov, 2005) and because the basin has shifted between wet and dry regimes within the past decade.

The STARS algorithm identifies regime shifts by continuously comparing means using the Student's t-test at a predetermined cutoff length interval l, a time span from the first measurement until the first perceived regime shift. When the difference between two means within the interval is statistically significant, STARS reports a regime shift (Rodionov, 2004). The STARS method includes an optional prewhitening approach to reduce noise in the time series data prior to regime shift detection analysis to correct for serial autocorrelation in the data (Rodionov, 2006). Of the four methods commonly used, estimating autocorrelation bias using ordinary least squares (OLS) regression is considered an older standard and struggles to accurately remove strong bias and noise on time scales that record monthly or smaller increments (Rodionov, 2006). Inverse proportionality with 4 corrections (IP4) is an alternative approach that is based on the assumption that the bias is approximately inversely proportional to sample size, allowing for more accurate results with smaller subsets of data by reducing the likelihood of a biased result and regime mean overestimation (Rodionov, 2006). For the purposes of this study, we considered IP4 best suited for our data but also repeated our analysis using OLS prewhitening for comparison.

To statistically test regime shifting of flow patterns in the Larned non-perennial stream system using STARS, we used the RSTARS package in Rstudio by Stirnimann and Conversi (Stirnimann et al., 2019; Rodionov, 2004; Rodionov, 2005). The time series input to RSTARS was the Larned site's USGS gage 07141220 discharge data, limiting our time series between October 1, 1998, and December 31, 2020. Initially, cleaned discharge data were aggregated into daily, weekly, and monthly time scales, but using discharge data with STARS did not provide clear results of regime shifting because of the highly skewed nature of discharge data. In other words, the data have a high volume of low discharge values (i.e., less than 1 cms), which, considered relative to the full range of recorded discharge values, are grouped in the same regime as 0 cms despite the important hydrologic difference between low flow and no flow. Instead, we were more interested in the frequency and duration of no-flow conditions (rather than low-flow conditions), so we transformed discharge data into the (1) percent of no-flow days per week and (2) percent of no-flow days per month to better evaluate the presence of possible regime shifts between wet and dry regimes using different temporal resolution of the input data.

We ran STARS with four different scenarios to compare how regime shift detection was sensitive to the prewhitening method and temporal resolution: (1) weekly no-flow percent and OLS prewhitening, (2) weekly no-flow percent and IP4 prewhitening, (3) monthly no-flow percent and OLS prewhitening, and (4) monthly no-flow percent and IP4 prewhitening (table 2). We used a probability value ($\hat{p}$) of 0.05 to identify significant changes and selected the cut-off length *l* by identifying the number of weeks and months between the first timestep and the first no-flow day (185 weeks and 43 months, respectively).

Table 2. The four approaches and selected parameters used for STARS analysis. The prewhitening methods ordinary least squares (OLS) and inverse proportionality with 4 corrections (IP4) were used to initially clean the time series data. The time series data were aggregated by percent of no-flow days per week or percent of no-flow days per month. The cutoff value (*l*) for the STARS algorithm was determined by the number of weeks or months from the initial date the first no-flow day occurred in the time series — 185 weeks or 43 months.

Approach	Prewhitening Method	Temporal Aggregation	Cutoff Value *l*
1	OLS	Weekly	185
2	IP4	Weekly	185
3	OLS	Monthly	43
4	IP4	Monthly	43

4.3 Testing System-Driver Relationships

Identifying important influences of potential drivers on environmental systems is easier with a longer time series of data (Spanbauer et al., 2014; Reynolds et al., 2015; Taranu et al., 2018). Since we had only 23 years of streamflow data, and an even shorter period of groundwater-level data, measurements from remote sensing provided a potential longer time scale for analysis. We investigated land surface temperature (LST) and the enhanced vegetation index (EVI) as two potential indicators of ecosystem dynamics at the site.

4.3.1 LST and Stream Stage

Land surface temperature (LST) is the temperature of the land surface as viewed from space and includes vegetation, streams, and exposed streambeds in a given location (Zink et al., 2018). As a result, LST serves as an indicator of the relative wetness of the site, with cooler temperatures associated with water in either streams or healthy transpiring vegetation. Raw LST data in Celsius were compiled, cleaned, and screened for cloud cover from a collection of Landsat images taken between December 6, 1982, and May 15, 2021, for the Larned Research Site (fig. 1, blue-shaded region). Cleaned Larned LST data were then transformed from daily temperature values to yearly temperature range values, calculated as the difference between the minimum and maximum LST value of each year (Range $LST_{\text{Year N}}$ = Maximum $LST_{\text{Year N}}$ - Minimum $LST_{\text{Year N}}$).

To visualize the distribution of yearly LST ranges during periods of regime shifting, yearly LST range data were grouped into the six regimes identified from the results of the STARS analysis (section 4.2). We hypothesized that when the system is experiencing a dry regime, the LST range would be wider than the LST range in a wet regime since there would be higher summer temperatures due to a lack of evapotranspiration at the site. Furthermore, we compared LST time series data with LWPH4a data using Pearson's product-moment correlation to get a correlation coefficient. This analysis was used to specifically quantify the relationship between the change in LST range and the change in groundwater levels.

4.3.2 EVI and Stream Stage

The enhanced vegetation index (EVI) offers insight into the presence and health of vegetation (Kang et al., 2016). Similar to LST, EVI data were compiled, cleaned, and screened for cloud cover from a collection of Landsat images taken between December 6, 1982, and May 15, 2021, with the spatial area limited to the Larned Research Site. From cleaned EVI data, the yearly max EVI value from each year's summer period (defined as April 1–September 30) was isolated and then graphed using a line plot.

To visualize the distribution of yearly EVI summer maximum values during periods of regime shifting, yearly EVI maximums were grouped by the regimes identified using the STARS algorithm described in Section 4.2. Our hypothesis was that EVI would be lower during a dry regime than during a wet regime because there would be less water available for vegetation during these periods.

As we did for LST, we calculated Pearson's product-moment correlation between the cleaned Larned bimonthly EVI measurements and LWPH4a well measurements to directly compare stream stage and EVI movement over time. Again, being able to directly measure the change in EVI with the change in stream change offers a way to quantify the relationship between vegetation activity and groundwater levels.

5. Results

5.1. Identification of Regime Shift Hints

5.1.1 Critical Slowing Down

During streamflow recession events, we see that streamflow decreases rapidly when it passes below 20 cms, beginning to slow at around 5 cms and asymptoting close to 0 cms (fig. 4). This general pattern is true for both dry and wet regimes, though dry regimes appear to generally asymptote at a lower value since they eventually reach 0 cms. This asymptotic behavior is characteristic of slowing rates of change before a regime shift from flow to no-flow conditions and suggests feedback causing the stream system to be resistant to change until the system is pushed past a tipping point. When using a log-scaled hydrograph to investigate dynamics during these asymptotic periods, we found two distinct patterns of behavior during dry regime recession events (fig. 5). One grouping decreases to 0 relatively quickly (less than one month), while the other mimics the asymptote behavior of wet regime recession events before eventually drying. One possible explanation for this differentiation is the infiltration behavior into the subsurface. We would expect the more rapid drying events, which have a larger second derivative, to occur when groundwater levels are lower and surface water can quickly drain into a relatively dry alluvial aquifer. These rapid drying events are therefore characteristic of ephemeral, precipitation-driven flow events. In contrast, the asymptotic behavior of the more prolonged drying events may be characteristic of conditions in which groundwater levels are near the streambed elevation and slowly recede until they drop below the streambed elevation and the river dries. Future investigation of the factors differentiating these two types of drying recession curves could provide insight into the drivers of regime shifts in future work.

