Design of an Agricultural Runoff Monitoring and Reward System for the Upper Chesapeake Bay

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Abstract — The Chesapeake Bay currently suffers pollution due to excess nitrogen and phosphorus coming from agricultural runoff. To reduce agricultural runoff, systems must be introduced to monitor nutrient levels on farmland and incentivize farmers to adopt best management practices (BMPs). This project uses the upper Chesapeake Bay in Maryland as a case study. Results indicate that fixed-wing and rotorcraft unmanned aerial vehicles (UAVs) with a multispectral imagery subsystem would offer the greatest balance of cost and utility for monitoring farmland. However, because commercial-use of UAVs are not currently legal, a manned aircraft such as a Cessna 152 is recommended to test the proof of the concept. The Federal Aviation Administration (FAA) is moving toward allowing commercial UAV-use for agricultural applications. If the proof of concept for monitoring nitrogen and phosphorus on farmland succeeds, it is recommended that monitoring operations be moved to the UAV platform for sustained operations once UAVs are legalized for agricultural applications. To incentivize increased utilization of BMPs, a green-yellow-red classification system is proposed in which farmers have access to incentive options based on the nutrient concentration on their farm determined by a normalized difference vegetation index captured by the monitoring system. By measuring progress with a monitoring system and tying that in with an incentive system to encourage BMP utilization, environmental organizations can track progress in cleaning up our waters while rewarding actors contributing to that cause.

Index Terms — Agricultural Runoff, Monitoring System, Spectral Imaging, Incentives

Introduction

While water pollution is commonly thought of as debris being dumped into the waters, it also comes in the form of a nutrient imbalance. These nutrients, such as nitrogen and phosphorus, are essential to a balanced aquatic ecosystem. Excess nitrogen and phosphorus in bodies of water lead to algal blooms. Excessive algae deter recreational use and hurts small business that rely on the waters for their livelihood. As algae die and decompose, they consume oxygen and lead to dead zones. Oxygen-deprived dead zones make the waters uninhabitable for fish and other living organisms, ultimately killing them [1].

The EPA classifies water pollution sources as two types: point and nonpoint sources. Point sources are static and clearly identifiable. Nonpoint sources are dynamic and are spread over a wide area from uncontrolled sources. Agricultural runoff is an example of nonpoint source pollution. As farmers fertilize their crops and their animals defecate, nitrogen and phosphorus is left in the ground. When there is rainfall or snowmelt, the water runs across the ground and carries these nutrients into nearby bodies of water [2].

Research has shown that much of the excess nutrients entering the Chesapeake Bay are from agricultural runoff. Over-fertilized crops, pesticides, livestock manure, and other farm operations greatly contribute to agricultural runoff and account for 41% greater contribution of nitrogen and 152% greater contribution of phosphorus than the second greatest contributor, wastewater runoff [3].
In order to reduce the amount of excess nitrogen and phosphorus in agricultural runoff, farmers need to increase their utilization of best management practices or BMPs. These are various technologies and practices that can be implemented on farmlands, which optimize farm operations. In addition to optimizing operations for the farmer, BMPs reduce the amount of excess nutrients left in the ground to be carried away by rainfall and snowmelt. While BMPs are available to farmers, they may or may not be utilized due to cost and time constraints.

Census data on BMP utilization trends show that some basins in the Maryland watershed have made significant improvements from 2000 to 2014. However, other basins have minimal improvements made in increased usage of BMPs [4].

The U.S. Environmental Protection Agency (EPA) set total maximum daily load (TMDL) goals for the Chesapeake Bay, which they want to attain by 2025. The TMDL is the ideal “pollution diet” as determined by the EPA. The Chesapeake Bay Program periodically measures nitrogen and phosphorus loads in the Bay’s watershed as it works toward TMDL goals. These measurements have been taken on an annual basis since the introduction of the TMDL in 2010 [3].

**STAKEHOLDER ANALYSIS**

Stakeholders identified for this case study include the West/Rhode Riverkeeper, the Maryland farmers, and the Environmental Protection Agency (EPA). The West/Rhode Riverkeeper seeks to protect its watershed from pollution through community relations, monitoring for compliance with environmental laws, promoting restoration, and advocating better environmental policies. The Maryland farmers contribute to pollution by the agricultural runoff coming from their farms. The EPA seeks to protect the environment by encouraging “national efforts to reduce environmental risk”, establishing environmental policies, funding environmental organizations, and ensuring that “laws protecting human health and the environment are enforced fairly and efficiently” [5]-[6].

