Reducing current and future risks: Using climate change scenarios to test an agricultural conservation framework

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ABSTRACT

Evaluating the potential effect of changes in climate on conservation practices can help inform strategies to protect freshwater biodiversity that are robust, even as conditions change. Here we apply a climate change “test” to a framework for estimating the amount of agricultural conservation practices needed to achieve desired fish conservation outcomes for four watersheds in the Saginaw Bay region of Michigan, USA. We developed three climate scenarios from global climate model outputs (high emissions scenario, “2080s” timeframe) to provide insight on potential impacts of a climate driver that represents a key uncertainty for this management system, the amount and timing of spring and summer precipitation. These scenarios were used as inputs to agricultural watershed models, which produced water quality outputs that we compared to thresholds in fish biodiversity metrics at the subwatershed scale. Our results suggest that impacts of climate change on evaporation rates and other aspects of hydrology will shift the relative importance of key stressors for fish (i.e., sediment loadings vs. nutrient concentrations) across these different watersheds, highlighting the need to design resilient implementation plans and policies. Overall, we found that changes in climate are likely to increase the need for agricultural conservation practices, but that increasing the implementation rate above current levels will likely remain a good investment under current and future climate conditions.

KEY WORDS

Climate adaptation; Climate change; Great Lakes; Fish; Conservation outcomes; Agricultural impacts; Nutrient loading

INTRODUCTION

Achieving water quality and stream health standards in agricultural landscapes remains a persistent challenge, despite substantial research and investment in agricultural conservation practices (Sowa et al., 2016; Tomer et al., 2014). In watersheds across the US Great Lakes region, a variety of stakeholders are developing and testing innovative solutions to increase the effectiveness of conservation investments, including new or improved practices, multi-scale targeting, and new financial mechanisms (e.g., Bosch et al., 2013; Douglas-Mankin et al., 2013; Kalcic et al., 2015a, 2015b; Legge et al., 2013; Tomer et al., 2013). While these innovations represent important advances, there is increasing evidence that the performance of many agricultural conservation practices can be influenced by climatic factors (Delgado et al., 2013; Garbrecht et al. 2014; Hatfield et al., 2013). As a result, it is quite likely that current site- and regional-scale solutions for addressing agricultural nonpoint source pollution will need to be updated over time to account for the effects of climate change. We suggest that framing the risks that changes in climate drivers pose to these innovative solutions is an essential component of crafting approaches that will help us achieve and sustain desired conservation outcomes.

The Nature Conservancy (TNC) and many partners are working to achieve strategic agricultural conservation across the Saginaw Bay basin in Michigan, USA, a body of work described in Fales et al. (2016). These collaborative efforts focus on developing and testing different methods to more effectively and efficiently implement conservation practices, including establishment of outcome-based performance goals, targeting practices, reducing administrative burdens, and tracking and assessment of progress. Much of this work was made possible by analyses and models described in Sowa et al. (2016), which established spatially-explicit relations between conservation practices, water quality, and fish community health in four watersheds. Here we use a series of models, such as the Soil and Water Assessment Tool (SWAT; Arnold et al. 1998, 2012), and statistical analyses to develop dose-response relationships between the percent of agricultural land that is managed by a suite of conservation practices (the “dose”) that is intended to address water quality variables limiting the fish community, which, results in improved fish health (the “response”; Sowa et al., 2016). These relationships can be used to ask “how much conservation is enough” to achieve fish community health goals for

specific watersheds or subbasins, which can inform the establishment of short and long-term implementation goals (Fales et al. 2016).

There is broad agreement in the conservation community that conservation approaches such as the ones described in Fales et al. (2016) will be more successful if practitioners implement an adaptive management approach (The Conservation Measures Partnership, 2013) that enhances learning from the management experience. While adaptive management can help practitioners update approaches as climate change occurs, the magnitude of potential climate risks and time required to modify established management systems and policies require a need to anticipate, rather than just react to, ongoing changes (Bierbaum et al., 2013). Building on previous climate change vulnerability and adaptation frameworks (e.g., Cross et al., 2012; Glick et al., 2011; Stein et al., 2014) and assessments (e.g., Bierbaum et al., 2013; Pacifici et al. 2015; McDowell et al., 2016), we anticipated that directly exploring potential impacts of climate change on climate-sensitive elements of conservation strategies would be the most effective way to appreciate climatic risks to conservation outcomes. Further, we suggest that the process of assessing the “vulnerability” of a conservation approach can help us identify components or tools that imply the false assumption that the climate drivers of the systems will remain “stationary” (i.e., will vary within the same distribution over time; Milly et al. 2007), potentially contributing to inappropriate conservation decisions.

