Increasing Effectiveness and Reducing the Cost of Non-Point Source Best Management Practice Implementation: Is Targeting the Answer?

I. Introduction

As the Chesapeake Bay Program (CBP) passes the mid-point assessment, point source discharges will have achieved (or nearly achieved) their final Total Maximum Daily Load (TMDL) nitrogen (N) and phosphorus (P) wasteload allocations. Jurisdictions, however, still need to achieve substantial nutrient and sediment reductions from agricultural and urban nonpoint sources. Based on current understanding and modeling, the CBP estimates that agriculture and urban nonpoint sources need to achieve an additional 35 million and 12 million pounds of N reductions, 1.3 and 0.6 million pounds of P reductions, and 941 and 594 million pounds of sediment, respectively, to meet TMDL goals. State and local governments are poised to spend hundreds of millions of additional dollars to meet these goals, primarily by installing nonpoint source best management practices (BMPs).

Thus, BMP implementation stands at the center of efforts to meet TMDL requirements. Yet, water quality monitoring suggests that the link between BMP implementation and load reductions is tenuous at best. The CB watershed model estimates substantial reductions in agricultural loads, but monitoring data suggests little to no change in these loads between 1992-2012 (Keisman et al. 2018). In a recent STAC review, Keisman et al. (2018) state “current research suggests that the estimated effects of conservation practices have not been linked to water quality improvements in most streams.” This is a familiar outcome. In general detecting observed changes in ambient conditions from nonpoint source control efforts is a challenge common across the country (Osmond et al 2012; Perez 2017).

A critical question is why? Potential explanatory factors include inadequate BMP coverage, poor implementation/maintenance, lag times between implementation and water quality response, inadequate participation, and inability to target BMPs to critical pollutant source areas (Easton et al. 2017). Improved targeting of nonpoint source controls to areas with high pollutant loss rates (both at the field and watershed level) is often proposed as a way to produce better outcomes (Shortle et al. 2012; Perez 2017; Osmond et al 2012).

Many studies have noted that areas of high nutrient loss are site specific and highly localized. If BMPs tend to get applied in lower risk areas rather than targeted to areas where nutrient loads are more likely to originate, nutrient load reduction effectiveness will be overestimated. Many studies suggest that between 5 - 20% of the land area generates 50-90% or more of the nonpoint source loads (NPS), particularly for pollutants such as P and sediment (Heathwaite et al. 2000; White et al. 2009; Qui, 2009; Wagena and Easton, 2018; Rao et al. 2009; Yu et al. 2019).In the Chesapeake Bay watershed, 80% of cropland loses less than 40 lbs/acre of N per year, while the remaining 20% loses up to 300 lbs/acre (USDA, NRCS, 2011a). Losses may also originate from a disproportionate share of farms that lack effective nutrient management. Within fields, nutrient losses may be confined to relatively small areas (Easton et al. 2008a), that with the correct targeting and incentives may be treated at relatively low cost. Yet few NPS implementation programs have been designed to identify and treat high pollutant loss areas, including those in the Chesapeake Bay watershed. NPS implementation programs typically apply BMPs and other treatment measures based on factors including the willingness of landowners to participate, access to sites, and distribution of financial incentives. In addition, some programs cannot or do not identify and credit treatment of high impact areas. For instance, modeling capacities may not be spatially or analytically refined enough to identify localized areas of high loss and by extension areas that would be critical to target with BMPs.

Numerous studies have found that targeting NPS reduction projects to sites with higher pollution potential and low implementation costs has the potential to improve cost effectiveness of pollution reduction efforts (Carpentier et al 1998; Khanna et al. 2003; Yang and Weersink 2004; Yang et al. 2005; Giri et al. 2012; Perez 2017; Xu et al. 2019; Fleming et al. 2019). Studies have shown that targeting BMPs or a land retirement payment scheme by flow paths, sub-catchment, soil erodibility, or other land and soil characteristics instead of applying BMPs randomly or uniformly can reduce costs of meeting a given water quality goal (Yang and Weersink 2004). Multiple policy designs could be pursued to better target cost-effective nonpoint source reduction investments, each with different strengths and limitations (Ribaudo 2015).

Can targeting of nonpoint source controls be improved to get more pollutant reductions for less cost in the Chesapeake Bay region? In general, targeting programs must answer two basic questions: how pollutant loads are identified/quantified and how are stakeholders motivated to cost-effectively identify and reduce NPS loads? There is a multitude of ways these two simple questions can be answered. Selecting among the wide range of possible answers to these two questions is a critical challenge and one in which this workshop will attempt to provide insight.

The objectives of this synthesis are1) to summarize the range of options available for identifying high loss areas and measuring the effectiveness of nonpoint source control measures; 2) to identify and summarize incentive and behavioral approaches to encourage decision-makers to adopt cost-effective treatment options; 3) to summarize the criteria that define success of such programs, and 4) to describe the design and outcomes of several targeting programs that have been piloted or implemented. This document is intended to provide background information and resources and serve to facilitate discussion and consideration of targeting at the workshop.

II. What is Targeting?

“Targeting” in voluntary nonpoint source control programs is a widely used term that can describe a diverse range of program designs. For the purposes of this workshop/synthesis targeting is defined in three dimensions, 1) targeting landscape NPS areas that produce disproportionate loads, 2) incentivizing people to treat those loads with NPS control measures, and 3) selecting the most cost-effective NPS control measures to treat those areas. Targeting may occur at different spatial scales, ranging from the watershed, field level, or subfield level. Targeting may also mean identifying land managers whose managed lands produce disproportionately high loads and providing additional assistance and incentives to successfully manage those loads.

In general targeting is undertaken to improve the effectiveness of nonpoint source control investments and to reduce the costs of achieving any given amount of pollutant abatement (cost effectiveness). Targeting most frequently occurs at the watershed and subwatershed levels. Geographic targeting of impaired, high pollutant loss, or environmentally risky/sensitive subwatersheds to address water quality issues has been used in several USDA conservation efforts over the years and is used in the CBP to prioritize high loss land river segments. The Rural Clean Waters Program (1980s) and the President’s Water Quality Initiative (1990s) are two examples. The USDA Environmental Quality Incentives Program (EQIP) targets ecologically important areas (e.g., Chesapeake Bay and western Lake Erie) and incorporates ranking criteria in selecting contracts at the local level. However, other programs may merely prioritize the implementation of particular practices thought to be particularly effective in reducing pollutants. For example, Maryland emphasizes the implementation of cover crops. Virginia has adjusted cost-share arrangement to prioritize stream fencing. Pennsylvania is currently focusing on forest riparian buffers through the Keystone Ten Million Trees partnership (http://www.tenmilliontrees.org/). While these are laudable goals and aimed at trying to reduce the cost of NPS control, they are not in a strict sense targeting.

Within the confines of the existing Chesapeake Bay Program modeling and accounting system, targeting is essentially limited to the land river segment level. Differential pollutant losses and nutrient reduction credit at the field and subfield level are not currently recognized. Furthermore, it is difficult to identify and receive credit for working with land managers that contribute disproportionate loads. The questions confronting nonpoint source water quality managers are, can more refined targeting improve program outcomes (load reductions, cost savings, etc) and if so, how can this be accomplished in the Chesapeake Bay region?

III. Defining Success in Targeting Programs

The criteria for evaluating the success of a targeting program represents an important consideration, regardless of the particular program design. In the context of NPS load reductions, the primary objective of a targeting program is to secure more pollutant reductions for any given amount of effort or resources. Given the primary objective, examples of useful evaluative criteria include achievement of stated objectives, cost effectiveness, participation, certainty, administrative costs and burdens, and equity and fairness.

Achieving Nonpoint Source Load Reductions/Water Quality Objectives. While it is perhaps obvious, the overriding goal of targeting is to secure reductions in nutrient and sediment loads. As stated in the introduction, achieving demonstrative results in this area of NPS control is a vexing policy challenge. A premise of targeting is that identifying, managing, and treating high loss areas will generate greater reductions. If effective, these efforts should produce observable changes in ambient outcomes.

When considering the overall effectiveness of a targeting program in achieving load reductions it is necessary to consider the total system changes stimulated by the policy. Water quality managers must consider unintended behavioral consequences of focusing on high loss areas. For example, will such a focus inadvertently reduce effort in less critical areas? Similarly, how will larger incentive payments targeted to high loss areas affect behavior within those areas?[1] .

Cost Effectiveness. Cost effectiveness can broadly be defined as the total cost per unit of pollutant reduced (e.g. dollars spent per kg of N, P, or sediment), and a policy that improves cost effectiveness is one that will achieve the most pollutant load reduction for a given budget. Costs include not only expenditures to install or construct a pollutant control practice but also

---

[1] Slippage or leakage is a concern of any voluntary incentive program. In the context of NPS pollution, this refers to the tendency of incentive payments for practices that reduce load on high loss areas (e.g. no-till or manure storage) to make intensive production models relatively more profitable within those areas, in comparison to alternative land uses. For example, payments for practices that reduce erosion and nutrient loss on marginal land will make intensive crop production on that land relatively more attractive, in comparison to more environmentally benign land uses like perennial hay or pasture (Lichtenberg and Smith-Ramirez 2011). Because intensive crop production produces greater NPS runoff in comparison to perennial grasses--even when it is treated with conservation practices--slippage will lead to worse environmental outcomes when it occurs (Fleming et al. 2018). The consequences of targeting programs on the entire system should be considered, in order to secure the actual load reductions that are intended.

other opportunity costs to private citizens such as reduced production, forgone land use, etc. Decision-makers must have the ability and knowledge to select combinations of BMPs that match perceptions of stakeholders and reduce the most pollutants at the lowest possible cost. Cost effectiveness also requires the identification and participation of stakeholders within a watershed who can reduce the largest pollutant load at the lowest possible cost.

Since targeting necessarily includes some criteria of improved efficiency--i.e. more load reductions per unit of effort, per project implemented, per land area treated, and so forth--improved cost effectiveness can be considered an overarching goal of targeting programs by definition. Moreover, absent large increases in funding levels, the only way to achieve more NPS reductions is to get more out of the nonpoint source programs currently available. Thus, cost effectiveness is critical to overall program success.

