Overview of Hydrological and Ecological Drought Assessment

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*What it is*

The impacts of ecological drought depends on the magnitude of the water shortage, as well as the vulnerability of an ecosystem to a reduction in the water supply (Zargar et al. 2011).

*What can we do to extend records? What can we do to identify causal factors*

*Ideal case:*

Indices of Biotic Integrity (IBI) developed from flow-based water quality standards to assess carrying capacity of catchments during predictable droughts, rank restoration priorities at a catchment scale, and to assess future water use scenarios based on trade-offs between socioeconomic benefit and environmental cost.

*What the methods are*

*Problems – not sufficient data – hydrologic drought, ecological drought* does not currently have specific indices to quantify it

**What It Is**

Drought a complex and poorly understood natural hazard that simultaneously affects many economic sectors and people (Wilhite 2000). Changing climatic conditions and increases in extreme climate events have resulted in increased concern about drought frequency, severity, and duration (Peterson et al. 2013). Drought can be defined as the extreme persistence of precipitation deficit over a specific region for a specific period (Zargar et al. 2011). However, a single definition of drought is not possible because drought effects vary geographically, temporally, and by economic and environmental sectors impacted by a reduction in the water supply (Heim 2002). Different drought types are defined based on the system of interest with operational definitions used for parts of the hydrologic cycle that experience drought and conceptual definitions used for societal or ecological systems that depend on a water supply for which factors outside of the physical nature of drought exist (Tsakiris and Vangelis 2005).

Drought impacts available water supply to economic and social sectors, and ecosystems. During drought, a fundamental tension exists between socioeconomic sectors and ecosystems as water use among socioeconomic sectors, for example, public water supply, agriculture, industry, mining, aquaculture, tends to be extractive, and aquatic ecosystems rely on water remaining as surface or ground water, in other words, instream water use. *Socioeconomic drought* occurs when water demand is greater than water supply and results from increased water demand by growing populations or economic sector development, over-allocation among competing beneficial uses, or non-sustainable groundwater use (Frick et al. 1990; Heim 2002; Svoboda and Fuchs 2016). Socioeconomic drought magnitudes have increased in recent years as a result of the narrowing of the gap between water supply and water demand (Hayes et al. 2011). *Ecological drought* is defined as a “shortage of water causing stress on ecosystems, adversely affecting the life of plants and animals” (Lake 2011). Unlike other forms of drought, *ecological drought* does not currently have specific indices to quantify it (Lake 2011; Svoboda et al. n.d.). Ecological and socioeconomic drought impacts depend on the magnitude of the water shortage and the vulnerability of the ecosystem or socioeconomic sector to a reduction in the water supply (Zargar et al. 2011). Comprehensive drought mitigation strategies are often complicated by States water laws that narrowly define water use as consumptive use (Wilkinsen, 2015).

Meteorological, agricultural, and hydrological drought are operationally defined by duration, magnitude, geographic extent, and frequency, as well as by drought impacts, indicators, and indices

(Wilhite and Glantz 1985; Wilhite et al. 2014; Zargar et al. 2011). Indicators are used in combination to simplify complex interrelationships these parameters to derive a drought index. A *drought index* is a numerical standard based on water-balance or hydrological models and professional judgment (i.e., the US Drought Index) (Svoboda et al. 2015). A drought index objectively compares cumulative effects of a prolonged and abnormal moisture deficiency and recurrence probability from region to region and historical drought to current conditions (Heim 2002; Svoboda and Fuchs 2016; Zargar et al. 2011).

Communication of climate anomalies using drought indices can facilitate the planning the development of water resources as part of drought risk management (Wilhite 2000). *Duration* is the length of a drought, usually of a minimum of two to three months to become established and continuing for months to years. *Magnitude* is the accumulated deficit of water (e.g., precipitation, soil moisture, or runoff) below some threshold during a drought period.Drought magnitude is closely related to the *timing* of the onset of the precipitation shortage, its intensity, and the duration of the event*.* *Intensity* is the ratio of drought magnitude to duration (Zargar et al. 2011). The degree of a precipitation shortfall and the severity of associated impacts are often measured by a departure from expected or average normal precipitation for a period ranging from one to twelve or more months. Drought intensity and duration determine the extent of drought impact (Wilhite 2000). *Geographic extent* is the areal coverage of the drought which is variable during the event (Zargar et al. 2011). *Drought frequency* or average return period is defined as the average time between drought events that have a severity that is equal to or greater than a threshold (Zargar et al. 2011). *Drought impacts* are defined as an observable loss or change at a specific time because of drought. Along with precipitation deficit, *drought indicators* are combinations of climate parameters: evapotranspiration, temperature, streamflow, groundwater and reservoir levels, soil moisture and snowpack (Svoboda and Fuchs 2016).

*Meteorological drought* is an extended precipitation deficit over an extended period between the actual depth of precipitation received and the expected precipitation depth (Heim 2002). Meteorological drought, which can develop quickly and end abruptly, leads to other types of drought. Agricultural drought can rapidly follow a meteorological drought, particularly during a period of high temperatures and windy conditions (Heim 2002; Wilhite 2000). Agricultural drought, defined by sustained soil moisture deficits, leads to low recharge from the soil to surface and ground waters and may result in hydrological drought.

*Agricultural drought* “is typically defined as a period when soil moisture is inadequate to meet evapotranspiration demands to initiate and sustain crop growth” (Changnon 1987). Soil moisture availability is the difference between actual and potential evapotranspiration (Tate and Gustard 2000). The potential evapotranspiration (PET) equals the actual evapotranspiration (AET) when an adequate supply of moisture in the soil is available to meet vegetation moisture demands. Otherwise, the actual evapotranspiration is less than the potential evapotranspiration. While solar radiation is the dominant factor for evapotranspiration, direct measurements of solar radiation are often unavailable; and mean daily temperature, latitude, and time of year are used to approximate PET. Soil infiltration rates, soil moisture capacity, and the magnitude and timing of precipitation (Heim 2002; Lake 2011). Wilhite (2000) suggests an operational definition of agricultural drought by comparing precipitation to AET to determine the rate of soil water depletion, then expressing the relationship on soil moisture effects on plant development.

*Hydrological drought* emphasizes interactions between the natural characteristics of meteorological drought and the human activities that depend on precipitation to provide adequate water supplies to meet societal and environmental demands (Wilhite et al. 2014). Hydrological drought is “a period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance” (AMS Council 2013). A hydrological drought has two components: surface water drought and groundwater drought, “with the latter lagging well behind surface water drought in both commencing and finishing” (Bond et al. 2008).

Hydrological drought determination is based on the effects of the precipitation shortfall on the surface or subsurface water supply, rather than the magnitude of the precipitation deficiency (Dracup et al. 1980; Wilhite 2000). Antecedent soil moisture and aquifer conditions, hot temperatures, low relative humidity, and desiccating winds are other factors that may result in agricultural and hydrological droughts following a short-term absence of precipitation (Heim 2002). Because time elapses before precipitation deficiencies become evident as reduced streamflow, reservoir, and groundwater levels, hydrological drought, is often out of phase with the occurrence of meteorological and agricultural drought. A hydrological drought may continue for months or years beyond the termination of other drought types because of the long time needed to recharge reservoirs or groundwater (Wilhite 2000).

Hydrological drought designation is often based on streamflow (Heim 2002) because streamflow integrates hydrologic processes at the watershed level. Streamflow at the watershed level includes *direct runoff* from the ground surface to a channel, *interflow* of water into the stream channel from saturated soils, and *base runoff* from groundwater outflow. Reduced stream flows in upstream segments of a basin may result in lower reservoir and groundwater levels at downstream locations, even though meteorological drought does not extend to lower portions. Reduced streamflow impacts public water supply, hydroelectric power production, recreation, transportation, and agriculture, leading to conflicts between upstream and downstream water users (Wilhite 2000).

Quantification of hydrologic drought impacts are further complicated by multiple and often competing uses of stored water, such as irrigation, recreation, tourism, flood control, hydroelectric power production, domestic water supply, protection of endangered species, and ecosystem preservation. Timing between meteorological drought and hydrological drought depends on watershed storage and recharge rates. Recovery from a hydrologic drought recovery lags the return to normal meteorological conditions with a length of the lag related to the groundwater recharge rate that varies with watershed geology and vertical connectivity (Wilhite et al. 2014).

*Ecological drought* is defined as a shortage of water causing stress on ecosystems, adversely affecting the life of plants and animals (Lake 2011). Drought stress is a ramp disturbance that steadily builds in strength and spatial extent as water availability declines (Humphries and Baldwin 2003). While hydrology fundamentally influences ecosystem dynamics, life history strategies, and diversity patterns in streams (Schriever et al. 2015), water workers have only recently identified ecological drought as a disturbance. Stream channel water levels (e.g., stream stage) drops during a hydrologic drought leading to a weakening of lateral connectivity as water recedes from the riparian and littoral zones and backwaters (Boulton, 2003). Hydrological drought results in a stage reduction caused by decreased lateral connectivity as waters recede from the riparian and littoral zones and backwaters, and groundwater flow. Flow reduction causes several abiotic changes including reduced organic C, N, and P inputs from the riparian zone, higher water temperatures caused by reduced riparian shading, high air temperatures, increased salinity, alkalinity, pH, Mg/Ca ratios, hypoxic conditions, and decreased water clarity. A stream may become intermittent later in a hydrologic drought, and in streams with high particulate organic matter concentrations "blackwater conditions" can increase turbidity (Lake 2011; Russell and Johnson 2007). The abiotic effects of hydrological drought often result in stream ecosystem changes, including increases in filamentous algae and decreased heterotrophic production. The ecologic response depends on the magnitude of the precipitation drought, streamflow permanence, and ecosystem resiliency (Bonada et al. 2007; Bond et al. 2008; Humphries and Baldwin 2003; Resh et al. 2013). Several authors have distinguished predictable *seasonal drought,* allowing for evolutionary or life history adaptations to dry periods, from an unpredictable *supra-seasonal* drought that can result in abrupt long-term changes in community structure (Boersma et al. 2014; Bogan et al. 2013; Humphries:2003tna Lake 2011).