Here we evaluate how several exploratory climate change scenarios influence the relationships between conservation practices, water quality and fish community health established in Sowa et al. (2016). The objectives of our project were to assess if 1) under these climate change scenarios, the amount of conservation practices needed to achieve fish community health would change and 2) the underlying framework of this approach (e.g., models and conservation practices used) was likely to be sensitive to changes in climate drivers. Collectively addressing these objectives provides insight into how we might need to modify the scientific framework of Sowa et al. (2016) and the conservation strategies that build upon it (Fales et al. 2016) to be better prepared to meet conservation goals as climate conditions change.

METHODS

Study Area

As described in detail in Sowa et al. (2016), we evaluated variations in modeled conservation outcomes as a function of changes in conservation investments within four watersheds of the Saginaw Bay drainage to Lake Huron (eastern Michigan, USA; Figure 1). Agriculture is a dominant land use across the Saginaw Bay region, but there is substantial heterogeneity in its intensity (Figure 1). The four focal watersheds represent a gradient, ranging from 8% agricultural land use in the Rifle River watershed, to 41-42% percent in the Cass and Shiawassee, respectively, and 68% in the Pigeon-Pinnebog. While impacts on water quality are detectable in each watershed, especially those with more land in agriculture, all continue to provide important habitats for aquatic biodiversity, and all have been identified as high priority watersheds for conservation (TNC, 2001).

Projected climate change impacts

Within the Great Lakes region, we expect to see continued increases in temperature, leading to multiple impacts due to increases in the length of the growing season, evapotranspiration rates, and drought risk (Mishra et al., 2010; Pryor et al., 2013, 2014). While there is strong agreement across Global Circulation Model (GCM) projections for future temperatures, projections for precipitation are highly variable. Ensembles of GCM outputs for annual total precipitation for the mid and late century include projections of both increases and decreases in annual totals, and outputs for the same end date and emissions scenario vary across models with respect to seasonal and geographic patterns of change (Pryor et al., 2013, 2014).

Development of climate scenarios

Our use of the term climate “scenario” follows the Intergovernmental Panel on Climate Change definition, which describes scenarios as plausible descriptions of future conditions (not forecasts), that can be used to reflect the range of uncertainty in climate projections (IPCC 2001, Chapter 3). Our scenarios focus only on variations in climate drivers. While we recognize that many other important factors, such as land use patterns, agricultural

practices, and species distributions are likely to change over time and influence conservation outcomes, these factors are beyond the scope of our assessment. To evaluate the sensitivity of conservation outcomes based on Sowa et al. (2016), we needed exploratory climate scenario datasets that we could input to the SWAT watershed models. To develop these datasets, we used the set of 16 GCM projections for multiple carbon dioxide emissions scenarios that were produced as part of the World Climate Research Programme's Coupled Model Intercomparison Project, Phase 3 (CMIP3). These model runs informed the Intergovernmental Panel on Climate Change's (IPCC's) Fourth Assessment Report (2007), and monthly averages were readily available for visualization and download from the ClimateWizard data portal (Girvetz et al., 2009; www.climatewizard.org). Given that these climate datasets were the first inputs to a complex set of linked models, we limited our assessment to three future climate scenarios, with the intent of maximizing ecologically-relevant variation in climate drivers across those three scenarios

To create the three future climate scenarios, we first evaluated variation across GCMs for our focal region from all 16 GCMs under lower (B1) and higher (A2) carbon dioxide emissions scenarios for the IPCC's "end of century - 2080s" time period (monthly means averaged across 2070-2089), as made available in ClimateWizard (Figure 2). While it is common to adopt the IPCC's emissions scenarios and then use the average temperature or precipitation values (black lines in Figure 2, A-D) from the ensemble of GCM outputs as inputs to watershed models (e.g., Bosch et al., 2014; Woznicki et al. 2011), we did not follow this convention. Our goal was not to illustrate the sensitivity of Sowa et al.'s (2016) conservation approach to higher or lower rates of emissions; rather, we wanted to provide insight on potential changes in practice performance, or in key limiting variables, that might arise as climate conditions change. To develop scenarios that rigorously "tested" the conservation approach, we focused on higher emission scenario (A2) datasets, which provided a stronger climate signal (larger temperature increase). Both sets of precipitation projections (Figure 2 C,D) indicated high model variability (i.e., high uncertainty) in future patterns of precipitation, including patterns of increase and decline that are masked when the suite of models is represented by the ensemble average (shown in black). To maximize insight from our exploratory scenarios, we focused on capturing the range of variation within the

precipitation data in runs, and paired three sets of precipitation values with the same set of values for future temperature.