Participation. For voluntary conservation programs, landowner participation is critical. Even when the best targeting program is devised, cost-effectiveness may be limited when farmers or landowners do not participate in conservation programs (non-participation) or stop using practices after the end of a conservation program contract or the life of the practice (dis-adoption) (Claassen et al. 2008; Just and Horowitz 2013). The level and type of participation both matter to program effectiveness. Not only does the level of participation matter (ex. # landowners), *who* participates also matters to program success. Just as there is spatial variability of loads across the watershed, there is variability in the effort and motivation of land managers. A nonpoint source control policy that solicits high levels of participation from the same set of conservation-minded landowners may not produce large or inexpensive reductions because each added BMP is treating a smaller and smaller remaining load. However, a nonpoint source program that can involve land managers of operations with particularly large pollutant loads, or those that have little experience adopting conservation practices, may be able to produce larger and less costly reductions.

A critical challenge in voluntary incentive programs is ensuring that funds induce *more* participation. When landowners receive payments for practices that they would have adopted without a payment (non-additionality), no new participation in conservation activities is achieved. This problem has been shown empirically to have substantial effects on both the changes in water quality that can be attributed to a program, as well as the program’s cost-effectiveness (Chabe-Ferret and Subervie 2013; Mezzatesta et al. 2013). However, the size and scope of non-additional payments vary across different NPS practices (Claassen et al. 2018).

To address the challenges related to landowner participation, there are often trade-offs between program goals. For example, increasing incentive payments to encourage greater participation rates will also increase the profitability of existing production models, thereby encouraging slippage (Fleming et al. 2018). Setting stricter baseline requirements for conservation behavior on a farm as a condition for program participation--in order to reduce non-additional adoption--will also tend to reduce participation rates (Just and Horowitz 2013). Moreover, landowners may be able to shift baseline levels of practice adoption on their farms to take advantage of payment programs (Bosch et al. 2013).

Certainty. The degree of certainty with which water quality improvements are achieved is another necessary consideration when evaluating the success of targeting programs. In general, NPS actions that improve certainty of outcomes are preferred. NPS control efforts are often modeled rather than measured, since many types of NPS losses (e.g., sediment and nutrient runoff from agricultural fields, N leaching to groundwater) are difficult, costly, or even impossible to measure. Modeling introduces a considerable amount of uncertainty in the estimates (e.g., uncertainty related to input parameters, model processes, and system variability). Thus, estimates of cost and NPS control effectiveness can vary widely based on the assumptions used. To allow for meaningful comparisons of pollutant control effectiveness across programs and practices, analyses of NPS control cost-effectiveness should provide greater transparency in the assumptions and sources of uncertainty underlying the estimates (Wieland et al. 2009; Chesapeake Assessment Scenario Tool (CAST) 2019; Fleming 2019).

While uncertainty exists in estimating nonpoint source loads and control effectiveness, can targeting programs increase the level of certainty in pollutant control performance over outcomes that would be achieved under the status quo policy? Targeting programs may result in greater confidence in outcomes, given their emphasis on identifying and, to the extent possible, measuring and monitoring water quality effects.

Administrative Costs & Burdens. Another critical aspect of targeting is administrative cost. Participation and outcomes are improved when participants can identify reduction opportunities and adjust management at modest costs. In general, better targeting requires landowner outreach, resources to predict and measure outcomes, time to consider and evaluate options, and technical support. Yet, effort comes at a cost. Tradeoffs may exist between increasing targeting complexity and the time and compliance costs to participate.

Equity & Fairness. All else equal, programs perceived as fair generate more interest, participation and support. Different targeting program designs will produce different distributions of resources and benefits. Targeting of an impaired sub-watershed may involve higher payment rates to landowners in that watershed, reflecting the greater potential benefits to be achieved in that area. However, differential payment rates to landowners in different areas may lead to political push-back from those receiving the lower payment rates, thus jeopardizing public support for the program. For example, the USDA's Water Quality Incentives Program (WQIP) targeted specific watersheds for funding, and the program was discontinued in part due to political resistance to these differential payments. Targeting programs should be designed and evaluated in consideration of their fairness and distributional impacts, which will ultimately impact the viability of these programs.

IV. Elements of Targeting Programs

Section III outlined the primary goals for designing nonpoint source programs. This section will outline the tools and targeting design options available to achieve these outcomes. This will include both technical options for identifying and measuring the effectiveness of controls to reduce high NPS pollution loads (IV.A) and policy design options for reducing these loads within a framework of voluntary landowner participation (IV.B).

A. Targeting/Identification of Pollutant Source Areas

i. Introduction/Challenge

The need for identification and spatial targeting of landscape areas generating disproportionate NPS pollution losses is driven by the heterogeneity of pollution sources and transport pathways. Figure 1 illustrates that differences in pollution generation over orders of magnitude can occur across small spatial domains and are driven by hydrology (Fig. 1a), land use/soils (Fig. 1b,e), terrain (Fig. 1c), and morphometric features (Fig. 1d) . Approaches to identify these NPS pollution "hot spots" or "critical source areas" (CSAs) can depend on the pollutant, its transport pathway, and the geographical scale of targeting. We define CSAs broadly to include all source/pathway combinations generating disproportionately high NPS pollution loads. We describe available approaches for targeting CSAs (IV.A.ii), how their applicable spatial scales and data requirements differ (IV.A.iii), and how BMP performance variability can affect targeting strategies (IV.A.iv).

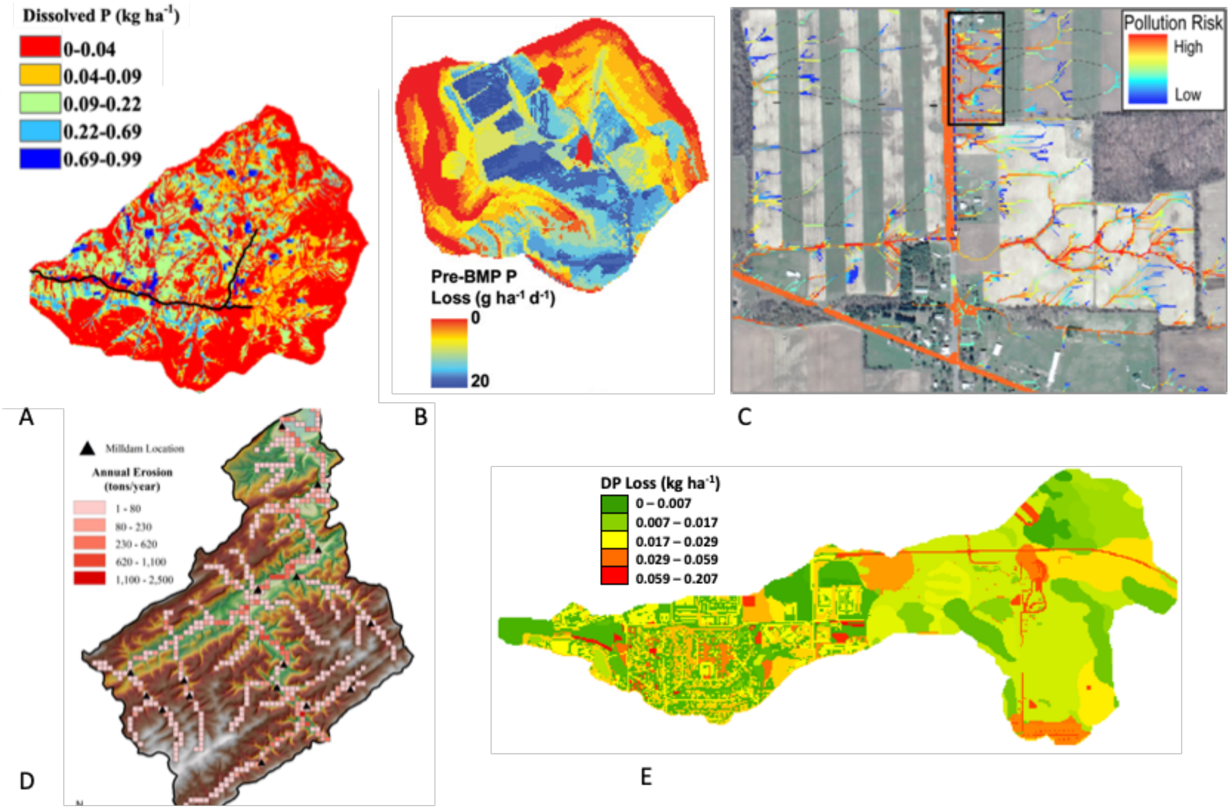

Figure 1. Examples of spatial heterogeneity and different targeting approaches at various scales: landscape hotspots of phosphorus (P) loss from agricultural watersheds at 37 km^2 (A) and 1.6 km^2 (B) scales, variable landscape connectivity over several farm fields of ~5 ha (C), streambank erosion heat map across a ~40 km^2 watershed (D), and dissolved P loss in a 3.3 km^2 urban watershed (E).

ii. Modeled or Measured Approaches to Determining Target Areas

Ecohydrological models are the most comprehensive but most computationally intensive approaches to characterizing NPS pollution generation and transport. Depending on the geographical area of interest, these process-based models can identify priority subbasins (Rabotyagov et al. 2010), hydrologic response units (coincidence of land use/management, slope, and soil properties, Rodriguez et al. 2011), or even areas within an individual farm fields (Easton et al. 2008a). Examples of such models include the Agricultural Policy / Environmental eXtender (APEX), SPAtially Referenced Regression On Watershed attributes (SPARROW), Soil and Water Assessment Tool (SWAT), and extensions of SWAT including SWAT-VSA (variable source area) and SWAT/HUMUS (Hydrologic Unit Model of the United States) or other integrated modeling approaches. One advantage of ecohydrological models is that they can be used to identify CSAs of N, P, and sediment simultaneously. Additionally, the effects of BMP implementation on pollutant loading to target water bodies can be simulated, and the impacts of climate change or landuse change on water quality and the efficacy of BMPs can be evaluated. However, some limitations of these models include their inability to adequately capture stream bank erosion, which is an important source of sediment, lag times between BMP implementation and water quality improvements, and groundwater processes, which can be a significant source of N in baseflow (causing a lagged water quality response to management changes). Furthermore, Osmond et al. (2012) emphasizes that most models consistently overestimate control effectiveness. There is also the need for sufficient data to calibrate and evaluate the models and potentially significant degrees of uncertainty to consider.

