**UAV, Machine Learning, And GIS for Wetland Mitigation in Southwestern Utah, USA**

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**Abstract:** This research focusses on wetland mitigation as a part of a highway project through the use of Unmanned Aerial Vehicles (UAV) called AggieAir and state-of-the-art wetland classification technique. The study area is a wetland in the Southern Parkway construction site in Washington County, Utah, United States. The Utah Department of Transportation (UDOT) needs to build a road through the wetland connecting the southern parkway to the new Saint George International airport and hence wetland mitigation measures are required. Wetland mitigation means the replacement of the exact function and value of specific habitats that would be adversely affected by the proposed project. AggieAir was used to acquire high-resolution aerial imagery of the study area to aid UDOT to map the wetland. AggieAir flew over the wetland on different dates and imagery was acquired in the visible and NIR bands. The multiclass- relevance vector machine algorithm was used to classify the georeferenced UAV imagery of the area. The UDOT field crew collected ground truthing samples of eight classes of wetland species from within the Utah Lake Wetlands prior to the UAV flight. The imagery and GPS data was imported into ArcGIS for creating a map of the study area. The MCRVM machine was trained for ten classes namely Phragmites, Baltic rush, Beaked sedge, Hardstem bullrush, Saltgrass, Broad leaf cattail, Narrow leaf cattail, water, snow and concrete. The training data set for the MCRVM model was prepared in ArcGIS using the ground truthing for various species of wetland grass and visually picking up samples on snow, concrete and water. The classification results from the RVM model were used to create class map of the area in ArcGIS. The results showed considerable accuracy and good agreement with the actual classes. It was concluded that the UAV may prove to be a viable and cost-effective option for wetland mitigation for highway management as information processing is faster and more accurate with the use of state-of-the-art classification models with the UAV.

**About the Author:**

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Dr. Bushra Zaman received a Ph.D degree & and completed Post-Doctorate in Civil and Environmental Engineering from Utah State University, Logan, Utah, USA. She received an M.Tech in Water Resources Engineering from Indian Institute of Technology, Delhi, India, in 2002 and graduated with a B.Tech. degree in civil engineering from Bihar Institute of Technology, Sindri, Bihar, in 1999. She is currently working as a Professor in the department of Civil Engineering at MM University, Sadopur Campus, Ambala. She has over 14 years of industry & academic experience. She has research experience in water resources management and remote sensing & GIS applications at Utah Water Research Lab, Department of Space Engineering, Utah State University, USA, Envision Utah USA & IIT Delhi; Her professional experience is in consulting and infrastructure companies of repute like Delhi Metro Rail Corporation, Delhi and Tata Consulting Engineers, Mumbai; Her research interests involve remote sensing and GIS applications in water resources engineering, state of- the-art learning machine tools, hydrologic modeling, evolutionary computation, and data-assimilation.

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Introduction

Unmanned Aerial Vehicles (UAVs) are being used very successfully for scientific applications worldwide. The Utah Water Research Laboratory (UWRL) and the Center for Self-Organizing Intelligent Systems (CSOIS) at Utah State University (USU), USA have developed UAVs for scientific application related to water resources engineering and management. The UAV platform, named “AggieAir,” is capable of carrying multiple cameras that capture imagery in the visible, near-infrared and thermal bands at a spatial resolution of 2.5 to 25 cm, depending on the altitude of flight. This paper discusses one such application related to wetland mitigation in the Utah Lake Wetlands in South Western Utah, USA. The Utah Department of Transportation (UDOT) used this UAV technology for wetland mitigation banking while building a highway connecting southern parkway to the new Saint George International airport in Utah. Since the highway passes through the wetland, the wetland mitigation measures required mapping of the wetland vegetation. High resolution images of the wetland were acquired using AggieAir. The images were mosaicked, ortho-rectified and imported into GIS for further analysis. The processed images were classified using the multiclass relevance vector machine tool developed at UWRL (Tipping 2001; building on previous algorithms developed by Thayananthan et al. 2008).

Study Area

The area of study is the wetland situated at the northeastern part of Utah Lake, in Utah, United States. Approximately 3.2 square kilometers of the study area was chosen for classification of wetland species and other features for wetland mitigation banking.