The temperature and precipitation outputs from each GCM may be one plausible future, but our confidence in that plausibility increases when other models show similar patterns. To develop scenarios that captured major patterns of variation in precipitation across GCM outputs, yet reduce reliance on individual models, we created subsets of three models with similar seasonal patterns, and averaged monthly values within these subsets. In selecting which models to include in our averages, we prioritized variation in two critical seasons; the early spring, when water quality consequences of runoff can be most severe due to a lack of agricultural vegetation, and late summer, when reduced precipitation can contribute to low flows and concentrated nutrient inputs to streams. Our original plan for creating scenarios was to compare “wet”, “average”, and “dry” spring precipitation scenarios, as this simple set would facilitate communication with stakeholders. However, the “wet spring” subset of GCM outputs had divergent patterns for the rest of the growing season. Rather than averaging these opposite patterns, we selected subsets that were similar in both seasons, and created a Dry spring-Dry summer scenario, and two wet spring scenarios (Wet-Dry, and Wet-Wet; Figure 3). The set of GCM outputs used to create each scenario are indicated by different colors in Figure 2D. Outputs from the other 7 GCMs from the full ensemble of 16 were not included in the precipitation scenarios. Thus, our method for developing scenarios averages data from all 16 models for temperature values and uses this average for all three scenarios, yet the precipitation component of each scenario is based on outputs from just three models with similar patterns. While this choice enhances our ability to interpret our results and discuss them with stakeholders (temperature regime is the same across all scenarios), it does reduce the coherence and perhaps the plausibility of each scenario, in that variation in precipitation has been separated from temperature variation.

Overall, the Wet-Wet and Dry-Dry scenarios for future precipitation showed similar seasonal patterns, but varied in the magnitude of precipitation (Figure 3). In contrast, the Wet-Dry scenario showed more variation in magnitude across the seasons, with a strong decline in June and July, followed by fall conditions that were closer

to the Wet-Wet scenario. Relative to our Current climate scenario, the two wet spring scenarios had an earlier peak, while timing of peak precipitation in the Dry-Dry scenario was more similar to the current average. For the rest of the growing season, the Wet-Wet scenario was most similar to current conditions, with the other two scenarios suggesting much less precipitation in June and July. The temperature component of the scenarios (derived from the 16 GCM ensemble average monthly mean values for 2080s, A2 scenario) corresponded with an average warming of approximately 4.5 °C (7 °F) above the “Current” temperature regime.

Modeling responses of fish biodiversity to changes in conservation practices

Sowa et al. (2016) forecast cumulative benefits and costs of agricultural conservation practices on stream health by using a series of analytical steps to develop empirical models for the relationships between the extent of conservation practice implementation, water quality conditions, and biological outcomes. Here, we briefly outline the major steps in this process that directly underlie this climate change application; for details, see Sowa et al. (2016). The first step involved estimating the maximum attainable value (i.e., ceiling) for metrics of fish assemblage health as a function of water quality using the Soil Water Assessment Tool (SWAT; in ArcSWAT version 2.3.4) watershed model (Arnold et al., 1998, 2012) as parameterized for the region by Nejadhashemi et al. (2012). We ran SWAT with “current” climate data (daily averages from 1990-2009) to attain a comprehensive set of water quality estimates, and changes in hydrologic processes, for all major stream reaches across the region. Next, SWAT water quality estimates were related to IBI scores based on fish occurrence data (Seelbach and Wiley, 1997; Wang et al., 2011), and we identified seven key limiting water quality variables that exhibited impairment thresholds with limitation ceilings (Sowa et al., 2016): nitrate in surface runoff, summer sediment concentration, spring-rising organic P, spring-falling organic P, summer organic P, fall-winter organic P, and summer total P. Linking these datasets allowed us to calculate maximum attainable fish IBI scores from estimates for these water quality variables. Next, we used SWAT to evaluate water quality/quantity changes from conservation practice implementation under three scenarios: a) current conditions with respect to proportion of agricultural land in some form of conservation practice, b) an increase in conservation practice implementation to 25% (i.e., 25% of row-crop agricultural lands had practices applied), and c) a 50%

conservation practice scenario. By linking these results with the seven impairment thresholds, we developed “dose-response” relationships between practice implementation rate and fish IBI. We then estimated the maximum attainable IBI score for each of the 153 subbasins within the four watersheds, and mapped this value (Sowa et al., 2016, see their Figure 13). The most limiting variable in the subbasins varied spatially, and changed with the practice implementation scenario (Sowa et al., 2016).