Less computationally intensive approaches tend to rely on terrain metrics derived from Digital Elevation Models (DEMs) overlaid with land use and management information and sometimes combined with soils data. Targeting CSAs by Topographic Index (TI) has produced promising results and improved prediction of pollutant delivery (see Figure 1 A & B) from diffuse sources compared to approaches that do not consider topography, such as water body proximity (Buchanan et al., 2014; Hahn et al., 2014; Easton et al., 2007a,b; 2008a,b; 2011; Schneiderman et al., 2007). For example, Wagena and Easton (2018) demonstrated that 30% of agricultural land in the Susquehanna River Basin, about 42% of the Chesapeake Bay watershed (71,000 km^2), generated the majority of the agricultural NPS pollution. This conclusion was evidenced by simulations with SWAT-VSA predicting nearly the same N, P, and sediment load reductions to the Bay with BMP implementation on 30% of the agricultural land compared to 100% of the agricultural land. In a study explicitly evaluating cost, Xu et al. (2019) found that targeting hydrologically active areas, as defined by a terrain model, reduced the cost of achieving N load reductions by 30-40% in a 7.3 km^2 watershed in Pennsylvania under current and future climate scenarios.

Beyond simulation studies, the identification of CSAs may be accomplished using observable indicators. Identification through observable indicators has historically been limited in geographic scope and feasibility for NPS pollutants; however ,improvements in the quality of airborne light detection and ranging (LiDAR) data have made it possible to locate and quantify stream bank erosion rates at watershed-scales and target CSAs with precision (Walter et al. 2017; Fleming et al. 2019). Stream bank erosion may now be the one NPS pollutant pathway for which landscape-scale measurement data can be collected at reasonable costs. The measurement of vertical and horizontal changes at fine levels of detail (sub-meter) is available both through point cloud and digital elevation model (DEM) differencing in an approach referred to as change detection (http://gcd.riverscapes.xyz/). Improved methodologies exist to account for uncertainty and the presence of vegetation during leaf-season or in high-density wooded areas (Wheaton et al. 2010, James et al. 2019). In addition to being scalable, change detection can be done over long periods of time if LiDAR data are acquired during different years. Practitioners and government agencies have a need for additional LiDAR data within key watersheds to allow for comparisons across time.

In small watersheds, specific farmers or fields can be identified as CSAs using in-stream water quality monitoring or field-level data collection. Field-level data collection can support calculations of sediment loss or the P Indices. Nearly every state in the US has developed and use P Indices to improve nutrient management by indicating agricultural fields with the highest risk of P loss (Sharpley et al., 2003, 2008). P Indices are primarily based on P source characteristics (fertilizer and manure composition, rate, timing and method of application) and surface transport factors. In one example, targeting farms with the highest soil P Index values in a 50 km^2 watershed resulted in a 55% reduction of in-stream storm flow P loads within four years of practice adoption (Perez, 2017). In another case, specific fields were targeted by collecting in-stream N measurements, moving sequentially upstream until high concentrations were detected, and implementing riparian buffers on the adjacent farmland (Maille et al., 2009).

The difficulty in identifying the small percentage of land contributing disproportionately high NPS loads has been emphasized in the Conservation Effects Assessment Project (CEAP) reports. The Lake Eerie CEAP report raised the issue that while soils are very heterogeneous and occur as a mosaic in the landscape, many farms/fields are managed according to the dominant soil type. In a case study of a field that is managed appropriately for the three soil types that comprise 98% of the area, the remaining 2% of the land had high vulnerability to N, P, and/or sediment loss that required additional control measures (NRCS, 2016). These vulnerable soils would only be detected with strategic soil sampling (according to a grid or zone) and would likely require precision agricultural practices to address their loss vulnerability (NRCS, 2016). The report highlighted field-scale mapping of soil properties and variable rate nutrient application technology as important components of managing small, discrete CSAs in the landscape, particularly for addressing subsurface and soluble P losses (NRCS, 2016). An analogous conclusion can be drawn with respect to site hydrology. Although hydrologically active areas can often be identified within fields using terrain models, on the ground site assessment is critical to detect unmapped artificial drainage features.

iii. Effectiveness of Approaches

1. Criteria

In the context of the Bay, targeting programs should focus on areas of the watershed that deliver the greatest loads of a pollutant to the Bay, and not necessarily on where the largest edge-of-field loads are generated. In the Chesapeake Bay watershed, water quality improvement in small tributaries will be observable and attributable to targeted conservation efforts much sooner than in the Bay itself. Lag times between practice implementation and measurable improvements in water quality in receiving water bodies with large watersheds (e.g., Chesapeake Bay, Gulf of Mexico) are on the order of decades and make detecting measurable changes in water quality difficult within short time frames. For this reason, it is important to set interim water quality targets in smaller streams where water quality responds more quickly to intervention. Perez (2017) provides an approximate time frame of 4-8 years for achieving measurable and attributable water quality improvements in response to conservation efforts for watersheds up to about 400 km^2 , based on an analysis of six “water quality targeting success stories” that were part of the NRCS Regional Conservation Partnership Program. Therefore, it may take years for water quality improvements to be realized from even the most scientifically robust targeting programs.

2. Strengths and Weaknesses

Comparing the efficacy of methods to identify CSAs for treatment is complicated by several factors. The accuracy of CSA identification using a particular approach depends on how well the dominant pollutant sources and loss pathways are represented, the heterogeneity of the watershed, data availability, and scale. Different identification approaches are more appropriate in different scenarios. For example, collecting in-stream water chemistry measurements in a small watershed may pinpoint specific farmland with high NPS contributions, but this approach becomes increasingly costly and labor intensive as the watershed size increases. In contrast, model-based approaches can be applied to much larger watersheds. Some models (e.g., SWAT) require extensive watershed data, including detailed information about existing land use and management practices, while others, like terrain models, have relatively low data needs. There are also differences in model complexity, data needs, and utility at the field scale. For example, the soil P index has relatively modest data needs compared to process-based models, like APEX, but cannot be used for identifying N or sediment losses. While a number of modeling tools are geared toward identifying NPS pollution generated by surface processes, there is increasing technological capacity to measure and identify streambank-derived pollution using change detection tools such as point cloud or DEM differencing. Tool selection will depend on which pollutants and loss pathways are prioritized. Table 1 summarizes tools available for CSA targeting and indicates their relative cost, relevance to different target pollutants, and data needs.

Table 1. Summary of modeling and physical options to guide targeting.

Options	**Effort to Accomplish (H, M, L)**	**WQ Concern Addressed**	**Data Needs (H, M, L)**	**Scale**
Models				
APEX	H	Hydro, WQ	H	Field
SWAT	H	Hydro, CSA, WQ	H	Sub-Field to watershed
P Index	L (conducted as part of NRCS 590 regs)	Primarily WQ (P)	M	Field
CB Model	H	Hydro, WQ	H	Watershed to region
Terrain models	L	Hydro, CSA, WQ	L	Sub-Field to watershed
Distributed models	H	Hydro, CSA, WQ	H	Pixel to watershed
Physical				
WQ measurements	H	Hydro, WQ	H	Various
Soil/tissue	H	nutrient mass balance	M	Sub-Field to field
Wet boot/eye test	L (although time intensive)	Hydro, CSA	L	Sub-Field to field

In the WQ Concern Addressed column, Hydro refers to hydrology, WQ refers to water quality in terms of N, P, and sediment loading, and CSA refers to identification of critical pollution source areas, and H, M, and L as High, Medium, and Low.

A few studies have explicitly compared different approaches to spatial targeting. One compared genetic optimization to simpler approaches previously applied in CEAP where target areas were defined by areas of moderate to high conservation need and projected that the former could reduce the cost of intervention by half (Rabotyagov et al., 2014). Another compared four CSA identification approaches based on targeting the highest pollutant concentrations in sub-watershed reaches, total pollutant load from the reach, pollutant load per subbasin, or average pollutant load per unit area (Giri et al., 2012). Notably, the most effective approach for reducing sediment loads (targeting the highest load per subbasin) differed from that for reducing nutrient loads (targeting land adjacent to stream reaches with the highest N and P concentrations), and, somewhat surprisingly, targeting the highest pollutant load per unit area was not the best approach.

Apart from the accuracy of targeting tools, their utility to watershed managers must be considered with respect to the technical capacity of targeting program administrators. The degree of sophistication necessary in targeting methodologies or tools to identify CSAs across spatial scales remains an open research question. Targeting is most effective as a staged approach in the conservation planning process, at the watershed scale to drive regional prioritization or resource allocation, and down to the field scale to select and implement appropriate BMPs.

iv. Modeled and Measured Effectiveness of BMP Implementation

1. Technical Aspects

Landowner BMPs options can be divided into several different classes. Numerous methods for organizing BMP types have been utilized, and these include source vs. transport BMPs, structural vs management BMPs, and typologies based on pollutant transport pathways. The usefulness of these different organizing typologies largely depends on the context in which they are applied. Source BMPs are those that aim to reduce the amount of nutrients introduced into the system, while transport BMPs attempt to reduce the mobilization of nutrients or sediment by altering hydrologic production. Structural BMPs are those that attempt to prevent or reduce the discharge of pollutants in stormwater; many urban BMPs are structural, such as infiltration basins and bioretention. Management BMPs, as the name suggests, are BMPs that alter some form of management to prevent or reduce pollutant mobilization or transport; BMPs, such as no-till and nutrient management plans (NMPs), are management BMPs.

BMPs can also be differentiated by the pollutant transport pathways that they address. This allows landowner management options to be matched with the CSA identification tools mentioned above. BMPs that address surface-pathway NPS pollution (runoff, erosion) include conservation tillage, contour-strip farming, riparian buffers, and cover crops, as well as production models that reduce erosion (e.g. grass-fed vs. feeding of commodity crops). BMPs that address subsurface-pathways (leaching to groundwater) include cover crops, well-established buffers, nutrient management plans, as well as changing inputs to reduce nutrient application / deposition (e.g. fertilizer use, animal feed options). Finally, BMPs that address mobilization of NPS pollutants in stream banks (sediment and associated nutrients) include stream restoration, off-stream fencing for livestock, and legacy sediment stream or wetland restorations.

