

# Using GIS to Develop a Network of Acoustic Environmental Sensors

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## ABSTRACT

Ecological applications typically employ spatial data derived from visually apparent mediums, for the area of interest. We map what we can see. Comparatively little attention has been paid to sound. Acoustic data may offer an exciting alternative approach for characterizing key environmental indicators such as biodiversity. Preliminary research at Michigan State University has identified several important considerations in the deployment of acoustic sensor networks for this purpose. This paper highlights one key issue: where within a region of interest should sensors be deployed? GIS brings together several important components for the analysis and modeling of sensor distribution including base data integration, analysis (including spatial statistics) capacity, and representation and mapping. We consider the capacity of GIS to develop an effective spatial distribution of acoustic environmental sensors, and report on work to develop a network of such sensors for a study region in Michigan.

## I. INTRODUCTION

A balanced ecosystem is one of the most important sources of and indicators for the wealth of a nation. Both because of and despite this, ecosystems are under terrific and increasing pressure across much of the planet due to human activity. For many decades, aspects of environmental quality have been declining even as information technologies used to study the environment have been steadily developing. We believe that spatial information technology must play a role in understanding and finding solutions to difficult environmental challenges. This paper reports on a creative approach to the systematic application of such technologies to environmental monitoring and modeling.

In particular, we are interested in developing regional maps of biodiversity. Biodiversity is a very general term; one definition is (World Bank, 2004):

*The variety and variability among living organisms and the ecosystems in which they occur. Biodiversity includes the number of different items and their relative frequencies; these items are organized at many levels, ranging from complete ecosystems to the biochemical structures that are the molecular basis of heredity. Thus, biodiversity encompasses expressions of the relative abundances of different ecosystems, species, and genes.*

The present paper is concerned with reporting fauna species presence and possibly abundance using the non-standard sensory medium of sound. The paper first describes

the relationship between sound and biodiversity. Then we consider the challenge of sampling a large spatial region using acoustic sensors to identify spatial patterns in biodiversity measurement. Several plausible alternatives are presented. Sensors might be deployed in a regular pattern, such as a square grid, across the domain of interest. An alternative would be to use indicator data, such as land cover, to stratify a random sampling campaign. For example, if the spatial region consisted of 10% wetland, one might want 10% of the sensors to be in wetlands. Section II of the paper reports on the methodology employed to 1) extract the sounds made by individuals from a single acoustic signal; 2) identify the statistical properties of a stratified sampling scheme using point pattern analysis techniques 3) consider the depth of coverage provided by a uniform spatial sampling scheme across the domain of interest. The paper concludes with thoughts on the challenges and opportunities offered by environmental sensor networks.

### Acoustics as a Measurement of Environment

Sound is an important factor in our daily lives but it is most often overlooked. We receive constant auditory input but often it goes unnoticed unless it suddenly ceases or becomes a nuisance. Consciously or sub-consciously, sound has a dramatic impact on our emotional state and decision-making. In our environment sound plays an important role as an indicator of ecological activity, especially when humans cause disturbances. Environmental monitoring using sound has been accomplished using acoustic sensors. For example, sonograms were employed for the tracking of fish species such as tuna (Josse et al., 1998).

For the purposes of employing sound for monitoring of the environment, it is useful to define taxonomy of sound. The acoustic spectrum can be classified into 3 parts, called Anthrophony, Biophony and Geophony. Anthrophony is the series of sound signals caused by human activities in the soundscape. Biophony is the series of biological sounds in the soundscape resulting from the environment's vocal organisms, like birds, insects, and other species. Geophony is the series of signals from physical environmental characteristics like wind.