To explore potential responses of fish IBI to changes in conservation practice implementation and climate change, we followed the methods above, except we used our future climate scenarios as inputs to SWAT. We ran 12 combinations of scenarios: Current climate, and Dry-Dry, Wet-Dry, and Wet-Wet future climate scenarios, paired with each of three conservation practice scenarios (Current, 25% and 50%). The “Current” climate runs, historic land cover reference point used in dose-response curves, and parameterization of the SWAT model for each conservation scenario matched that described in Sowa et al. (2016). To prepare the future climate projections for input to SWAT, we created custom spatial data sets in ClimateWizard (Girvetz et al., 2009) by selecting three sets of GCM outputs with similar precipitation patterns (Figure 2D), and then submitting a request to the ClimateWizard tool for an averaged spatial data layer for each month. SWAT inputs weather data as point locations, so we converted the spatial averages for each scenario to point datasets by extracting values for the point locations for the weather stations that were the sources for the “Current” climate data. We used a similar spatial data averaging procedure to extract the temperature average across all 16 models to develop the temperature component of our three climate scenarios. SWAT runs on daily climate values, so we used the delta change method (Fowler et al. 2007; Hay 2001) to convert the monthly climate averages into daily values.

RESULTS

To illustrate watershed-scale sensitivity to our climate scenarios, we present a subset of hydrologic and water quality results from the SWAT runs for each climate scenario under the current level of conservation practices (Table 1). Under the future climate scenarios, we found increases of 6-29% in evapotranspiration rates across all watersheds (Table 1). Evapotranspiration increases for the Cass and Shiawassee watersheds, which are

intermediate in terms of agricultural land use (41 and 42% row crop agriculture), were consistently higher than the other two (Rifle and Pigeon-Pinnebog, 8 and 68% in row crops, respectively). Average annual discharge decreased markedly for all watersheds under the Dry-Dry scenario, and for the Cass and Shiawassee watersheds under the Wet-Dry scenario. The Rifle and Pigeon-Pinnebog showed slight reductions in discharge under the Wet-Dry, and increases under the Wet-Wet scenario. Even under this wettest scenario, discharges in the Cass and Shiawassee decreased slightly. Changes in movement of nitrate in surface runoff and sediment-bound mineral P followed the discharge patterns (declines in all watersheds) for the driest scenario, but showed more variation across watersheds in the wetter scenarios. Nitrate in runoff also declined in the Wet-Dry scenario, but mineral P showed little change, except in the Rifle watershed where it increased. For the Wet-Wet scenario, losses of mineral P increased, and nitrate in runoff showed little change, except in the Cass where it declined.

Patterns of variations in loadings and concentrations results (Table 1) suggest that climate drivers, hydrology, land use patterns within each watershed, and transport mechanisms for different stressors interact to determine changes in conservation practice performance at the watershed scale. Under the Dry-Dry scenario, loadings of nutrients and sediments decreased in all or most watersheds, while concentrations of NH_4 increased in all watersheds. Concentrations of organic P and sediment appeared less sensitive to changes in climate inputs, with P tending to increase, and sediment concentrations declining slightly in three of the four watersheds. Under the Wet-Wet scenario, outputs were more similar to current conditions; but both loadings and concentrations tended to increase, most notably for NH_4 . Sediment loadings and concentrations in the Cass and Shiawassee, and organic P concentrations in Pigeon-Pinnebog declined slightly under this scenario. Responses were even more variable under the Wet-Dry scenario. Both loadings and concentrations increased in the Rifle, but the Cass and Shiawassee showed decline in loadings for both nutrients and sediments, paired with increases in nutrient concentrations, but slight decreases in sediment concentrations. The most agricultural watershed, the Pigeon Pinnebog, showed a mix of relatively small changes in loadings and concentrations under the Wet-Dry scenario.