Accounting for site-specific BMP performance is necessary to predict the impact of CSA targeting and to compare the potential environmental outcomes of different targeting approaches. For example, two locations may generate equivalent pollutant loads but have different load reduction potentials due to their suitability for treatment with BMPs or greater effectiveness of a particular BMP at one of the sites. Without predicting the effects of BMP implementation at the two sites, they would be treated as equivalent in a targeting program though the latter would provide an opportunity for more cost-effective treatment. Practice effectiveness can be related to landscape characteristics and hydrology and is affected by the conditions under which the practices are tested, including temporal features of seasonality, climate patterns, and climate change (Ahmadi et al., 2014). Site-specific practice effectiveness can be simulated using biophysical models (e.g., APEX, SWAT) and provide insight into which practices or suite of practices perform better for a particular area or under particular conditions (e.g., climate change projections). However, the lack of descriptive data for practices relating to other factors affecting performance, namely design, implementation, and maintenance, is a significant constraint.

2. Assumptions

Data needs stand at the center of targeting approaches. In order to effectively target, data--either model derived or, ideally, measured--must provide contextual evidence of pollution generating areas. The data required to develop and inform a targeting program must address issues of source, scale, timing, and delivery. Spatial targeting by identification of CSAs using landscape metrics (e.g., soil wetness index), high resolution digital elevation models or point clouds (to determine streambank erosion rates), or ecohydrological models relies on the availability and accuracy of data, such as soil characteristics, land use, LiDAR (light detecting and ranging), and the location of existing BMPs. The latter has proven a perpetual challenge in the absence of disaggregated and spatially explicit data for BMPs implemented with federal cost-share (Kurklova et al. 2015). Having reliable baseline data--knowledge of the location and operational status of existing BMPs--is essential for any targeting strategy. Spatial targeting decisions based on biophysical simulations can only be as good as the data used to parameterize such models and are dependent on the accuracy of pollutant generation, transport, storage, and transformation processes. Strengths and weaknesses in these representations differ across models, suggesting the value in pursuing multiple lines of evidence or model ensemble approaches. One notable limitation shared across models predictive of water quality is the representation of pollutant storage and resultant lag times in pollutant delivery to target water bodies, which is discussed subsequently as a critical issue that needs to be considered for targeting strategies (4.A.iv.3). All models are subject to the constraints of incomplete data regarding land use and land management practices. Thus, sensitivity analysis and explicit examination of model uncertainty must inform decision-making. Data tend to be the most incomplete at farm or field scales, the scales at which critical targeting decisions are made, and this has been identified as a major hurdle to spatial targeting (NRCS 2016; Wardropper et al., 2015).

3. Problematic Issues in Targeting Programs

Several issues exist that could be problematic for any targeting program; specifically, the nutrient mass balance in many regions of the watershed and the impact of lag-times in pollutant delivery yielding legacy impacts. Efforts to address these two issues must be made in order for a targeting program to be effective.

Nutrient Mass Balance. Large mass balance issues exist in many agricultural dominated regions of the Bay (inputs of feed and fertilizer exceeding local assimilative capacity). Continued growth in intensive animal agriculture has and will continue to compound this issue (Yagow et al., 2016). However, targeted feed management has been shown to significantly reduce nutrient excretions in manure and is thus a potential option for mitigating nutrient mass imbalances, particularly in livestock intensive operations. In the New York City watershed, Ghebremichael et al. (2009) demonstrated significant reductions in P excretions of 5.5 kg/cow/yr (about 23%) when using a precision feed management strategy, with no reduction in herd productivity. Targeting with respect to animal agriculture nutrient mass balances should focus on those herds with excessive nutrient excretions as determined by nutrient content in the manure. More generally, mass imbalance, at the field, farm or watershed scale, are difficult to control with targeted BMPs, as there are very few that reduce nutrient input into the system.

Lag-times in Nutrient and Sediment Delivery. Legacy nutrients result from excess input of anthropogenic nutrients and their subsequent accumulation and storage in soil, sediment, or groundwater. Notably, nutrients leached through soils into groundwater may take decades to eventually be discharged to surface waters. For example, the lag time of groundwater being discharged into surface water in the Chesapeake Bay watershed has been identified as a significant nutrient source (Easton et al., 2017; Lindsey et al., 2003; Phillips and Lindsey, 2003), and can be characterized by lag times ranging from less than a year to more than 50 years (Sanford and Pope, 2007; Meals et al., 2010). Sediment delivery can take even longer, largely due to storage of sediment behind stream impediments, such as the numerous historic mill dams that exist in the Chesapeake watershed (Walter and Merritts 2008; Yagow et al., 2013). Understanding the impact of lag times is critical to setting expectations for water quality responses to BMP targeting, because failing to account for these pollution sources can mask the outcomes of targeting and cause a delay in their detection. Targeting areas with shorter lag times could improve water quality more quickly but may sacrifice some cost efficiency in the long term. Targeting shorter lag-times may also be justified on environmental grounds, as areas with longer lag times may provide more opportunities for natural attenuation and ultimately require less treatment.

B. Decision Making

A major challenge confronting voluntary targeting programs is motivating participants to put the right control actions in the right place to achieve maximum water quality benefit. This challenge is compounded by the physical reality of NPS pollution, which is extensive and heterogeneous (Nowak, Bowen, and Cabot, 2006). Furthermore, farmers and landowners hold a variety of different motivations and interests. Some participants may be strongly motivated by a conservation ethic while others maybe more focused on financial returns (Ribaudo 2015). Different incentive program designs can significantly impact who participates and is engaged in pollution control efforts. For instance, financial incentive programs premised on sharing costs of BMP installation may not motivate a subset of land managers to participate. Adding resources to such a program may face diminishing results if new participants (potentially those with high pollutant losses) are not motivated to act.

This section describes different targeting program design choices that structure and incentivize landowners' choices to select and participate in nonpoint source reduction measures. This discussion will assume questions related to how NPS outcomes can be identified and quantified (see discussion above) have been addressed, and we will now focus on how program participants' conservation choices can be structured.

IV. B.1. Farmer/Landowner Choices Over NPS Control Options

An important dimension for the cost effectiveness of targeting programs is degree of choice over NPS control options given to decision-participants. Other factors equal, the more options a participant has on how NPS can be controlled, the more cost effective the result. For instance, if a landowner is offered only a few BMPs that may be used to control, more effective and lower cost alternatives better tailored to the specific site or farm operation could be foregone. For a targeting program, choice flexibility extends also to decisions about where control activities are applied. For instance, targeting a few critical source areas of a farm operation may generate large reductions in pollutant loads at relatively low costs. Requirements to treat all areas in the farm operation, regardless of the pollutant contribution of these areas, would limit choice, and reduce cost effectiveness.

However, offering more NPS control choices is not without tradeoffs. As the number of control options increase, so do the cognitive demands on decision-participants. The time required to consider and evaluate choices increases, thus increasing costs to participate.

IV.B.2. Structure of Financial Incentives/Subsidies

Financial assistance or cost-share programs are a key policy mechanism to induce the voluntary adoption of NPS management practices in the Chesapeake Bay region. Such programs are the primary methods to incentivize landowners and decision makers in the agricultural sector to change management practices and reduce NPS loads. Similar financial assistance programs are used in urban stormwater programs to encourage households and stormwater managers to implement stormwater controls (Ando and Netusil 2013; Gonzalez et al. 2018). Such financial incentive programs can be structured in a myriad of ways (Engel 2016). In general, all must answer a few basic questions: 1) what is paid for, 2) how is the level of compensation determined, 3) how are people selected to receive the funds (or conversely, how do program administrators ration limited program funds)?

Pay-for-Practice Programs. Traditional financial assistance programs generally answer these questions in similar ways. First, these programs pay participants to adopt specific practices. In other words, participants' financial payment is conditioned on the implementation of a particular activity or practice, called "pay for practice". Second, the amount of compensation is typically based on a percentage of the actual or estimated costs of installing//adopting the practice. Finally, while financial assistance funds may be targeted to particular areas, the funds are generally distributed based on a first come, first serve basis.

A variety of incentive designs can be employed to direct funds and focus pollution controls and efforts in a pay for practice program. For example, pay-for-practice type program may be modified to vary the amount of financial assistance based on the location or type of practice. For example, the Honey Creek Project (Oklahoma) adjusted the relative financial assistance rates for selected practices based on categorical assessments of the environmental benefit of the project and the likelihood of adoption. Practices that were unlikely to be adopted without financial assistance (high potential additionality) carried more financial assistance (Perez 2017). Similarly, the Maryland Agricultural and Water Quality Cost Share (MACS) program offered higher payment rates to farmers within certain targeted watersheds, including the Eastern Shore of the Chesapeake Bay. (However, these differential payments were subsequently discontinued, in part due to perceptions of fairness and equity.) In general, water quality managers adjust cost-share rates based on spatial targeting of high loss fields using modelled outcomes (e.g. SWAT, CBP water quality model). For programs such as the Honey Creek Project, the ability to establish and maintain variable compensation rates was possible because program managers were able to secure non-traditional funding sources that granted flexibility in how funds were spent.

Pay-for-Performance Programs. A more direct targeting approach could pay recipients directly for the level of pollutant removal services provided (e.g. paying directly for the outcome desired), called pay-for-performance (Ribaudo et al. 1999; Ferraro and Simpson 2002; Shortle et al 2012; Savage and Ribaudo 2016). Pay-for-performance programs could also be called pay for services because payments are conditioned on the level of service provided (e.g. pollutant reduction) rather than the installation of a practice that generates the service. Participants who generate greater levels of the service receive more compensation. Conceptually, participants have an incentive to undertake actions that generate the greatest reductions per dollar of practice implementation cost. If performance metrics are appropriately scaled, then pay-for-performance systems provide direct incentives to treat high loss areas.

To calculate removal services, program rules typically define a starting point (baseline or reference point) from which to quantify the level of service provided. Total compensation paid would not be based on costs incurred by the landowner, but on the quality of service provided (e.g. the pounds of nutrients reduced) multiplied by the price or value of the service (e.g. $/lb).

In such a system, the landowner must evaluate various options to reduce nutrient loads (BMPs and NPS control options described above), the reduction achieved for each option, and what must be given up (costs) to achieve them. In such a program, compensation received can exceed observed financial costs of practice implementation, resulting in a potentially new profit-making option for landowners. The policy does not presume knowledge of a participant's opportunity costs. Rather, it relies on participants to determine whether the payment provides sufficient compensation to provide the reductions or services requested.