**Methods for Assessing Hydrological Drought**

The World Meteorological Organization (WMO) recommends the use of drought indices for measuring meteorological, agricultural and hydrologic drought magnitudes (Hayes et al. 2011). The recommended drought indices are the Standardized Precipitation Index (SPI) for meteorological drought, the Standardized Precipitation Evapotranspiration Index (SPEI), another soil moisture or water balance index, or the normalized difference vegetation index (NDVI) for agricultural drought. The WMO discussed the potential for use of the streamflow drought index (SDI) but did not come to a consensus on a single hydrological drought index. The WMO has not developed recommendations for ecological drought.

Drought monitoring in regions where drought occurs mainly because of precipitation variability is well-represented by SPI because the index measures the total precipitation deviation from normal over a monthly or longer averaging period (Fiorillo and Guadagno 2009; Khan et al. 2008; Vicente-Serrano and López-Moreno 2005). SPI has a solid theoretical development, is robust to missing data, and is characteristic of a moving process (Guttman 1999; Heim 2002; Redmond 2002; Svoboda and Fuchs 2016). SPI index values are normally distributed, uniquely related to the probability of occurrence and can be used to calculate a running precipitation deficit to indicate drought duration and intensity (Tsakiris et al. 2006). Since SPI is normalized, it is comparable across wetter and drier locations, time periods and scales (Tigkas et al. 2014; Vicente-Serrano et al. 2012). Different drought types can be identified by SPI, which is a valuable property of the index because hydrologic systems (i.e., precipitation, soil moisture, streamflow), and regions (i.e., headwaters, valley fill, karstic) can respond to drought conditions at different time scales (Vicente-Serrano and López-Moreno 2005). Heim (2002), and Svoboda and Fuchs (2016) suggest the following time-steps for SPI calculations for different drought types: one to three months correspond with meteorological drought, three to six months correspond with agricultural drought, and time steps of twelve months or longer correspond with hydrological drought. The SPI requires 20 to 30 years of time series data with additional years of data having more extreme wet and extreme dry observations resulting in more robust results (Guttman 1999; Svoboda and Fuchs 2016).

The SPI is a dimensionless index that relates dry and wet periods to frequency and duration. SPI transforms a long-term precipitation record to standardized series with an average of zero and a standard deviation of unity. More negative numbers indicate high intensity and less probable dry events, and, correspondingly, more positive numbers indicate high intensity and less probable wet events (Svoboda and Fuchs 2016). I provide the mathematical basis for SPI following Vicente-Serrano’s description fitting observations to the Pearson III distribution (Vicente-Serrano 2006). McKee's (1993) original method used a two-parameter gamma distribution with parameters estimated by the maximum likelihood method; however, Guttman (1999) found Pearson III distribution provides the better goodness of fit. The probability density function for a Pearson III distributed variable is expressed as:

where α, β and γ are the shape, scale and origin parameters, respectively, for precipitation values *x* > 0; and (β) is the Gamma function of β. The Pearson III distribution parameters are obtained from L-moment ratios. The first L-moment ratio, τ2 = λ2/λ1 is analogous to the coefficient of variation, and the second and third L-moment ratios, τ3 = λ3/λ2 and τ4 = λ4/λ2 are analogous to coefficients of skewness and kurtosis, respectively

(Hosking 1990). L- moments are linear combinations of probability weighted moments (PWM), which can be calculated using the formulae:

λ1 = α0

λ2 = α0 − 2α1

λ3 = α0 −6α1 +6α2

λ4 = α0 −12α1 +30α2 −20α3

so PWM of order *s is* calculated using:

where *xi* is the data from a given precipitation series, *Fi* is the frequency estimator, *i* is the range of observations arranged in rising order, and *N* is the number of data points (Vicente-Serrano 2006)

If τ3 ≥ 1/3, then τ*m* = 1 − τ3 and β can be obtained using the formula:

If τ3 < 1/3, then τ*m* = 3π τ32and β can be obtained using the following expression:

The probability distribution function of *x* given by and are calculated analytically:

Pearson III distribution is not defined for *x* = 0; however, precipitation series may include months in which there is no precipitation. An adapted statistic *H*(*x*) can be calculated using the following formula:

where *q* is the probability of zero precipitation and is calculated as *m*/*n*, where *n* is the total number of months and *m* is the number of months with no precipitation. The cumulative probability *H(x)*, is then transformed to the standard normal random variable *z* with mean zero and variance of one. Fortunately, SPI can be calculated using either a stand-alone package available through the University of Lincoln Drought Mitigation Center webpage (Svoboda and Fuchs 2016) or using the SPEI package (Beguería and Vicente-Serrano 2017) in the R statistical programming language (R Core Team 2018).

McKee et al. (1993) state that drought begins at an SPI of zero or less; however, some researchers choose a drought threshold that is less than zero, but not quite −1 (Svoboda and Fuchs 2016). The drought event continues until SPI reaches a value greater than zero. A potential weakness of the SPI is that the index by itself may not account for a particular region's overall water balance and water use if different temperatures occur for similar SPI values (Svoboda and Fuchs 2016). Drought magnitude is the positive sum of the SPI for each month during the drought event (Hayes et al. 2007). A composite table of narrative drought classes is shown below with DI (drought index) indicating SPI (meteorological drought), SPEI (soil moisture drought), or SDI (hydrological drought) (Lloyd-Hughes 2002; Tigkas et al. 2014)

Table 5: Drought states, descriptions, index values and frequencies

|  |  |  |  |
| --- | --- | --- | --- |
| Drought State | Description | Criterion | Percent frequency |
| 0 | Extremely wet |  | 2.3 |
| 0 | Very wet |  | 4.4 |
| 0 | Moderately wet |  | 9.2 |
| 0 | Mildly wet |  | 34.1 |
| 0 | *Non-drought* |  | *50.0* |
| 1 | Mild drought |  | 34.1 |
| 2 | Moderate drought |  | 9.2 |
| 3 | Severe drought |  | 4.4 |
| 4 | Extreme drought |  | 2.3 |

The Standardized Precipitation Evaporation Index (SPEI) is the preferred index for the overall water balance and water use of a region, in which temperature variation is non-stationary, or potential evapotranspiration (PET) is non-negligible (Svoboda and Fuchs 2016). The SPEI represents departures in the difference between water availability and the atmospheric water demand, the "climate water balance." SPEI has been shown to be more effective than SPI in correlating streamflow deficits, reservoir storage, and water demand, and therefore, is assumed to provide a reasonable estimate of soil moisture (Lorenzo-Lacruz et al. 2010; Svoboda and Fuchs 2016). A potential weakness of the SPEI is that the index requires a serially complete dataset for both temperature and precipitation (Svoboda and Fuchs 2016). The SPEI algorithm calculates effective precipitation by subtracting PET from precipitation, with PET estimated by the Thornwaite (Thornthwaite 1948), Penman-Monteith (PM) (Walter et al. 2000), or Hargreaves equation (Droogers and Allen 2002; Hargreaves and Samani 1985).

The SPEI is mathematically similar to SPI, except that the input for the index is effective precipitation (Beguería et al. 2013; Svoboda and Fuchs 2016); and a log-logistic distribution provides the better goodness of fit than the gamma distribution in the estimation of SPEI values (Vicente-Serrano et al. 2010a). I provide below the mathematical basis for SPEI following Beguería et al. (2014); Vicente-Serrano et al. (2010a, 2010b, 2011, 2012) provide a complete description of the theory behind the SPEI, the computational details, and comparisons of SPEI with other drought indicators. The probability distribution function of a variable *D* according to a log-logistic distribution is given by:

where *α, β* and *γ* represent the scale, shape, and location parameters that are estimated from the sample D, which is the difference between precipitation and PET. An unbiased plotting estimator based on probability-weighted moments (Hosking 1986) is the default plotting position method implemented in the SPEI package in R as:

Nalbantis and Tsakiris (Nalbantis and Tsakiris 2009) derived the standardized streamflow index (SDI) from the SPI to identify hydrologic drought. The SDI uses monthly streamflow values and the methods of normalization associated with SPI for developing a drought index based upon streamflow data (Svoboda and Fuchs 2016). However, it may be difficult to select the most appropriate distribution to calculate a streamflow drought index over a wide area because topography, lithology, vegetation, and human management may increase flow variability within a basin and change statistical properties of downstream reaches, (Vicente-Serrano et al. 2012). I provide the mathematical basis for SPI following Tigkas (2014). The cumulative streamflow volume *Vi k* is calculated from the equation:

for monthly streamflow volumes *Qi j*, in which *i* denotes the hydrological year, *j* the month within that hydrological year (*j* = 1 for October and *j* = 12 for September), and *k* the reference period, *k* = 1 for October-December, *k* = 2 for October-March, *k* = 3 for October-June, and *k* = 4 for October-September. The Streamflow Drought Index (SDI) is defined for each reference period *k* of the *i*-th hydrological year based on the cumulative streamflow volumes *Vi,k* by:

in which *Vk* and *sk* are the mean and the standard deviation of cumulative streamflow volumes of the reference period *k.* The resulting index is equal to the standardized streamflow volume. To reduce skewness and because streamflow tends to be well-approximated by a Gamma distribution, Nalbantis and Tsarkaris recommend logarithmic transformation of streamflow volume is before SDI calculation such that

where

***Index of Biotic Integrity & Sustainable Growth***

*Sustainable growth means to design for scarcity by maximizing the ratio of socioeconomic benefits to environmental costs.*

*Water is a scares resource in the West*

*IBI indices link water quality standards to stream biotic integrity.*

*IBI indices can be used*

*IBI indices for each physiographic region that are robust to natural flow variability and sensitive to land use change that would*

*Maximize ratio of societal benefits to environmental costs*

*Mitigate environmental costs*

*allow policy-makers*

*cost-benefit*

*with information to manage risk.*

*on restoration priorities and*

*What are water quality standards?*

*What is a water use? Spiritual use?*

*Environmental vs ecological?*

**What the Methods are for Ecological Drought**

Streams are increasingly understood as the central agent at the interface of the co-evolution of climate, geology, topography and ecology and their transient and long-term responses to change (Hrachowitz et al. 2014; Thorp 2014). Hydrological systems respond differently at various time scales because of lithologic and geometric watershed differences (Lopez-Moreno et al. 2013). Effective prediction of streamflow responses to drought is increasingly understood in managing for sustainable water supply (Vörösmarty et al. 2000) and water quality (Kundzewicz et al. 2008).