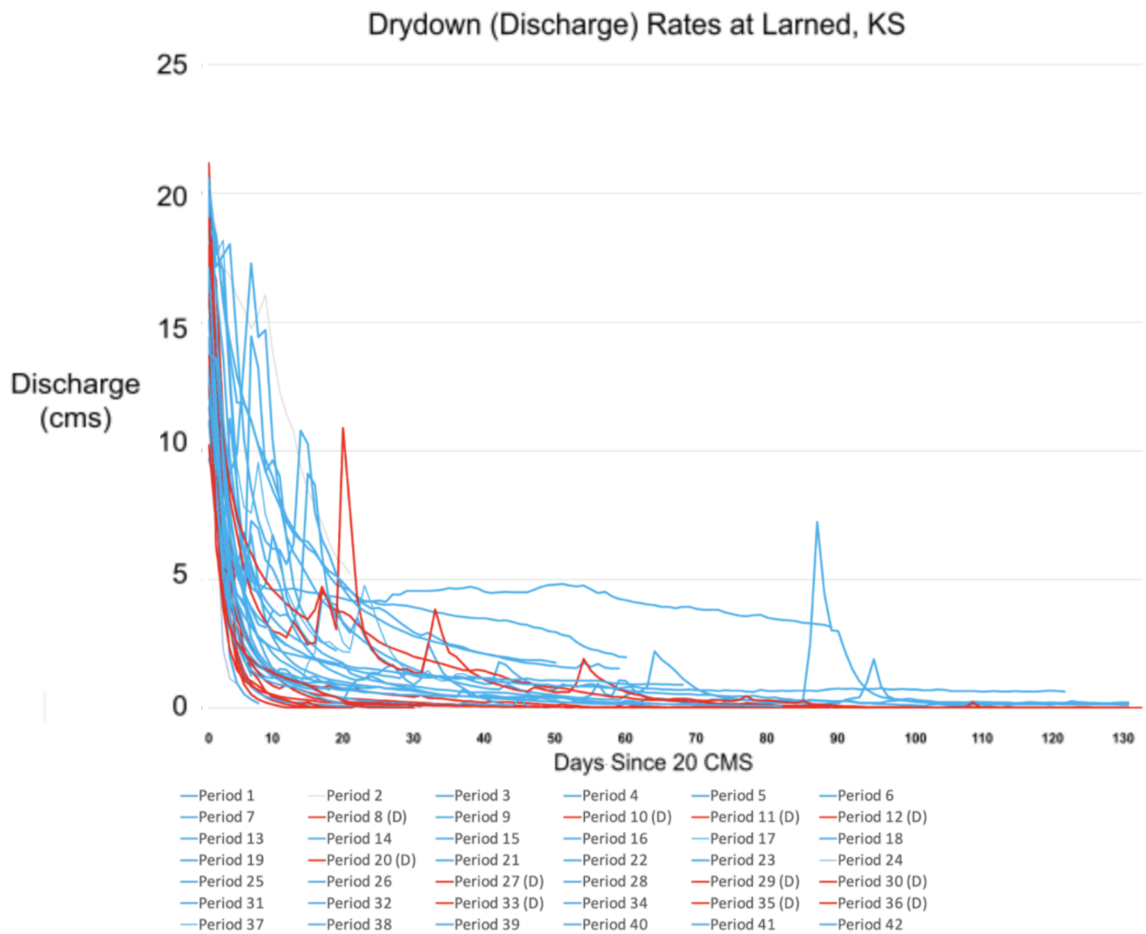

Figure 4. Discharge rates at Larned, Kansas. Blue lines indicate drydown periods that do not reach a no-flow condition, and red lines indicate drydown periods preceding no-flow events. Time is expressed as the number of days since discharge last exceeded 20 cms. The x-axis is cut off at 130 days.

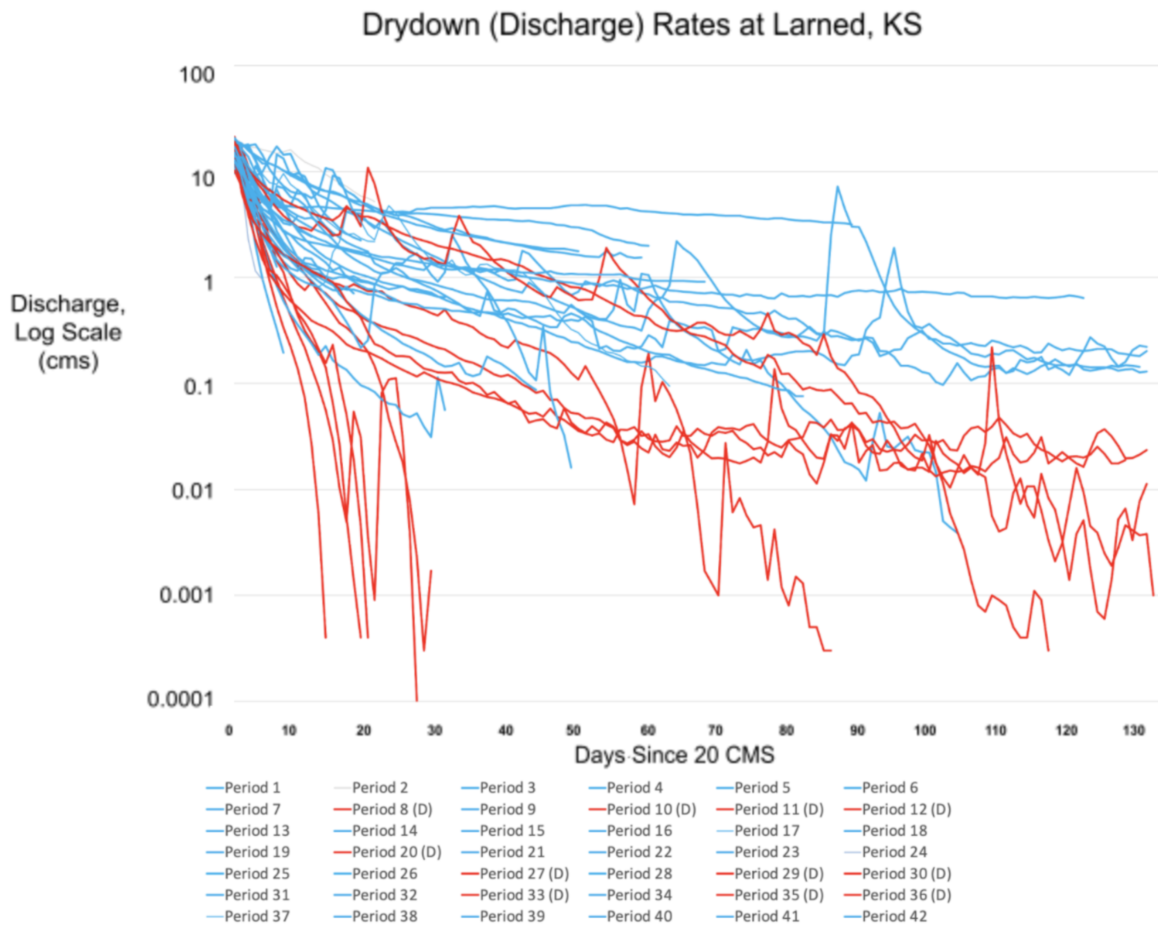

Figure 5. Discharge rates at Larned, Kansas, with base-10 logarithm scale on the y-axis. Blue lines indicate drydown periods preceding recharge events, and red lines indicate drydown periods preceding no-flow events. Time is expressed as the number of days since discharge last exceeded 20 cms. The x-axis is cut off at 130 days.