A purported advantage of a pay for performance program for targeting is that it directly identifies and pays for the desired water quality change. Conceptually, such an approach incentivizes consideration of a wider array of pollutant control strategies and allows participants to select the type and location of activities that generate the most reductions for the least cost. Choice flexibility is essential since individual circumstances, costs, and physical conditions vary among landowners (Fisher et al. 2016). Importantly, those who can provide the most abatement at the lowest cost have the largest economic incentive to act. This means that landowners who may not have traditionally participated in conservation programs might have a strong incentive to do so. Such an approach is "self-targeting" in that those who can provide the most environmental benefit at least cost stand to gain the greatest economic benefit. Another advantage of a pay for performance program is that it will reveal information about the location and costs of available abatement options. Yet, to be effective, the method of measuring or monitoring outcomes must be refined enough to capture the heterogeneity described in the previous section, accurate enough to be build trust among different stakeholders, and straight-forward enough to be accessible and manageable for the program participants.

How is Compensation Determined? - Design Considerations of Pay-for-Performance Programs. Obviously, the choice of the definition and measure of service change (performance measures) is critical. Pay-for-performance targeting programs could quantify pollution removal services based on predicted performance (pay-for-modeled performance) or observed (pay-for-demonstrated performance) (Winsten et al 2011). If multiple outcomes/services are desired, compensation could be based on an index of predicted environmental outcomes.

The most common approach is to base payments on modeled changes in nutrient loads (Fales et al. 2016; Winsten and Hunter 2011; Fisher et al 2016). For instance, a pay for performance program in Michigan afforded farmers a flat payment ($225) for every ton of sediment reduced based on a model that translated specific actions and BMPs into reductions of sediment load (Fales et al. 2016; Wickerham 2019). Winrock International has piloted several programs in the

Midwest and Vermont that compensated landowners based on the pounds of P removed and not on the number of BMPs installed (Fisher et al. 2016; Winrock 2010). Maryland's recently revised nutrient trading program allows farmers and municipalities to receive payment for NPS pollution reductions based on outcomes modeled in the Maryland Nutrient Trading/Tracking Tool (MNTT) (Maryland Dept. of Environment 2017). Obviously, the NPS control options that participants may select is limited to BMPs explicitly included in the model. Moreover, credible field-scale models also have intensive data requirements (Muenich et al 2017), highlighting a tradeoff between complexity/accessibility, accuracy/uncertainty, and cost.

Performance-based incentive programs, however, could condition payments based on actual outcomes rather than predicted/modeled outcomes. Given the cost of direct monitoring and the stochastic nature of nonpoint source loads, direct measurement of changes in pollutant reduction poses a challenge, particularly for surface-flow and groundwater pathway pollutants. However, the ability to measure/monitor stream bank erosion introduces new opportunities in relation to pay for performance programs. Along with direct measurement, pay for performance programs may base compensation on some other observable outcome that could be used as an indicator of service provision. For instance, pilot programs have paid landowners based on soil nutrient levels or nutrient levels in post-harvest plant tissue (Winrock 2010). Note that compensation does not necessarily need to be based on a specific quantity of load reduction, but on whether a particular target indicator is achieved. Program designers must be reasonably confident that the performance metric provides a reliable indicator of the final outcome being sought (pollutant reductions). Some pay for performance schemes pay a "performance bonus" based on achievement of some benchmark indicator.

A pilot program in West Virginia developed a group payment scheme based on achievement of ambient outcomes such as N concentration at a subwatershed level (Maille et al 2009). A group of landowners in a small watershed (Culler's Run) received lump sum payments based on the flow-weighted metric of N at the outlet of the watershed. The group then used these resources to help install N reduction practices in the watershed.

Pay-for-performance programs must also consider the method for setting the price paid for the service change (e.g. price per lb. of pollution reduction). Price per unit can be fixed or negotiated (Engel 2016). Fixed price systems offer a single price for the service, though the price may need to be adjusted based on how participants respond. For example, one pay for performance program in Michigan's Saginaw Bay Watershed initially estimated the price per ton of sediment reduced to be less than $100/ton but had to increase the payment rate to $225/ton to induce higher levels of participation (Fales et al. 2016; Wickerham 2019). In contrast, if the price is negotiated among participants, the landowner/farmer (service provider) must be willing and able to develop an estimate of an acceptable price (Claassen et al 2008). Requiring the participant to develop plans for both the pollution control strategies and bid price can complicate the decision process and create significant disincentives to participate (Palm-Forster et al 2016).

The timing of financial incentive payments is another issue to address. In a traditional cost-share program, participants typically receive financial assistance when the practice is installed. Thus, financial assistance is provided before the service is actually delivered. However, in pay for performance programs, the program sponsor/funder may wish to see some evidence that the service is provided in order to make a payment. A pay for services program in the Northern Everglades paid landowners annual payments only after the demonstration of service provision (i.e. retaining water in designated wetland) (Lynch and Shabman 2011; Shabman et al. 2013). To reduce uncertainty and risk from the landowner's perspective, the annual service payment was coupled with a more conventional financial assistance program that reimbursed participants for upfront installation costs.

Who Receives Funds? - Further Design Considerations. Targeting programs that rely on financial incentives for landowners must also determine who receives funds. How are recipients and projects selected? Moving beyond a first-come, first-serve model, some programs rely on a ranking process to prioritize projects. The ranking system could be based on a number of factors including estimated water quality impact or previous participation. Other programs may use competitive processes to select projects and recipients of funding (Claassen et al., 2008). Competitive bidding processes would require potential recipients to compete to deliver the NPS pollution reduction service at the lowest possible cost, as in reverse auction designs. Such processes have been used in Florida to reduce P (Shabman et al. 2013). Maryland has implemented a bid process to solicit and identify cost effective restoration projects. Competitive bidding processes, however, require additional costs and effort on the part of participants. In some cases, the effort required to formulate bids may dramatically dampen participation (Palm-Forster et al 2016).

IV.B.3. Support, Outreach and Nudges for Decision-Making in Targeting Programs

Like all voluntary nonpoint source control programs, targeting programs requires effective technical support, communication, and persuasion to induce behavioral change. In targeting programs, such support takes on critical importance because of the additional attention and intellectual resources needed to identify critical source areas, evaluate nutrient reduction options, or work with land managers with particularly high loss rates. Building and maintaining trust between water quality managers and landowners, a commonly accepted condition for a successful program, is universally cited as essential when developing new information and incentives that might be required under a targeting program. The challenge is designing and implementing programs that build that trust and social relationships.

Studies implementing targeting programs have noted some common themes for effective engagement and trust building with land managers/program participants. For example, multiple targeting efforts have noted the benefits of directly involving farmers and other land managers directly into planning and implementation of conservation programs (Mailles et al 2009; Winrock International 2010; Perez 2018). Pilot programs have experimented with involving landowners in multiple ways, ranging from designing of ranking schemes to facilitate implementation. In a West Virginia pilot, a group of farmers assumed leadership in identifying and prioritizing implementation of BMPs in their subwatershed. Based on extensive in-stream monitoring, these farmers identified N hot spots. In one case these landowners were able to convince a neighboring landowner to allow the installation of a constructed wetland, which produced ambient reductions in summer nitrate levels (Collins and Gilles 2014).

Nudges. There is increasing evidence of the effects of different behavioral nudges on landowner participation in NPS programs and water quality management (Ferraro et al. 2017; Palm-Forster et al. 2019). Some of the most promising behavioral interventions in this area include feedback on outcomes, salience, and information provision coupled with peer comparisons. These insights can be applied to improve the design and outreach efforts of targeting programs.

Feedback. A common theme in the conservation literature is the value of visible feedback of outcomes for increasing program interest, commitment, and participation. In short, participation and willingness to engage in targeting programs is improved if participants can see observable and positive outcomes produced by their efforts (Wilson et al. 2014; Perez 2017) This may occur from observing biological improvements in local streams (e.g. increased fish abundance) or in-stream monitoring of ambient outcomes (Miao et al. 2016). On-field indicators could include reduced sedimentation of ditches, decreasing levels of surplus nutrients in soil tests, and decreased undermining of riparian areas due to stream bank erosion / retreat. Arguably, targeting programs contain more design features that potentially offer such feedback to landowners and program managers.

Salience. Increasing the salience of issues related to NPS runoff can be another important method that may increase landowner participation in targeting programs, particularly given that farmers' attention is divided among numerous competing priorities. For example, reminder letters were found to significantly increase re-enrollment in the USDA's Conservation Reserve Program (CRP), at a relatively modest cost to the program. Reminders coupled with public disclosure of other landowners' interest in re-enrollment also led to higher re-enrollments in the CRP, but no higher than the simple reminder itself (Wallander et al. 2017).

Information Provision and Peer Comparisons. Targeting programs can potentially induce participation and behavior change through social referencing and peer comparison. For example, farmers have long referenced their farming skills by comparing their crop yield with neighbors. And in other environmental contexts--such as household energy and water use--information provision and social comparisons have been shown to significantly increase household willingness to engage in conservation behavior (Allcott 2011; Ferraro and Price 2013). The same appears to hold true in the context of NPS pollution. In an Iowa pay for performance pilot, field level P and soil index results were posted on the local watershed council's webpage. This public information (coded for confidentiality) created competitive behavior from farmers to meet a benchmark level of performance (Winrock 2010; Perez 2018). Information provision at the farm-level on stream bank erosion rates led to substantially larger landowner investments in stream restoration when paired with peer comparisons (Goodkin et al. 2019). Farm- or parcel-level information provision and peer comparisons has historically been difficult to provide for NPS pollution--given the challenges of identification and measurement mentioned above (4.A). However, improved NPS monitoring tools, such as the aerial imagery and mapping technology for stream bank erosion, provide an opportunity to implement such parcel-level informational targeting in practice.

V. Targeting Programs: Promise and Challenges

A. Putting the Pieces Together: Illustrations of Targeting Programs

As described in Section IV, nonpoint source targeting programs can take on a variety of designs or forms. A sample of the diversity of targeting program designs that have been implemented or piloted is summarized in Table 2. These programs demonstrate diversity in the approaches used to identify and target nonpoint source loads, as well as program designs used to induce NPS reductions. Table 3 summarizes the targeting tools applied in several BMP targeting projects and how the monitoring was used to link water quality outcomes to practice implementation. These tables are intended to summarize in succinct form the numerous examples of targeting efforts to date that were described in Section IV.

