The Nutrient Reduction Index:

A minimalist and continuous measure of conservation practice adoption among farmers

Abstract: A Nutrient Reduction Index (NRI) was developed to assist investigators who wish to explore the impacts of interventions, individual difference factors, and farm characteristics on nutrient-focused conservation practices. Comparing the effectiveness of different interventions or understanding the effects of different farm and farmer characteristics can be difficult in the absence of a single and standardized measure of conservation practices (Anderson 2020; Loken and Gelman 2017; Lilienfeld and Strother 2020). Across two data sets (*N* = 1,452), the continuous NRI was calculated by weighting several in-field practices (tillage, cover crops, small grains in rotation) by their actual impact on nutrient reduction (Iowa State University 2019; Ha et al. 2020). The NRI was shown to have a smoother distribution than individual conservation behaviors, and convergent validity was demonstrated with thmpsonconservation-related constructs like conservationist identity and use of filtering practices. The NRI also correlated with farm size, greater formal education, and lower farmer age, consistent with previous work regarding general conservation practices. This measure of nutrient reduction practices can help reduce error associated with dichotomization of practice adoption (MacCallum et al. 2002) and testing multiple measures (Banerjee et al. 2009; Anderson 2020), and its weighted nature better reflects the impact of practice adoption on actual nutrient reduction.

Key words: conservation agriculture—farmer behavior—measuring conservation practices—nutrient reduction—soil health

The field of farmer behavior endeavors to discover means by which conservation agriculture can be encouraged, as doing so is a crucial component of soil and water conservation goals. Excess nitrogen and phosphorus entering water systems contribute to harmful algal blooms (Hunt, Hill and Liebman 2019), which are further exacerbated by climate change (Paerl and Scott 2010). Because nutrient application is often necessary for crop production, best management practices aimed at greater precision and retention in nutrient applications are recommended, rather than ceasing the application of nutrients altogether (Hedley 2015; FAO 2022). However, current outreach and incentive programs have not been sufficient to increase adoption of recommended practices to the level needed to meet nutrient reduction targets (Wilson et al. 2019; Martin et al. 2021). Because of this gap, best practices in behavioral science are being used to encourage changes in practices beyond those achieved by traditional conservation programs (Prokopy et al. 2019; McGuire et al. 2015; Reimer et al. 2012). As these applications grow, the effectiveness of these various interventions will need to be compared to discover the best options for increasing nutrient management practices on farms. To do so, comparable outcome measures will be needed to support direct comparisons.

The scientific literature surrounding the measurement of behavior has developed several overarching principles that guide quantitative measurement. Several of these principles are directly relevant to measuring conservation practices among farmers and testing the factors that influence practice adoption. These principles include: (1) minimizing familywise (or cumulative) Type I error, (2) validity, (3) appropriateness of the measure for statistical models, and (4) consistency between studies. Currently, the discipline of farmer behavior research has not developed a wide-used measure of nutrient reduction practices that addresses all these principles. The current investigation aimed to do so, focusing on nutrient management practices that are relevant to the growth of row crops, which accounts for 56.5% of all United States crop acreage (USDA 2021).

Minimizing Familywise Type I Error

First, the construct of "level of adoption of nutrient management practices" should be represented as a single measure whenever possible. This is because when a construct is measured as a series of separate behaviors, multiple statistical tests must be performed to examine the relationship between the predictor variables and behaviors. Because of the nature of null hypothesis significance testing, performing multiple tests in this way inflates Type I error (Anderson 2020), or the chance that a statistically significant finding is actually due to chance. Applying more stringent conventions of statistical significance is not always sufficient to accommodate this increased Type I error (Anderson 2020). Also, simply averaging multiple behaviors together would assume that each behavior is an equal representation of conservation, when in reality, some practices have a greater environmental benefit than others (Iowa State University 2019; Ha et al. 2020).

Accordingly, the proposed Nutrient Reduction Index (NRI) weighs three conservation practices – reduced tillage, diverse crop rotations, and cover crops - by their scale of on-farm implementation (proportion of acres or proportion of years in practice) and each practice's relative potential for nutrient reduction, as determined by data from Iowa State University (2019) and nutrient reduction goals of the USDA (2022). Many published works review the benefits of these practices for reducing nutrient runoff, or improving soil health to reduce the need for nutrient application (e.g. Blanco-Canqui 2018; Hunt et al 2019; Koropeckyj-Cox et al. 2021; Nunes et al. 2020). Here, we used estimates of reductions in nutrient load from Iowa State

University (2019) as these estimates were drawn from a similar study area as the present data. The full method of calculation is listed in the Supplemental Materials. These practices were chosen for four primary reasons: (1) they are considered central parts of conservation agriculture (FAO 2022; USDA 2022); (2) they are commonly measured in-field practices across studies of farmer behavior (Schenpf and Cox 2006; Baumgart-Getz et al. 2012; Carlisle 2016; Prokopy et al. 2019; Luther et al. 2020, Lu et al. 2022); (3) are directly or indirectly relevant to the nutrient reduction and soil health goals of many incentive-based programs (Claassen et al. 2018; Reimer and Prokopy 2014; USDA 2022), (4) and are relevant to the production of row crops, which are grown in most states and make up about 56.5% of all cropland acres in the United States (USDA 2021).