5.1.2 Increase in Autocorrelation of Groundwater Levels

Stream discharge is typically highly autocorrelated because, in the absence of major hydrometeorological changes such as precipitation, discharge on a day of interest is typically very similar to discharge on the preceding days (Yue et al., 2002). As a result, the 28-day rolling autocorrelation (AR[28]) is very high, typically above 0.75 except during high discharge events, where it decreases briefly to the 0.25–0.5 range. The high baseline level of autocorrelation makes it difficult to discern indicators of regime shifts in AR(28) time series data (fig. 6a). However, the boxplots (fig. 6b) show AR(28) is highest during dry regimes, intermediate during intermediate regimes, and lowest during wet regimes. The lower autocorrelation during wet regimes is the result of greater variability in groundwater levels during these periods, which is due to the close relationship between water levels in the alluvial aquifer and the stream, while during dry regimes the groundwater levels in the alluvial aquifer tend to change relatively slowly (fig. 2). Although there are many instances of local increases in AR(28) before no-flow events, these are comparable in magnitude to other local maxima and therefore do not provide a clear early warning signal for regime shifts.

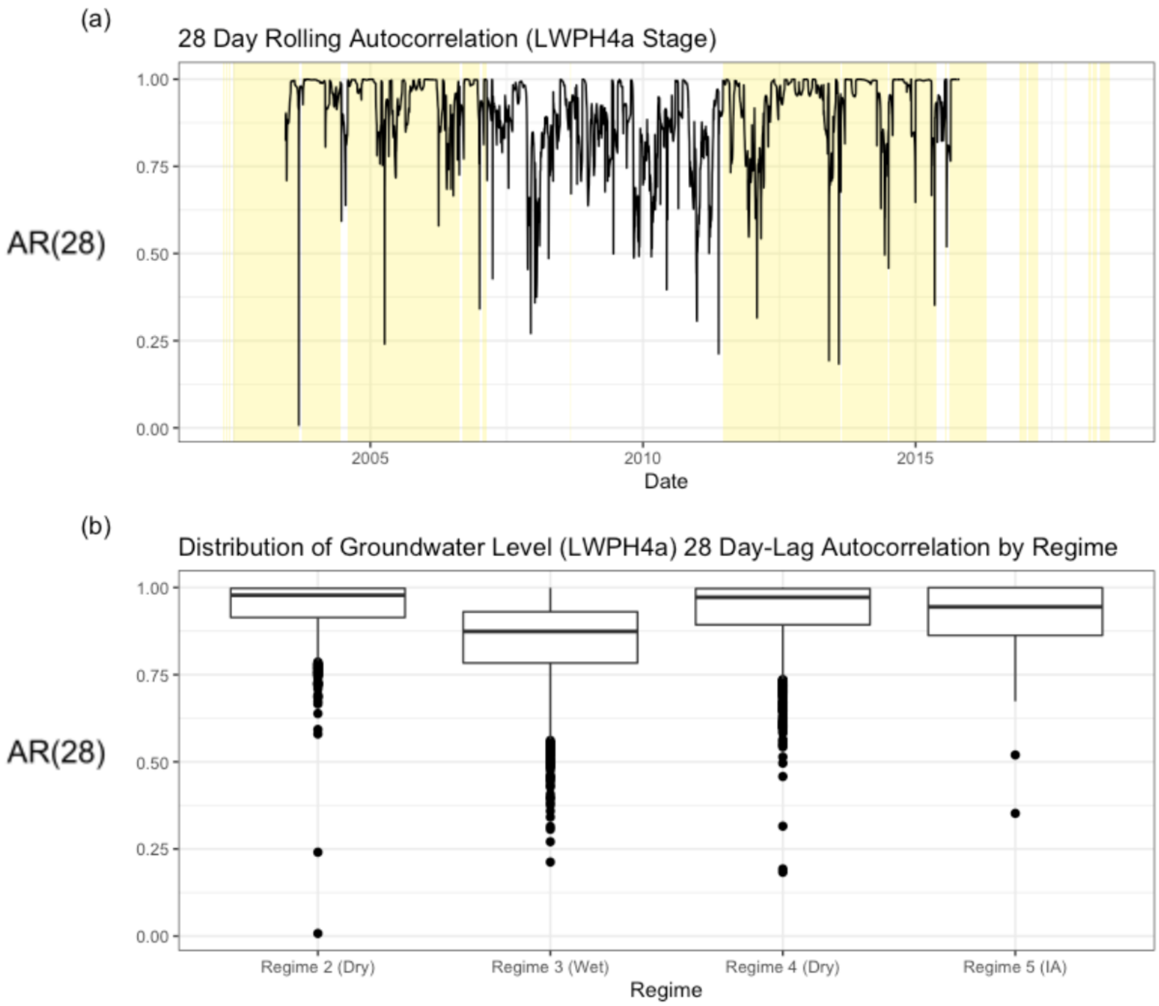

Figure 6. (a) Time series for 28-day lag autocorrelation, AR(28), of LWPH4a well levels, where yellow shading illustrates periods of no surface flow. (b) Distribution of AR(28) of LWPH4a well levels for each regime identified in the STARS analysis (section 4.2) between 2003 and 2016. "Wet" regimes have surface flow, "dry" regimes have no surface flow, and "IA" regimes are an intermediate regime with periods of both flow and no flow.

5.1.3 Increase in Variance of Stream Stage and Groundwater Levels

Increases in variation in alluvial aquifer groundwater levels, stream stage, and discharge are associated with transitions from no-flow to flow conditions (fig. 7). Variance in stream stage and alluvial aquifer groundwater levels is primarily associated with changes in flow, which are driven by wet meteorological conditions but may also be associated with pumping and other drivers (Compare et al., 2021). For example, variability in LWPH4c (fig. 2) appears driven by seasonal water use in the High Plains aquifer. Further study of dynamics in LWPH4c could provide insight into the role of irrigation and other water use practices that could affect the aquifer and streamflow in the future.

Interpreting the variance within the system is challenging due to the presence of zeros and very low values in stage and discharge measurements associated with low-flow conditions. Because streamflow is by definition low immediately prior to drying and generally follows a relatively smooth, asymptotic recession (figs. 4–5), there are no increases in variance associated with wet to dry regime shifts. Given the time series data, it is difficult to interpret whether both variance and autocorrelated measurements match patterns associated with regime shifts as described in the literature, and if they do align, whether they reflect a regime shift change.