Hydrology fundamentally influences ecosystem dynamics, life history strategies, and diversity patterns in streams (Belmar et al. 2013; Bonada et al. 2007; Gallart et al. 2012; Ledger et al. 2013a; Lytle and Poff 2016; Olden and Poff 2003). Differences in streamflow dynamics result in strong habitat-filters favoring taxa adapted to particular hydrological extremes as well as habitat generalists capable of persisting in a variety of habitats (Schriever et al. 2015). Ecological community composition can remain stable for a long time and rapidly transition into an alternative stable state (Bogan and Lytle 2011; Bogan et al. 2015; Yodzis 1989). Hydrologic drought results in a progressive habitat loss, depletion of food resources, and increased predation and interspecific competition that puts aquatic biota under stress (Bond et al. 2008).

Stream biota exhibit a variable response to seasonal and supra-seasonal drought; tending to exhibit high resistance to seasonal drought, and low resistance and variable resilience to supra-seasonal drought (Boersma et al. 2014; Bogan et al. 2015). Native biota in drought-prone systems has evolved resistance or resilience traits that allow them to survive predictable drought (Boersma et al. 2014; Lytle and Poff 2016; Robinson et al. 1992; Stanley et al. 1994; Stubbington et al. 2016), including flow cessation resulting in >95% habitat contraction (Bogan and Lytle 2007). Biota with resistance traits to ‘sit out the drought' either possess desiccation resistant life-history stages or utilize ‘refugia,' habitats that offer less harsh conditions in an otherwise drought-affected environment (Adams and Warren 2005; Arthington et al. 2005; Bond et al. 2008; Stubbington 2012). Biota with resilience traits have mechanisms allowing widespread and rapid dispersal among suitable habitat patches (Bond et al. 2008; Boulton 2003; Fritz and Dodds 2004; Humphries and Baldwin 2003). Community recovery, particularly in perennial streams, tends to be rapid following seasonal drought, with resilience mechanisms responsible for a greater portion of recovery (Datry et al. 2014). However, supra-seasonal drought may cause stream intermittency and community turnover in which short-lived (<1 year) strong dispersers replace relatively long-lived (≥1 year) weak dispersers. The regime shift may delay or preclude recovery to pre-drought conditions, and potential for community recovery from extreme drought decreases with greater drought magnitude and duration, hydrologic connectivity, and proximity to drought refuges (Bogan et al. 2015; Robson et al. 2011).

A literature review returned some prior work on stream community alteration and recovery from drought in Great Plains streams. Dodds (2004) summarized macroinvertebrate recovery in the Great Plains following drought. He found community composition immediately following a drought is dominated by taxa with drought-resistant traits with a general colonization sequence reflecting life-cycle length. Initial recruitment following a drought is made up of upper-reach drift of resistant taxa plus resilient taxa, such as chironomid midges, with high growth and reproduction rates that aerially colonize stream reaches. Larger invertebrates with slower lifecycles, stoneflies and caddisflies, tend to arrive one to two months post-drought (Dodds et al. 2004).

Miller and Golladay (1996) investigated effects of seasonal drought the macroinvertebrate community in an intermittent stream in southeastern Oklahoma. Invertebrate density in pools doubled during a gradual five-month summer drying event and increased six-fold during a spring drying event. The density increase was dominated by biting midges (ceratopogonids) and nonbiting midges (chironomids) and aquatic worms (oligochaetes) during both drying events. Small squaregill mayfly (caenids), which were the major taxon in riffles, density in pools increased during the spring drying event, but did not increase during the summer drying event. Post-drought recovery in riffles was first dominated by black flies (simuliids), until three-months later when rolled-winged stoneflies (leuctrids) became the most dominant taxon. Water scavenger (hydrophilid) beetle density did not substantially change during drought (Miller and Golladay 1996).

Research in semi-arid regions outside the Great Plains (Bêche et al. 2009; Bogan et al. 2015; Pace et al. 2013), arid regions (Sponseller et al. 2010), and mesocosms (Ledger et al. 2013a; b) provides other analogs for Pine Ridge reservation stream community alteration and recovery from drought. Resh, Bêche, and others (2013) provide general description of the effects of drought stress in their synthesis of community change in Mediterranean-climate streams in California. They found severe drought resulted in macroinvertebrate community shifts, and rapid changes in age-structure from multi-cohort to single-cohort that recovered slowly (~10 years). Bogan and Lytle (2011) found temperature and pool area, and conductivity accounted for nearly 90% of variance as a stream shifted from perennial to intermittent during a supraseasonal drought. Pre-drought conditions were characterized by a diverse low-resilience and long-lived community of skimmer dragonflies (libellulids), giant water bugs (belostomatids), broad-shouldered water striders (veliids), and beetles (coleopterans: dryopids, dytiscids, haliplids). The post supra-seasonal drought community was equally diverse. However, short-lived vagrile taxa characterized the post-drought community of baetids, veliids, water striders (gerrids), diving water beetles (dytiscids), and minute moss-beetles (hydraenids) (Bogan and Lytle 2011).

Bêche and others (2009) used indicator species analysis to characterize successional communities pre-drought and following a supra-seasonal (1.3% recurrence interval) drought. They found the dominant taxa for the pre-drought period included northern and mortar-joint casemaker caddisflies (limnephilids and odontocerids), creeping water beetles (naucorids), and stratiomyids. Post-drought dominant early successional taxa included hydroptilids, and stratiomyids followed by mid-successional dytiscids, hydrophilids, and sandflies (ceratopogonid), and late-successional comb-mouthed mayflies (ameletids), baetids, and green stoneflies (chloroperlids) became dominant in late succession. Crane flies (tipulids) were drought indicators in all successional stages. They concluded there was no evidence of a complete post-drought community recovery following the supra-seasonal drought (Bêche et al. 2009)

Pace and others (2013) studied the drought response of mayflies, stoneflies, and caddisflies, collectively (EPT) in wet- and dry- Mediterranean climate streams in a Catalonia, Spain between 1995-2008. They found the EPT compositional shifts from drought were less extensive in the wet mesoclimate streams that experienced a less-severe drought and had greater baseflow. The EPT community in wet mesoclimate streams shifted from a pre-drought community of prong-gilled mayflies (leptophlebiids), chloroperlids, and nemourids to a post-drought community of baetids, stripetail stoneflies (perlodids), and saddle casemaker (glossosomatid), limnephilid and bushtailed (sericostomatid) caddisflies. The EPT community in dry mesoclimate streams shifted from a pre-drought community of flat-headed mayflies (heptageniids) and hydropsychids to a post-drought community of baetids, limnephiloids, hydropsychids, and net-tube caddisflies (psychomyiids)

Bogan, Boersma and others (2014, 2015) identified drought-intolerant and drought-tolerant taxa. The seasonal-drought intolerant taxa included small minnow(baetid) mayflies, small winter (capniid) and spring (nemourid) stoneflies, net-spinning (hydropsychid) caddisflies, riffle (elmid) and water-penny (psephenid) beetles, and naucorids. Seasonal drought-adapted (e.g., resistant) taxa included calamoceratid caddisflies, diving beetles (dytiscids), giant water bugs (belostomatids), true flies (dipterans; including ceratopogonids, chironomids, corydalids, simuliids, stratiomyids and tabanids), and non-insects (copepods, amphipods, and mites). Instream colonizers included primitive-minnow (siphlonurid) mayflies, tube-case (limnephilid) caddisflies, capniids, net-winged midges (blepharicerids). Drought-resilient early-areal colonizers following seasonal drought including backswimmer and water-boatman (notonectid and corixid) water bugs, and diving and water scavenger (dytiscid and hydrophilid) beetles. Drought-resilient late-areal colonizers included hydroptilids, spread-winged damselflies (lestids), and drain flies (psychodids).