Validity

Quantitative measures of a construct, in this case nutrient management practices, should demonstrate *convergent* validity with other constructs that ought to be related (Campbell and Fiske 1959). Previous work has demonstrated that in general, in-field conservation practices are related to other conservation-focused practices such as edge-of-field nutrient management (Prokopy et al. 2019). Further, a farmer's conservationist identity, or the extent to which the farmer believes that a "good farmer"—or a best-practice farmer—engages in conservation practices, correlates with higher actual conservation practices (Morton et al. 2017).

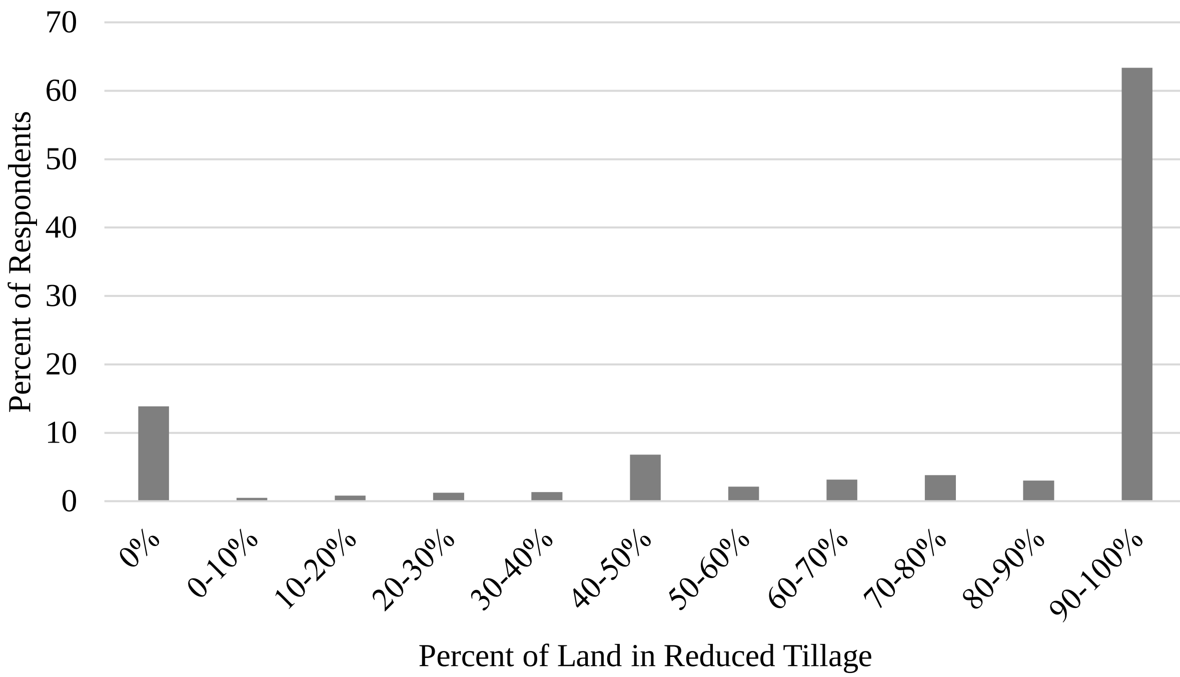
Next, a measure should also demonstrate *divergent* validity by showing that the measure is distinct from other variables that could be correlated with it, and therefore the measure adds a deeper understanding of the implementation of conservation practices. For example, larger farms tend to implement more conservation practices, as do younger farmers and those with higher formal educational attainment (Prokopy et al. 2019). This is most likely due to differences in resource availability, such as the per-acre cost of implementation decreasing with larger farm size, persons further from retirement receiving more long-term benefits of conservation practices, and having more engagement with university extension offices. To establish divergent validity when testing the effect of past conservation practices on future practice implementation, these variables would need to be statistically controlled to establish a unique effect of past practices. The present investigation sought to investigate the validity of the NRI by replicating the above findings from previous work.