![Study Area](image_url)

**Fig: 1 – Study Area**
The AggieAir UAV Platform

AggieAir Flying Circus is a service center at the Utah Water Research Laboratory which provides high-resolution, multi-spectral aerial imagery using a small, unmanned aerial system called AggieAir. The UAV aircraft is equipped with computer, avionics, global positioning system (GPS), radio control (RC), flight control, and payload management software. AggieAir platform is battery powered, fully autonomous or RC, easy to use. No runway is needed for its operation and is coven-capable. The data is acquired in the visible, near-infrared (NIR) and thermal infrared (TIR) bands. The details about the TIR System can be found in Sheng et al. (2010). The small unmanned aerial system (sUAS) used in this study was the first-generation “flying wing” aircraft in a series of sUAS developed by the Utah Water Research Laboratory (UWRL) at Utah State University. The latest in the series is “BluJay” and it is traditional fixed-wing aircraft with a wingspan of 10 ft and a length of 5 ft. BluJay has a max takeoff weight of 26.5 lbs, which includes the AggieAir standard payload. The aircraft runs on two 22 A.h. lithium polymer batteries and can fly for 200 min and cruises at 51 miles/hour.

AggieAir Sensors

The instrument used by Flying wing UAV was the RGB digital camera, Canon PowerShot SX100, which had a 9-megapixel CCD sensor and an ISO range from 80 to 1600 and the digital imaging core (DIGIC) III processor. The radiometric resolution of the camera is 8-bit. Figure 3 (a) shows the spectral response curves of the flying wing UAV. BluJay’s current multispectral payload consists of 12MP scientific-grade Lumenera RGB and grayscale cameras which can be combined with any optical filter to provide specific spectral data. Combined with a 640x480 thermal infrared camera and optional SWIR camera, the payload is standardized at 4.2 pounds, is able to capture time-synchronized images at 1.5 FPS across all sensors, and includes 1Tb of onboard storage for possible mission times of over three hours. Figure 3(b,c) shows the spectral response curves of the cameras on BluJay UAV.

Fig 3: (a) Color Quantum Efficiency Curves for (a) Flying wing aircraft sensors; (b,c) BluJay aircraft sensors

Source: http://aggieair.usu.edu/aircraft
Methodology

Images of the study area were obtained from AggieAir UAV in the visible and near infrared bands. The spatial resolution of the imagery was 17 cm and radiometric resolution was 8 bits. The imagery was classified using the MCRVM supervised classification model prepared in MATLAB. The training and test classes for the MCRVM model were prepared using the available ground samples for seven vegetative species/wetland grass namely Phragmites, Baltic rush, Beaked sedge, Hardstem bulrush, Saltgrass, Broadleaf cattail, Narrowleaf cattail and visually picking up samples from the UAV imagery for water, ground and concrete. There were a total of 263 training points and 130 test points. The accuracy assessment was done in MATLAB by randomly selecting samples from the classified imagery and comparing it with the ground truth samples.

Multiclass Relevance Vector Machine (MCRVM)
The RVM was originally introduced by Tipping (2001). Thayananthan (2006) proposed an extension of the sparse Bayesian model developed by Tipping to handle multiclass outputs. Thayananthan’s multi-class relevance vector machine (MCRVM) code is an open source code which extends Tipping’s binary RVM classification scheme (Tipping 2001) to a multi-class classification algorithm. This code was used as a base to build the MCRVM model used in this application.

(i) General background of RVM

“Sparse Bayesian Learning” is used to describe the application of Bayesian automatic relevance determination (ARD) concepts to models that are linear in their parameters. The motivation behind the approach is that one can infer a regression or classification model that is both accurate and sparse in that it makes its predictions using only a small number of relevant basis functions that are automatically selected from a potentially large initial set. A special case of this concept is the RVM which is applied to linear kernel models. The data set is in the form of input-output pairs, \( \{ x_i, y_i \}_{i=1}^{N} \). The major goal is to learn a model of dependency of the targets on the inputs with the objective of making accurate predictions for previously unseen values of the inputs, \( x \) (Tipping 2001). This model is defined as some function \( y(x) \) whose parameters are found as:

\[
y(x; w) = \sum_{n=1}^{N} w_n \varphi_n(x) = w^T \varphi(x)
\]

where the output \( y(x; w) \) is a linearly weighted sum of \( M \), generally nonlinear and fixed basis functions \( \varphi(x) = (\varphi_1(x), \varphi_2(x), \ldots, \varphi_M(x)) \) and \( w = (w_1, w_2, \ldots, w_M)^T \), called weights, are adjustable parameters. Equation (1) can result in a number of different models, of which RVMs are a special case. This procedure is highly perceptive, which helps in extracting predictors that are very sparse, with few non-zero \( w \) parameters.

