USING UNMANNED AERIAL VEHICLES TO MODEL SURFACE RUNOFF DURING WELL PAD DEVELOPMENT¹

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Abstract. Unmanned Aerial Vehicles (UAVs) can be applied to collect valuable information during the construction of oil and gas well pads. The aerial photos from a UAV provide high spatial and temporal information and when built as orthomosaics and digital surface models, can map the sources and paths of runoff for better sediment management. The objective of this work was to use UAV imagery to predict total suspended solid runoff resulting from the construction of an oil and gas well pad. We collected true-color images with a Phantom 4 Pro and processed the imagery to create an orthomosaic and a digital surface model (DSM). The orthomosaic was classified using a maximum likelihood classifier to determine cover types and the DSM was processed to create a runoff grid. Annual total suspended solid (TSS) loading rates were assigned to the cover type classes and modeled with an annual runoff grid. We were able to identify three locations with elevated TSS loading values that could be detrimental to downstream aquatic systems and suggest the use of mitigation activities at these sites to prevent potential impacts. The use of UAVs in the oil and gas industry proved to be a viable option for better sediment management during pad construction.

Additional Key Words: Site planning, Site design, Runoff model, Watershed management, Aquatic system, Drones.

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Introduction

When Unmanned Aerial Vehicles (UAVs) or drones were first available, flying them was relatively easy and straightforward, but the challenge was in making them useful (Jacobs, 2013). Now, they are considered flying computers as more and more technology and advancements have made them a necessary tool for mapping the landscape at a high spatial and temporal resolution. In West Virginia, where the landscape has been used for energy extractive industries, UAVs can play a critical role in managing the intersection of energy and natural resources.

Before UAV use, global positioning systems, geographic information systems, and remote sensing were the main geospatial technologies used to analyze the extractive industry for site design and planning. Burley et al. (1992) and Burley and Brown (1992) provided early examples of how these technologies can aid in land use reclamation by mapping locations, analyzing spatial characteristics, and classifying disturbance extents across the landscape. Even as new technologies continue to advance in areas such as computing power, higher resolution satellites, and spatial analysis algorithms, a common theme is that understanding what is where continues to be an important need for reclamation applications. The ability to capture information quickly and at a high resolution has led researchers to recognize the potential utility of UAVs.

UAV use in natural resource management has increased greatly in the past five years. Improvements in technology and sensors have led to UAV use being applied to inventory many natural landscape features. As noted by Perez (2015), more and more use is now occurring in other industries such as the construction industry where these tools have the potential to provide high-resolution aerial imagery and remote sensing data that can assist inspectors in performing focused and strategic site inspections of erosion and sediment control practices in an efficient and effective manner. With increasingly stringent construction storm water regulations, inspections have become an integral component in ensuring adequate protection of our nation's waterbodies.

UAV technology has been shown to benefit oil and gas operations in three main ways. As noted by Gallagher (2018), 3D mapping, safer inspections, and real time aerial information on leaks and spills are some of the more obvious advantages. Others include the benefits to uncover trends invisible to the human eye, support for cost efficiency, and offering productivity gains to be more competitive with competitors (Gallaher, 2018).

An early application example of this technology in the oil and gas industry, was conducted by Hausamann et al. (2005). They provided two different scenarios for a UAV-based gas pipeline monitoring system which included small and lightweight low altitude UAV and a medium-size medium-weight mid-altitude UAV. They noted that UAVs can provide the appropriate platforms for a remote sensing-based inspection system. The development of appropriate small and medium size UAVs is technically feasible in controlled as well as in uncontrolled airspace.

In another study, Tokarczyk et al., (2015) used UAV imagery to derive high-resolution impervious maps for urban areas and used the information as input for urban drainage models. They found that UAV imagery was a valuable data source compared to more traditional fixed wing aerial photography and provided a high degree of spatial detail for the overland flow drainage modeling efforts.