Appropriateness for Statistical Models

To test whether a program significantly increased practice adoption beyond chance levels, statistical tests must be performed. This significance testing in behavioral science and program evaluation is often done using ordinary least squares (OLS) linear regression modeling (Long 2008). Other types of statistical approaches like analysis of variance are possible (Roberts and Russo 2014), but all OLS regression models require that there is no systematic error in estimating what the effect of an independent variable (such as enrollment in a program, farmer conservation identity, or farmer age) is on the dependent variable (such as practice adoption). This is called homogeneity of error variance. When a variable is highly skewed, there can *sometimes* be systematic error in the statistical model, as the mean is not an accurate measure of central tendency (Osborne and Waters 2002). Very often, levels of conservation practice adoption are highly skewed. For example, Figure 1 shows the distribution of the percent of acres that a farmer has in continuous no-till. This data was collected from farmers in the Great Lakes region and is described in the Supplemental Materials.

Figure 1

Distribution of Percent of Land in Continuous No-Till among 1452 U.S. Great Lakes Region Farms



Note: As is the case here, the distribution of amount of land in a reduced tillage system is often highly skewed. *N* = 1452 farmers in the U.S. Great Lakes Region.

When skewed data causes the assumptions of statistical tests to be violated, one common strategy is to dichotomize the variable. For example, measuring no-till practices as either happening on some land (a value of “1”), or not (a value of “0”). However, doing so loses variability associated with different levels of practice implementation. This loss of variance can lead to spurious results in statistical models, as well as incorrectly concluding that an intervention was not effective (Dawson and Weiss 2012).

The proposed Nutrient Reduction Index was developed to help accommodate this issue associated with quantitative measures of practice adoption by combining several practices. It was reasoned that separately, each practice has low levels of adoption, but together, their distribution among farmers would be less skewed and smoother.

Consistency Between Studies

Finally, in order to compare the effectiveness of various interventions or programs, or the effect of farm and farmer characteristics, on practice adoption, comparable measures are needed in order to draw robust conclusions across multiple studies. Currently, published studies exhibit variability in how conservation practice adoption is quantified (e.g. Prokopy et al. 2019, Lu et al. 2022). For example, some studies quantify practices individually, often measuring adoption in a yes/no dichotomous fashion. Although these methods are individually sound, comparing the size of the effect of interventions across unequal measures is difficult, prohibiting conclusions about which effects are strongest, which method or intervention could be most effective at inducing change, or whether the same intervention is consistently and reliably effective (Prokopy et al. 2019). The proposed Nutrient Reduction Index can be used in future works to facilitate comparability of effects across published studies by being calculated in addition to, or in place of, other measures.

Study Overview

The present study aimed to develop a single and easily calculable index of nutrient reduction practices, using commonly-measured practices that are often the target of nutrient management programs, and on-farm conservation more broadly (Schenpf and Cox 2006; Baumgart-Getz et al. 2012; Carlisle 2016; Prokopy et al. 2019; Luther et al. 2020; Lu et al. 2022; USDA 2022). This was accomplished by examining survey data collected from farmers in the Great Lakes Region. These surveys measured practice adoption, farm characteristics, and individual difference factors like farmer conservation identity. The surveys were designed to integrate predictors of heterogeneity in conservation practice adoption with simulation models of watershed quality. Therefore, the analyses presented here are secondary analyses.

Materials and Methods

Study Population. Survey data was collected from 1,517 farm operators in the Great Lakes Region across two survey projects. These paper-and-pencil surveys were collected contemporaneously via mail in 2019, without overlap in study populations (for full details on population selection and distribution methods, see Supplemental Materials). Respondents were free to skip any questions that they did not wish to answer. For the variables that comprise the Nutrient Reduction Index, complete data was collected from 1,452 participants.

Measures. To replicate existing findings in the literature, the present study tested the relationship of the Nutrient Reduction Index with other (non-in-field) conservation practices, farmer conservation identity (Arbuckle 2013; McGuire et al. 2015), farm characteristics, and demographic factors. For full measurement details, descriptive statistics, and full survey instruments see the Supplemental Materials.

Nutrient Reduction Index: The Nutrient Reduction Index was calculated from tillage practices (proportion of land in conventional tillage, conservation tillage, rotational no-till, continuous no-till), proportion of land in cover crops, and proportion of years having small grains in rotation. Each practice was then weighted by its relative impact on nutrient reduction, using metrics developed by Iowa State University (2019). Finally, the weighted values for each practice were added together, such that possible scores on the index range from 0 to 1.65.