The next step in Sowa et al's (2016) modeling process connects SWAT outputs to fish IBI response curves for seven apparent limiting variables for each of 153 subbasins. We used these relationships to identify the most limiting variable in each subbasin, and to estimate a subbasin-specific maximum IBI score for each combination of conservation practice implementation rate and climate change scenario. The variation in dose-response curves for the different future climate scenarios at the subbasin scale are illustrated by the set of curves for four of the limiting variables (Figure 3). The four plots in Figure 3 are not directly comparable to each other, as they were developed for individual subbasins within different watersheds. We include them to provide insight into the complexity of relationships we observed between climate drivers, practice implementation rate, and stressor levels, and to provide examples of the outputs we can share as examples of climate impacts with local stakeholders. In the suspended sediment example (Figure 4A), the Wet-Dry and Dry-Dry scenarios would lead to lower stressor levels at current and increased rates of practice implementation, but these reductions would not show a benefit in the subbasin, because they were all within a range of values that are not limiting to fish IBI. In contrast, the NO₃ surface runoff example (Figure 4B) indicates that IBI limitation can be reduced in this subbasin quite effectively by increasing investment in conservation practices, but that the maximum IBI attainable at each level of investment would be lower under the Wet-Wet and Wet-Dry climate scenarios relative to the Dry-Dry scenario, or to current conditions. The final two plots indicate changes in organic P concentrations, either in early spring (Figure 4C) or late spring (Figure 4D). In both, increased investments in conservation reduces the extent to which organic P limits maximum IBI, but Figure 4D shows a strong reduction in benefits under all of the future climate scenarios, while in Figure 4C, the benefits of conservation investments are more similar across current and future scenarios.

Identifying patterns in ecological conditions and conservation opportunity at the watershed scale required summarizing the large collection of subbasin-scale dose-response relationships, which we did by mapping the degree of IBI limitation for the most limiting of the seven stressor variables (Figure 5). With no increase in conservation practices (Figure 5, first column), many subbasins experienced severe declines in fish assemblage health under each climate scenario, especially the Dry-Dry. But with 50% of the watershed in conservation

practices (Figure 5, third column), the overall health across subbasins was similar under all climate scenarios, except to some extent the Dry-Dry which continued to have a few subbasins in very poor quality. Under current conservation practice levels and current climates (Figure 5, upper left), the connection between percent of land in agriculture (Figure 2) and limitations on fish IBI are clear: subbasins with the most agriculture (i.e., those in the Pigeon-Pinnebog watershed) have the lowest predicted IBI maximum values. Under current conservation practice levels, the level of limitation in this highly agricultural watershed showed little change, and even some improvement (Wet-Wet scenario) under the future climate scenarios. Trends in the Rifle River watershed, which has the least agriculture and the highest maximum IBI values, are similar, i.e., little change or some improvement under the future climate scenarios. In contrast, subbasins within the two larger watersheds with intermediate levels of agricultural land use (Cass and Shiawassee) tended to become more limited under future climate scenarios (especially the Dry scenarios), although a few subbasins improved, and many stayed the same. Projected maximum IBI declined the most within subbasins in the Cass, where nutrient concentrations generally increased the most (Table 1).

Under both current and future climate scenarios, increasing investments in conservation provided benefits by increasing the maximum attainable IBI for many subbasins, although limitations on IBI persisted in many subbasins, even at the highest (50%) investment level. Subbasins in the Rifle showed the least change, retaining or increasing their high IBI maximum values in all scenarios. When the stressor variables that drive these limits in IBI maximum value were mapped in the same format as Figure 5 (see Sowa et al., 2016), spring organic P concentrations followed by summer sediment values and summer organic P were associated with the most limited areas in the Shiawassee and Cass watersheds, while sediments, summer organic P, and nitrate in runoff were key limiting variables in the Pigeon-Pinnebog. When compared across conservation and climate scenarios, maps of the most limiting variables indicated that both conservation and climate change can shift patterns of what factors are most important to address (data available from the authors).

DISCUSSION

Climate change impacts on the amount of conservation needed

If current levels of conservation practice implementation are maintained, our results suggest that stream fish assemblage health in many subbasins is likely to decline as a result of the climate change scenarios we investigated. However, increasing investments can help reduce these impacts, especially if practices are implemented strategically, based on projected relationships between conservation practices and stream health. Under high rates of implementation (50%), current stream health will generally improve, and many subbasins appear to have the potential to maintain condition even as climate conditions change, although some subbasins are still likely to show declines in fish assemblage health under both current and future conditions. These encouraging results about the continued value of conservation practice investments generally agree with other assessments and recommendations (see review by Delgado et al., 2013, Whitehead et al. 2006). For watersheds that drain into the western basin of Lake Erie, Bosch et al. (2014) concluded that conservation practices can help offset nutrient and sediment increases that result from climate changes, though they found that conservation practices appeared to become less effective with more “pronounced” (higher emissions scenario) climate changes.