Bogan and others (2015) describe macroinvertebrate community trajectories following extreme supra-seasonal droughts as having little effect on aquatic invertebrate taxon richness, but significantly altering community composition from a pre-drying community dominated by relatively large, long-lived and sedentary taxa to smaller, shorter-lived and highly vagile taxa, including strong aerial dispersers post-drought. They documented an eight-year (2001-2009) community transition in an ecologically isolated series of travertine (limestone springs) pools in south-eastern Arizona. The pre-drought community was diverse and characterized by long-lived, poor-dispersing, taxa made up of large-sized water bugs, libellulids, calamoceratid caddisflies; and mid-sized veliids, whirligig and creeping water beetles (gyrinids and halipids). The mid-drought community was dominated by mosquito larvae (culicids). The post-drought community was characterized by hydrophilids, dytiscids, and veliids. Three common species and three uncommon species were extirpated from the post-drought community (Bogan and Lytle 2011), potentially as a result of low resilience (e.g. low dispersal from refugea) (Phillipsen et al. 2015).

Bogan and others (2015) synthesized findings from geographically separated semi-arid harshly intermittent desert mountain streams to update a conceptual model of post-drought recovery trajectories developed by Boulton (2003) to include seasonal vs. supra-seasonal drought. The model predicts that low isolation streams following a predictable, mild seasonal drought should exhibit high species richness as lotic and lentic taxa ‘time-share' between wet and dry season. Highly isolated streams following a low severity drought should exhibit reduced species richness as weak dispersers experience stochastic extirpations. As some sensitive taxa and weak dispersers disappear in moderately isolated streams following a moderate severity drought should experience reduced species richness. Non-isolated streams following a high severity drought should experience reduced species richness as populations of resistant taxa recover and colonists from nearby refuges return. Highly isolated streams experiencing a severe drought should experience substantial reductions in species as only the most resistant taxa remain (Bogan et al. 2015).

Storey (2016) investigated macroinvertebrate community compositional differences drought in forested and pasture-land intermittent streams in New Zealand. Perennial forested streams were dominated by leptophlebiid and coloburiscid mayflies, Stony-cased (pycnocentrod) and conoesucid caddisflies, and elmids, with lesser abundances of chironomids, and austroperlid and gripopterygid stoneflies. Perennial pastureland streams were similar to perennial forested streams with the addition of higher abundances of hydroptilids. In contrast, forested and pastureland intermittent streams were dominated by gastropods, chironomids, simuliids, and oligachaetes, with lesser abundances of leptophbiid mayflies, polycentropodid caddisflies, ostracod and cladoceran shrimps. Oligochaetes, chironomids, and nematodes increased during dry years, while mayflies, caddisflies and beetles decreased in intermittent streams, with ‘weeks of no flow’ as the strongest predictor variable.

Sponseller and others (2010) studied macroinvertebrate community recovery following spring floods from 1983–1999; including a supra-seasonal 1989-1990 drought in an intermittent desert stream in Arizona and found antecedent flow conditions were the best predictor of macroinvertebrate community structural changes. They found baetid, snail-case caddisfly (helicopsychid), tipulid, and stratiomyid abundance decreased following drought and recovered during wet periods (e.g., drought resilience). Hydropsychids, which were abundant before a supra-seasonal drought, were extirpated. Gastropod and ceratopogonid abundance increased during drought, most likely because of their tolerance to increased water temperature and corresponding hypoxic conditions. The early colonizers (e.g. r-selected taxa), chironomids and ceratopogonids, were dominant in early post-drought successional stages but were replaced in dominance in later successional phases by more slowly-growing hydropsychids, helicopsychids, and gastropods.

Ledger and others simulated the effect prolonged drought on the structure and functioning of complex food webs with a two-year experiment using stream mesocosms (Ledger et al. 2013b; a). The results of their experimental study are consistent with the results of field studies summarized above: drought triggered losses of species, especially engulfing macropredators and changes in trophic interactions resulting from top-down food web erosion leading to their partial collapse. The recurrent drying disturbances resulted in a macroinvertebrate community shift to transient communities dominated by relatively few, r-selected (e.g., multivoltine) and smaller-bodied species (>50% decline in secondary production), and functional feeding group increases in gastropod grazers. Compensatory dynamics sustained total macroinvertebrate densities (e.g., count per sampling effort), in part through increased amorphous detritus fluxes to chironomids. Ledger and others found no evidence that drought promoted trophic generalists over specialists through indirect effects on food supply. Instead, drought increased physiological stress, with large-bodied species being most strongly affected, directly increasing consumer mortality. Similar regime shifts following a supra-seasonal drought were reported in a UK chalk stream. The drought reduced taxa richness and abundance, particularly baetids, ephemerellids, small squaregill mayflies (caenids) hydropsychids, sericostomatids and leptocerids (Stubbington et al. 2009).

**Summary**

An inherent challenge to effective watershed management is that aquatic communities are reliant on streamflow that varies in time and space. A second challenge is the management of water resources among stakeholders as increasing human populations and declining water resource (groundwater) availability are increasing overall water resources demand. These related challenges are most pressing during times of drought. The emergent topic of ecological drought provides a context to link aquatic communities with hydrologic process. I plan to contribute to our understanding of ecological drought by testing the hypothesis that drought is a key driver of macroinvertebrate community regime shift in Northern Great Plains streamsand incorporate study results into the Oglala Sioux Tribe watershed protection plan. I propose to use the most current drought indices, geographic information systems (GIS) and machine learning techniques to identify relationships among different drought types in watersheds of different geologies within Pine Ridge Reservation administrative boundaries. Next, I plan to use statistical approaches from community ecology to identify the extent of aquatic community changes are caused by drought. Last, I plan to identify drought-resilient taxa, incorporate them into indicators of biotic integrity (IBI) metrics, and adopt the updated metrics into the Oglala Sioux Tribe’s watershed protection plan. I expect the results of my research will depend on whether a drought is seasonal, resulting in a long-term recovery, or supraseasonal, resulting in an altered community. My original contribution to the body of work on streamflow drought is the quantification of drought intensity into aquatic community regime shifts. These results are potentially impactful to the water resources community because it represents a novel approach to link the natural flow regime into IBI metric determination.

**Introduction**

The natural flow history of a stream includes high flow periods, wet conditions, normal conditions, dry conditions, and low flow periods; each of which elicits distinct responses from the landscape and the biological community (Thorp 2014). Sharp, rapid changes in stage (flow pulses or floods) caused by a precipitation excess characterize high flow periods, while steadily decreasing flow and occasionally sharp step-like events (thresholds) of zero flow characterize low flow periods (Lake 2011). Foods and low flow periods are disturbances that can result in either population changes and subsequent recovery or irreversible changes in the biological population (Palumbi et al. 2008; Yodzis 1989). Droughts are temporary climate features “determined relative to the prevailing normal conditions of a locality” (Lake 2011) that differ from aridity, which is a normal climate feature defined by low-average precipitation, available water, or humidity. (AMS Council 2013; Heim 2002). Droughts are “disturbance(s) of deficiency rather than excess” that are characterized by their severity, intensity, duration, spatial extent, frequency (probability of recurrence) and timing (initiation and termination in calendar time)” (Bond et al. 2008). “We understand how freshwater communities persist during normal or high flows better than we understand the ecological effects of droughts” (Lake 2011).

Naturally flowing streams and their valleys (i.e., watersheds, catchments, basins) experience high flow periods (floods), normal flow periods, and low flow periods (droughts). Effective management of stream-valley systems requires understanding to what extent freshwater communities change as a result of rare streamflow events, floods and droughts, as well as to what extent human activities influence freshwater communities. Floods and droughts are extreme hydrologic events and ecological drivers for freshwater communities; with droughts resulting in substantial stress to freshwater communities. I propose to test the hypothesis that **drought is a key driver of macroinvertebrate community regime shift in Northern Great Plains streams** and incorporate results into the Oglala Sioux Tribe watershed protection planning process.

In recent years the research community has defined operational drought types and criteria, and has identified species adaptations to predictable seasonal drought (Bonada et al. 2007; Svoboda and Fuchs 2016; Williams and Trexler 2006). However, quantitative approaches to linking ecosystem responses to supra-seasonal drought are lacking (Lake 2011). Ecological drought, defined as "a prolonged and widespread deficit in naturally available water supplies — including changes in natural and managed hydrology — that create multiple stresses across ecosystems" (Svoboda et al. n.d.) is a topic of increased research consideration. Managers and policy makers observe and predict present and future streamflow regime changes from perennial to intermittent streamflow resulting from changes in land and water use and climate (Leigh et al. 2016). I propose a novel approach to evaluate seasonal and supra-seasonal droughts and their effects on the macroinvertebrate community in a semi-arid ecosystem using existing drought indices and tools, Standardized Precipitation Index (SPI), Standardized Precipitation Evaporation Index (SPEI), Streamflow Drought Index (SDI), and the Drought Monitor. The results of the proposed work have potential National and global significance by improving the ability of watershed managers to establish differential Indicators of Biological Impairment (IBI) metrics based on antecedent moisture conditions.