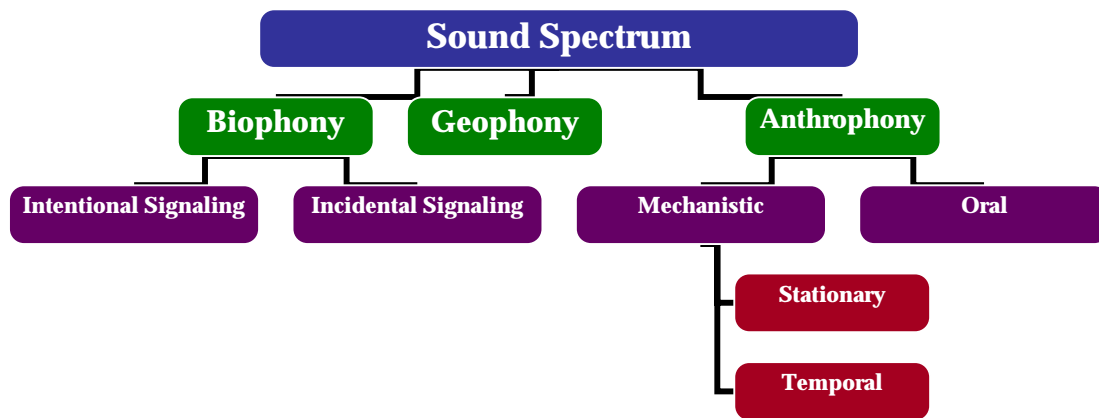


Figure 1: Taxonomy of Acoustics: Adapted from Napolentano (2004)

## Hypothesis

The research hypothesis is that change detection measurement through acoustic sounds is correlated with changes in land use/land cover and affects ecological integrity. Human activities can alter the habitat and degrade ecosystems. So quantifying relationships between specific human activities and biodiversity through acoustics will enable accurate prediction of ecological changes. This quantification will then be correlated to landscape analysis, remote sensing data, and land use/land cover data to develop an index of disturbance regimes for land use changes and land development. Simultaneously, by making this information available to the public in real time through the clickable ecosystem concept, the research team hopes to bring a general understanding of ecological systems, and help in policy decisions, and public education, thereby helping to develop a society that is better informed and more capable of making intelligent ecological decisions.

As part of our ongoing preliminary research at Michigan State University we are monitoring the environment through acoustic sensors placed in different ecological parts of Michigan and in other locations in the USA. Data is received at ½ hour intervals. Compression techniques, database, and statistical tools are used for transfer and store these data. Below is a schematic representation of the flow of information from the field.