Bayes’s rule states that the posterior probability of \( w \) is obtained by combining the likelihood and prior as:

\[
p(w|t, \alpha, \sigma^2) = \frac{p(t|w, \sigma^2) p(w|\alpha) / p(t|\alpha, \sigma^2)}
\]

where \( \sigma^2 \) is the error variance, \( p(t|w, \sigma^2) \) is the likelihood of target \( t \), \( p(w|\alpha) \) is the prior, and \( p(t|\alpha, \sigma^2) \) is the evidence. In the case of classification, we apply the logistic sigmoid link function \( \sigma(y) = 1/(1+e^{-y}) \) to \( y(x) \), and adopt the Bernoulli distribution for \( p(t|w, \sigma^2) \). Hence the likelihood can be written as:

\[
p(t|w) = \prod_{k=1}^{K} \left[ \sigma(y(x_k; w)) \right]^{t_k} \left[ 1 - \sigma(y(x_k; w)) \right]^{1-t_k}
\]

where \( t_k \) is the target class \( \in \{1, 2, 3, 4, 5, 6\} \) in this paper. A true multiclass likelihood was specified in Zhang and Malik (2005) by generalizing Equation (3) to multinomial form given by:

\[
p(t|w) = \prod_{k=1}^{K} \prod_{i=1}^{N} \sigma(y_i, y_1, y_2, \ldots, y_N)
\]
where the predictor $y_n$ of each class was coupled with the multinomial logit function given by

$$\sigma(y_n; y_1, y_2, ..., y_N) = \frac{e^{y_n}}{e^{y_1} + ... + e^{y_N}}$$

A zero mean Gaussian prior distribution is applied over $w$ and is given by

$$p(w|\alpha) = \prod_{i=1}^{N} \frac{\alpha_i}{2\pi} \exp\left(\frac{-\alpha_i w_i^2}{2}\right)$$

(6)

Here each of the N independent hyperparameters, $\alpha = (\alpha_0, \alpha_1, ..., \alpha_N)^T$, individually control the strength of the prior over its associated weight and is eventually responsible for the sparsity of the model (Tipping 2001). The closed-form expression for the weight posterior $p(w|t,\alpha,\sigma^2)$ and evidence of hyperparameters $p(t|\alpha,\sigma^2)$ are intractable. Hence, a Laplacian approximation is used.

Since $p(w|t,\alpha) \propto p(t|w)p(w|\alpha)$, with a fixed given $\alpha$, the maximum a posteriori estimate (MAP) of weights can be obtained by maximizing $\log(p(w|t,\alpha,\sigma^2))$ or by minimizing the following cost function (Camps-Valls 2007):

$$\log(p(w|t,\alpha,\sigma^2)) = \sum_{i=1}^{N} \frac{\alpha_i w_i^2}{2} \log(y_i) + (1-t_i) \log(1 - y_i)$$

(7)

The Hessian of $\log(p(w|t,\alpha,\sigma^2))$ is given by

$$H = \nabla^2 \log(p(w|t,\alpha)) = \Phi^T B \Phi + A$$

(8)

where matrix $\Phi$ is the $N \times (N+1)$ ‘design’ matrix with $\Phi_{nm} = k(x_n, x_m)$. $k(x_n, x_m)$ is the Gaussian kernel and has the form: $k(x_n, x_m) = \exp(-r^2 | x_n - x_m |^2)$, where $r$ is the kernel width. $A = \text{diag}(\alpha_1, ..., \alpha_N)$, and $B = \text{diag}(\beta_1, \beta_2, ..., \beta_N)$ is the diagonal matrix with $\beta_n = \sigma(y(x_n)) [1 - \sigma(y(x_n))].$ The hyperparameters $\alpha$ are iteratively updated using the covariance $\Sigma$ and mean $\mu_{MP}$ of the Gaussian approximation.

The following equation is used for updating the hyperparameters (Tipping 2001):

$$\alpha_{i}^{new} = \frac{1 - \alpha_i}{\mu_i}$$

(9)

where $\mu_i$ denotes the $i^{th}$ posterior mean weight from (11), $\Sigma_{ii}$ is the $i^{th}$ diagonal element of the posterior weight covariance (10), and the quantity $1-\alpha_i \Sigma_{ii}$ is a measure of the degree to which the associated parameter $w_i$ is determined by the data (Khalil et al. 2005). During the re-estimation process the $\alpha_i$ tend to infinity, making $p(w|t,\alpha,\sigma^2)$ highly peaked at zero. This makes the associated weights zero. Hence, the associated basis functions are discarded making the machine sparse.