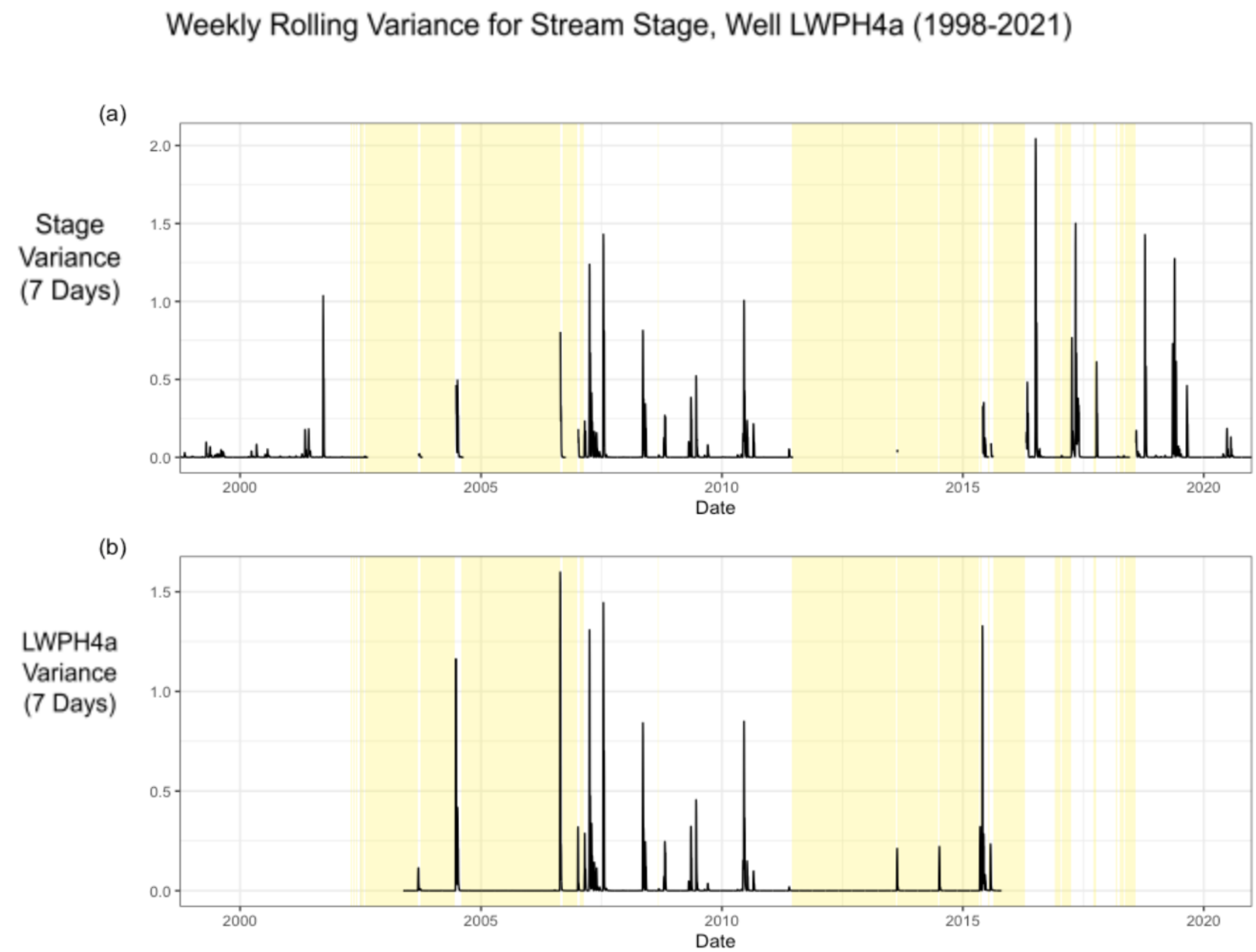

Figure 7. (a) Time series of calculated rolling variance for stream stage and (b) alluvial aquifer water levels from well LWPH4a. Raw stream stage and well-level data were collected and cleaned from USGS gage 07141220 and LWPH4a. Stream stage data span 1998 to 2021 and LWPH4a data span 2003 to 2015. Yellow shading indicates periods of no surface flow.

5.1.5 Asymmetry and Skewness of No-Flow Distribution

Both skewness and multimodality are visually apparent in the no-flow distributions at monthly and annual timescales (fig. 8). However, the skewness coefficient Skp is not statistically significant for either distribution (0.206854 %NFD/Yr, 0.2629865 % NFD/Mo). A possible explanation for this is that depending on the usage, skewness can be a difficult hint to work with in ecosystem assessment (Meng et al., 2021), where temporal methods are more descriptive, and the skewness coefficient is not well suited for strongly bimodal data. We observe that the large majority of both months (fig. 8a) and years (fig. 8b) have less than 10% or more than 90% no-flow days, making both distributions bimodal. The locations of the modes within the distribution explain the lack of skewness. Because both modes are on the farthest ends of the histograms, both distributions are almost balanced and reflect the system's distribution between dry regimes (100% no-flow days) and wet regimes (0% no-flow days).

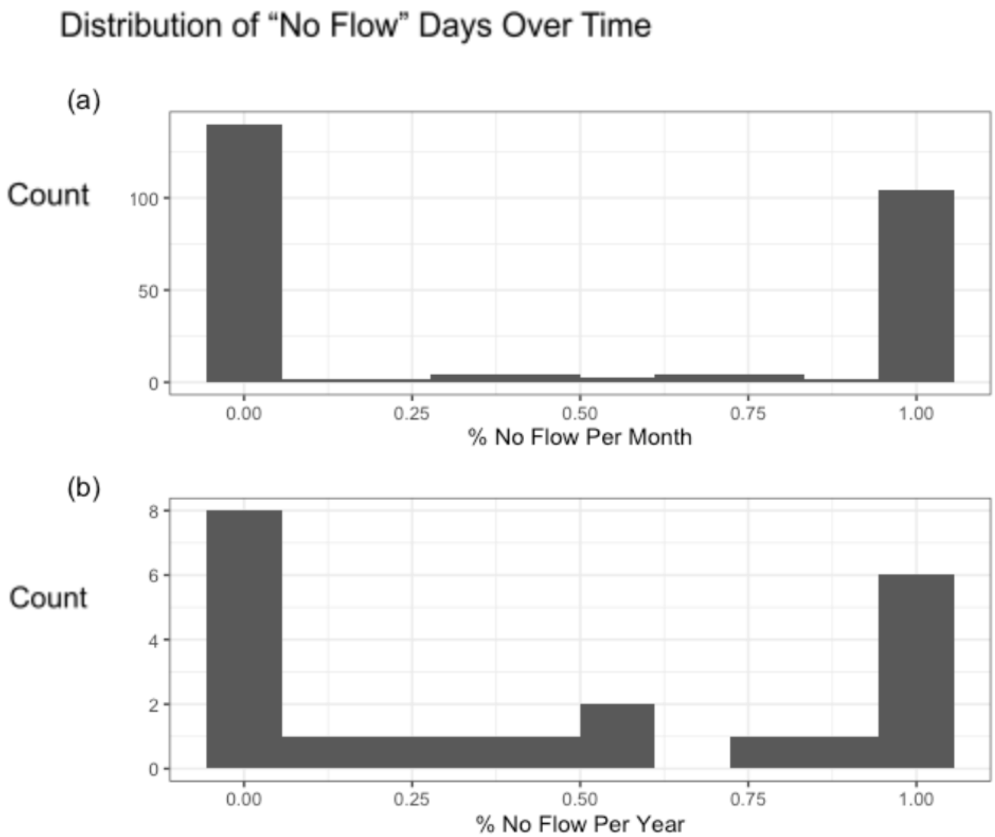

Figure 8. Distribution of no-flow days at (a) monthly and (b) yearly timescales, as a proportion of total days. Both show a clear bimodal distribution with modes of 0 and 1.