**Study Area Description**

The study area is the 5,600 mi2 (9,000 km2) Pine Ridge Reservation (PRR) of the Oglala Sioux Tribal Nation. The study area, located within the Region 5 climate division in South Dakota, is classified as a semi-arid mid-latitude cold steppe climate (BSk) except the extreme south-eastern portion of the study area, which is classified as a dry-summer subarctic climate (DSc) (Kottek et al. 2006).The

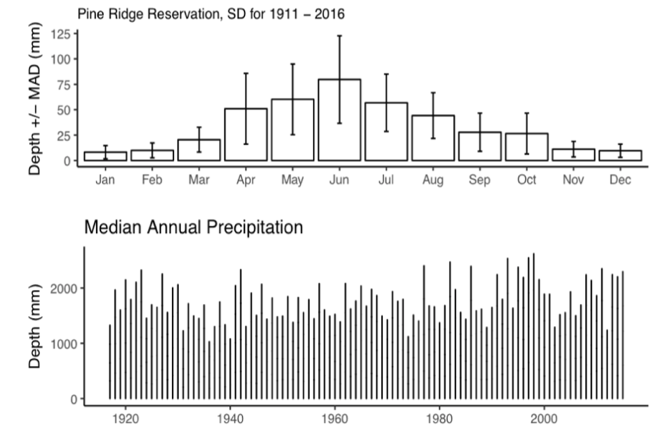


Figure 2: Monthly and annual precipitation variation for the Pine Ridge Reservation

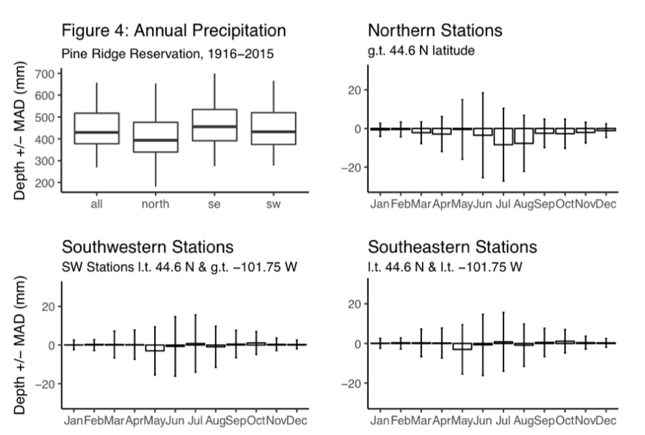


Figure 2: Spatial variation among Pine Ridge Reservation weather stations

median precipitation of the study area varies spatially, and temporally (Figures 1 & 2), with average annual depth ranging from about 15.8 inches (400 mm) in the north to about 17.2 (450 mm) in the southeast (Bryce et al. 2003). Mean January, and July minimum and maximum temperatures are 90 and 350, and 580 and 910 Fahrenheit, respectively. The growing season, expressed as the number of frost-free days, ranges from 120-140 days. Table 1 identifies the long-term weather stations nearest to the study area.

The study area is near the center of the contiguous United States, geographically located between 430 and 43.80north latitude with an elevation of over 3,700 ft (1,130 m) in the southwest to about 2,250 ft (690 m) above sea level in the northeast (Bryce et al. 2003). The physiography, which is typical for the Northern Great Plains, is as mesic/ustic rolling shale, siltstone, and sandstone plains punctuated by occasional buttes and badlands. The vegetation, which is influenced by limited moisture in part from the Black Hills rain shadow, is dominated by mixed-grass prairie with Ponderosa Pine savannah limited to north facing slopes. Because of erratic interannual precipitation patterns and limited irrigation availability, cattle ranching is the predominant land use in the region. Crops are limited to minor alfalfa, hay, and wheat in the north, and irrigated corn, millet and sugar beet crops where sandy soil in the southern portion of the study area limits non-irrigated agriculture.

Table 1: South Dakota Drought Risk Atlas stations on or near the Pine Ridge reservation

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Station ID and Name | Location | Homogenous Division | Climate Division and notes | Time Period |
| 396937  RAPID CITY RGNL AP | Lat: 44.043  Lon: -103.054  Elev. (ft): 3160  Pennington, SD | Wyoming – South Dakota | Division 5 | 1/1/1949 - 12/31/2016  Years on Record: 67  Percent Complete: 95% |
| 394007  HOT SPRINGS | Lat: 43.438  Lon: -103.474  Elev. (ft): 3560  Fall River, SD | Wyoming – South Dakota | Division 4 | 1/1/1908 - 12/31/2016  Years on Record: 108  Percent Complete: 95% |
| 396212  OELRICHS | Lat: 43.188  Lon: -103.237  Elev. (ft): 3348  Fall River, SD | Wyoming – South Dakota | Division 5 | 1/1/1957 - 12/31/2016  Years on Record: 59  Percent Complete: 95% |
| 394184  INTERIOR 3 NE | Lat: 43.748  Lon: -101.941  Elev. (ft): 2440  Jackson, SD | Central South Dakota - Nebraska | Division 5  The station is discordant in Winter | 1/1/1956 - 12/31/2016  Years on Record: 60  Percent Complete: 95% |
| 391972  COTTONWOOD 2 E | Lat: 43.961  Lon: -101.861  Elev. (ft): 2414  Jackson, SD | Central South Dakota - Nebraska | Division 5 | 6/1/1909 - 12/31/2016  Years on Record: 107  Percent Complete: 95% |
| 394983  LONG VALLEY | Lat: 43.46  Lon: -101.496  Elev. (ft): 2470  Jackson, SD | Central South Dakota - Nebraska | Division 5 | 1/1/1936 - 12/31/2012  Years on Record: 76  Percent Complete: 95% |
| 393574  HARRISON | Lat: 43.165  Lon: -101.257  Elev. (ft): 2980  Bennett, SD | Central South Dakota - Nebraska | Division 8 | 10/5/1960 - 12/31/2012  Years on Record: 52  Percent Complete: 95% |

The study area primarily classified into four Level IV ecoregions mostly within the Northwestern Great Plains Level III ecoregion (Table 2): Nebraska Sand Hills, Keya Paha Tablelands, Pine Ridge Escarpment, and White River Badlands (Bryce et al. 2003). The Level IV ecoregion classifications are broadly a result of the underlying regional geology that influences watershed-scale hydrologic process and vegetation structure. The Nebraska Sand Hills is in the south-eastern portion of the study area. The Nebraska Sand Hills region is a mostly treeless region of grass-stabilized Quaternary-age dunes overlying Keya Paha Tablelands sand- and siltstones. The Nebraska Sand Hills are the recharge zone for the High Plains aquifer, with groundwater supporting the relatively constant annual discharge. The Keya Paha Tablelands of the central portion of the study area is level to rolling plains of Miocene-age soft sandstone and siltstone of the Ogallala and Arikaree Formations. A closed-canopy ash-elm riparian overstory shades Keya Paha Tablelands streams. The Pine Ridge Escarpment bisects the study area from the southwest to the northeast and is characterized by alternating ridges and valleys with entrenched channels, rolling plains, tablelands, and Miocene sandstone outcrops of the Arikaree Formation. Closed-canopy ash-elm or Ponderosa forest shades Pine Ridge Escarpment streams. The White River Badlands in the northern portion of the study area is a highly-dissected landscape of eroded walls, escarpments, and perched "sod tables." A dense network of turbid ephemeral streams with limited cottonwood-willow overstories drain the White River Badlands.

Table 2: Pine Ridge Reservation predominant soil order and type, temperatures, and vegetation types

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Ecoregion | Elevation and Relief (feet) | Soil Order | Soil Series | Vegetation Types |
| Nebraska Sand Hills | 2900 – 3500  120 -300 | Entisols (Ustipsamments) | Valentine | Sand associated grasses: Sand bluestem, Little bluestem, Prairie sandreed. Big bluestem and Switchgrass in wetter interdune areas. |
| Keya Paha Tablelands | 2,250 – 3,600  20 - 800 | Mollisols (Argiustolls, Haplustolls), Entisols (Torriorthents) | Anselmo, Kadoka, Keith, Manter, Rosebud, Epping, Keota, Ronson, Vetal. | Blue grama, Sideoats grama, Western wheatgrass, Little bluestem, and Needleandthread |
| Pine Ridge Escarpment | 3,000 – 3,700  50 - 700 | Entisols (Torriorthents), Mollisols (Argiustolls, Haplustolls) | Ogallala, Canyon, Kadoka, Epping, Rock outcrops | Ponderosa pine savannah with eastern redcedar, western snowberry, skunkbush sumac, chokecherry, and rose. Grassland: little bluestem, western wheatgrass, green needlegrass, prairie sandreed |
| White River Badlands | 2,250 – 3,600  20 - 800 | Aridisols (Camborthids), Entisols (Torriorthents), Inceptisols (Ustochrepts) | Conata, Epping, Imlay, Orella, Bufton | Sand sagebrush, silver sagebrush, western wheatgrass, grama grass and buffalograss |

Streams in the study area tend to exhibit a dune-ripple morphology with low-gradient meandering channels (e.g. a glide-run rather than a riffle-pool morphology) and tend to have well-developed floodplains.The Little White River drains Nebraska Sand Hills watersheds. Little White River streams are eastward flowing, ground-water flow dominated, low turbidity, and generally, follow an E5 stream type following the Rosgen classification system (Rosgen 1996). Other streams in the study area originate in Keya Paha Tablelands watersheds and flow northerly, transitioning into Pine Ridge Escarpment watersheds then White River watersheds in the west; and into White River watersheds in the east before their capture by the White River. The stream segments within Keya Paha Tablelands and Pine Ridge Escarpment watersheds exhibit mixed-flow, low turbidity, and C6 or E6 stream-type geometries. Rapid changes in streamflow caused by precipitation events dominate the annual White River Badlands streamflow budget. The rapid stage change rapidly erodes stream channel walls, increases turbidity, and leads to constant stream channel adjustment between C6 – G6 – F6 – E6 morphologies. The USGS operates several streamflow-gaging stations on or near the study area (Table 3).