The covariance $\Sigma$ is given by the inverse of the Hessian (8):

$$\Sigma = (H)^{-1} = (\Phi^T B \Phi + A)^{-1}$$

(10)

and the mean is given by

$$\mu_{MP} = \Sigma \Phi^T B \hat{t}$$

The new predicted classes are given by:

$$\hat{t} = \Phi \mu_{MP} + B^{-1}(t - y)$$

(12)

**Results**

The MCRVM model produced results with considerable accuracy. Figure 4 shows the classified image of the wetland produced by the MCRVM model in MATLAB. The images show the pseudo color coded 10 classes namely Phragmites, Baltic rush, Beaked sedge, Hardstem bulrush, Saltgrass, Broadleaf cattail, Narrowleaf cattail, water, ground and concrete. The results from accuracy assessment are presented in Table 1 which shows the
detailed misclassification of each species. Out of 10 test cases of Hardstem bullrush 3 have been classified as Baltic rush giving an accuracy of 60%. Phragmites and Saltgrass do not have any misclassification and hence the classification accuracy is 100%. Beaked sedge has been misclassified as Saltgrass on three occasions giving an accuracy of 70%. The table shows 86.7% user’s accuracy, 83% producer’s accuracy and an overall accuracy of 84.6%. Table 2 shows the area of the seven wetland vegetation grass species likely to be affected by the highway development project. The area gives us the precise measure of area of each species which will be considered for wetland mitigation banking.

![Classified imagery of the study area using MCRVM model in MATLAB](image)

Table 1
Confusion matrix of the MCRVM supervised classification

<table>
<thead>
<tr>
<th>Predicted Class</th>
<th>Actual Class</th>
<th>Baltic Rush</th>
<th>Beaked Sedge</th>
<th>Broadleaf Cattail</th>
<th>Hardstem Bullrush</th>
<th>Narrowleaf Cattail</th>
<th>Phragmites</th>
<th>Saltgrass</th>
<th>Row Total</th>
<th>UA(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baltic Rush</td>
<td></td>
<td>16</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>24</td>
<td>67%</td>
</tr>
<tr>
<td>Beaked Sedge</td>
<td></td>
<td>0</td>
<td>14</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>16</td>
<td>88%</td>
</tr>
<tr>
<td>Broadleaf Cattail</td>
<td></td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>100%</td>
</tr>
<tr>
<td>Hardstem Bullrush</td>
<td></td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>21</td>
<td>86%</td>
</tr>
<tr>
<td>Narrowleaf Cattail</td>
<td></td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>6</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>80%</td>
</tr>
<tr>
<td>Phragmites</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>0</td>
<td>20</td>
<td>100%</td>
</tr>
<tr>
<td>Saltgrass</td>
<td></td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
<td>23</td>
<td>87%</td>
</tr>
<tr>
<td>Col. Total</td>
<td></td>
<td>20</td>
<td>20</td>
<td>10</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>130</td>
<td>86.7%</td>
</tr>
<tr>
<td>PA(%)</td>
<td></td>
<td>80%</td>
<td>70%</td>
<td>60%</td>
<td>90%</td>
<td>80%</td>
<td>100%</td>
<td>100%</td>
<td>82.9%</td>
<td>84.6%</td>
</tr>
</tbody>
</table>
Table 2
Area in square kilometers of the seven species for wetland mitigation banking

<table>
<thead>
<tr>
<th>Species to mitigated</th>
<th>Area (Sq. Km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phragmites</td>
<td>0.168</td>
</tr>
<tr>
<td>Baltic Rush</td>
<td>0.106</td>
</tr>
<tr>
<td>Beaked Sedge</td>
<td>1.667</td>
</tr>
<tr>
<td>Hardtem Bullrush</td>
<td>0.073</td>
</tr>
<tr>
<td>Saltgrass</td>
<td>0.382</td>
</tr>
<tr>
<td>Broadleaf Cattail</td>
<td>0.003</td>
</tr>
<tr>
<td>Narrowleaf Cattail</td>
<td>0.070</td>
</tr>
</tbody>
</table>

Conclusion
The results showed considerable accuracy and good agreement with the actual classes. It was concluded that the UAV may prove to be a viable and cost-effective option for wetland mitigation for highway management as information processing is faster and accurate. The MCRVM model results were easily imported into ArcGIS and accurate qualitative as well as quantitative measure of each species were obtained using GIS tools. The procedure outlines in the paper can make wetland mitigation banking very easy and much less cumbersome as compared to the manual valuation employed in the process.

References
1. [http://aggieair.usu.edu/](http://aggieair.usu.edu/)