5.2 Sequential T-test Analysis of Regime Shifts (STARS)

STARS identified multiple regime shifts for both weekly and monthly percent no-flow days. For each regime, STARS provides the start date, end date, and mean value during that regime. Regardless of the approach used, STARS identified similar timing of regime shifts that closely align with the observed shifts between flow and no-flow on the hydrograph. The primary difference between the weekly and monthly approaches was that using STARS on weekly resolution data identified one additional intermediate flow regime from 2015 to 2017 (table 3 and fig. 9), which was not identified in the monthly data (fig. 10). The prewhitening methods more heavily filtered the weekly time series compared to the monthly time series, which decreased the estimated regime means relative to the raw data. Due to IP4's superior performance in past work (Rodionov, 2006), IP4 outputs were used for further comparisons.

Table 3. STARS output using approach 2 from table 2 (weekly aggregation, IP4 prewhitening method, cutoff value l = 185, subsample size M = 62). STARS detected six distinct regimes using this approach, with regime 5 illustrating an "intermediate" alternate state.

Regime	Regime Type	Start Date	End Date	Mean Value [% No-Flow Days/Week]
	Wet	10-02-1998		0
2	Dry	04-17-2002	12-27-2006	48.3%
3	Wet	01-03-2007	06-15-2011	0.2%
4	Dry	06-22-2011	04-29-2015	49.5%
5	Intermediate	05-06-2015	03-29-2017	32.8%
6	Wet	04-05-2017	12-29-2020	1.8%

Six regimes were detected using weekly data, and five regimes were detected using monthly data. The regime mean estimates for monthly no-flow days are higher than for weekly no-flow days due to more pronounced prewhitening effects on the weekly data. Differentiation between start and end dates for regimes 1–3 for yearly and monthly data is marginal but shows that weekly percentages more precisely mirror first and last flow dates recorded in the discharge data because of the finer temporal resolution of the input data. The monthly and weekly approaches differ most in regimes 4–6, as STARS does not register a sixth regime change for monthly no flow and instead interprets regime 5 as an "intermediate regime" balanced by a high frequency of flickering. For weekly no flow, regime 5 also serves as an intermediate regime before the stream transitions into regime 6, a true dry regime.

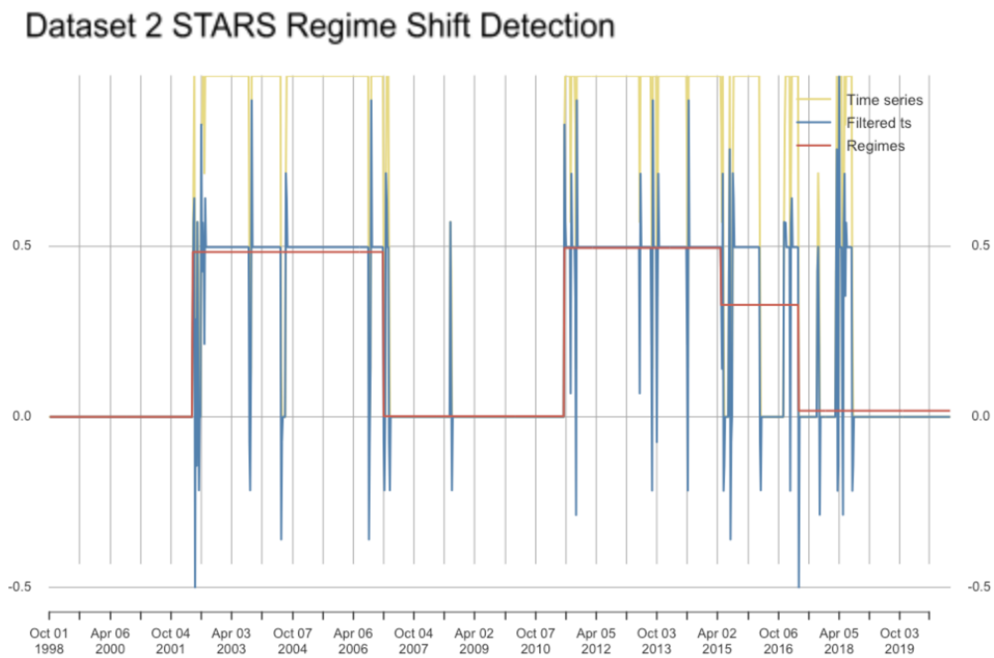

Figure 9. Output of STARS algorithm using approach 2 (weekly aggregation, IP4 prewhitening method, cutoff value *l* = 185, subsample size *M* = 62). Six regimes were detected between October 1, 1998, and January 1, 2021, illustrated by the red line. The blue line indicates the prewhitened filtered time series, and the yellow line indicates the original time series.

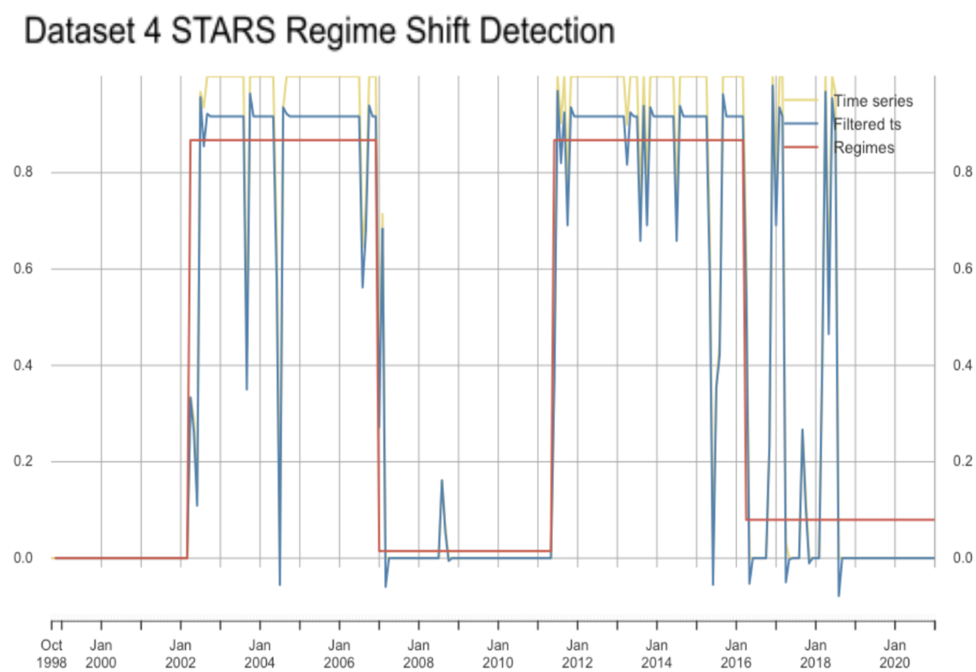

Figure 10. Output of STARS algorithm using approach 4 (monthly aggregation, IP4 prewhitening method, cutoff value *l* = 43, subsample size *M* = 14.667). Five regimes were detected between October 1, 1998, and January 1, 2021, illustrated by the red line. The blue line indicates the prewhitened filtered time series, and the yellow line indicates the original time series.

For time frames in which no-flow data show flickering, classifying those periods as "intermediate" regimes may be temporary as more data are gathered to gain a better understanding of general trends. As future data are collected, STARS would be able to accurately reinterpret changes of regimes based on the new discharge data toward the end of the time series.

5.3 Testing System-Driver Relationships

Qualitatively, yearly LST range values (fig. 11a) appear to trend upward before a drying event and decrease toward the end of and after a dry regime. Overall, however, there are no clear and consistent patterns for how LST varies between wet and dry regimes, though the LST range is often larger during dry regimes than wet regimes. The highest median LST range occurs during the first dry regime (regime 2), while the lowest median LST range occurs during wet regimes (regime 1 and regime 6). Since this Larned Research Site is heavily vegetated (fig. 1), and much of the vegetation at the site is phreatophytic (Butler et al., 2007), the higher temperature range during dry regimes may also indicate that the vegetation is experiencing greater stress during these periods.