Table 3: USGS streamflow-gaging stations near the study area

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Station ID | Station Name | Sub-watershed | Ecoregion | Period of Record | Drainage Area (mi2) |
| 06445685 | WHITE R NR NE-SD STATE LINE | Upper White River | Keya Paha Tablelands | 1987-10-01 to 2018-02-07 | 1,367 |
| 06446000 | WHITE R NEAR OGLALA SD | Upper White River | Keya Paha Tablelands | 1943-10-01 to 2018-02-07 | 2,853 |
| 06445980 | WHITE CLAY CR NEAR OGLALA SD | Upper White River Tributary | Keya Paha Tablelands | 1965-10-01 to 1999-09-29 | 375 |
| 06446500 | WHITE R NEAR INTERIOR, SD | Middle White River | Badlands | 1928-10-01 to 2018-02-07 | 4,094 |
| 06446100 | WOUNDED KNEE CREEK AT WOUNDED KNEE, SD | Middle White River Tributary | Keya Paha Tablelands | 1992-06-04 to 1997-09-30 | 73.5 |
| 06446700 | BEAR IN THE LODGE CR NEAR WANBLEE, SD | Middle White River Tributary | Keya Paha Tablelands | 1992-10-01 to 2018-02-07 | 423 |
| 06447000 | WHITE R NEAR KADOKA, SD | Lower White River | Badlands | 1942-07-01 to 2018-02-07 | 4,953 |
| 06447230 | BLACK PIPE CREEK NR BELVIDERE, SD | Lower White River Tributary | Badlands | 1992-04-08 to 2018-02-07 | 273 |
| 06447500 | LITTLE WHITE R NEAR MARTIN, SD | Middle Little White River | Sand Hills | 1938-03-01 to 2018-02-07 | 299 |
| 06449000 | LAKE CR BELOW REFUGE NEAR TUTHILL, SD | Middle Little White River Tributary | Sand Hills | 1938-10-01 to 2018-02-07 | 121 |
| 06449100 | LITTLE WHITE R NEAR VETAL, SD | Lower Little White River Tributary | Sand Hills | 1959-08-01 to 2018-02-07 | 571 |
| 06440200 | SOUTH FORK BAD R NEAR COTTONWOOD, SD | Watershed north of the study area | Sub-humid Pierre Shale Plains | 1988-10-01 to 2018-02-07 | 257 |
| 06441000 | BAD R NEAR MIDLAND, SD | Watershed north of the study area | Sub-humid Pierre Shale Plains | 1945-10-01 to 2018-02-07 | 1,466 |

Macroinvertebrate populations in the study area differ by land use intensity within a basin, ecoregion, and over time. As part of the watershed protection plan of the Oglala Sioux Tribe (OST), macroinvertebrate populations in a subset of approximately 40 watersheds have been sampled annually in 1993-1996, 2008, 2010- present (Table 4). The OST follows the US Environmental Protection Agency (US EPA) recommended Index of Biotic Integrity (IBI) framework for macroinvertebrate sampling (Barbour et al. 1999). Biological monitoring indicates tolerant taxa abundance correlates with increasing land use intensity, taxa diversity inversely correlates with streamflow variability, and tolerant taxa abundance inversely correlates with annual streamflow.

Table 4: Surface water monitoring stations within the study area

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Abbrev | Stream Name(s) | Sub-Watershed | Ecoregion(s) | # Stations | Confluence |
| WHR  WCC | White River  White Clay Creek | Upper White River | Keya Paha Tablelands | 1  3 | White Clay Creek |
| WHR  WOK  POR | White River  Wounded Knee Creek  Porcupine Creek | White River - Wounded Knee | Sand Hills / Escarpment /  Tablelands / Badlands | 1  4  3 | Porcupine Creek |
| WHR  MER  AMH  NFL  RED | White River  Medicine Root Creek  American Horse Creek  No Flesh Creek  Redwater Creek | White River – Medicine Root | Escarpment /  Tablelands / Badlands | 1  3  1  1  1 | Redwater Creek |
| WHR  POT  LOD  COR  BEA  BLC  EAN | White River  Potato Creek  Lost Dog Creek  Corn Creek  Bear Creek  Bear in the Lodge Creek  Eagle Nest Creek | White River – Bear in the Lodge | Tablelands / Badlands | 1  1  1  1  3  2  2 | Eagle Nest Creek |
| WHR  CRA  LON  BUZ  PAS  BLP | White River  Craven Creek  Long Creek  Buzzard Creek  Pass Creek  Black Pipe Creek | White River – Pass | Tablelands / Badlands | 1  1  1  1  3  1 | Reservation Line |
| LWR | Little White River | Little White River | Sand Hills | 4 | Reservation Line |

Fish species richness of the study area is most likely similar to the State of Nebraska with diversity increasing from west to east (Hrabik 2015). Relatively common species include Sand Shiner, Fathead Minnow, Flathead Chub, Shorthead Redhorse, White Sucker, Black Bullhead, White Crappie, Green Sunfish, Bluegill, Black Bullhead (Tinant *unpublished data*). Species richness is low in the White River Badlands, which have records of historically supporting trout populations and other cool-water fish including Longnose Dace, Creek Chub, Mountain Sucker and Goldeye. The Pine Ridge Escarpment has higher fish diversity, supporting cool-water fish populations including trout, dace, and suckers in the 1990s. Fish species in the Pine Ridge Escarpment may be vulnerable to flow reductions, as water withdrawals in Western High Plains of Nebraska have reduced or eliminated fish populations in several streams (Hrabik 2015). Fish diversity is highest in Keya Paha Tablelands and Nebraska Sand Hills ecoregion, which most likely support similar fish populations.  Because of stable temperature and groundwater flow, these ecoregions support glacial-relict cold-water fish populations, including rarer minnows such as Common Shiner.

**Materials and Methods**

I propose to test the hypothesis that **drought is a key driver of macroinvertebrate community regime shift in Northern Great Plains streams** and incorporate results into the Oglala Sioux Tribe watershed protection planning process. The steps for completing these tasks are outlined below in Table 6. The first generalized task is to characterize the hydrology of study area watersheds by evaluating streamflow differences among watersheds with streamflow records, then downscale results to ungauged watersheds using similar watershed properties. The second step is to relate streamflow drought magnitudes and potential anthropogenic drivers to macroinvertebrate community responses. The final step is to incorporate the results into the watershed protection planning process for streams managed by the Oglala Sioux Tribe. Analysis will be primarily conducted within the R statistical programming environment (R Core Team 2017) using RStudio {RStudioTeam:2015uf} and the Tidyverse environment (Wickham 2017). I plan to make raw data and analysis code available through GitHub.

Table 6: Original Scope by Dissertation Tasks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Broad Question | Hypothesis or task | Datasets | Statistical or Computational Method | Outcome |
| Identify relationships among drought types | Calculate SSI, SPEI, and SDI | Monthly precipitation, monthly mean temperature (Table 2); Monthly mean daily streamflow (Table 3) | SPI and SPEI by CRAN ‘SPEI’ package  Develop an approach to calculate SDI in R | SPI, SPEI, and SDI time series at 3-, 6- 9- and, 12-month scales |
|  | Pair weather stations with stream gages | Geographic coordinates of weather and streamflow stations | Thiessen polygons by CRAN  'deldir' package | Paired datasets for comparison |
|  | Characterize hydrologic droughts | SPI, SPEI, and SDI time series at 3-, 6- 9- and, 12-month scales | Coefficient of determination (r) | Identify watershed characteristics |
|  | Cluster similar watersheds with streamflow records | Mean daily streamflow (Table 3) | Method determination by ‘clValid’ package  Clustering by CRAN ‘vegan’ package | Identify watershed groups by streamflow similarity |
|  | Identify hydrologic group membership for ungauged watersheds | SD and Nebraska gSSURGO data | Watershed delineation by ‘Hydrology Toolset’ in ArcGIS  Classification by CRAN ‘randomForest’ package | Predict drought characteristics for ungauged watersheds |
| What are the abiotic drivers of regime shift? | Visualize compositional species patterns | Taxa – site matrix, environmental – site matrix | Non-metric dimensional scaling (NMS) ordination by CRAN ‘vegan’ package | Estimate environmental gradients |
|  | Compare community structure differences for non-drought, and drought years | Taxa – site matrix, environmental – site matrix | PERMANOVA | Test drought hypothesis |
| Which taxa groups are drought-resilient and indicate water quality? | Identify drought and water quality indicators | Taxa – site matrix, environmental – site matrix | Generalized indicator species analysis by CRAN ‘indicspecies’ package | Classification of drought-resilient taxa |
|  | Develop robust macroinvertebrate community metrics for water quality | List of drought-resilient taxa;  List of existing biotic integrity metrics | Engineering judgment | Updated biotic integrity metrics |
|  | Incorporate ecological drought into watershed protection | Updated biotic integrity metrics;  Existing Watershed Protection Plan | Engineering judgment | Updated Watershed Protection Plan |