**PROBLEM & NEED**

The EPA’s Clean Water Act currently addresses point source pollution. However, addressing nonpoint source pollution such as agricultural runoff is still in an early stage.

In order to reduce excess nutrients from entering the Chesapeake Bay watershed, systems must be introduced to remotely, and non-intrusively monitor progress on farms. A reward system must also be introduced to positively encourage farmers to adopt Best Management Practices (BMPs) for reducing excess nutrients in agricultural runoff.

**CONCEPT OF OPERATIONS (CONOP)**

**I. Requirements**

- **R.1** The incentive system shall positively encourage farmers to introduce Better Management Practices (BMPs).
- **R.2** The monitoring system shall detect nitrogen and phosphorus levels.
- **R.3** The monitoring system shall be nonintrusive to farmers.
- **R.4** The monitoring system shall be remote.
II. CONOP

A monitoring system can be used to detect nitrogen and phosphorus levels on farmland. Organizations such as Riverkeepers can use the data from these systems to give incentives to local farmers based on a green-yellow-red classification system. By implementing BMPs, farmers can reduce excess nutrients on their farm in order to improve their classification level and receive incentives.

FIGURE 6
CONOP

MONITORING SYSTEM ALTERNATIVES

I. Spectral Imagery Subsystem

Nitrogen and phosphorus levels can be detected with spectral imagery. As objects on the ground absorb sunlight, they give off a reflectance. The relative intensity of this reflectance is different at certain wavelengths for certain elements, which gives a chemical element’s spectral signature. Multispectral and hyperspectral systems are the two primary systems used today. The two types differ in that hyperspectral systems offer narrower bandwidths and a greater number of spectral bands, though at a significantly greater cost ($35,000 for hyperspectral versus $4,000 - $6,000 for multispectral).

II. Vehicle Platforms

Spectral imagery systems are a means of measuring nutrient levels on the ground. As objects on the ground absorb sunlight, these objects give off a reflectance. This reflectance can be measured by its relative intensity for a given wavelength in nanometers (nm). The various reflectance intensities at particular wavelengths make up a chemical element’s spectral signature. This signature is unique to each element.

To monitor farmland with a spectral imagery subsystem, it must be mounted on a vehicle platform. Four high-level types have been identified for this analysis: ground, unmanned aerial vehicles (UAVs), manned aerial vehicles (MAV’s), and satellites. UAVs separated into rotorcraft and fixed-wing types due to differing average velocities. MAV’s are evaluated at 500 ft. above ground level (AGL) based on the Federal Aviation Administration’s (FAA) minimum height requirements and at 3,000 ft. AGL based on the limitations of the less robust multispectral imagery subsystem [7].

TABLE 1
MONITORING SYSTEM ALTERNATIVES

<table>
<thead>
<tr>
<th>Vehicle platform</th>
<th>Spectral Imagery Subsystem</th>
<th>Approximate System Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satellite (Ex. DEIMOS-1)</td>
<td>Multi (Ex. Eastman Kodak KLI Linear CCD)</td>
<td>$0.11/km²</td>
</tr>
<tr>
<td>MAV (Ex. Cessna 152)</td>
<td>Multi (Ex. ADC Air)</td>
<td>$38,505</td>
</tr>
<tr>
<td>Fixed-Wing UAV (Aero-M)</td>
<td>Multi (Ex. ADC Lite)</td>
<td>$23,895</td>
</tr>
<tr>
<td>Rotorcraft UAV (Ex. X8-M)</td>
<td>Multi (Ex. ADC Lite)</td>
<td>$54,509</td>
</tr>
<tr>
<td>Ground (Ex. XUV-550)</td>
<td>Multi (Ex. ADC)</td>
<td>$17,295</td>
</tr>
<tr>
<td></td>
<td>Hyper (Ex. Pika II)</td>
<td>$46,909</td>
</tr>
</tbody>
</table>

INCENTIVE SYSTEM ALTERNATIVES

The proposed incentive system is based on three classification levels – green, yellow, and red. These classifications will be based on a normalized difference vegetation index (NDVI), which uses the ratio between near infrared (NIR) and visible light (VIS) wavelengths reflecting off the Earth to determine the density of healthy vegetation [8].

\[
NDVI = \frac{NIR - VIS}{NIR + VIS}
\]

Farms will be classified into green, yellow, and red categories based on the following ranges:

TABLE 2
CATEGORY LEVELS AND ASSOCIATED NDVIS

<table>
<thead>
<tr>
<th></th>
<th>Category Levels and Associated NDVIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>0.8 – 1.0</td>
</tr>
<tr>
<td>Yellow</td>
<td>0.4 – 0.7</td>
</tr>
<tr>
<td>Red</td>
<td>0.0 – 0.3</td>
</tr>
</tbody>
</table>

A monitoring system can periodically track nutrient concentrations on farmland for purposes of identifying a farm’s classification. Based on which classification a farmer falls under, they can be offered incentive options. The incentive options used in this framework will be determined following weight elicitation from the West/Rhode Riverkeeper in regards to the following:

1. A nitrogen and phosphorus report informing farmers of the nitrogen and phosphorus concentration on their farm.
2. A TMDL Goal Membership Card, which would get farmers discounts with local area businesses.
3. An awareness report of current federal and state programs that farmers can take advantage of.
4. A legislation change for Farmer’s Insurance to extend coverage to BMP implementation, mitigating risks for farmers introducing new BMPs on their farm.
5. A legislation change for a technology assistance program that would aid farmers who may not be able to afford BMP systems.

**METHOD OF ANALYSIS**

*I. Spectral Imagery Subsystem Analysis*

A stochastic simulation was developed in order to compare the accuracy of multispectral and hyperspectral imagery subsystems. The input parameters include the spectral range and resolution as well as a distribution of chemical elements and their concentrations in parts per million (ppm). The evaluated imagery system “detects” elements in the simulation. Error is incorporated by a normal distribution with 95% confidence where the tails are determined based on the percent error input into the simulation model. The mean of these distributions are the actual relative intensity at a given wavelength. The purpose of this simulation is to compare the error rates of the two spectral imagery subsystems used in this analysis and determine whether the less-expensive multispectral system would be sufficient for purposes monitoring farmland.

The simulation algorithm was developed based on the principles of Beer’s Law, which states that there is a proportional relationship between absorbance and concentration for elements. A proportional relationship is a linear relationship and thus as concentration increases, absorbance is additive.

By making the assumption that all vehicle platforms housed the same spectral imagery subsystem for purposes of comparison, a unitless coefficient was derived for use in this analysis. Combining (2), (3), and (4) gives,

\[
ACR \propto \frac{GSD^4}{SNR^2 \times K^4}
\]

Arranging the variables to combine the spectral imagery subsystem parameters simplifies to

\[
ACR \propto \frac{(\text{pixel size})^4}{d^2 \times \left(\frac{h_g}{c_k}\right)^3 \times K^4}
\]

Given the 250-acre area coverage for a 40 min runtime given by the manufacturer of the fixed-wing UAV example [10],

\[
ACR = \frac{250 \text{ acres}}{40 \text{ min}} = 1.01171 \text{ km}^2 \text{ min}^{-1}
\]
\[
\frac{\text{pixel size}}{d^2 \times K^3 \times c_k} \propto 10.8089 \text{ (unitless)}
\] (9)

With this coefficient to represent using the same spectral imagery subsystem, vehicle platforms were compared based on the following equation:

\[
ACR \propto 10.8089 \left( h_g \times v \right)
\] (10)

This equation was used to calculate the ACR for each vehicle platform. The ACR values were then used to calculate the ACR per dollar in a 10-year period. Additionally, monitoring system platforms were also compared by ground resolution in inch per pixel as supplied by manufactures.

**TABLE 4**

<table>
<thead>
<tr>
<th>Vehicle Platform</th>
<th>ACR [km²/min]</th>
<th>ACR/Dollar [km²/ft]</th>
<th>Average N Detection Error (%)</th>
<th>Average P Detection Error (%)</th>
<th>Combined Average Error (%)</th>
<th>Difference in Average Errors (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground</td>
<td>0.01</td>
<td>3</td>
<td>&lt;1.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UAV (rotorcraft)</td>
<td>0.62</td>
<td>137</td>
<td>400</td>
<td>1.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UAV (fixed-wing)</td>
<td>1.01</td>
<td>223</td>
<td>400</td>
<td>1.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAV (min height)</td>
<td>2.3</td>
<td>314</td>
<td>700</td>
<td>3.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAV (max height)</td>
<td>13.97</td>
<td>1907</td>
<td>3000</td>
<td>14.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satellite</td>
<td>~</td>
<td>0.0003</td>
<td>2180000</td>
<td>866</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**RESULTS**

The spectral imagery simulation was run for 100,000 iterations at 0.5%, 1.0%, 1.5%, 2.0%, 2.5%, and 3.0% device error rates for the multispectral and hyperspectral imagery subsystem. The determined concentration for nitrogen and phosphorus were compared to the actual concentration in the simulation to calculate the detection error for nitrogen and phosphorus amongst the noise of other elements. An average was taken for the mean detection error for nitrogen and phosphorus and plotted against the device error in order to compare the error trends for multispectral and hyperspectral imagery subsystems.