The distribution of LST ranges for dry regimes have a narrower total range (fig. 11b). The difference is in part due to regime periods (i.e., regime 5) being only a couple of years long, while other regime periods are almost a decade and will naturally have larger LST range variations. With an increase in LST range indicating more variability in LST values, even local climatic conditions are exhibiting increases in variability similar to other environmental drivers analyzed at smaller time scales. Comparing cleaned LST time series data with LWPH4a data, Pearson's product-moment correlation between Larned bimonthly LST measurements and LWPH4a well measurements produced a positive weak correlation ($R = 0.139$) with a p-value of 0.0124. This positive correlation could indicate underlying vegetation-driven dynamics that force the system into a dry regime, but those dynamics are not readily apparent given the scope of this analysis.

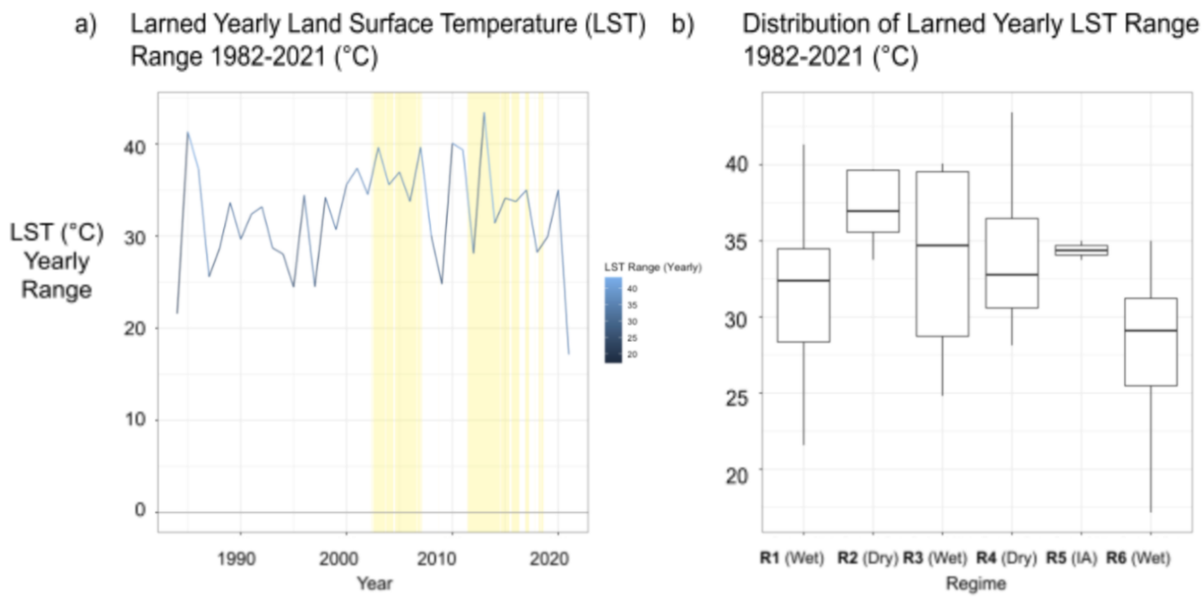

Figure 11. (a) Larned yearly land surface temperature (LST) range between 1982 and 2021. Yellow shading indicates observed no-flow periods in the stream. (b) Distribution of Larned yearly LST ranges using the data from (a). The regime time periods correspond to STARS output using approach 2 (table 2).

For EVI, the temporal pattern is less clear than for LST, but there is a stronger relationship with groundwater-level data. With respect to EVI yearly summer maximums (fig. 12a), EVI increases before drought periods but decreases shortly before or in the first year of a dry regime. The decrease in EVI during dry regimes further supports the effect of phreatophyte-water table interactions in vegetation; phreatophyte activity reaches a peak, then dramatically declines, potentially triggered by a lack of water availability. Distribution of Larned yearly EVI maximums (fig. 12b) generally illustrates that dry regimes have a lower median than wet regimes and exhibit a wider and more skewed distribution compared to wet regimes, with the exception of regime 1, which included a longer series of data (1982–2003) that included a long-term increase in maximum EVI potentially associated with the expansion of phreatophytic vegetation at the site. A smaller EVI maximum range during wet and intermediate regimes could indicate that phreatophyte activity is more consistent in the wet regimes, when the plants are able to access groundwater within their root zone, as opposed to dry regimes, when the water table can drop below the root zone. This suggests that the terrestrial ecosystem at the Larned Research Site is adapted to the stable wet state. Furthermore, the Pearson's product-moment correlation between Larned bimonthly EVI measurements and LWPH4a well measurements produced a positive weak correlation ($R = 0.204$) with a p-value of 0.0002, a stronger relationship than between LST and LWPH4a measurements. With phreatophyte activity so closely connected to water table and thus alluvial aquifer levels, the stronger correlation is consistent with the interpretation that phreatophytes can both influence and drive a response to groundwater levels at the site.

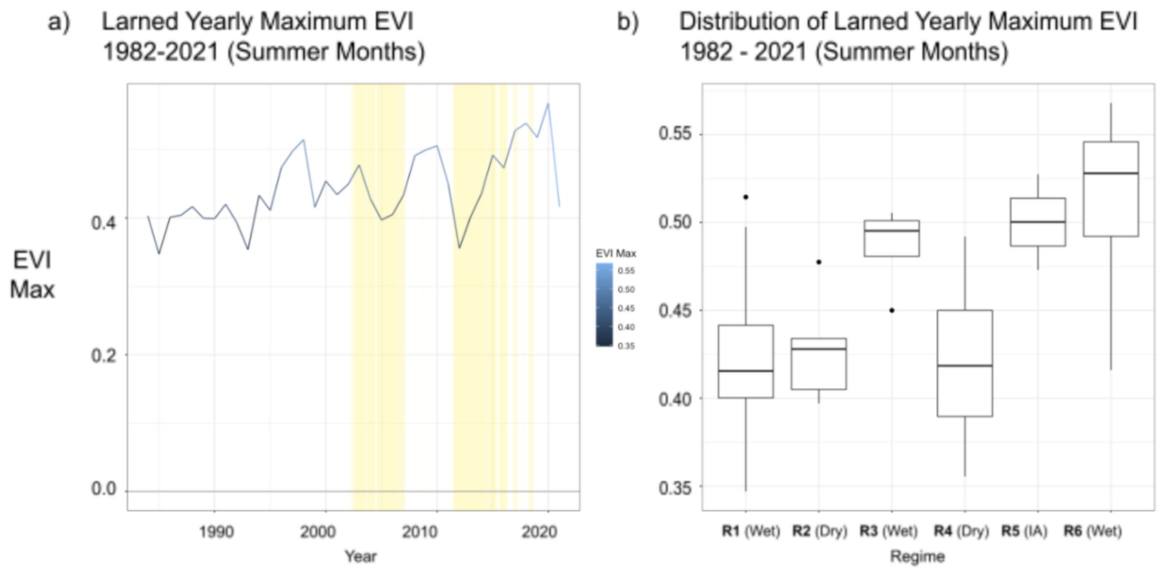

Figure 12. (a) Larned yearly maximum summer month EVI values between 1982 and 2021, where summer months were defined as April 1–September 30. Yellow shading indicates observed no-flow periods in the stream. (b) Distribution of Larned yearly maximum summer month EVI values using the same data as (a). The regime time periods correspond to STARS output using approach 2 (table 2).