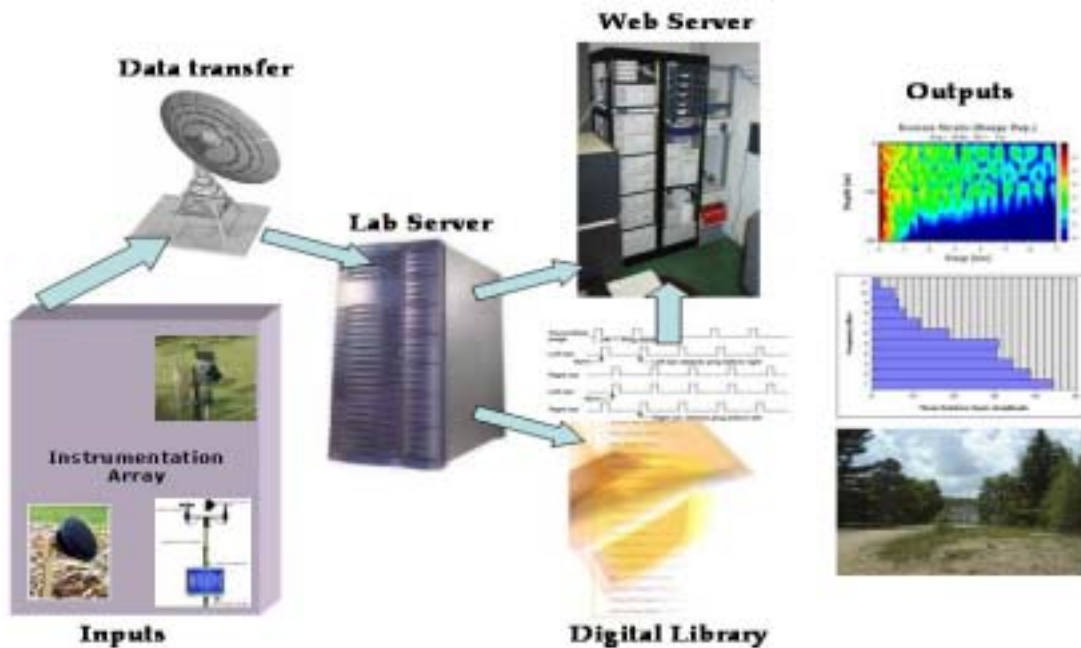
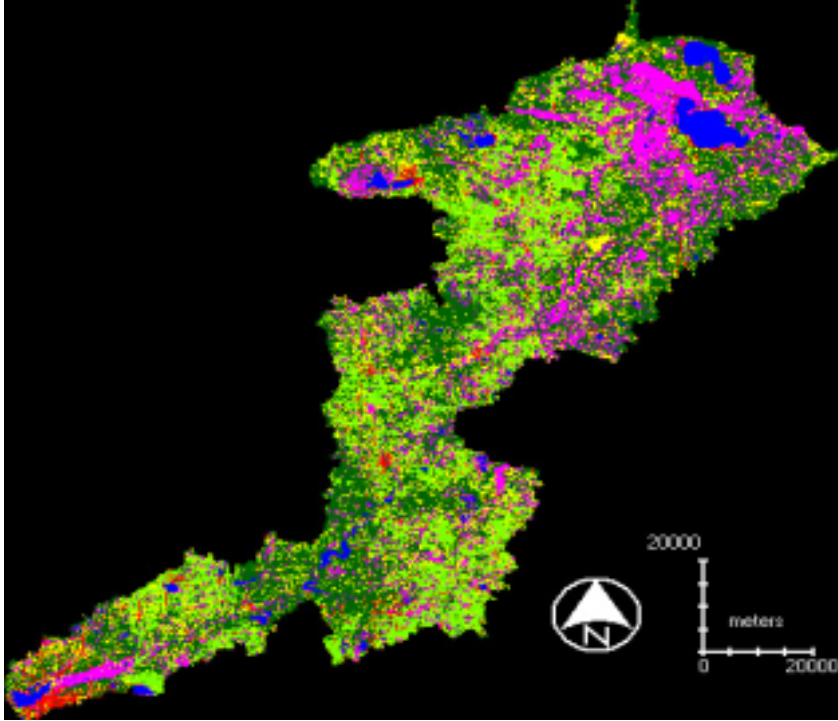


Figure 2: Flow of information from the field

## Study Area

The study area is the Muskegon River watershed, Michigan, USA. The Muskegon River watershed drains approximately 4,357 square miles of land. Additional facts about the data are: Cell resolution: 30 \* 30 sq meters; Projection/Coordinate system: UTM, WGS 84. Source of Land Cover: Landsat ETM plus (2001).



| Class | Histogram | Color       | Land Cover  |
|-------|-----------|-------------|-------------|
| 1     | 289002    | Red         | Urban       |
| 2     | 1423836   | Light Green | Agriculture |
| 3     | 1249005   | Yellow      | Rangeland   |
| 4     | 3183018   | Dark Green  | Forest      |
| 5     | 319494    | Blue        | Water       |
| 6     | 1373815   | Magenta     | Wetland     |
| 7     | 20821     | Brown       | Barren Land |

Figure 3: Muskegon River Watershed and Table

## II. METHODS

The methods employed in the research are:

1. Acoustic Data Analysis
2. Pattern Analysis of 1000 Acoustic Sensors (Stratified Random Sampling)
3. Regular Spatial Arrangement of 10, 25, 50, 75, 100, 500 and 1000 Sensors

### 1. Acoustic Data Analysis

Acoustic data analysis is similar to vegetation classification in remote sensing. In remote sensing different reflectances determine the type of vegetation from agriculture, forest, barren land and so on. Similarly in acoustic data analysis the template of each specific type of bird is identified and a library is generated. Then this library can be employed to

identify individual birds in a complex acoustic signal using Pattern Classification techniques (Fischer 1999; Lloyd & Bunch 2003; Schowengerdt 1997).