Table 2. Nonpoint Source Targeting Programs

Program	**Targeting Method /Tools**	**Level of Targeting**	**Incentive Payments**	**Payment Rate**
Saginaw Bay Pay-for Performance	GLWMS	Field and watershed level	Pay for performance ($/ton of sediment)	Flat payment ($225/ton)
Milwaukee River Pay-for-Performance		Field and watershed level		
Hewitt Creek, Iowa	P & soil condition indices, corn stalk NO_3 test	Field and watershed level	Pay for performance + performance bonus payments for achieving benchmarks	
Cullers Run WVa	Ambient monitoring	Watershed	Group payment	Based on ambient outcomes (N) and allocated based on group decision-making
Honey Creek Oklahoma.	SWAT	Field and watershed level	Cost-share for practices	Differential cost share rates

Table 3. Measured/modeled outcomes of nonpoint source targeting programs.

Study	**Targeting Approach**	**Monitoring/Attribution**	**Outcomes**
Bishop et al. 2005 Delaware River Basin	Detailed farm survey , CSA identification	Paired watershed (Farm and forested watersheds), 2 yrs pre BMP, 5 yrs post BMP	- reduced dissolved P in stormflow by 43% (95% confidence interval is 36% to 49%) and particulate P in storm flow by 29% (15% to 41%)

Easton et al. 2008b, Delaware River Basin	Used soil topographic index in VSLF mode	-measured TP at watershed outlet (164 ha farm) -modeled paired watershed to isolate BMP impacts	- 36% reduction in dissolved P, 47% reduction in TP - Simulated and measured load reductions were equivalent
Rao et al. 2012, Delaware River Basin	Used results from Easton at al. 2008, above	-measured TP at watershed outlet (164 ha farm) -modeled paired watershed to isolate BMP impacts	-targeting buffers to the 50% of the land producing the most runoff resulted in a 73% cost reduction
Fleming et al. 2019, Mill Creek watershed, PA	Identified streambank erosion hotspots with DEM differencing using LiDAR data	-before/after restoration monitoring (15 yrs)	-restoration at 18 sites reduced sediment loads ~8,524 tn along with bound nutrients with very high cost-effectiveness, $0.03, $19, and $14 per pound for sediment, P, and N, respectively
Perez 2017 Honey Creek, OK	Identified P hotspots with SWAT and verified with site inspections	-upstream/downstream -paired watershed - 320 km^2 project design	- 28% P reduction, 35% NO3-N reduction - Participation of nearly half of priority farmers
Perez 2017 Hewitt Creek, IA	Collected field data for soil P index, soil conditioning index, and corn stalk nitrate test	- in-stream chemical monitoring, design insufficient to attribute reductions to BMPs -93 km^2 watershed	- Downward trends in turbidity and TP attributable to BMPs because independent of rainfall - impact on suspend solids unclear -N loads not reduced
Perez 2017 Pleasant Valley, WI	-Previously identified as priority subwatershed - riparian site assessments - inventoried 90% of ag land to calculate soil P index and sediment loss (RUSLE2)	- before/after fisheries and quantitative habitat assessment - before/after instream P monitoring, paired watershed - 50 km^2 watershed	- 24,750 ft stream restoration for $10/ft - median storm load TP reduced by 55%

B. Remaining Challenges/Barriers

A review of targeting programs reveals a number of challenges confronting successful implementation. This includes issues over distributional consequences of targeting, funding & regulatory constraints, technical support and costs, and the ability to scale-up or replicate findings from pilot programs.

Distributional Consequences. Voluntary targeting incentive programs are premised on the notion that financial incentive payments go to areas that are able to achieve the greatest reductions for the lowest cost. Consequently, financial payments will necessarily be distributed unevenly across a watershed and decision participants. In some cases, land managers long considered "good stewards" may realize few financial opportunities from a targeting program, while others with high loss rates may be poised to receive a large share of funding. Establishment of baselines can help address this issue, but these will reduce incentives for some high impact/low cost landowners to participate (Ribaudo et al 2014). Targeting pilot programs frequently confront the tradeoffs between building participant support and distribution of program benefits.

Funding Constraints. Federal and state financial assistance programs intended to incentivize NPS reduction actions often have requirements and restrictions concerning the distribution of funding within districts or regions, the total level of individual award levels, and how the funds are spent. These restrictions can significantly limit the effectiveness of a targeting program by limiting the choices and incentives of land managers. Political considerations and individual award caps limit the amount of funds that may be devoted to addressing high loss regions or projects. Finally, financial assistance may only cover certain types of practices or costs, limiting or distorting choices of the most cost effective treatment options. Given the need for flexibility in targeting financial assistance, it is unsurprising that targeting program administrators note the critical importance of securing funding that is relatively unencumbered by formula or administrative restrictions (Fales et al. 2016, Lynch and Shabman 2011; Perez 2017).

Administrative and Technical Challenges. Nonpoint source pollution is field and farm specific. Pollutant loading and the effectiveness of control actions can vary tremendously between watersheds and farms, and even within farms. Are technical tools and indicators available to effectively capture these differences and convey them in a way that is accessible for landowner participants and program managers? Furthermore, can the treatment of these high loss areas be acknowledged and rewarded within established TMDL accounting frameworks? More work is needed to better understand the administrative costs of targeting programs, particularly relative to conventional programs.

Scaling-Up/Replication. There is little experience in scaling up incentive-based targeting programs. Most success stories are focused on efforts at relatively small scales. Program administrators often note that success depended on personal relationships that fostered the trust and credibility necessary for successful implementation. How and whether these dynamics can be replicated and sustained on larger scales is a largely unanswered question.

Most of the evidence on targeting program outcomes have been case-specific observations. Very few formal evaluations of pilot programs have been conducted in a way that allows for rigorous evaluation of program effects in comparison to what would have been achieved without targeting. Similarly, the relatively limited number of pilot programs, and the variability of program design, limits the ability to draw inferences on targeting program effects based on design features. The heterogeneity across watersheds, large differences in program administrative costs, and a lack of consistency regarding which expenditures are counted toward pollutant unit reduction costs (i.e. practice maintenance costs, program monitoring costs, regulatory and permitting costs) collectively limit the conclusions that can be drawn about the cost-effectiveness of a targeting program by comparing unit removal costs under different program structures.

C. Targeting Outcomes - Opportunities and Promise

Despite the real challenges that exist, the evidence synthesized above on technical tools for targeting and program design features suggests there are also real opportunities for improving the outcomes of conventional programs through targeting.

In several instances, targeting programs/efforts have been able to produce demonstrative reductions in ambient (in stream) nutrient levels. For example, according to paired-watershed comparisons, the Wisconsin Pleasant Valley and Oklahoma’s Honey Creek targeting pilot projects produced detectable reductions in ambient P loads (Perez 2017). Effective targeting of attention and control efforts is a noted element in CEAP projects that produced observable improvements in ambient pollution levels (Osmond et al 2012; Kurkalova 2015; NRCS 2016). However, whether these reductions will be sufficient to overcome water quality impairments in those watersheds is a question that merits further research.

Researchers consistently find large potential cost savings from NPS targeting. The potential magnitude of cost savings appears to be significant, typically 30 to 50% based on modeling studies (Carpentier et al 1998; Rabotyagov et al., 2014; Xu et al., 2019; Geng et al. 2019). Savage and Ribaudo (2016) estimated that pay for performance programs in the Chesapeake

Bay Watershed would achieve a water quality goal at a much lower cost than payments based on practice costs, even with targeting. However, such projections of cost savings typically do not attempt to account for constraints imposed by the regulatory environment and actual behavioral response of participants (Wardropper et al. 2015).

Behavioral and cost evidence from pilot programs do suggest significant promise. For instance, administrators of the Saginaw sediment pay for performance program estimate that paying directly for sediment reductions using a model that estimates sediment losses at the subfield level can purchase 4 times the amount sediment reductions than the conventional financial incentive program operating in the same watershed (Winkerham and Fales 2019). Program administrators attribute this increase in cost effectiveness primarily to the ability to devote funds specifically toward areas experiencing high sediment losses. This is consistent with findings in the Mill Creek watershed of Lancaster County, Pennsylvania, where newly available tools to identify stream bank erosion hotspots have been piloted, and substantial reductions of sediment and P can be achieved at a fraction of the land area, number of landowner contracts, and overall cost required by other control practices (Fleming et al. 2019). The ability to devote not only funds but also administrative outreach to a few high-loss areas presents a major opportunity to improve the efficiency of existing NPS programs.

The extent to which targeting changes participation rates or reaches landowners who typically do not participate in conservation programs is another area needing further study. However, common themes emerge from reported behavior and participation rates in successful applications of targeting programs. A shift in participant mindsets due to increased attention on outcomes (lbs. reduced) and observable results heightened interest in conservation activities. Pilot programs provide numerous examples of participants working collaboratively and productively to identify and treat high loss areas. The flexibility to target funds to high needs areas is consistently noted as essential to targeting program success. A pilot program in Ohio (Alpine Cheese) documented how farmers who never participated in conservation assistance programs were willing to address observable and highly farm specific nutrient loss areas because funding and effort was explicitly directed to those specific problem areas, and the time and administrative costs for the landowner were minimal.

VI. Next Steps

Targeting programs offer one avenue to secure additional nonpoint source reduction with greater certainty in outcomes without necessarily relying on additional revenue streams. The questions confronting water quality managers in the Chesapeake Bay are:

Is the potential for more effective nonpoint source targeting worth further time and effort to pursue?

What efforts are needed to improve nonpoint source targeting in the Chesapeake Bay and what form should improved targeting take?

References

Allcott, H. 2011. Social Norms and Energy Conservation. Journal of Public Economics 95:1082–1095.

Ando, A.W. and N.R. Netusil, 2013. A Tale of Many Cities: Using Low-Impact Development to Reduce Urban Water Pollution. Choices 28 (3): 1-6.

Bishop, P.L., W.D. Hively, J.R. Stedinger, M.R. Rafferty, J.L. Lojpersberger, and J.A. Bloomfield. 2005. Multivariate analysis of paired watershed data to evaluate agricultural best management practice effects on stream water phosphorus. J. Environ. Qual. 34:1087–1101.