While our analyses indicate that conservation practices—if implemented aggressively—provide a buffer against climate change, our results suggest that we need to be ready to shift practices to address changes in the specific patterns and types of non-point source pollution. When compared across climate and conservation scenarios, trends in stressors varied across the four focal watersheds (Table 1), and we found that most limiting variables in each subbasin often varied, suggesting a need for adaptive policies and practices. Further, along with others (e.g., Bosch et al, 2014; Woznicki et al. 2011), we found substantial changes in modeled concentrations of some stressors, including ones that were not identified as limiting (i.e., NH_4 , Table 1). If in the future these stressors exceed historic levels, we would not have prior relationships to draw from to understand potential impacts, and link impacts to fish IBI scores. Thus, one important “check” that we can implement for the Sowa et al. (2016) approach is to monitor how the range of SWAT outputs compares to the ranges used to develop the threshold

relationships, and re-evaluate if values go beyond those used to calibrate the fish outcome metric. Similarly, the impact of the same water quality variables could change with increases in water temperature, though this is a more challenging problem to track. As these examples suggest, the process of evaluating our results, and the components of our approach, has provided many important insights that we can use to make pro-active improvements. While there is much to explore in the specific patterns of results, we focus the rest of our discussion on addressing our second objective, evaluating the vulnerabilities of our study framework.

Climate change vulnerabilities within our framework

Given that increased precipitation increases erosion risk and increases in erosion impacts under climate change have been emphasized in recent climate change research papers and guidance documents (e.g., Delgado et al., 2013; Garbrecht et al., 2014; Nearing et al., 2004; Soil and Water Conservation Society 2003, 2007), we expected that the substantial increases in precipitation in the two wet spring scenarios would produce consistent increases in surface flows and sediment loading that would drive reductions in fish IBI. Instead, while sediment loads did increase in both Wet scenarios for the Rifle and for the Wet-Wet scenario for the Pigeon Pinnebog, sediment loading declined in other watersheds, and changes in IBI maximum were more often driven by changes in organic P at the subbasin scale. Using scenarios with temperature increases more representative of mid-century projections (in contrast to our hotter estimates for the 2080s), Bosch et al. (2014) found results that were closer to what we were expecting, with increases in surface and tile drainage flows (not included in our models) driving water quality impacts. This result highlights the importance of retraining ourselves to be more aware of the role of past experiences, and how they shape the questions we ask in our work. We carried what we know about how increases in precipitation should affect systems now (under lower temperatures and evaporation rates) into our expectations for how these changes will influence the system decades from now. In effect, this was a clear reminder of the need to check for hidden assumptions of climate stationarity (Milly et al., 2008); our next set of climate change scenarios will vary temperature as well as precipitation.

As indicated by the example above, one important role for integrative use of modeling tools is that they can provide a tangible way of testing assumptions. However, like our mental models for specific systems, they may also incorporate assumptions that undermine our ability to plan effectively for continual change in climate drivers. For example, our future climate scenario datasets were created with monthly averages, but we needed to convert these to daily values for input in SWAT. We used the delta method for this conversion, which scales the inputs by the changes in maximum and minimum values, with no change in the variability (potential for extremes), or pattern of wet and dry days (Fowler et al., 2007). Given that we expect to see more extremes in the future, this data preparation choice represents a “hidden” assumption of stationarity that could easily be corrected in future efforts. Given future projections for precipitation that are already thought to underrepresent extreme events (Mishra et al., 2012; Pryor et al., 2013, 2014; Trenberth 2011) and the critical role that major storms, and periods of drought (e.g., Magalhaes et al., 2007; Matthews and Marsh-Matthews, 2003) have on current water quality and fish health, we would likely learn more about both current and future risks to our conservation strategies system if we explicitly varied extreme events in our scenarios, and changed the distribution of these events over the time period covered by our future climate scenarios.