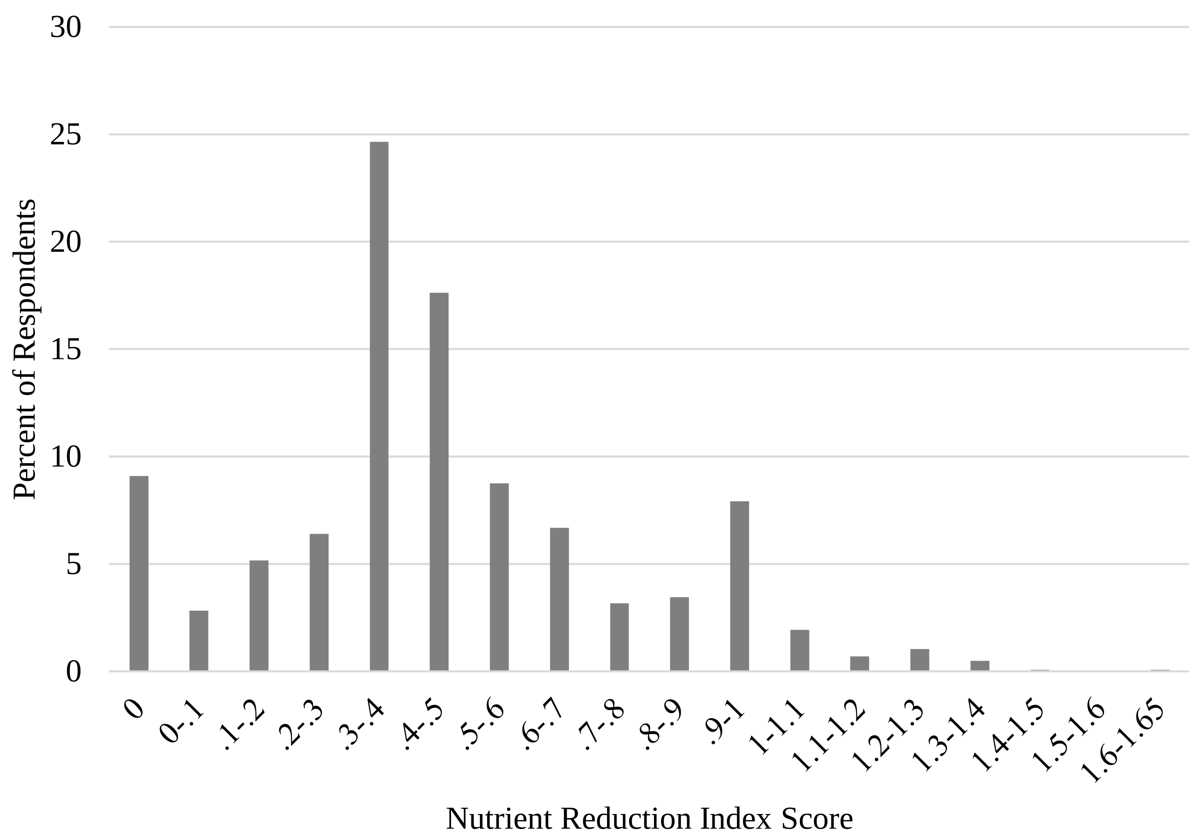
Analytic Strategy. After the Nutrient Reduction Index was calculated its distribution was examined. Next, correlations between the variables were examined using two-tailed pairwise correlations. To account for overlapping variance amongst these variables, significant corollaries of interest were entered into a multiple linear regression model predicting NRI scores. Model assumptions of normality of residuals and homogeneity of error variance were also examined to test the appropriateness of the NRI for ordinary least squares statistical tests.

Results and Discussion

Nutrient Reduction Index. The NRI followed a multi-modal distribution (see Figure 2). Specifically, scores are clustered around values of 0.00, 0.47, and 0.93. Zero corresponds to a value of not having implemented any conservation practices on one's farm, 0.47 corresponds to having fully implemented no-till practices but no small grains or cover crops, and 0.93 corresponds to implementing continuous no-till on one's farm, but no other practices. Unlike the distribution of the individual conservation practices (see Figure 1), the distribution of the NRI was smoother.

Figure 2

Distribution of Nutrient Reduction Index Scores Across 1452 Farms in the U.S. Great Lakes Region



Note: Distribution of the Nutrient Reduction Index, which has three modes and more closely approximates a normal distribution, compared to the distribution shown in Figure 1. *N* = 1452 farmers in the U.S. Great Lakes region.

Correlations. As expected, the NRI significantly correlated with greater conservationist identity and having more land in dedicated edge-of-field practices. This helps to establish the *convergent* validity of the NRI (see Table 2). Consistent with previous meta-analyses examining correlates of conservation practices (Prokopy et al. 2008; 2019), the NRI also correlated with having a larger farm and livestock, as well as higher formal educational attainment and lower farmer age. Importantly, each of these correlations was small, indicating that none of these variables is sufficient to account for all variability in nutrient reduction practices. This helps to argue for the *discriminant* validity of the measure.