Bosch D.J., Pease J.W., Wieland R., and D. Parker, 2013. Perverse incentives with pay for performance: Cover crops in the Chesapeake Bay watershed. Agricultural and Resource Economics Review 42 (2):491-507.

Buchanan, B.P., Fleming, M., Schneider, R.L., Richards, B.K., Archibald, J., Qiu, Z., Walter, M.T., 2014. Evaluating topographic wetness indices across central New York agricultural landscapes. Hydrol. Earth Syst. Sci. 18, 3279–3299.

Carpentier, C., B. Bosch, and S. Batie.1998. Using Spatial Information to Reduce Costs of Controlling agricultural nonpoint source pollution. Agricultural and Resource Economic Review. 27(1): 72-84.

Chabé-Ferret, S., and J. Subervie, 2013. How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. Journal of Environmental Economics and Management 65 (1): 12-27.

Claassen, R., A. Cattaneo, and R. Johansson. 2008. Cost-effective design of agri-environmental payment programs: U.S. experience in theory and practice. Ecological Economics 65(4): 737-752.

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

Collins, A. and N. Gilles. 2014. Constructed Wetland Treatment of Nitrates: Removal Effectiveness and Cost Efficiency. J of the American Water Resources Association 50 (4): 898-908.

Easton, Z.M., D. Scavia, R. Alexander, K. Boomer, P. Kleinman, A. Miller, J. Pizzuto, D. Smith, C. Welty. 2017. EPA Scientific and Technical Advisory Committee review of the Chesapeake Bay Program Phase 6 Watershed Model. Aug 2017.

Easton, Z.M., P. Gerard-Marchant, M.T. Walter, A.M. Petrovic, and T.S. Steenhuis. 2007a. Identifying dissolved phosphorus source areas and predicting transport from an urban watershed using distributed hydrologic modeling. Water Resour. Res. 43. W11414. doi:10.1029/2006WR005697.

Easton, Z.M., P. Gérard-Marchant, M.T. Walter, A.M. Petrovic, and T. S. Steenhuis. 2007b. Hydrologic assessment of an urban variable source watershed in the Northeast United States. Water Resour. Res. 43. W03413. doi:10.1029/2006WR005076.

Easton, Z.M., D.R. Fuka, M.T. Walter, D.M. Cowan, E.M. Schneiderman, and T.S. Steenhuis. 2008a. Re-Conceptualizing the Soil and Water Assessment Tool (SWAT) model to predict runoff from variable source areas. J. Hydrol. 348: 279-291.

Easton, Z.M., M.T. Walter and T.S. Steenhuis. 2008b. Combined monitoring and modeling indicate the most effective agricultural best management practices. J. Environ. Qual. 37:1798–1809.54)

Easton, Z.M., M.T. Walter, D.R. Fuka, E.D. White, and T.S. Steenhuis. 2011. A simple concept for calibrating runoff thresholds in quasi-distributed variable source area watershed models. Hydrol. Proc. doi:10.1002/hyp.8032, 2011.

Easton, Z.M., E.M. Bock, and K. Stephenson. 2019. Feasibility of employing bioreactors to treat legacy nutrients in emergent groundwater. Environ. Sci and Technology. http://dx.doi.org/10.1021/acs.est.9b04919

Engel, S. 2016. The Devil in the Detail: A Practical Guide on Designing Payments for Environmental Services. International Review of Environmental and Resource Economics, 9: 131-177.

Fales, M., R. Dales, M.E. Herber, S.P. Sowa, J. Asher, G. O'Neil, P.J. Doran, and B. Wickerham 2016. "Making the Leap from Science to Implementation: Strategic Agricultural Conservation in Michigan's Saginaw Bay Watershed". J. of Great Lakes Research 42(6): 1372-1385.

Ferraro, P. J., and Price, M. K., 2013. Using Nonpecuniary Strategies to Influence Behavior: Evidence from a Large-Scale Field Experiment. The Review of Economics and Statistics 95:64-73.

Ferraro, P.J., Messer, K.D., and S. Wu, 2017. Applying Behavioral Insights to Improve Water Security. Choices 32 (4): 1-6.

Fisher-Vanden, K., and S. Olmstead. 2013. Moving pollution trading from air to water: Potential, problems, and prognosis. Journal of Economic Perspectives 27 (1): 147-172.

Fisher, K.A., J.R. Winsten, E. Spratt, R. Anderson, and R. Smith. 2016. Pay-for-Performance Conservation: A How To Guide. Report from Winrock International and the Delta Institute.

Fleming, P. 2017. Agricultural Cost Sharing and Water Quality in the Chesapeake Bay: Estimating Indirect Effects of Environmental Payments. American Journal of Agricultural Economics 99 (5): 1208-1227.

Fleming, P., E. Lichtenberg, and D.A. Newburn. 2018. Evaluating impacts of agricultural cost sharing on water quality: Additionality, crowding in, and slippage. Journal of Environmental Economics and Management 92:1-19.

Fleming, P.M., 2019. Cost effectiveness of legacy sediment mitigation at Big Spring Run in comparison to other best management practices in the Chesapeake Bay watershed. Water Science Institute, Lancaster, PA.

Garnache C., Swinton, S.M., Herriges, J.A., Lupi, F., and R.J. Stevenson, 2016. Solving the phosphorus puzzle: Synthesis and directions for future research. American Journal of Agricultural Economics 98:1334-1359. 22, pp. 581-592

Geng, R., Yin, P. Sharpley, A., 2019. A coupled model system to optimize the best management practices for nonpoint source pollution control. Journal for Cleaner Production.

Ghebremichael, L. T., T. L. Veith, C. A. Rotz, P. E. Cerosaletti;,D. E. Dewing. 2009. Exploring economically and environmentally viable northeastern US dairy farm strategies for coping with rising corn grain prices. Journal of dairy science, ISSN: 1525-3198, Vol: 92, Issue: 8: 4086-99.

Giri S., A.P. Nejadhashemi, S.A. Woznicki. 2012. Evaluation of targeting methods for implementation of best management practices in the Saginaw River Watershed. J. Environ. Manag. 103:24–40.

Goodkin, J.M., Kelley, L.E., Fleming, P.M., and L.H. Palm-Forster, 2019. Willingness to Invest in Legacy Sediment Mitigation: Results from a Field Experiment with Rural Landowners. Water Science Institute, Lancaster, PA.

Hahn, C., Prasuhn, V., Stamm, C., Milledge, D.G., Schulin, R., 2014. A comparison of three simple approaches to identify critical areas for runoff and dissolved reactive phosphorus losses. Hydrol. Earth Syst. Sci. 18, 2975–2991.

Heathwaite, L., A. Sharpley, W. Gburek. 2000. A conceptual approach for integrating phosphorus and nitrogen management at watershed scales. J. Environ. Qual. 29:158-166. doi:10.2134/jeq2000.00472425002900010020x

Horowitz, J.K., and Ri.E. Just. 2013. Economics of additionality for environmental services. Journal of Environmental Economics and Management 66 (1): 105-122.

James, M., J. Chandler, A. Eltner, C. Fraser, P. Miller, S. Robson, S. Lane. 2019. Guidelines for the use of structure-from-motion photogrammetry in geomorphic research.Earth Surf. Process. Landforms 44, 2081–2084.

Khanna M., W. Yang, R. Farnsworth, H. Önal. 2003. Cost-effective targeting of land retirement to improve water quality with endogenous sediment deposition coefficients. Am J Agric Econ 85(3):538–553.

Kurkalova, L.A., 2015. Cost-Effective Placement of Best Management Practices in a Watershed: Lessons Learned from Conservation Effects Assessment Project. JAWRA Journal of the American Water Resources Association, 51(2), pp.359-372.

Lichtenberg, E., and R. Smith-Ramirez. 2011. Slippage in conservation cost-sharing. American Journal of Agricultural Economics 93 (1): 113-129.

Lindsey, S., Phillips, C. Donnelly, G. Speiran, L. Plummer, JK. Böhlke, M. Focazio, W. Burton, and E. Busenberg. 2003. Residence Times and Nitrate Transport in Ground Water Discharging to Streams in the Chesapeake Bay Watershed. USGS. Water-Resources Investigations Report 03-4035

Lynch, S. and L. Shabman. 2011. Designing a Payment for Environmental Services Program in the Northern Everglades. National Wetlands Newsletter 33(4):12-15.

Maille, P., A.R. Collins, and N. Gillies. 2009. Performance Based Payments for Water Quality: Experience from a Field Experiment. J. of Soil and Water Conservation. 64(3): 85A-87A.

Maryland Department of the Environment, and Maryland Department of Agriculture. 2017. Maryland Trading and Offset Policy and Guidance Manual: Chesapeake Bay Watershed. Annapolis, MD. https://mde.maryland.gov/programs/water/Documents/WQTAC/TradingManualUpdate4.17.17.pdf

Meals, D.W., S.A. Dressing, T.E. Davenport. 2010. Lag time in water quality response to best management practices: A review. Journal of Environmental Quality. 39:85-96. doi:10.2134/jeq2009.0108

Mezzatesta, M, D. A. Newburn, and R. T. Woodward. 2013. Additionality and the adoption of farm conservation practices. Land Economics 89 (4): 722-742

Miao, H., Fooks, J.R., Guilfoos, T., Messer, K.D., Pradhanang, S.M., Suter, J.F., Trandafir, S., and E. Uchida, 2016. The impact of information on behavior under an ambient-based policy for regulating nonpoint source pollution. Water Resources Research 52 (5): 3294-3308.

Muenich, R.L., M.M. Kalcic, J. Winsten, K.Fisher, M. Day, G. O'Neil, Y-C Wang, and D Scavia. 2017. Pay-for-performance conservation using swat highlights need for field-level agricultural conservation. Transactions of the ASABE 60(6): 1925-1937.

Natural Resources Conservation Service. United States Department of Agriculture. 2016. Effects of Conservation Practice Adoption on Cultivated Cropland Acres in Western Lake Erie Basin, 2003-06 and 2012. Special Study Report. https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcseprd889806.pdf

Osmond, D., Meals, D., Hoag, D., Arabi, M., Luloff, A., Jennings, G., Mcfarland, M., Spooner, J., Sharpley, A. And Line, D., 2012. Improving conservation practices programming to protect water quality in agricultural watersheds: Lessons learned from the National Institute of Food and Agriculture—Conservation Effects Assessment Project. Journal of Soil and Water Conservation, 67(5).