Building upon these two studies, we wanted to effectively capture the unique temporal and spatial information from the typical construction of oil and gas well pad development in West Virginia to help identify potential water runoff issues at the site. The West Virginia Geologic and Economic Survey updates daily the Marcellus shale wells that are completed, permitted, and cancelled episodes (WVGES, 2020). This information was useful in our study to identify permitted sites and contact representative operators for permission to analyze the pad. Our decision to use UAVs for the project followed the work by Morton (2018) who listed six main questions regarding if UAVs are appropriate for a project. They include: Is there a need for complex data, detailed measurement? Is the study area located in a challenging area? Is there a requirement for very hi-resolution imagery? Are frequent acquisition cycles desired? Are there any safety concerns for manned operations? What are the time and cost saving opportunities on the project? As for project size, Morton (2018) found that the cost-effective area to use most UAVs is up to 1,000 acres in size. After this size, the costs become more effectively spent on manned aircraft.

Following the framework by Tokarczyk et al. (2015), we designed our study to use UAV imagery to delineate the impervious and developed areas of an oil and gas well pad and predict the total suspended solids from runoff using average annual flow and loading rate modeling. This area of the pad is of interest because the impervious surface can reduce the infiltration of water into the soil and lead to higher runoff rates. As noted by Tokarczyk et al., (2015), analyzing the

imperviousness level is important as it directly impacts many environmental processes. An increasing percentage of impervious surfaces increases surface runoff volume and peak discharge and decreases soil moisture compensation and groundwater recharge (Tokarczyk et al., 2015). Moreover, increased peak runoff volumes together with an inefficient drainage network can not only cause urban floods, but also lead to an increased hydraulic stress and increase the risk of loading waterbeds with sediment, and its associated constituents (e.g., nutrients, contaminants, and micro-pollutants) (Tokarczyk et al., 2015).

Our approach to using UAVs for surface runoff modeling provides another example of the continued advancements in watershed and site hydrology as outlined by Wu et al., (2018). The authors provide a historical perspective about managing pollutant loadings and note how the prediction of water quality has taken time to develop, but the equations we use to link land cover to water quality produce a relatively accurate estimation for a water body (Wu et al., 2028). They focused on the land use loading coefficients for nitrogen and phosphorus while in our work we focused on total suspended solids since the converted land cover was barren and not agriculture row crops. Our work provides an extension to modeling land cover loading rates in the resource extraction industry using high resolution and high temporal resolution imagery to aid in site design and planning.

Methods

Study site description

The unconventional oil and gas (UOG) study site was located approximately 40 km west of Morgantown in Monongalia County, West Virginia (39.6216 N, -80.2786 W) and is operated by Northeast Natural Energy (Fig. 1). It is considered unconventional because it is a site which cannot be explored, developed, and produced by conventional processes just in using the natural pressure of the wells and pumping or compression operations (NNE, 2020). Northeast Natural Energy is an independent oil and gas exploration and production company headquartered in Charleston, West Virginia (WV). The well planned for this site was located at 430 m above sea level and the proposed target formation was the Marcellus shale at an approximate depth of 2.5 km. The lateral bore for the UOG well was planned for 2.2 km. The permitted site plan estimated a total of 117 ha of disturbed area, which includes all roads, soil stockpile areas, pits, and other infrastructure.

- 2) correspondence, where each detected point is matched with its correspondences in different images;
- 3) point filtering is performed to remove erroneous positions;
- 4) scene geometry reconstruction, where the SfM is applied to calculate the cameras parameter and positions;
- 5) scale and georeferencing, where a transformation from an arbitrary to a known coordinate system is performed, usually using GCPs;
- 6) densification, when MVS (Multi View Stereo) algorithms are applied to create a dense cloud from the sparse point cloud generated in the first step;
- 7) interpolation, step where an interpolation method is applied to create a regular grid from the point cloud; and
- 8) orthorectification and mosaicking, when defects caused by the images angle and surface are removed using the grid created, and the images already corrected are merged together, providing a product called an orthomosaic.

The points generated in step 6 are representations of the surface objects visualized in the pictures, therefore the interpolation in step 7 provides a Digital Surface Model (DSM). In some cases, it is possible to filter the points that are located in the ground and perform the interpolation with only those, obtaining a Digital Terrain Model (DTM). The produced model is an important source of elevation, being both high temporal and high spatial resolution which has many benefits for water resource management. This model is also necessary in the orthorectification process. The process of creating an orthomosaic is important because it is possible to measure angles, distances, positions, and area on the images since the objects are represented orthogonally (meaning, with adjusted angles) (Wolf et al., 2014). Yet, since the orthomosaic is corrected with the interpolated grid (being or a DTM or a DSM), its precision is directly related to the grid precision, and when a DSM is used, it is common to observe distortions and irregular aspect (Whitehead and Hugenholtz, 2014).