Table 2

Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) nutrient reduction index	1.000						
	1452						
(2) conservationist identity	0.242	1.000					
	(0.000)						
	1383	1389					
(3) percent of land in non-in-field conservation	0.156	0.105	1.000				
	(0.000)	(0.000)					
	1452	1389	1458				
(4) farm size	0.064	0.060	0.057	1.000			
	(0.016)	(0.025)	(0.030)				
	1445	1387	1451	1451			
(5) livestock on farm	0.092	0.023	0.011	0.095	1.000		
	(0.001)	(0.387)	(0.685)	(0.000)			
	1427	1376	1433	1432	1433		
(6) farmer age	-0.057	0.009	-0.050	-0.139	-0.148	1.000	
	(0.033)	(0.736)	(0.060)	(0.000)	(0.000)		
	1410	1372	1416	1413	1401	1416	
(7) farmer education	0.112	0.022	0.051	0.132	0.034	-0.157	1.000
	(0.000)	(0.407)	(0.053)	(0.000)	(0.196)	(0.000)	
	1452	1389	1458	1451	1433	1416	1458

Note: Pairwise correlations between the nutrient reduction index and all variables of interest. Because participants were free to skip any question, *N* varies for each pairwise correlation.

Regression Analyses. Because the NRI was observed to have a multimodal distribution in the present sample, it was not appropriate to use statistical models that rely on mean values of the dependent variable to indicate centrality (i.e. OLS regression). Indeed, after fitting an OLS regression model and plotting the error residuals, they were not normally distributed. Further, residuals were not homogeneous across values of the NRI.

As such, it was concluded that a heteroskedastic regression model would be estimated, which does not make assumptions about the distribution of residuals, but instead explicitly models heterogeneity of error variance, and is more robust to misspecification (Leslie et al. 2007). Exploratorily, we also modeled the effect of the predictors on the NRI at each of the aforementioned modes in the distribution using simultaneously-estimated quantile regression, which does not assume normality of residuals nor homogeneity of error variance. Quantile regression allows for models to be estimated at specified quantiles of the dependent variable, with robust standard errors estimated using bootstrapping (Hao et al. 2007). A regression model was estimated for each quantile that corresponds to each mode.

Heteroskedastic Regression Model. A heteroskedastic regression model was estimated that predicted the NRI from conservationist identity, farm size, the presence of livestock on one's farm, farmer age, and farmer education. Conservation identity, farm size, and farmer age and education were standardized using z-scores. This sets each variable in the model to have a mean of zero and standard deviation of one. In this way, the model estimates meaningful zero values of the predictors, and creates more comparable coefficients. Results of the model showed that once overlapping variance between the predictors is accounted for, only conservation identity, the presence of livestock on the farm, and formal educational attainment correlated with the NRI (see Table 3).

Table 3

Heteroskedastic Linear Regression Results

Parameter	β	95% C.I. *LL*	95% C.I. *UL*	*SE*	*p*
Intercept	0.449	0.431	0.467	0.009	< .001
conservationist identity	0.057	0.043	0.071	0.007	< .001
farm size	0.005	- 0.007	0.018	0.007	.406
livestock	0.060	0.028	0.091	0.016	< .001
farmer age	- 0.007	0-.023	0.007	0.008	.302
farmer education	0.024	0.008	0.039	0.008	.003

Note: The regression model [χ^2(5, 1353) = 98.12, p < .001] found that at average levels of the predictor variables, the average NRI score is 0.45, out of a possible highest score of 1.65. A one standard-deviation increase conservation identity predicted a 0.057-unit increase in the NRI. The presence of livestock predicted a 0.060-unit increase, compared to no livestock. Finally, compared to a person with average farmer education (some college) a person with an associate's or bachelor's degree is predicted to have higher NRI scores by 0.024 units.

Quantile Regression Model. In the quantile regression analysis (see Table 4), at mean values of nutrient reduction practices, the NRI is predicted by conservationist identity and having livestock. At the lowest mode of no NRI-related practices, conservationist identity does not predict the NRI, but it is predicted by larger farm size and having livestock. Finally, at the highest mode, which corresponds to implementing no-till on all acres but no other practices, the NRI is only predicted by conservationist identity.

Table 4

Quantile Regression Model Results

Parameter	*β*	*SE*	95% C.I. *LL*	*UL*	*p*	R^2_{pseudo}
.091 quantile (NRI = 0.00)						.047
intercept	0.058	0.019	0.020	0.095	.003	
conservationist identity	0.021	0.013	-0.004	0.046	.100	
farm size	0.039	0.010	0.020	0.058	< .001	
livestock	0.122	0.033	0.058	0.187	< .001	
farmer age	-0.015	0.012	-0.037	0.007	.193	
farmer education	-0.001	0.008	-0.018	0.015	.870	
.630 quantile (NRI = 0.43)						.037
intercept	0.475	0.012	0.452	0.498	< .001	
conservationist identity	0.058	0.011	0.037	0.080	< .001	
farm size	0.001	0.008	-0.016	0.017	.921	
livestock	0.076	0.023	0.030	0.122	.001	
farmer age	-0.019	0.010	-0.037	< 0.001	.050	
farmer education	0.017	0.011	-0.004	0.039	.119	
.934 quantile (NRI = 0.93)						.035
intercept	0.936	0.019	0.899	0.972	< .001	
conservationist identity	0.076	0.022	0.032	0.119	.001	
farm size	0.003	0.019	-0.033	0.040	.854	
livestock	0.022	0.040	-0.056	0.099	.583	
farmer age	0.026	0.019	-0.012	0.064	.178	
farmer education	0.034	0.022	-0.009	0.078	.124	

Note: Above are results of the simultaneous quantile regression model, with robust standard errors estimated using 10,000 bootstrapped replications. Coefficients are comparable across models by examining the confidence intervals. The first model corresponds to a starting point of not engaging in any of the conservation practices that are part of the NRI; the to sample mean NRI values; and the third engaging in all no-till but no other practices.