While the above example of a “stationary” climate assumptions can be addressed through a simple modification in our data preparation steps, others are more challenging to address. Our modeling of the performance of conservation practices used a constant value of rainfall erosivity, the R factor in the Revised Universal Soil Loss Equation version 2 (RUSLE2; Foster, 2008). Typically, R values calculated from multi-decadal averages of climate conditions are used to parameterize the relationship between precipitation and erosion risk in specific locations (Dabney et al., 2012). Observed increases in peak rainfall intensities (Groisman et al. 2012) in this region are expected to lead to increases in rainfall erosivity (Biasutti and Seager, 2015; Nearing, 2001). Yet, such increases in erosivity would not be fully captured in watershed models such as SWAT if “R” values are held constant in the equations used to represent erosion, even if inputs for mean monthly/daily precipitation were increased. If rainfall erosivity was underestimated in the suite of equations that represent conservation practices, erosion would also be underestimated, leading to potentially inflated estimates of effectiveness at reducing erosion-

related stressors. It seems likely that for some locations, using R values that have not been recently updated may represent a source of bias even in work that focus just on current conditions. We echo Biasutti and Seager's (2015) call for investment in updated calculations of R using more comprehensive, and more current, precipitation and erosivity datasets, so the R values that have been used for decades can be re-evaluated. These investments could improve work like ours that is focused on identifying how much conservation is needed to reach specific conservation outcomes, could improve guidance given to farmers on how to implement field practices, and could be used to update approaches that use SWAT to inform payments for sediment reductions (e.g., Douglas-Mankin et al., 2013).

An additional insight related to the vulnerability of our modeling approach comes from recent work by Lofgren et al. (2012), which provides a highly relevant example of the importance of checking for assumptions that are embedded within the model code. In a key model used to estimate Great Lakes basin hydrology, Lofgren et al. (2012) found that potential evapotranspiration (PET) rates were too high when the model was run with the higher peak temperatures in future projections – a problem that was not detected in earlier applications of the model that projected changes in Great Lakes water levels. Our SWAT runs used the Hargreaves et al. (1985) method for estimating potential evapotranspiration, which similar to the method within the model evaluated by Lofgren et al. (2012) is derived using only changes in temperature as an input. Work by Lofgren and colleagues (2012, 2013) leads us to suspect that PET was positively biased in our work as well. A positive bias in PET would result in a complex set of impacts within SWAT that are likely to include inflated concentration estimates for various stressors. In our study, this might mean that we are underestimating runoff in our future scenarios, which could result in higher nutrient or sediment concentrations that don't allow conservation practices to provide the level of benefit we saw in our results. Sensitivity testing would help us understand the impacts of this parameter, but we suggest that improvements in how PET is handled is likely to be an important next step toward producing more robust models of future conditions.

Finally, while our intent was to “test” the use of a new analysis framework to evaluate the potential influence of climate change on the performance of agricultural conservation practices, we are fully aware that insights based on our approach are “vulnerable” due to our assessment’s limited scope. Our work to evaluate the effects of variation in future precipitation regimes only addresses a small fraction of the full set of potential climate impacts on fish assemblage health. We also did not address possible human responses to climate impacts, such as changes in crop mixes, farming practices, and water demand, or broader scale changes in population density and land use patterns. These potential changes could ease or compound efforts to improve and maintain stream health. A comprehensive climate change vulnerability assessment for fish in the Saginaw Bay region would need to include many additional factors, and would not only inform management priorities more broadly, but would likely identify additional important ways to modify Sowa et al.’s (2016) framework. For example, we expect increases in water temperature to be a critical stressor on many fish species, and that a lack of connectivity in the streams within these watersheds will hinder the ability of fish to move into habitats that are more suitable (Hall 2012; Lyons et al., 2010; Steen et al., 2010). Temperature, and other important stressors that will be influenced by climate change, will need to be integrated into the framework to ensure that Sowa et al.’s approach retains value over time.

CONCLUSIONS

While many are familiar with the idea of evaluating social or ecological systems with respect to identifying potential vulnerabilities to climate change, the approach can be “vulnerable” as well, in that performance may be strongly dependent on specific climate assumptions. The information generated from incorporating climate scenarios into Sowa et al.’s (2016) framework was valuable both in terms of what the results suggest, and what we learned in the process. We found that the Sowa et al. framework was effective for evaluating what today’s conservation practice investments might mean for the future health of Saginaw Bay streams. We can now use these projections, and the strategy-linked climate scenarios we used to create them, to work with our partners to further test and improve our strategies. The message that the level of conservation investments needed to

make improvements in stream health today will also make these watersheds more resilient to climate change is one we can share with decision-makers in this region to help promote implementation, as well as providing additional support for the strategic conservation approach described in Fales et al. (2016). In conclusion, given limited time and resources available for crafting and testing conservation approaches, it is tempting to look at Sowa et al.'s multi-step goal setting framework, and the many sources of uncertainty in this coupled human-natural system, and make a choice to skip the additional complexity and uncertainties of conducting a climate change assessment. Our experience evaluating the climate change vulnerability of this approach suggests that such efforts provide a high return on time invested by revealing patterns that lead to insight, and by producing tangible examples of possible impacts and key relationships that can inform strategy improvements.