Figure 2 shows the created orthomosaic and DSM for the study area compared to the pre-construction image. The pre-construction image was from the National Agriculture Imagery Program (NAIP). The NAIP imagery was obtained from a fixed-wing manned aircraft at a 1 m

resolution and the UAV imagery was collected on June of 2018 and produced a 2 cm nominal pixel resolution.

Figure 2. Study site before and after the construction of the well pad.

Preparing the elevation surface for hydrological processing

Digital elevation models have been used as early as 1986 by Band (1986) to automatically map the stream channel and diversion or flow paths in a watershed. Band (1986) referred to the elevation as a topographic skeleton in which the watershed can be partitioned into subregions and the streams linked to track all flow paths and connections. To run a surface runoff model to estimate total suspended solids requires the conditioning of the elevation surface for hydrological modeling. Many of the functions in the overland flow modeling rely on DEMs and their derivatives, which include flow direction and accumulation (Greenlee, 1987; Jenson and Domingue, 1988) and also requires hydrologically corrected DEMs and stream data. A hydrologically corrected DEM means that the cells must provide a path to the lowest point in the watershed when a flow direction algorithm is performed. Sinks or “pits” in the DEM must be filled to prevent an interruption in the flow path.

By using the hydrologically corrected DEMs, accurate flow direction and flow accumulation grids can be created (Jenson and Dominque, 1988). These grids assure that overland flow estimates and watershed boundaries can be delineated efficiently. In addition, runoff and cumulative runoff grids are created from these grids to capture the relationship between precipitation and stream flow with average annual precipitation grids at 800 m resolution (PRISM, 2018), and historical stream flow records from USGS gauging stations. This method is explained in more detail by Saunders and Maidment (1996) and also demonstrated in WV by Morris et al., (2008) and Strager et al., (2010).

In this study we produced the hydrologically corrected elevation surface using the DSM obtained by the structure from motion approach discussed previously. The DSM was used in an ArcGIS model (ESRI, 2017) to create a hydro corrected elevation and surface runoff model, as show in Fig. 3.

Figure 3. Creation of hydro corrected surface runoff models.

Image classification

For this study, our goal was to classify the impervious surfaces in the image and assign loading rates to the classes. As noted by Tokarczyk et al., (2015) supervised classification consists of three

main steps: (i) extraction of the features from a raw input image, (ii) training the classifier using a small, manually annotated training set (not necessarily from the same image), and (iii) classification of all pixels in the area of interest, using the classifier trained in the previous step.

The maximum likelihood (ML) classifier is a popular classification method. It is a simple approach which assumes that the image features within each target class follow a normal distribution (Tokarczyk et al., 2015). It is based on a Bayes theorem and makes use of a discriminant function to calculate the highest likelihood of a pixel based on evidence that is assembled for the training classes that are defined (Ahmad and Quegan, 2016). Essentially, it takes the training data examples as a priori and calculates the probability of all other cells that meet the similar characteristics and signatures to determine how to assign the output by considering both the variance and covariances of classes. In this study, we classified the RGB orthomosaic using the maximum likelihood classifier implemented in ArcGIS software (ESRI, 2017).

The first step was to create polygon training data of the classes of interest. The classes we targeted were: imperviousness, soil, forest, and grass. With the training data defined, the next step was to run the maximum likelihood classification. We used the Image Analyst extension tool in ArcGIS (ESRI, 2017) and chose an equal a priori probability weighting. The classified image is shown in Fig. 4.

Water quality estimation process

The water quality estimation process used the hydrological grid outputs (DEM, flow direction, flow accumulation, runoff, and cumulative runoff) with the classified land use. The main sources of runoff for our study area came from impervious and exposed soil areas. The impact of these locations was modeled to estimate total suspended solids (TSS), and the cumulative effects across the landscape.

