PREDICTION OF OPTICAL AND NON-OPTICAL WATER QUALITY PARAMETERS IN OLIGOTROPHIC AND EUTROPHIC SYSTEMS USING A SMALL UNMANNED AERIAL SYSTEM

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Introduction

Hypothesis and Objectives

Methodology

Results
SPECTRAL SIGNATURES

![Graph showing spectral signatures of different materials]

- Snow
- Sand
- Vegetation
- Concrete
- Water

% reflectance vs. λ (μm)

B, G, R, NIR, SWIR
<table>
<thead>
<tr>
<th>Satellite</th>
<th>Launched Year</th>
<th>Spatial Resolution</th>
<th>Temporal Resolution (Day)</th>
<th>Spectral Resolution</th>
<th>Radiometric Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-5</td>
<td>1984</td>
<td>30 m. multispectral 120 m. TIR</td>
<td>16</td>
<td>Blue, Green, Red, NIR, SWIR-1, SWIR-2, TIR</td>
<td>8-bit</td>
</tr>
<tr>
<td>OrbView–2</td>
<td>1997</td>
<td>1130 m.</td>
<td>1</td>
<td>8 bands (0.402 to 0.885 μm)</td>
<td>12-bit</td>
</tr>
<tr>
<td>IKONOS</td>
<td>1999</td>
<td>1 m. panchromatic 4 m. multispectral</td>
<td>3</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>11-bit</td>
</tr>
<tr>
<td>Landsat-7</td>
<td>1999</td>
<td>15 m. panchromatic 30 m. multispectral 60 m. TIR</td>
<td>16</td>
<td>Panchromatic, Blue, Green, Red, NIR, SWIR-1, SWIR-2, TIR</td>
<td>12-bit</td>
</tr>
<tr>
<td>Terra - MODIS</td>
<td>1999</td>
<td>250 m. B1 – B2 500 m. B3 – B7 1000 m. B8 – B36</td>
<td>1-2</td>
<td>36 bands (0.620 – 14.385 μm)</td>
<td>12-bit</td>
</tr>
<tr>
<td>EO-1 ALI</td>
<td>2001</td>
<td>10 m. panchromatic 30 m. multispectral</td>
<td>16</td>
<td>10 bands (0.450 – 2.350 μm)</td>
<td>12-bit</td>
</tr>
<tr>
<td>QuickBird-2</td>
<td>2001</td>
<td>3 m. panchromatic 15 m. multispectral</td>
<td>1-3</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>8-bit</td>
</tr>
<tr>
<td>OrbView-3</td>
<td>2003</td>
<td>1 m. panchromatic 4 m. multispectral</td>
<td>3</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>11-bit</td>
</tr>
<tr>
<td>GeoEye-1</td>
<td>2008</td>
<td>0.41 m. panchromatic 1.64 m. multispectral</td>
<td>3</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>11-bit</td>
</tr>
<tr>
<td>Landsat-8</td>
<td>2013</td>
<td>15 m. panchromatic 30 m. multispectral 60 m. TIR</td>
<td>16</td>
<td>Panchromatic, Coastal, Blue, Green, Red, NIR, SWIR-2, SWIR-4, TIR</td>
<td>12-bit</td>
</tr>
<tr>
<td>Gaofen-1</td>
<td>2013</td>
<td>2.0 m. panchromatic 8 m. multispectral</td>
<td>4</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>14-bit</td>
</tr>
<tr>
<td>Sentinel-2</td>
<td>2015</td>
<td>10 m. multispectral 20 m. 60 m.</td>
<td>5</td>
<td>13 bands (0.43 – 2.28 μm)</td>
<td>12-bit</td>
</tr>
<tr>
<td>GeoEye-2</td>
<td>2016</td>
<td>0.31 m. panchromatic 1.24 m. multispectral</td>
<td>3 days</td>
<td>Panchromatic, Blue, Green, Red, NIR</td>
<td>11-bit</td>
</tr>
</tbody>
</table>
• Data lost due to cloud coverage
• Only optical variables:
  • Chl-a
  • Turbidity
  • SDD
  • TSS
HYPOTHESIS AND OBJECTIVES
HYPOTHESIS

• A combination of bands from images captured by a multispectral sensor attached to an sUAS can predict optical (TSS, Chl-a, SDD) and non-optical (TP, TN) water quality parameters in reservoirs with different trophic states.