Palm-Forster, L.H., S.M. Swinton, SM Redder, T.M. DePinto, and J.V. Boles. 2016. Using Conservation Auctions Informed by Environmental Performance Models to Reduce Agricultural Nutrient Flows into Lake Erie. J. of Great Lakes Research. 42(6): 1357-1371.

Palm-Forster, L.H., Ferraro, P.J., Janusch, N., Vossler, C.A., and K.D. Messer, 2019. Behavioral and Experimental Agri-Environmental Research: Methodological Challenges, Literature Gaps, and Recommendations. Environmental and Resource Economics 73 (3): 719-742.

Perez, M. and S.,Walker, 2014. Improving Water Quality (1 of 3) A Review of the Mississippi River Basin Healthy Watersheds Initiative (MRBI) To Target US Farm Conservation Funds.

Perez, M. 2017. Water Quality Targeting Success Stories; How to Achieve Measurably Cleaner Water through U.S. Farm Conservation Watershed Projects. May. Report. Washington, DC: American Farmland Trust and World Resources Institute.

Phillips, S.W. and B.D. Lindsey. 2003. The Influence of ground water on nitrogen delivery to the Chesapeake Bay. USGS Fact Sheet FS-091-03.

Qui, Z. 2009. Assessing critical source areas in watersheds for conservation buffer planning and riparian restoration. Environmental Management (2009) 44:968–980 DOI 10.1007/s00267-009-9380-y

Rao, N.S., Z.M. Easton, E.M. Schneiderman, M.S. Zion, D.R. Lee, T.S. Steenhuis. 2009. Distributed modeling of agricultural best management practices to reduce phosphorus loading. J. Environ. Mang. 90: 1385-1395.

Rao, N.S., Z.M. Easton, D.R. Lee, and T.S. Steenhuis. 2012. Economic analysis of best management practices to reduce watershed phosphorus losses. J. Environ. Qual. doi:10.2134/jeq2011.0165.

Rabotyagov, S., Campbell, T., Jha, M., Gassman, P.W., Arnold, J., Kurkalova, L., Secchi, S., Feng, H. and Kling, C.L., 2010. Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone. Ecological Applications, 20(6), pp.1542-1555.

Rabotyagov, S., A. M. Valcu, and C. L. Kling. 2013. Reversing property rights: Practice-based approaches for controlling agricultural nonpoint-source water pollution when emissions aggregate nonlinearly. American Journal of Agricultural Economics 96 (2): 397-419.

Rabotyagov, S.S., Campbell, T.D., White, M., Arnold, J.G., Atwood, J., Norfleet, M.L., Kling, C.L., Gassman, P.W., Valcu, A., Richardson, J. and Turner, R.E., 2014. Cost-effective targeting of conservation investments to reduce the northern Gulf of Mexico hypoxic zone. Proceedings of the National Academy of Sciences, 111(52), pp.18530-18535

Rodriguez, H., J.,Popp, C.,Maringanti, I., Chaugbey, 2011. Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed. Water Resources Research. 47(W01507.

Ribaudo, M., 2015. The limits of voluntary conservation programs. Choices: the magazine of food, farm, and resource issues. 30(2), pp. 1-5.

Sanford W. and J.P. Pope. 2007. A simulation of groundwater discharge and nitrate delivery to Chesapeake Bay from the lowermost Delmarva Peninsula, USA. International Symposium: A New Focus on Groundwater - Seawater Interaction.

Schneiderman, E.M., T.S. Steenhuis, D.J. Thongs, Z.M. Easton, M.S. Zion, G.F. Mendoza, M.T. Walter, and A.L. Neal. 2007. Incorporating variable source area hydrology into the curve number based Generalized Watershed Loading Function model. Hydrol. Proc. 21:3420-3430. doi: 10.1002/hyp6556.

Shabman, L., S. Lynch, and E. Boughton. 2013. Acquiring Water Services from Northern Everglades Ranchlands: Assuring Buyers that That They Get What They Pay For. Rangelands, 35(5):88-92

Sharpley, A.N., J.L., Weld, D.B., Beegle, P.J.A., Kleinman, W.J., Gburek, P.A., Moore, G., Mullins, 2003. Development of phosphorus indices for nutrient management planning strategies in the United States. J. Soil Water Conserv. 58, 137–152.

Sharpley, A., Bolster, C., Conover, C., Dayton, E., Davis, J., Easton, Z.M., Good, L., Gross, C., Kleinman, P., Mallinaro, A., 2013. Technical Guidance for Assessing Phosphorus Indices.

Sharpley, A.N., Kleinman, P.J., Flaten, D.N., Buda, A.R., 2011. Critical source area management of agricultural phosphorus: experiences, challenges and opportunities. Water Sci. Technol. 64, 945–952.

Shortle, J.., M. Ribaudo, R.D. Horan, and D. Blandford. 2012. Reforming Agricultural Nonpoint Pollution Policy in an Increasingly Budget-Constrained Environment. Environmental Science and Technology 46: 1316-1325.

Shabman, L. and S. Lynch. 2013. Moving from Concept to Implementation: The Emergence of the Northern Everglades Payment for Environmental Services Program. RFF DP 13-27. Resources for the Future, Washington DC

Shortle, J. 2013. Economics and environmental markets: Lessons from water-quality trading. Agricultural and Resource Economics Review 42 (1): 57-74.

Shortle, J.S., and R.D. Horan, 2017. Nutrient pollution: A wicked challenge for economic instruments. Water Economics and Policy 3:1-39.

STAC (Chesapeake Bay Program Scientific and Technical Advisory Committee). 2013. Incorporating Lag-Times Into The Chesapeake Bay Program. STAC Publ. #13-004, Edgewater, MD. 66 pp.

Stephenson, K., and L. Shabman. 2017. Can water quality trading fix the agricultural nonpoint source problem? Annual Review of Resource Economics 9: 95-116.

Van Houtven, G., R. Loomis, J.Baker, R. Beach, and S. Casey. 2012. Nutrient credit trading for the Chesapeake Bay: An economic study. RTI International, Research Triangle Park, NC.

Wagena, M.B. and Z.M. Easton. 2018. Conservation practices can help mitigate the impact of climate change. Science of the Total Environ. 635 (2018) 132–143. https://doi.org/ 10.1016/j.scitotenv.2018.04.110

Wallander, S., Ferraro, P.J., and N. Higgins, 2017. Addressing Participant Inattention in Federal Programs: A Field Experiment with the Conservation Reserve Program. American Journal of Agricultural Economics 99 (4): 914-931.

Walter, M.T., Walter, M.F., Brooks, E.S., Steenhuis, T.S., Boll, J., Weiler, K., 2000. Hydrologically sensitive areas: variable source area hydrology implications for water quality risk assessment. J. Soil Water Conserv. 55, 277–284.

Walter, R.C, D.J. Merritts, M. Rahnis, A. Gellis, J. Hartranft, P. Mayer, M. Langland, K. Forshay, J. Weitzman, E. Schwarz, Y. Bai, A. Blair, A. Carter, S. Sosenko Daniels, E. Lewis, E. Ohlson, E. Peck, A. Shilling, K. Schulte, D. Smith, Z. Stein, D. Verna, and E. Wilson. 2017. Sediment budgets and sources inform novel valley bottom restoration practice impacted by legacy sediment. 2017 Fall Meeting, American Geophysical Union, New Orleans, LA. https://agu.confex.com/agu/fm17/meetingapp.cgi/Paper/281212

Walter, R.C. and Merritts, D.J., 2008. Natural streams and the legacy of water-powered mills. Science, 319(5861), pp.299-304.

Wieland, R., Parker, D., Gans, W., and A. Martin, 2009. Costs and cost efficiencies for some nutrient reduction practices in Maryland. NOAA Chesapeake Bay Office and Maryland Department of Natural Resources, Annapolis, MD.

Wheaton J.M., Brasington J., Darby S.E. and Sear D. 2010. Accounting for Uncertainty in DEMs from Repeat Topographic Surveys: Improved Sediment Budgets. Earth Surface Processes and Landforms. 35 (2): 136-156

White, M. J., D.E. Storm, PR. Busteed, S. H. Stoodley, S.J. Phillips. 2009. Evaluating nonpoint source critical source area contributions at the watershed scale. J. Environ. Qual. 38:1654-1663. doi:10.2134/jeq2008.0375

Wilson, R.S., Howard, G., and E.A. Burnett, 2014. Improving nutrient management practices in agriculture: The role of risk-based beliefs in understanding farmers' attitudes toward taking additional action. Water Resources Research 50:6735–6746.

Winrock International. 2010. Pilot-Testing Performance-based Incentives for Agricultural Pollution Control.

Winsten, J.R. and M. Hunter 2011. Using Pay-for-Performance Conservation to Address the Challenges of the Next Farm Bill. J. Soil Water Conservation. 66(4), 111A-117A.

Winsten, J.R., C. Bauffaut, J. Britt, T. Borisova, C. Ingels, and S. Brown. 2011. Performance Based Incentives for Agricultural Pollution Control: Identifying and Assessing Performance Measures in the United States. Water Policy 13: 677-692.

Xu, Y., D. Bosch, M. Wagena, A. Collick, and Z.M. Easton. 2019. Meeting water quality goals by spatial targeting under climate change. J. Environ. Manage. 1-12. 10.1007/s00267-018-01133-8.

Yagow, G., Benham, B., Kline, K. and Mitchem, C.J., 2013. Developing Sediment Load Thresholds Protective of Aquatic Life. In 2013, Kansas City, Missouri, July 21-July 24, 2013. American Society of Agricultural and Biological Engineers.

Yagow, G., A. Collick, M. Ribaudo, W. Thomason, T. Veith. 2016. Scientific and Technical Advisory Committee Review of Nutrient Input Estimation for the Chesapeake Bay Watershed Model. STAC Publication Number 16-005, Edgewater, MD. 46 pp.

Yang W., A. Weersink. 2004. Cost-effective targeting of riparian buffers. Can. J. Agric Econ. 52(1):17–34