To calculate the TSS loading, literature-based values of mean annual TSS for the land use types were applied. These included 35 mg/L for barren or impervious at the pad and road, 30 mg/L for dirt or bare/sparsely vegetated cover, 16 mg/L for deciduous forest, and 19 mg/L for grassland herbaceous open land (Syed and Jodoin, 2006). The loading values assigned to each land use and cover type were then multiplied by the runoff grid, creating a cell-based annual loading grid (Strager et al., 2010). The cell-based loading grid was then cumulatively applied across the landscape to calculate the annual loadings for the drainage network. With this result, it is possible

to identify areas of high sediment loading and target areas for control practices. The assumptions of this overland flow, fate-transport advection-dispersion modeling are that the stream channels have the same width, depth, slope, and streambed roughness; the streams have the same reaeration, pollution decay, and sediment oxygen demand rates; and the approach does not consider infiltration, interflow, ground water flow additions, or any atmospheric conditions such as temperature or evapotranspiration in the watershed (Strager et al., 2010). The approach can be considered a conservative screening model which identifies the worst possible conditions.

Figure 4. Maximum likelihood classifier result.

Project overview

The project workflow is summarized in Fig. 5.

Figure 5. Workflow of project.

Results

The results include the runoff flow paths across the pad site, predicted sediment loadings and concentrations, drainage catchments, and the locations to manage runoff with remediation and sediment control. The mapping of the results is shown in Fig. 6, 7, 8, and 9.

Figure 6. Runoff grid showing stream flow paths across the pad (left over digital surface model and right over orthomosaic)

Figure 7. Total annual average concentrations (mg/L) and loadings (Kg/yr) of total suspended solids (TSS)

Figure 8. Catchments for each flow path in the study area (n=6,419).

Figure 9. Locations to focus on managing runoff after analysis of flow patterns and TSS calculations.

Discussion and Conclusion

The locations to focus on managing runoff were selected based on the results of the flow pattern analysis and TSS calculations for both concentrations and loadings. These locations are noted by stars in Fig. 9 and labeled numbers one, two, and three. These sites capture the cumulative contributions of the most severe loading values for TSS. Sediment control devices at these sites would greatly mitigate the runoff of the well pad to minimize downstream impacts. The 35 mg/L value of TSS that was predicted from the pad site runoff indicates a risk to downstream biological

condition as noted in Fig. 10 using the work by MPCA (2011). Figure 10 below highlights the threshold and biological impairments related to TSS concentrations. We conclude that to minimize aquatic life impacts from this pad site it is critical to mitigate the potential TSS concentrations possible from this site.

Figure 10. Relationship between the 90th percentile of TSS and the percent of centrarchid individuals for central streams with additive quantile regression smoothing line (red line). Image source MPCA (2011).

The high-resolution elevation surface in this study proved to be a critical input into hydrological modeling at this scale of a study site. This finding reinforces the work by DeBell et al. (2015) that noted how UAVs are set to become a key component of water resource management because of the growing need for fine-scale data, which cannot be delivered from satellites or aircraft in a cost-effective way. We found that combining imagery with fine-scale structure-from-motion topographic models can be a valuable approach to assist in water resource decision-making. UAVs provide a way to monitor the time component of polluting sources and the water paths and flows throughout the landscape (DeBell et al., 2015).

We agree with the results found by Barreiro et al., (2014) who showed UAVs are able to obtain accurate topographic information for smaller sized study areas. The authors used UAV photogrammetry and a point cloud converted into points through a triangulation process to create the initial elevation and runoff models.

We plan to further apply UAVs for watershed and overland flow runoff modeling due to the higher image resolution, quick deployment, access to hazardous areas, robust software, cost effective, fast data turnaround, GPS autonomous flight, and built in safety features (Morton, 2018). Also, as noted by Tokarczyk et al. (2015) we found that UAV imagery represents a valuable alternative data source for drainage model applications due to the possibility of flexibly acquiring up-to-date aerial images compared with off-the-shelf image products. We believe that in the future, drainage models representing a higher degree of spatial detail will fully benefit from the strengths of UAV imagery.

Based on the results from this study we can concluded that the UAV technology can be a valuable tool in water management and mitigation of mining activities due its very high temporal and spatial resolutions, allowing a quick and effective response to any aquatic problem related to such anthropic activities.

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