• By having the ability to capture free cloud images at a finer spatial resolution, sUAS models that predict optical and non-optical water quality parameters have the ability to generate more accurate data, than the models that rely on satellite data.
• To develop statistical models capable of predicting optical (TSS, Chl-a, SDD) and non-optical (TP, TN) water quality parameters in reservoirs with different trophic states

• To statistically compare and evaluate the accuracy of the data generated by water quality models that rely on satellite imagery and sUAS imagery
METHODOLOGY

Phase 1
- Data Collection
  - In-Situ Data
  - UAV Images

Phase 2
- Laboratory Analysis
- Real Reflectance Extraction
- In-Situ and Reflectance Dataset

Phase 3
- Model Development (50% Data)
- Model Validation (50% Data)
DATA COLLECTION AND ANALYSIS

MULTISPECTRAL DATA COLLECTION

LABORATORY ANALYSIS

<table>
<thead>
<tr>
<th>Analyte</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chlorophyll α</td>
<td>EPA 445.0</td>
</tr>
<tr>
<td>Total Phosphorus</td>
<td>EPA 365.3</td>
</tr>
<tr>
<td>Total Nitrogen</td>
<td>Multi N/C 2100S</td>
</tr>
<tr>
<td>Nitrate-Nitrogen</td>
<td>EPA 352.1</td>
</tr>
<tr>
<td>Ammonia-nitrogen</td>
<td>HACH 10031</td>
</tr>
<tr>
<td>Total Suspended Solids</td>
<td>EPA 160.2</td>
</tr>
<tr>
<td>Secchi Disk</td>
<td>-</td>
</tr>
</tbody>
</table>
MODEL DEVELOPMENT

Model Development (50% Data)
• Regression analyses
• Water quality parameter (dependent variable)
• Refraction data from multispectral image (independent variable)

Best Fit Determination
• Coefficient of determination ($R^2$)
• Akaike Information Criterion (AIC)

Model Validation (50% Data)
• Statistically comparison between in-situ water quality parameter measurements and predicted measurements
RESULTS
Total of 315 (single variable) linear models

- Point Extraction = 105
- Buffer Extraction = 105
- Kriging Extraction = 105

\[ Y_i = \beta_1 x + \beta \]
Model Development (50% Data)
  • Regression analyses
  • Water quality parameter (dependent variable)
  • Refraction data from multispectral image (independent variable)

Best Fit Determination
  • Coefficient of determination ($R^2$)
  • Akaike Information Criterion (AIC)

Model Validation (50% Data)
  • Statistically comparison between in-situ water quality parameter measurements and predicted measurements
LINEAR MODELS - EVALUATION
POINT EXTRACTION RESULTS

• TSS = 37.317*(Green/Red) - 47.273 \( (R^2= 0.821 \text{ p-val= 5.87e-7}) \)

• SD = -786.440*(Green) + 72.929 \( (R^2= 0.780 \text{ p-val= 2.56e-6}) \)

• Chl-a = 202.84*(Green/Red) - 262.58 \( (R^2= 0.810 \text{ p-val= 8.52e-7}) \)

• TN = 7.0435*(Green/Red) - 8.5676 \( (R^2= 0.844 \text{ p-val= 1.885e-7}) \)

• TP = 1.8392 *(Green/Red) - 2.4117 \( (R^2= 0.831 \text{ p-val= 3.46e-7}) \)
• TSS = 37.361*(Green/Red) - 51.626 \ (R^2= 0.759 \ p-val= 1.09e-5)

• SD = -875.989*(Green) + 77.687 \ (R^2=0.605 \ p-val= 2.469 \ e-6)

• Chl-a = 199.75*(Green/Red) - 280.56 \ (R^2= 0.730 \ p-val= 2.47e-7)

• TN = 6.991*(Green/Red) - 9.273 \ (R^2= 0.768 \ p-val= 8.39e-6)

• TP = 1.8464*(Green/Red) - 2.6307 \ (R^2= 0.764 \ p-val= 9.56e-6)
ORDINARY KRYING - NPA

TP

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

TN

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Model: Sph
Nugget: 0
Sill: 0.19
Range: 23'
Kappa: 5
ORDINARY KRIGING - NPA

SDD

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

TSS

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model
ORDINARY KRYING - NPA

Chl-a

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Distance

Semi-variance

Model: Sph
Nugget: 3.4
Sill: 11
Range: 19
ORDINARY KRIGING - NPB

TP

Kriging prediction

Kriging standard error

TN

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Experimental variogram and fitted variogram model
ORDINARY KRIGING - WWL

TP

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

TN

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

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ORDINARY KRIGING - WWL

SDD

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

TSS

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

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ORDINARY KRIGING - WWL

Chl-a

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Model: SVE
Nugget: 6
Sill: 40496
Range: 126
Kappa: 2
ORDINARY KRIGING - NPB

SDD

Kriging prediction

Kriging standard error

TSS

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Experimental variogram and fitted variogram model
ORDINARY KRIGING - NPB

Chl-a

Kriging prediction

Kriging standard error

Experimental variogram and fitted variogram model

Distance

Semivariance

Model: Sph
Nugget: 1.1
Sill: 2.1
Range: 25
• TSS = 31.694*(Green/Red) - 35.248 (R²= 0.787 p-val= 1.19e-78)

• SD = -875.989*(Green) + 77.687 (R²=0.699 p-val= 7.75e-58)

• Chl-a = 199.75*(Green/Red) - 280.56 (R²= 0.687 p-val= 1.34e-59)

• TN = 6.2312*(Green/Red) - 6.8654 (R²= 0.799 p-val= 6.39e-82)

• TP = 1.71343*(Green/Red) - 2.04546 (R²= 0.798 p-val= 1.71e-81)
• Statistical interpolation method (ordinary kriging) is un-necessary to improve the relationship between the different water quality parameters and the reflectance values