Table 7: Revised Dissertation Tasks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Broad Question | Hypothesis or task | Datasets | Statistical or Computational Method | Outcome |
| Identify relationships among drought types | Calculate SSI, SPEI, and SDI | Monthly precipitation, monthly mean temperature (Table 2); Monthly mean daily streamflow (Table 3) | SPI and SPEI by CRAN ‘SPEI’ package  Develop an approach to calculate SDI in R | SPI, SPEI, and SDI time series at 3-, 6- 9- and, 12-month scales |
|  | Pair weather stations with stream gages | Geographic coordinates of weather and streamflow stations | Thiessen polygons by CRAN  'deldir' package | Paired datasets for comparison |
|  | Characterize hydrologic droughts | SPI, SPEI, and SDI time series at 3-, 6- 9- and, 12-month scales | Coefficient of determination (r) | Identify watershed characteristics |
|  | Cluster similar watersheds with streamflow records | Mean daily streamflow (Table 3) | Method determination by ‘clValid’ package  Clustering by CRAN ‘vegan’ package | Identify watershed groups by streamflow similarity |
|  | Identify hydrologic group membership for ungauged watersheds | SD and Nebraska gSSURGO data | Watershed delineation by ‘Hydrology Toolset’ in ArcGIS  Classification by CRAN ‘randomForest’ package | Predict drought characteristics for ungauged watersheds |
| What are the abiotic drivers of regime shift? | Visualize compositional species patterns | Taxa – site matrix, environmental – site matrix | Non-metric dimensional scaling (NMS) ordination by CRAN ‘vegan’ package | Estimate environmental gradients |
|  | Compare community structure differences for non-drought, and drought years | Taxa – site matrix, environmental – site matrix | PERMANOVA | Test drought hypothesis |
| Which taxa groups are drought-resilient? | Identify drought and water quality indicators | Taxa – site matrix, environmental – site matrix | Generalized indicator species analysis by CRAN ‘indicspecies’ package | Classification of drought-resilient taxa |
|  | Develop robust macroinvertebrate community metrics for water quality | List of drought-resilient taxa;  List of existing biotic integrity metrics | Engineering judgment | Updated biotic integrity metrics |
|  | Incorporate ecological drought into watershed protection | Updated biotic integrity metrics;  Existing Watershed Protection Plan | Engineering judgment | Updated Watershed Protection Plan |

***Question 1: What are the relationships between meteorological, soil moisture, and hydrological drought?***

Hydrologic characterization involves collecting and analyzing data to understand water balance and movement. I will **calculate SPI, and SPEI at 3-, 6-, 9-, 12-, and 24-month time steps** for each of the precipitation stations using the SPEI package (Beguería and Vicente-Serrano 2017) to characterize precipitation input and soil moisture storage. I will **calculate SDI from streamflow depths** by implementing an SDI calculation approach in R. Streamflow volume can be characterized as an equivalent depth by dividing mean daily streamflow volume by watershed area. A function to calculate SDI in R is not currently available and will validate calculations using existing software available through the Drought Mitigation Center (Svoboda et al. n.d.) to characterize streamflow. A caveat in the SDI calculation approach I plan to implement is that, while SDI is most often calculated at the start of the hydrologic year (Sept. - Nov.), macroinvertebrate sampling in the occurs in June at the beginning of the low flow period for the region. I will **calculate time-shifted SDI** (Mar. – May, Jan. – May, Oct. – May, June – May) to align the index with the June macroinvertebrate sampling events.

As a first step to understanding hydrological balance within a watershed, I will **pair weather stations with stream gages** by Theissen polygons (Voronoi cells), described below, using the 'deldir' package (Błaszczyszyn 2017). I will use bivariate correlation to identify the strongest correlations between the 3-month SDI, and SPI and SPEI at 3-, 6-, 9-, 12-, 18-, and 24-months. The strongest correlations provide watershed -scale bulk estimates of transport processes: infiltration, percolation, interflow and groundwater flow, and storages as soil moisture and groundwater. Thiessen polygons are used to calculate the rainfall of an area, based on a series of point measurements. Given a set of points {*p*1, …, *pn*} in the Euclidean plane (the latitude and longitude of weather stations) the corresponding Theissen polygon *Rk* consists of every point in the Euclidean plane whose distance to *pk* is less than or equal to its distance to any other *pk*. Each Thiessen polygon is a convex polygon obtained from the intersection of half-spaces with line segments equidistant to the two nearest sites and vertices equidistant to three (or more) sites (Reem 2009).

I plan to **estimate stream gauging station groups** using clustering. Clustering involves deciding on a method, and determining the number of clusters that are most appropriate for the data to arrive at clusters that are simultaneously ecologically meaningful, compact, well-separated, connected, and stable (Legendre and Legendre 2012). The R package ‘clValid’ determines the most appropriate method for the data and the optimal number of clusters by calculating measures of internal validation and stability (Brock et al. 2008). Internal validation measures reflect cluster homogeneity or compactness, e.g., intra-cluster variance; connectedness or to what extent the algorithm places observations in the same cluster as their nearest neighbors in the data space; and separation or the distance between cluster centroids. The mathematical descriptions of internal validation of clusters are taken from (Brock et al. 2008). Compactness and separation are measured by the Dunn index and silhouette width, and the approach to calculate connectivity is given as

Where *N* is the number of observations in *K* disjoint clusters, *xi,nni(j)* is zero if *i* and *nni(j)* are in the same cluster and *1/j* otherwise, *nni(j)* is the *jth* nearest neighbor of observation *I*, and *L* is a parameter that determines the number of neighbors that contribute to the connectivity measure to minimize connectivity. The *Dunn index* is the ratio of the smallest distance between observations not in the same cluster to the largest intra-cluster distance. It is computed as

where *diam(Cm)* is the maximum distance between observations in cluster Cm. The Dunn index, which should be maximized, has a value between zero and ∞. *Silhouette width* is the average of each observation’s silhouette value, or the degree of confidence in the clustering assignment of a particular observation with a range of [-1, 1]. Silhouette values are calculated as

where *ai* is the average distance between *i* and all other observations in the same cluster, and *b*i is the average distance between *i* and the observations in the "nearest neighboring cluster," such that

where *C(i)* is the cluster containing observation *i*, *dist(i, j)* is the Euclidean, Manhattan, or other distance between observations *i* and *j*, and *n(C)* is the cardinality of cluster *C*. The silhouette width, which should be maximized, lies in the interval [−1, 1].

The stability measures compare the results from clustering based on the full data to clustering based on removing each column one at a time. These measures work well if the data are highly correlated, which is most likely the case with streamflow data. The R package ‘clValid’ calculates the stability measures of the average proportion of non-overlap (APN), the average distance (AD), the average distance between means (ADM), and the figure of merit (FOM). As above, the mathematical descriptions for stability measures are taken from (Brock et al. 2008).

The average proportion of non-overlap (APN) measures the average proportion of observations not placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed. The APN is in the interval [0, 1], with values close to zero corresponding with highly consistent clustering results. The algorithm calculates APN by letting *Ci ,0* and *Ci, l* represents clusters containing observation *i* using the original clustering and the cluster containing observation *i* where the clustering algorithm uses the dataset with column l removed, respectively. The APN measure is calculated by

The average distance (AD) measure computes the average distance between observations placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed. The AD measure has a value between zero and ∞ with smaller values preferred is calculated by

The average distance between means (ADM) measure computes the average distance between cluster centers for observations placed in the same cluster by clustering based on the full data and clustering based on the data with a single column removed. ADM, which has a value between zero and ∞ with smaller values preferred, is calculated in Euclidian space by

Where is the mean of the observations in the cluster which contains observation *i*, when clustering is based on the full data, and is the mean of the observations in the cluster which contains observation *i*, when clustering is based on one column removed.

The figure of merit (FOM) measures the average intra-cluster variance of the observations in the deleted column, where the clustering is based on the remaining (undeleted) samples to estimate the mean error using predictions based on the cluster averages. The FOM is multiplied by an adjustment factor *N*, to correct for the factor to decrease as the number of clusters increases. FOM, which has a value between zero and ∞ with smaller values equaling better performance, is averaged over all the removed columns. FOM is calculated in Euclidian space by

where *xi,l* is the value of the *ith* observation in the *lth* column, and is the average of cluster Ck(l).

The final step in generalizing hydrological drought relationshipsis to **identify hydrologic group membership for ungauged watersheds**. To identify hydrologic group membership for ungauged watersheds, I plan to summarize gridded Soil Survey Geographic data (gSSURGO) for South Dakota and Nebraska (NRCS staff 2016) by watershed. I plan to use either ‘Arc Hydro' tools in ArcGIS or the ‘r.watershed' module in GRASS to delineate watersheds from the 10-m resolution National Elevation Dataset (NED) (Gesch et al. 2009) and group watersheds will by the ‘randomForest' package in R (Liaw and Wiener 2002). I plan to create a preliminary random forest using median values of gSSURGO variables that may be related to watershed hydrology and then run a final random forest using only the most important variables from the first run. The gSSURGO Database contains all of the original soil attribute tables in an NRCS Soil Survey Geographic (SSURGO) Database reformatted as a 10-meter cell-size raster layer in an Albers Equal Area projection. The gSSURGO uses a raster map layer within a file geodatabase along with the original SSURGO data, and a new value-added look-up table containing "ready to map" attributes including ‘available water storage,' ‘National Commodity Crop Productivity Index,' and ' Potential wetland soil landscapes.'

The random forest algorithm divides training data to form a large group of “weak learners” or individual trees that are combined to form a “strong learner” for accurate classification or regression

(Benyamin 2012). The random forest uses a series of decision trees, which corresponds with weak learners. A decision tree is a structure in which an observation entered at the top of the tree gets bucketed into smaller and smaller groups. The random forest requires two user-defined parameters to generate a prediction model: the number of classification trees desired, *k,* and the number of prediction variables used. The “tuneRF” function in the ‘randomForest’ package automatically selects the optimal value of *m* to minimize model error.

I am summarizing several authors description of random forest algorithm below (Breiman 2001; Liaw and Wiener 2002; Peters et al. 2007; Rodriguez-Galiano et al. 2012). Some variables and terms need to be defined to understand the random forest algorithm. Let *j* be the class that is most often selected (i.e., voted on) by the *kth* tree in a random forest. Let *m* be a given predictor (i.e., variable or column) and *ntree* is a given observation (i.e., case or row). The random forest algorithm first draws *ntree* bootstrap samples from the original data, leaving out about one-third of the observations. Next, the algorithm grows *unpruned* decision trees from each of the bootstrap samples with one modification: the algorithm selects a random sample *mtry*ofpredictors from which to identify the best split. Last, the algorithm aggregates the predictions of the *ntree* trees to choose a ‘correct' classification by a majority "vote" with each tree in the forest "voting" for a particular classification. The random forest algorithm can also be used for regression by averaging results of the *ntree* trees.