Discussion. The present study aimed to develop a single, combinative measure of nutrient reduction practices, using commonly-collected farming practice data weighted by evidence-based effects on nutrient reduction goals (Iowa State University 2019). This Nutrient Reduction Index exhibited correlations that were consistent with existing literature examining the relationship between general conservation practices and farmer conservationist identity, farm characteristics, and demographic factors. As expected, the in-field nutrient reduction practices that were part of the NRI also correlated with edge-of-field conservation practices. Importantly, none of these correlations were high, suggesting that the NRI remains a useful measure beyond existing constructs that relate to conservation practices.

Another goal of the study was to evaluate the appropriateness of the Nutrient Reduction Index for common statistical techniques that use ordinary least squares estimation. Examining the distribution of the NRI revealed that there were multiple modalities. Specifically, there appeared to be normative trends in farmer behavior, such that there were some in the sample who engaged in none of the nutrient reduction practices measured (N= 132, or 9%), and others who had implemented continuous no-till on all of their acres but had no cover crops nor small grains (N = 83, or 6%). Other samples from different regions in the United States may not exhibit this trend, but the present sample illustrates the importance of choosing statistical tests that are appropriate for the nature of any measure of conservation practices.

The analyses further suggested that there may be meaningful heterogeneity in what drives the adoption of additional practices across different starting points of current practices (tillage, cover crops, and small grains), although causal conclusions are not possible due to the correlational nature of the data. Specifically, results were consistent with the idea that when farmers have not implemented NRI-related practices, if more farm resources were available with farm size—like income, labor, machinery, and lower costs per acre (Lu et al. 2022)—that might allow for greater adoption. Whereas when some conservation practices are already in place, conservationist identity predicted implementing more practices.

Summary and Conclusions

Limitations and Future Directions. The present study is limited in terms of accounting for all factors that might relate to the Nutrient Reduction Index. This is because the regression models could account for only about 5% of variability in the NRI. The strongest correlation observed was between the NRI, and conservationist identity. Future investigations could examine the relationship of the NRI to other individual difference factors that relate to pro-social or pro-environmental action, such as self-efficacy or perceived behavioral control (Perry and Davenport 2020; Gao and Arbuckle 2021) and perceived norms (Ranjan et al. 2019).

Second, it is important to point out that it is not the absolute values of the NRI that are meaningful, but rather relative scores. This is because after each practice (tillage, cover crops, and small grains) was weighted by their relative impact on actual nutrient reduction (as per Iowa State University 2019), they were added together. However, the actual impact of any combination of practices is not additive. Nevertheless, the NRI developed here does give credit to operators for not only the scale of practice implementation on their farm, but also that practice's actual impact on nutrient reduction. The weighting of the practices contained within this index could be updated in accordance with new evidence regarding how these practices combine to reduce nutrient loss. Finally, although the conservation practices that comprise the index are relevant to any place where row crops are grown, the data used here include only farms in the Midwest. As in the present data, across farms in the united states, non-conventional tillage predominates (Zulauf & Brown, 2019a), use of cover crops is low (Zulauf & Brown, 2019b), and in areas where corn is grown, rotations that include corn and soy are common (Wang et al. 2020). Therefore, we would expect that the distribution and utility of the Nutrient Reduction Index would not be limited to the Midwest. Nevertheless, future work will be needed to examine the distribution of NRI scores in other areas where row crops are grown.

Finally, a strength of this index is that it is able to measured via self-report surveys, using just a few items that can be completed quickly and with minimal recall effort. Thus, these items are brief enough to be included on larger surveys that may have other purposes, thereby minimizing costs and participant burden. An exciting future direction would be to explore the utility of estimating the Nutrient Reduction Index using remotely-sensed data, which has shown some promise detecting crop type and rotation (Rahman et al. 2019; Lin et al. 2022) and conservation tillage (Zheng et al 2013; Beeson et al. 2020)

Conclusion. The present study presents a suggested means by which conservation practices related to nutrient reduction can be assessed as a single, combinative measure. The Nutrient Reduction Index that was developed revealed nuanced correlates of farming practices; examining modalities in NRI scores suggested that when existing conservation practices are low, implementing further practices may be limited by a lack farm resources rather than a lack of pro-environmental goals. It is hoped that by calculating and analyzing NRI scores, results of future studies can be directly compared. Doing so would allow for comparing the effectiveness of different conservation interventions and other factors at encouraging the adoption of nutrient reduction practices across contexts and time.