**TABLE 5**

<table>
<thead>
<tr>
<th>Spectral Imagery Subsystem</th>
<th>Device Error (%)</th>
<th>Spectral Range (nm)</th>
<th>Spectral Resolution (nm)</th>
<th>Average N Detection Error (%)</th>
<th>Average P Detection Error (%)</th>
<th>Combined Average Error (%)</th>
<th>Difference in Average Errors (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi</td>
<td>0.5</td>
<td>520 - 920</td>
<td>10.0</td>
<td>2.29</td>
<td>2.20</td>
<td>2.24</td>
<td>0.14</td>
</tr>
<tr>
<td>Hyper</td>
<td>0.5</td>
<td>400 - 970</td>
<td>3.3</td>
<td>2.12</td>
<td>2.10</td>
<td>2.11</td>
<td></td>
</tr>
<tr>
<td>Multi</td>
<td>1.0</td>
<td>520 - 920</td>
<td>10.0</td>
<td>4.59</td>
<td>4.54</td>
<td>4.56</td>
<td>0.31</td>
</tr>
<tr>
<td>Hyper</td>
<td>1.0</td>
<td>400 - 970</td>
<td>3.3</td>
<td>4.29</td>
<td>4.21</td>
<td>4.25</td>
<td></td>
</tr>
<tr>
<td>Multi</td>
<td>1.5</td>
<td>520 - 920</td>
<td>10.0</td>
<td>6.89</td>
<td>6.87</td>
<td>6.88</td>
<td>0.47</td>
</tr>
<tr>
<td>Hyper</td>
<td>1.5</td>
<td>400 - 970</td>
<td>3.3</td>
<td>6.46</td>
<td>6.36</td>
<td>6.41</td>
<td></td>
</tr>
<tr>
<td>Multi</td>
<td>2.0</td>
<td>520 - 920</td>
<td>10.0</td>
<td>9.19</td>
<td>9.21</td>
<td>9.20</td>
<td>0.59</td>
</tr>
</tbody>
</table>

The percent difference between detection errors for the multispectral and hyperspectral ranged from 0.14% at a 0.5% device error rate to 0.86% at a 3.0% device error rate. Multispectral system costs range from $3,000 to $6,000 whereas hyperspectral systems cost $29,000 and up. With the difference in detection error tending to be less than 1%, the significant cost difference indicate that a multispectral system would be adequate for the purposes of monitoring nitrogen and phosphorus on farmland.

Weights were elicited from the West/Rhode Riverkeeper for this case study. The weights were based on ACR, ACR per dollar, and ground resolution for the monitoring systems. For the incentive system, the weights were based on implementation, sustainability, scalability, and the sense of community associated with each incentive alternative.

**FIGURE 11**

**VALUE HIERARCHY WITH WEIGHTS**

The weights elicited from the Riverkeeper were then used to evaluate the following ranking of alternatives,
Using the utility rankings determined for the monitoring system alternatives, the rankings were graphed against total system costs. The service for the satellite system offers its service as a rate of $0.11/\text{km}^2$. For comparison purposes, this rate was multiplied by the total area for farmland in Maryland, which equates to 2,030,745 acres or 8,218.13 km$^2$.

\textbf{RECOMMENDATION & CONCLUSION}

While the ground monitoring system shows high utility for lower cost, this system fails the requirement for the monitoring system to be non-intrusive. While both rotorcraft and fixed-wing UAVs have the best balance of cost and utility, commercial use of UAVs are currently illegal as of March 2015. The FAA published a Notice of Proposed Rule-Making (NPRM) in February of 2015 to officially move toward legalizing commercial of UAVs in the United States. This NPRM proposes an incremental approach to UAV legalization starting with agricultural applications [11].

Based on utility rankings, the legislative change for farmer’s insurance and the assistance program tied as the third highest-ranking alternative. Both of these incentive alternatives were included in the proposed incentive system shown below:

\textbf{ACKNOWLEDGMENTS}

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\textbf{REFERENCES}


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