6. Discussion

6.1 Conceptual Models

6.1.1 Larned Regime Model

Our results suggest that the Larned system can go back and forth between wet and dry regimes but can also linger in an unstable intermediate regime before transitioning (fig. 13). As of 2021, the system appears to have transitioned from an unstable intermediate regime back to a wet regime (table 3, figs. 9–10). However, this interpretation remains somewhat ambiguous depending on the temporal scale. Looking at the system over the 23 years of available data, there appear to be wet, dry, and intermediate regimes that last a few years in duration. However, zooming out to a larger temporal scale, it may make more sense to label the period of perennial flow prior to the first no-flow date as the only wet regime, and the past 20 years of wet/dry/intermediate regimes shifts we identify here may be one protracted intermediate regime as the system shifts from predominantly wet to predominantly dry. Which of these interpretations is correct will ultimately depend on the future trajectory of the system. At present, having three regimes better emphasizes the phases of transition and effect of the system's drivers on stream flow activity.

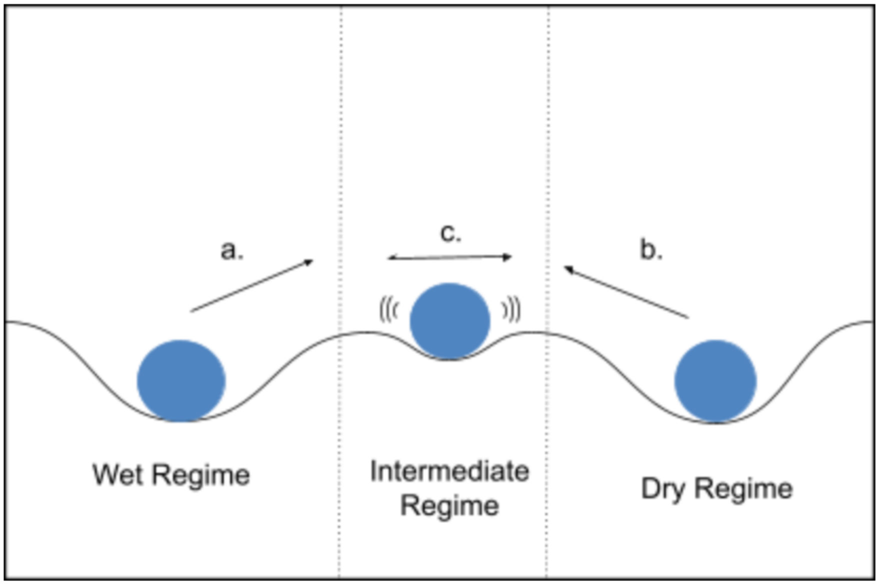

Figure 13. Updated ball-and-hill regime shift conceptual model for the Arkansas River near Larned, Kansas, non-perennial stream system derived from hydrological data. When the system (ball) is moving between the wet or dry stable states (arrows a, b), the system passes through an *intermediate unstable state* (c). The system, depending on the ecological drivers influencing movement, will stay in this intermediate state until pushed either direction into a stable state again.

6.1.2 Larned System Models

Six primary drivers that define regime activity at Larned were identified from regional hydrogeologic and remote sensing data: stream stage, solar radiation (land surface temperature), surface-aquifer interactions (LWPH4c well measurements), phreatophyte groundwater consumption (EVI), phreatophyte activity (EVI, land surface temperature), and groundwater pumping for anthropogenic use (consumption). Although we are able to directly observe the effects of some of these drivers (i.e., pumping, precipitation), drivers that have more gradual influence, such as phreatophyte activity, can lead to similar abrupt changes over a longer time scale. Combined, these factors create feedback loops that create stability in both the wet and dry regimes at the Larned system and can lead to unstable transitions when pushed beyond their normal limits. The specific roles and interactions of these drivers vary between wet and dry regimes.

In the wet regime, precipitation both at the site and upstream (fig. 14a) are sources of water that contribute to flow, and evapotranspiration (fig. 14b) is an outflow from the local hydrological system. Water movement between the stream (fig. 14c), the alluvial aquifer (fig. 14c.i), and the High Plains aquifer (fig. 14c.ii) can be either upward (toward the stream) or downward (away from the stream) because increased surface flow percolates into the subsurface to recharge the alluvial and High Plains aquifers when water levels in the stream are higher than those in the aquifer and groundwater feeds back to surface flow from the alluvial aquifer when water levels in the stream are lower than water levels in the aquifer. Phreatophyte water consumption (fig. 14d), phreatophyte primary production (fig. 14e), and anthropogenic water consumption via pumping (Fig. 14f) act as negative feedback that reduce the amount of water in the system and can therefore exacerbate drier conditions.

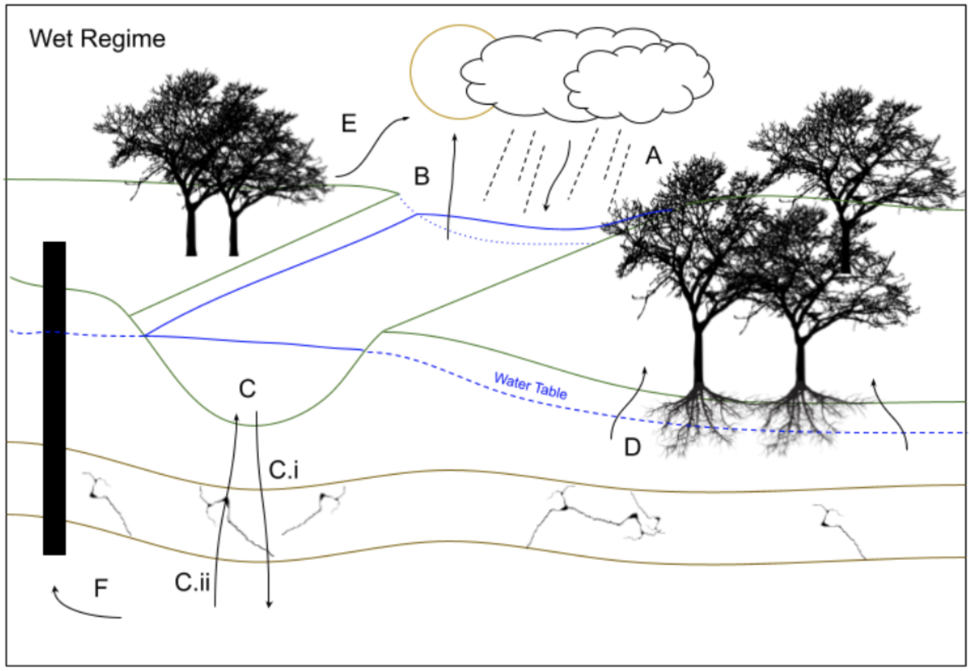

Figure 14. Conceptual system model for the Arkansas River reach near Larned, Kansas, during a wet regime. Precipitation (a) and evaporation (b) add water to and remove water from the surface. Water moves between surface water and the subsurface via the alluvial and High Plains aquifers (c, c.i, c.ii). Phreatophytes remove water via root uptake (d) and evapotranspiration (e). Human water use (f) can remove water at a much larger scale. Ultimately, the system is balanced by baseflow and precipitation counteracting the drying negative feedback mechanism.