References

Anderson, S. F. 2020. Misinterpreting p: The discrepancy between p values and the probability the null hypothesis is true, the influence of multiple testing, and implications for the replication crisis. Psychological Methods, 25(5): 596–609.

Arbuckle, J.G. 2013. Farmer support for extending conservation compliance beyond soil erosion: Evidence from Iowa. Journal of Soil and Water Conservation 68(2): 99–109. https://doi.org/10.2489/jswc.68.2.99.

Banerjee, A., Chitnis, U. B., Jadhav, S. L., Bhawalkar, J. S., and Chaudhury, S. 2009. Hypothesis testing, type I and type II errors. Industrial Psychiatry Journal, 18(2): 127.

Baumgart-Getz, A., Prokopy, L. S., and Floress, K. 2012. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. Journal of Environmental Management, 96(1): 17-25.

Beeson, P. C., Daughtry, C. S., & Wallander, S. A. (2020). Estimates of conservation tillage practices using landsat archive. Remote Sensing, 12(16), 2665.

Blanco-Canqui, H. (2018). Cover crops and water quality. Agronomy Journal, 110(5), 1633-1647.

Campbell, D. T., and Fiske, D. W. 1959. Convergent and discriminant validation by the multitree-multimethod matrix. Psychological Bulletin, 56: 81–105

Carlisle, L. (2016). Factors influencing farmer adoption of soil health practices in the United States: A narrative review. Agroecology and Sustainable Food Systems, 40(6), 583-613.

Claassen, R., Duquette, E. N., and Smith, D. J. 2018. Additionality in US agricultural conservation programs. Land Economics, 94(1): 19-35.

Dawson, N. V., and Weiss, R. 2012. Dichotomizing continuous variables in statistical analysis: A practice to avoid. Medical Decision Making, 32(2): 225–226.

Food and Agriculture Organization of the United Nations (FAO). 2022. Three principles of conservation agriculture. Conservation Agriculture. https://www.fao.org/3/cb8350en/cb8350en.pdf

Gao, L., and Arbuckle, J. 2022. Examining farmers' adoption of nutrient management best management practices: a social cognitive framework. Agriculture and Human Values, 39(2): 535-553.

Ha, M., Wu, M., Tomer, M. D., Gassman, P. W., Isenhart, T. M., Arnold, J. G., ... and Belden, B. 2020. Biomass production with conservation practices for two Iowa watersheds. JAWRA Journal of the American Water Resources Association, 56(6): 1030-1044

Hao, L., Naiman, D. Q., and Naiman, D. Q. 2007. Quantile regression. Sage.

Hedley, C. (2015). The role of precision agriculture for improved nutrient management on farms. Journal of the Science of Food and Agriculture, 95(1): 12-19.

Hunt, D. N., Hill, J. D., and Liebman, M. 2019. Cropping system diversity effects on nutrient discharge, soil erosion, and agronomic performance. Environmental Science and Technology, 53 (3): 1344-1352.

Iowa State University. 2019, October. Reducing nutrient loss: Science shows what works. Iowa State Extension Office. https://store.extension.iastate.edu/Product/Reducing-Nutrient-Loss-Science-Shows-What-Works-PDF

Koropeckyj-Cox, L., Christianson, R. D., & Yuan, Y. 2021. Effectiveness of conservation crop rotation for water pollutant reduction from agricultural areas. Transactions of the American Society of Agricultural and Biological Engineers, 64(2), 691-704.

Leslie, D. S., Kohn, R., and Nott, D. J. 2007. A general approach to heteroscedastic linear regression. Statistics and Computing, 17(2): 131-146.

Lilienfeld, S. O., and Strother, A. N. 2020. Psychological measurement and the replication crisis: Four sacred cows. Canadian Psychology, 61(4): 281–288.

Lin, L., Di, L., Zhang, C. et al. Validation and refinement of cropland data layer using a spatial-temporal decision tree algorithm. Scientific Data 9, 63 (2022). https://doi.org/10.1038/s41597-022-01169-w

Loken, E., and Gelman, A. 2017. Measurement error and the replication crisis. Science, 355(6325): 584-585.

Long, R. G. 2008. The crux of the method: assumptions in ordinary least squares and logistic regression. Psychological Reports, 103(2): 431-434.

Lu, J., Ranjan, P., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., ... & Prokopy, L. S. (2022). A meta-analysis of agricultural conservation intentions, behaviors, and practices: Insights from 35 years of quantitative literature in the United States. Journal of Environmental Management, 323, 116240.

Luther, Z. R., Swinton, S. M., & Van Deynze, B. (2020). What drives voluntary adoption of farming practices that can abate nutrient pollution?. Journal of Soil and Water Conservation, 75(5), 640-650.