The following are the steps for analysis of the acoustic data

- Selection of individual bird signals
- Preprocessing: Removal of noise through filtering from individual bird patterns
- Selection of templates: Possible pure bird signals
- Matched filtering: To recognize individual bird species
- Pattern Classification: To recognize all the known bird signals in the field data
- Count: Program to automatically display the number of times individual bird sounds in the given signal.

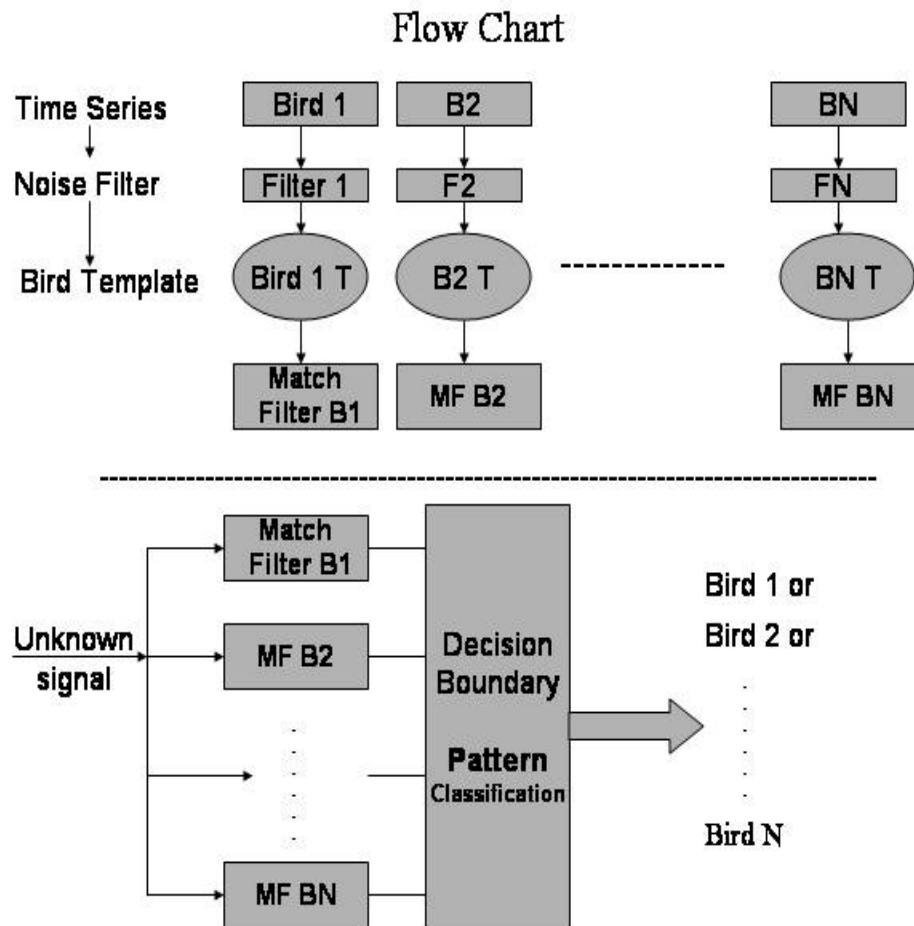
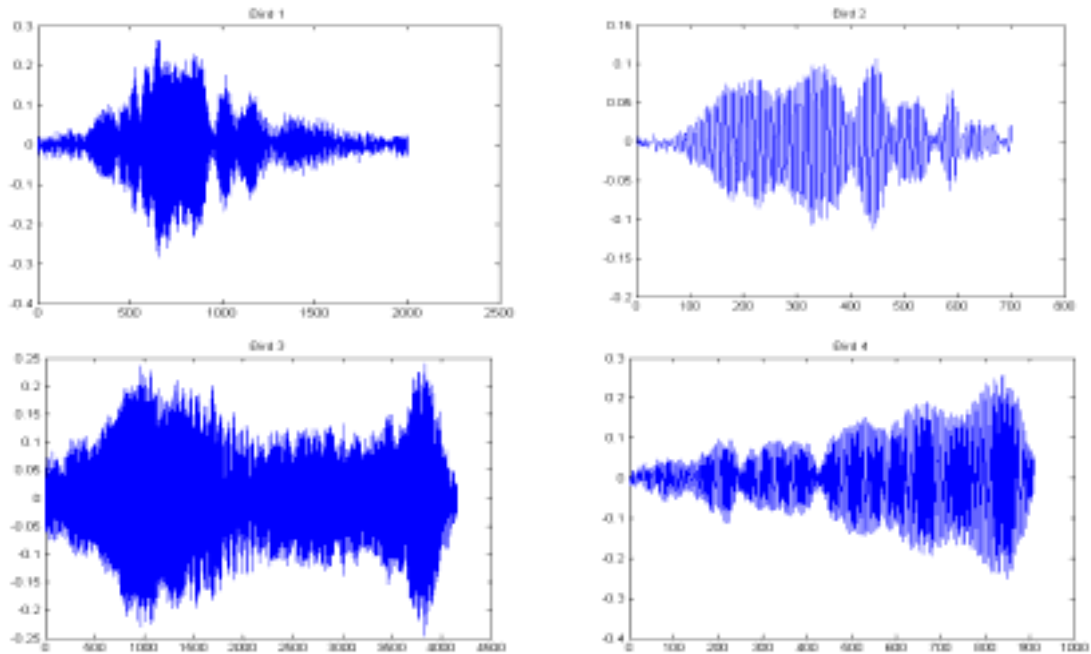