The random forest algorithm avoids overfitting by minimizing error. The error rate of a particular random forest depends on *mtry* andincreases with the correlation between any two trees in the forest and decreases with the number of trees in the forest with low error rates (i.e., strong classifiers). A smaller value of *mtry* reduces both correlation and strength, a larger value of *mtry* increases both correlation and strength. The algorithm uses the trees grown in each bootstrap to predict the data not selected in a bootstrap iteration, the OOB (out-of-bag) data. The algorithm aggregates the OOB predictions and calculates the OOB error.

The random forest algorithm has useful internal properties to validate classifications, estimate and visualize variable importance, and replace missing data. Random forests provide an unbiased estimate of the test set error, so there is no need for cross-validation. The OOB data is used to get a running unbiased estimate of the classification error as the algorithm adds trees to the forest. It is also used to estimate variable importance. The OOB error estimate for a particular tree is calculated as the proportion of times that *j* is not equal to the true *ntree* class averaged over all the observations. The importance of a given variable *m* is identified using a permutation test. For each tree grown in the forest, the algorithm counts the number of votes (correctly classified cases) for each of the OOB observations. Next, the algorithm randomly permutes values of *m* from the OOB observations, puts the observations down the tree. The algorithm subtracts the number of votes for the correct class in the variable-*m*-permuted OOB data from the votes for the correct class in the original OOB data. The average of the difference in untouched and permuted votes over all of the trees in the forest is the raw importance score for variable *m*. A local importance score for the variable *m* is calculated by subtracting the percentage of votes for the correct class in the permuted OOB data from the percentage of votes for the correct class in the untouched OOB data. The algorithm calculates Gini importance of each variable *m* by summing the decrease in the Gini impurity criterion for each split of a node for the variable *m.* The random forest uses proximities scores to produce low-dimensional views of the data, locate outliers, and replace missing data. The algorithm computes proximities for each pair of final observations with proximity increased by one for every two observations occupying the same terminal node and normalizes proximities calculations by dividing the proximity score by the number of trees in the forest. Proximities scores can be projected into low-dimensional Euclidian space by plotting the largest few eigenvalues of the cv matrix, and their corresponding eigenvectors.

***Question 2: What are the abiotic drivers of regime shift?***

I plan to follow prior drought stress and macroinvertebrate community recovery studies to identify effects of drought and elevated nutrients on macroinvertebrate community change, (Bêche et al. 2009; Boersma et al. 2014; Bogan et al. 2015; Ledger et al. 2013b; Pace et al. 2013; Sponseller et al. 2010). I plan to **visualize compositional species patterns** by ordination with non-metric multidimensional scaling (NMS) (Clarke 1993; Kruskal 1964a; b; Sponseller et al. 2010) at a family level of classification with Sørensen (Bray–Curtis) or Jaccard distance as a measure of assemblage dissimilarity using the ‘vegan’ package (Oksanen et al. 2018). Before ordination, I plan to delete rare taxa (<5% of sample units), apply a square-root transformation to reduce abundant taxa influence, then revitalize by dividing all taxa by their maxima and standardizing sites to unit totals (Wisconsin double standardization) (Bogan et al. 2013; McCune et al. 2002; Oksanen et al. 2018).

I plan to **compare differences in community structure for non-drought, and drought years** (possibly by seasonal and supra-seasonal groups) following NMS ordination by permutation-based MANOVA (PERMANOVA; formerly nonparametric MANOVA (Anderson 2001; Boersma et al. 2014) using the using the ‘vegan’ package. PERMANOVA provides similar results to Mantel tests, the multi-response permutation procedure (MRPP) (Bogan et al. 2013) and analysis of similarities (ANOSIM) (Sponseller et al. 2010), but allows for more complex experimental designs (Legendre and Legendre 2012; McCune et al. 2002). I may add a second grouping variable to identify among-group differences among low, medium, and high levels of anthropogenic disturbance following an exploratory analysis of bacteria and nitrate concentrations among sites depending on ordination results.

***Question 3: How do Pine Ridge Reservation results compare with other dryland studies?***

*Discuss using the results of thesis proposal defense*

**Expected Results**

The purpose of my proposed research is to contextualize the stream ecological community within antecedent flow condition in order to discriminate between drought-induced community change and anthropogenic community change. This proposal represents nearly a decade of rejecting hypotheses in an effort to explain stream ecological community change on the Pine Ridge Reservation. In the course of my work to understand the biotic integrity of these streams, I have renovated laboratory space and trained myself and students to identify macroinvertebrates at Oglala Lakota College (OLC), collected unpublished historical macroinvertebrate and water chemistry data, investigated limiting nutrients, gauged streams to quantify streamflow events and nutrient fluxes, measured reach geometries, updated biotic integrity metrics, and the Tribe’s Watershed Protection Plan. The results of my prior work indicate, by process of elimination, that drought is the most likely reason for the widespread aquatic community changes in study area streams. I expect to find that supra-seasonal drought has resulted in long-term aquatic community changes at some sampling locations. However, as the regional geology is complex, I expect aquatic communities at other sampling locations to have recovered to pre-drought conditions.

*Discuss following dissertation proposal defense – use presentation expected results.*

**Work Plan/Timetable**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Date | Major Task | Objective(s) | Minor Task(s) | Milestone(s) | Other |
| 2018 May | PhD Candidacy | Dissertation Committee Approval | Send proposal:  Review written comments;  Oral Defense | Send final draft;  Schedule proposal defense;  Defend Proposal | Finalize Committee Membership |
| 2018 May | Outline Dissertation;  Calculate SPI, SPEI | Develop Project Outline in Github: Begin Objective 1 Analysis | Download meteorological data | Complete data download | Bookdown format |
| 2018 June | Complete Objective 1 | Characterize droughts;  Characterize ungauged stations | Complete time-series clustering;  Watershed delineation; Watershed classification | SDI calculation;  pair stations; calculate Pearson r;  Download gSSURGO data; Random Forest classification; Write up results | Dissemination to NSF; Identify journal for Obj. 1 |
| 2018 July | Begin Objective 2 | Visualize taxa patterns | NMS Ordination | Manipulate taxa data for ordination | Dissemination to OST |
| 2018 August | Complete Objective 2 | Test drought hypothesis | PERMANOVA analysis | Write up results | Final check for PhD coursework; Identify journal for Objective 2 |
| 2018 September | Begin Objective 3 | Identify drought and water quality indicators | ISA analysis |  | Dissemination to OST |
| 2018 October | Complete Objective 3 | Incorporate into Watershed Protection Plan | Develop IBI metrics |  | Dissemination to SDSMT (seminar) |
| 2018 November | Write up Objective 3 results |  |  |  | Dissemination to OST |
| 2018 December | Finalize preparation for graduation | Schedule defense; finalize graduation paperwork | Final check with Graduate Office |  |  |

***Next Steps: which taxa groups are drought-resilient and indicate water quality?***

The broad purpose of my proposed research is to identify indicators that indicate land use changes affecting stream health that are robust to the occurrence of drought. Following PhD completion, I plan to **identify taxa indicative of pre-, during-, and post-drought and various bacterial and nutrient loading** levels using generalized indicator species analysis (ISA) in R. ISA predicts a taxon's indicator value (IV) as the product of its ‘faithfulness' and its ‘exclusivity.' McCune defines ‘faithfulness' as the proportional abundance of the taxon within the group relative to its abundance in all groups (relative average abundance), and ‘exclusivity' as the percentage of plots that the taxon occupies within a given group (relative frequency of occurrence) (McCune et al. 2002). The IV is at a maximum of 1.0 when all specimens of a taxon are found in a single sample group (for example pre-drought) and when the taxon occurs in all samples of that group. A taxon is considered an indicator of a group when its indicator value is significantly higher than expected by chance (Bêche et al. 2009; Bogan and Lytle 2007; Dufrêne and Legendre 1997; Legendre and Legendre 2012). The ‘indicspecies' package in R calculates ISA values by taxa combinations in addition to single taxa (De Cáceres and Legendre 2009) (De Cáceres et al. 2012).

ISA results should provide a list of drought-resilient taxa that I plan to incorporate into updated biotic integrity metrics for Pine Ridge Reservation streams. I plan to **incorporate ISA results into updated biotic integrity metrics** following recommendations by the International Society of Limnology Biological Working Group (Loeb and Spacie 1994), Environmental Protection Agency Staff (Karr 1999; Karr and Chu 1998; Stoddard et al. 2008), and meta-analysis of global monitoring approaches (Buss et al. 2014). I plan to identify an updated set of metrics and test them against existing wet and dry years to balance metric scores to **incorporate ecological drought into watershed protection.** A final step is to incorporate the updated IBI metrics into the OST Watershed Protection Plan. A potential approach to IBI incorporation is to use the Drought Monitor (source) to vary IBI scores for ‘threatened’ and ‘impacted’ determination.

My research advances a small and important component of ecological drought prediction by developing a quantitative approach to predict aquatic community resilience based on antecedent flow conditions. The proposed work is significant in terms of developing processes for water resources sustainability and drought resilience planning by improving the ability of watershed managers to establish Indicators of Biological Impairment (IBI) metrics based that are resilient to drought. I expect future work in this area to include: model validation using post-2015 macroinvertebrate data, model extension working with other researchers with long-term datasets, and future work with Dr. Capehart on regional drought prediction using SPI and SPEI.

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