MacCallum, R. C., Zhang, S., Preacher, K. J., and Rucker, D. D. 2002. On the practice of dichotomization of quantitative variables. Psychological Methods, 7(1): 19-40.

Martin, J. F., Kalcic, M. M., Aloysius, N., Apostel, A. M., Brooker, M. R., Evenson, G., ... and Wang, Y. C. 2021. Evaluating management options to reduce Lake Erie algal blooms using an ensemble of watershed models. Journal of Environmental Management, 280: 111710.

McGuire, J.M., L.W. Morton, J.G. Arbuckle, and A.D. Cast. 2015. Farmer identities and responses to the social-biophysical environment. Journal of Rural Studies 39: 145–155.

Morton, L. W., McGuire, J. M., and Cast, A. D. 2017. A good farmer pays attention to the weather. Climate Risk Management, 15: 18-31.

Nunes, M. R., Karlen, D. L., Veum, K. S., Moorman, T. B., & Cambardella, C. A. (2020). Biological soil health indicators respond to tillage intensity: A US meta-analysis. Geoderma, 369, 114335.

Osborne, J. W., and Waters, E. 2002. Four assumptions of multiple regression that researchers should always test. Practical Assessment, Research, and Evaluation, 8(2): 1-5.

Paerl, H. W., and Scott, J. T. 2010. Throwing fuel on the fire: synergistic effects of excessive nitrogen inputs and global warming on harmful algal blooms. Environmental Science and Technology, 44(20): 7756-7758.

Perry, V., and Davenport, M. A. 2020. An inductive framework of self-efficacy to understand and support farmers in conservation agriculture. Journal of Soil and Water Conservation, 75(2): 198-208.

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., ... and Singh, A. S. 2019. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. Journal of Soil and Water Conservation, 74(5): 520-534.

Rahman, Md. S., Di, L., Yu, E., Zhang, C., & Mohiuddin, H. 2019. In-season major crop-type identification for US cropland from landsat images sing crop-rotation pattern and progressive data classification. *Agriculture*, *9*(1), http://dx.doi.org/10.3390/agriculture9010017

Ranjan, P., Church, S. P., Floress, K., and Prokopy, L. S. 2019. Synthesizing conservation motivations and barriers: what have we learned from qualitative studies of farmers' behaviors in the United States? Society and Natural Resources, 32(11): 1171-1199.

Reimer, A. P., and Prokopy, L. S. 2014. Farmer participation in US Farm Bill conservation programs. Environmental Management, 53(2): 318-332.

Reimer, A. P., Weinkauf, D. K., and Prokopy, L. S. 2012. The influence of perceptions of practice characteristics: An examination of agricultural best management practice adoption in two Indiana watersheds. Journal of Rural Studies, 28(1): 118-128.

Roberts, M., and Russo, R. 2014. A student's guide to analysis of variance. Routledge.

Schenpf, M., and Cox, C. A. 2006. Environmental benefits of conservation practices on cropland: The status of knowledge. Soil and Water Conservation Society.

USDA, 2021, Mar. 31. Prospective Plantings. National Agricultural Statistics Service. https://downloads.usda.library.cornell.edu/usda-esmis/files/x633f100h/w6634x823/x633fv29f/pspl0321.pdf

USDA. 2022, Jan 10. USDA offers expanded conservation program opportunities to support climate smart agriculture in 2022. Natural Resources Conservation Service. https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/newsroom/releases/?cid=nrcseprd1867846

Wang, S., Di Tommaso, S., Deines, J. M., & Lobell, D. B. 2020. Mapping twenty years of corn and soybean across the US Midwest using the Landsat archive. Scientific Data, 7(1), 307.

Wilson, R.S., Beetstra, M.A., Reutter, J.M., Hesse, G., Fussell, K.M.D., Johnson, L.T., King, K.W., LaBarge, G.A., Martin, J.F. and Winslow, C., 2019. Commentary: Achieving phosphorus reduction targets for Lake Erie. Journal of Great Lakes Research, 45(1): 4-11.

Zheng, B., Campbell, J. B., Shao, Y., & Wynne, R. H. 2013. Broad-Scale Monitoring of Tillage Practices Using Sequential Landsat Imagery. Soil Science Society of America Journal, 77(5), 1755-1764.

Zulauf, C. and Brown, B. 2019a. Tillage Practices, 2017 US Census of Agriculture. Farmdoc Daily (9): 136. https://farmdocdaily.illinois.edu/2019/07/tillage-practices-2017-us-census-of-agriculture.html

Zulauf, C. and Brown, B. 2019b. Cover Crops, 2017 US Census of Agriculture. Farmdoc Daily (9): 135. https://farmdocdaily.illinois.edu/2019/07/cover-crops-2017-us-census-of-agriculture.html