In the dry regime, precipitation can generate brief periods of flow (fig. 15a), but unlike the wet regime, these are not sustained. Evapotranspiration (fig. 15b) and recharge into the alluvial and the High Plains aquifer (fig. 15c) are driven by the hydraulic gradient from the stream to the aquifers since dry regimes are associated with losing conditions for the stream. Phreatophyte water consumption (fig. 15d), phreatophyte primary production (fig. 15e), and anthropogenic water consumption via pumping (fig. 15f) further intensify dry conditions, maintaining the system in a dry regime. However, the system can transition from a dry regime to a wet regime when there is sufficient forcing from a large external climatic input, such as intense continuous precipitation events or flooding, which largely depends on climate and precipitation variability. That being said, it is difficult at this time to determine what magnitude of an input would recharge both aquifers and reinitiate surface flow if the Larned reach of the stream were in complete dry conditions.

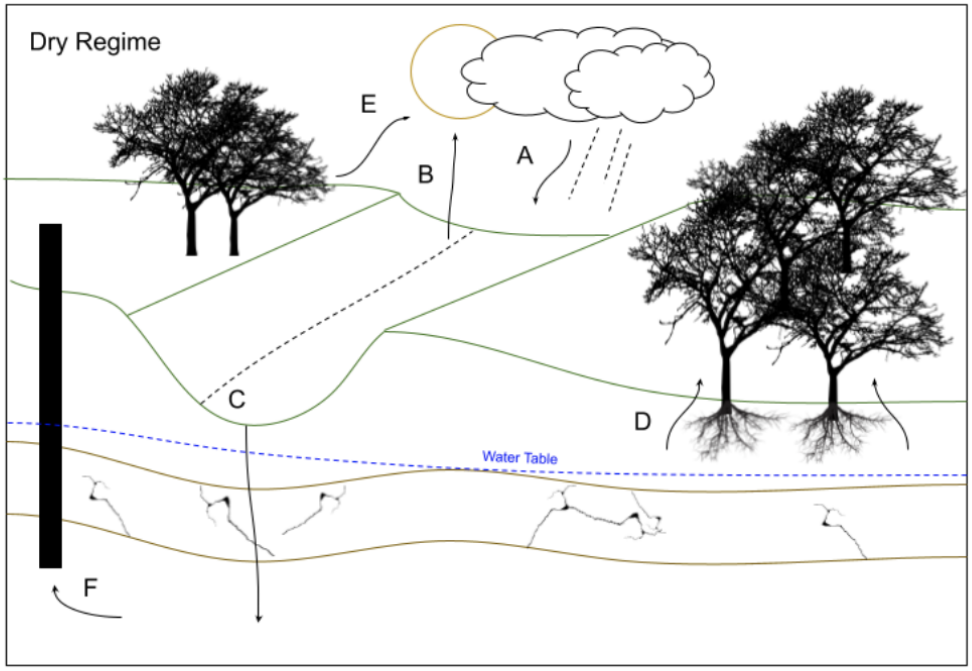

Figure 15. Conceptual system model for the Arkansas River reach near Larned, Kansas, during a dry regime. Precipitation (a) and evaporation (b) add water to and remove water from the surface. Water moves downward into the subsurface through the alluvial and High Plains aquifers (c). Phreatophytes remove water via root uptake (d) and evapotranspiration (e). Human water use (f) removes water, further promoting water depletion. Ultimately, the system is unbalanced and surface water depletes until dry conditions exist. The lack of baseflow cannot be recovered by precipitation and upstream flow, and the water table eventually lowers. The drying negative feedback mechanism is strengthened as water is constantly leaving the stream.

6.1.3 Limitations and Uncertainties

To best characterize the hydrological system at the Larned Research Site, using an appropriate temporal scale is extremely important. Time series shorter than a decade do not give complete and accurate signatures for many of the environmental "hints" used in regime shift theory, and smaller flickering events can be misinterpreted as larger regime shift dynamics. Even here, where we had 23 years of data, it is possible that the hints analyzed from results (section 5) could have different interpretations if the time series used were expanded as system perturbations became better contextualized. For example, hints such as an increase in variance close to a regime shift could be more clearly interpreted with respect to historical variability if there was a longer period of historical monitoring data that included both extensive wet and dry regimes and shifts between the two. Though statistical regression models have been used elsewhere (such as Irving et al., 2018) to lengthen hydrological time series, our finding that there may be wet and dry regimes at this site implies that extrapolating previous precipitation patterns and hydrological responses from a single gage could produce an oversimplified result due to the nonstationarity associated with multiple regimes and different feedback during these two regimes (see section 6.1.3).

If the relationship between the hydrologic system and environmental variables appears to be different with the addition of more data, defining specific regime periods and timelines of shift patterns would be time scale dependent. Regime shift identification requires an accurate time scale reference, especially if the temporal scale of the data is limited. This is shown in the STARS analysis (figs. 9–10), where even changing the temporal scale between weekly and monthly percent of no-flow days changed the number of regime shifts identified by the algorithm. If the time series is to be expanded to multiple decades, a monthly or even yearly temporal scale may more accurately describe larger system dynamics.

It is also possible that our conceptual models exclude an important driver that remains unrecognized or not explained properly given the complexity of the system. Though there has been substantial historical work at the Larned Research Site (reviewed in section 2), there is always the possibility of new findings and drivers to explore.

7. Conclusions and Future Research Needs

This report aimed to identify and evaluate potential regime shifts in the Arkansas River near Larned, Kansas, with the goal of exploring whether regime shift statistical methods are a useful framework to study non-perennial stream dynamics. We identified and aggregated data for potential environmental drivers of system behavior, used these data to investigate potential regime shifts, and developed environmental conceptual models to illustrate system dynamics and feedback mechanisms. Our analysis suggests that the Larned Research Site includes three possible regimes: a stable wet regime, an unstable intermediate regime, and a stable dry regime. The STARS algorithm identified the intermediate regime only when using weekly input data, illustrating how regime shift indicators may be dependent on temporal scaling.

Building on previous KGS research that identified controlling factors of perennial streamflow, we analyzed environmental variables potentially influential in surface water activity to look for regime shift signatures, including critical slowing down and changes in variance and asymmetrical state distribution. We successfully identified some signatures at the Larned Research Site, such as critical slowing down and state multimodality, while other signatures such as variance and autocorrelation were difficult to isolate from already highly correlated hydrologic data patterns and the presence of zeros in flow data. Datasets with longer time series from remote sensing data, such as LST and EVI, have weak correlations with stage flow but have larger variations during modern dry regimes, indicating instability consistent with the hypothesized intermediate regime state.

Future development of regime shift applications for non-perennial stream activity at Larned, Kansas, is necessary to understand implications of regime shifting for water availability, quality, and ecological health. Formal identification of regime shifting in non-perennial streams could provide a pathway to predict regime shifts of streams by looking at certain indicators such as precipitation, discharge, vegetative indices, and groundwater levels that signal changes in drying and wetting patterns. Quantifying and predicting regime shifts prior to stream drying and identifying pathways for the potential of reversal from a dry to a wet regime is imperative for projecting surface water and groundwater supply in western Kansas and other regions concerned with diminishing groundwater storage. To maintain non-perennial streams and their downstream receiving water bodies such as perennial rivers and reservoirs as viable sources for water supply, water managers should keep the vulnerability of non-perennial streams in mind when looking at local sources of water for irrigation. What is the history of the water source? Has it ever gone dry before and why? Are groundwater and surface water levels in the area unstable? What is the potential of destabilizing the system if that water is to be withdrawn? These are important questions that the regime shifting framework could help answer.

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