• Point extractions have higher $R^2$ values

• More doesn’t mean better!
MODEL DEVELOPMENT

Model Development (50% Data)
• Regression analyses
• Water quality parameter (dependent variable)
• Refraction data from multispectral image (independent variable)

Best Fit Determination
• Coefficient of determination ($R^2$)
• Akaike Information Criterion (AIC)

Model Validation (50% Data)
• Statistically comparison between in-situ water quality parameter measurements and predicted measurements
POINT EXTRACTION VALIDATION

TN Comparison

- TN Actual
- TN Predicted

p-val = 0.8942

TP Comparison

- TP Actual
- TP Predicted

p-val = 0.5998
Chl-a Comparison

- Chl-a Actual
- Chl-a Predicted

p-val = 0.7334
MULTIPLE VARIABLE RESULTS

• Total of 15 (multiple variable) linear models
  • Point Extraction

\[ Y_1 = \beta + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n \]

• Model Evaluation
  • Analysis of Variance (ANOVA)
MULTIPLE VARIABLE RESULTS

- **TSS** = 185.16*(Green/Red) – 148.15 (Green/Blue) – 264.48 (Blue/Red) + 215.32
  \( R^2 = 0.883 \) p-val= 1.872e-6

- **SD** = 78.67*(Green/Blue) – 108.33*(Green/Red) + 164.32*(Blue/Red) - 61.91
  \( R^2 = 0.605 \) p-val= 2.469 e-6

- **Chl-a** = -13359.30*(Red)+ 9158.79*(Green) + 27.99
  \( R^2 = 0.846 \) p-val= 2.05e-6

  \( R^2 = 0.9793 \) p-val= 3.429e-11

- **TP** = 8.8103*(Green/Red) – 6.9932*(Green/Blue) – 12.4408* (Blue/Red) + 9.9533
  \( R^2 = 0.984 \) p-val= 7.84e-12
## SINGLE VS. MULTIPLE VARIABLE

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Single Variable Model</th>
<th>$R^2$</th>
<th>Multi Variable Model</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>lm(formula = SD.sub$SD ~ SD.sub$PointGreen)</td>
<td>0.7809</td>
<td>lm(formula = SD.Mod.Data$SD ~ SD.Mod.Data$B.R + SD.Mod.Data$G.R + SD.Mod.Data$G.B)</td>
<td>0.8883</td>
</tr>
<tr>
<td>TSS</td>
<td>lm(formula = TSS.sub$TSS ~ TSS.sub$G.R)</td>
<td>0.8211</td>
<td>lm(formula = TSS.Mod.Data$TSS ~ TSS.Mod.Data$B.R + TSS.Mod.Data$G.B + TSS.Mod.Data$G.R)</td>
<td>0.9869</td>
</tr>
<tr>
<td>TN</td>
<td>lm(formula = TN.sub$TN ~ TN.sub$G.R)</td>
<td>0.8446</td>
<td>lm(formula = TN.Mod.Data$TN ~ TN.Mod.Data$B.R + TN.Mod.Data$G.B + TN.Mod.Data$G.R)</td>
<td>0.9793</td>
</tr>
<tr>
<td>TP</td>
<td>lm(formula = TP.sub$TP ~ TP.sub$G.R)</td>
<td>0.8316</td>
<td>lm(formula = TP.Mod.Data$TP ~ TP.Mod.Data$B.R + TP.Mod.Data$G.B + TP.Mod.Data$G.R)</td>
<td>0.9835</td>
</tr>
<tr>
<td>Chl-a</td>
<td>lm(formula = Chloro.a.sub$Chloro.a ~ Chloro.a.sub$G.R)</td>
<td>0.8104</td>
<td>lm(formula = CHL.A.Mod.Data$Chloro.a ~ CHL.A.Mod.Data$PointGreen + CHL.A.Mod.Data$PointRed)</td>
<td>0.846</td>
</tr>
</tbody>
</table>
MULTIPLE VARIABLE VALIDATION

TSS Comparison

SD Comparison

p-val=0.8402

p-val=0.7931
MULTIPLE VARIABLE VALIDATION

TN Comparison

- Red: TN Actual
- Blue: TN Predicted

Index

p-val=0.8821

TP Comparison

- Red: TP Actual
- Blue: TP Predicted

Index

p-val=0.6047
MULTIPLE VARIABLE VALIDATION

Chl-a Comparison

p-val=0.7362

Chl-a (ug/l)

Index

Chl-a Actual
Chl-a Predicted
NURSERY POND – WATER QUALITY
WASTEWATER LAGOONS – WATER QUALITY
• Optical and non-optical water quality parameters can be predicted using sUAS

• Statistical interpolation (ordinary kriging) does not improve the relationship between the different water quality parameters and the reflectance values

• Single linear models have the capability to predict different water quality parameters; however, multiple linear models can explain these relationships in a better way (higher R²)
THANK YOU
QUESTIONS?

The UNIVERSITY of OKLAHOMA
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School of Civil Engineering and Environmental Science