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Table. 1. Percent change between current climate conditions and the three climate scenarios for key hydrologic processes and water quality variables under the “current” level of conservation practices. Within each climate scenario, watersheds are arranged from lowest to highest percent row-crop agriculture. Increases relative to “current” climate conditions are shown in bold.

Climate Scenario	Watershed					Loadings at watershed outlet			Concentrations at watershed outlet		
		Evapo- transpiration	Discharge	NO ₃ in surface runoff	Mineral P released to stream reach	Organic P	NH ₄	Sediment	Organic P	NH ₄	Sediment
Dry-Dry	Rifle	7	-35	-38	-17	-21	4	-16	7	41	1
	Cass	14	-54	-44	-36	-44	-34	-58	22	44	-9
	Shiawassee	10	-51	-32	-37	-45	-34	-55	14	35	-10
	Pigeon/Pinn	6	-26	-21	-30	-36	-22	-43	-2	19	-7
Wet-Dry	Rifle	9	-7	-11	18	11	29	28	12	29	10
	Cass	23	-29	-23	-1	-15	-4	-31	21	35	-5
	Shiawassee	15	-26	-13	-6	-16	-5	-29	14	29	-6
	Pigeon/Pinn	9	-0.5	-6	-1	-10	7	-4	-3	15	4
Wet-Wet	Rifle	14	19	-3	19	15	41	27	2	25	8
	Cass	29	-7	-13	11	2	13	-7	9	21	-1
	Shiawassee	21	-2	0	9	2	15	-3	3	17	-2
	Pigeon/Pinn	13	13	-1	11	6	21	26	-12	1	12

FIGURE CAPTIONS

Figure 1. Map showing the Saginaw Bay basin (Michigan, USA) outline, and indicating locations of the four focal watersheds (Rifle, Shiawassee, Cass, and Pigeon-Pinnebog) where conservation and climate scenarios were evaluated. Dark gray shading indicates landcover that is dominated by agriculture, while light gray indicates urban areas, and white represents natural land cover.

Figure 2. Variability in climate change projections for mean monthly temperatures (top row) and monthly precipitation (bottom row) in the 2080s under B1 and A2 emissions scenarios from 16 Global Climate Models for the Saginaw Bay region of Michigan (downloaded from ClimateWizard, climatewiz.org). Dark lines in each figure indicate the ensemble mean. In the plot for precipitation under A2 emissions, dark blue lines indicate the three models used in to create the “Wet-Wet” scenario values, while light blue and red lines show the models incorporated in the “Wet-Dry” and “Dry-Dry” scenarios, respectively.

Figure 3. Precipitation scenarios for the 2080s used as inputs to SWAT. These “customized” scenarios represent an average of values from three Global Climate Models that showed similar seasonal patterns under the A2 (high) carbon emission scenario. For comparison, the dashed line shows monthly average precipitation from the recent past (1990-2009).

Figure 4. Example dose-response curves for subbasins in the A) Rifle River, B) Pigeon-Pinnebog, C) Shiawassee, and D) Cass Watersheds. Graphs show potential IBI (background shading) as a function of different water quality variables predicted by SWAT model runs under the three conservation practice and climate change scenarios.

Figure 5. Percent maximum attainable IBI score based on the most limiting water quality or flow variable for each subbasin across the four priority watersheds for each combination of conservation practice scenario (current, 25%, and 50%) and projected climate change scenario (Dry-Dry, Wet-Dry, Wet-Wet).

Subbasins in dark green are not limited by water quality or flow variables, while subbasins in orange or red are extremely limited.

Figure 1.

Figure 2.

A. Monthly mean temperature – B1 scenario

B. Monthly mean temperature – A2 scenario

C. Monthly precipitation – B1 scenario

D. Monthly precipitation – A2 scenario

Figure 3.

Figure 4.

Figure 5.