Figure 4: Acoustic data analysis

**Case study:** The case study involves selection of 4 individual bird signals which are sampled over a test signal which is a mixture of these 4 bird signals. Pattern classification identifies the individual birds from the test signal using matched filter technique (Duda et al 1960). The count program outputs the number of times individual bird sounds in the given signal.

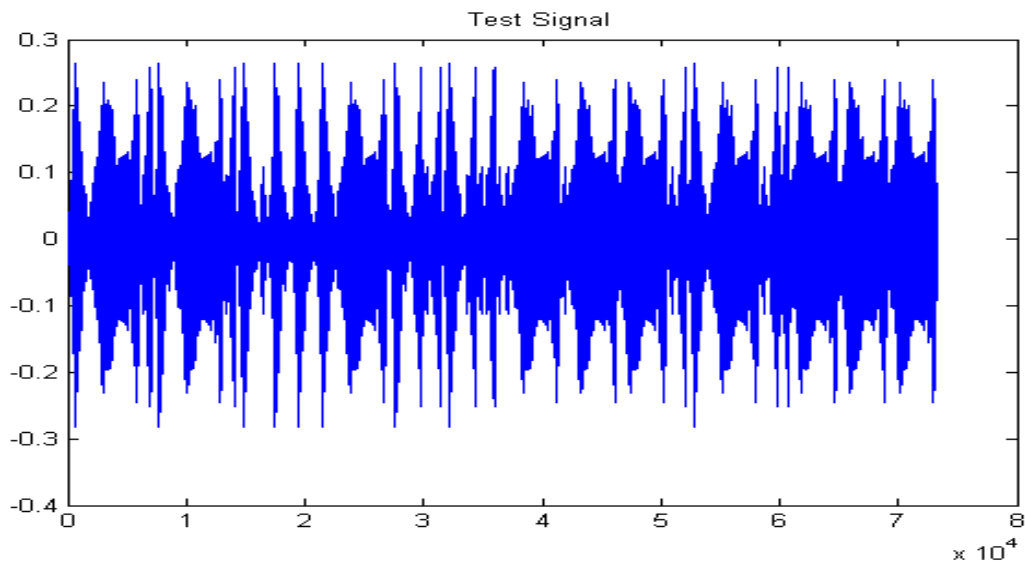
## Time series of 4 bird signals



Below is the test signal, the mixture of the above 4 bird signals

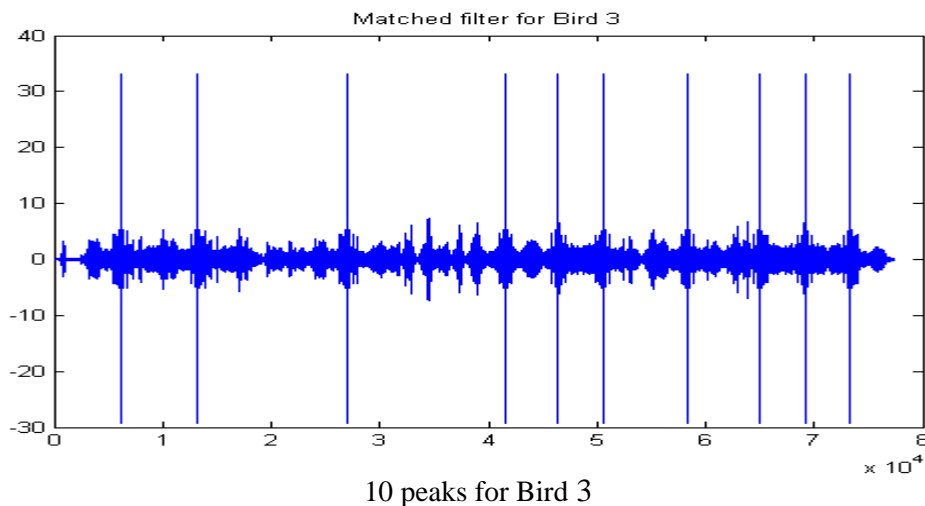
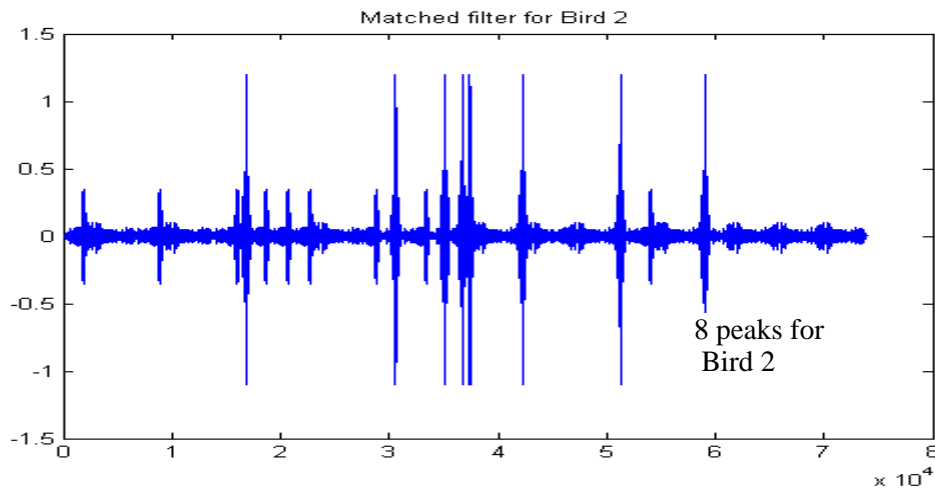
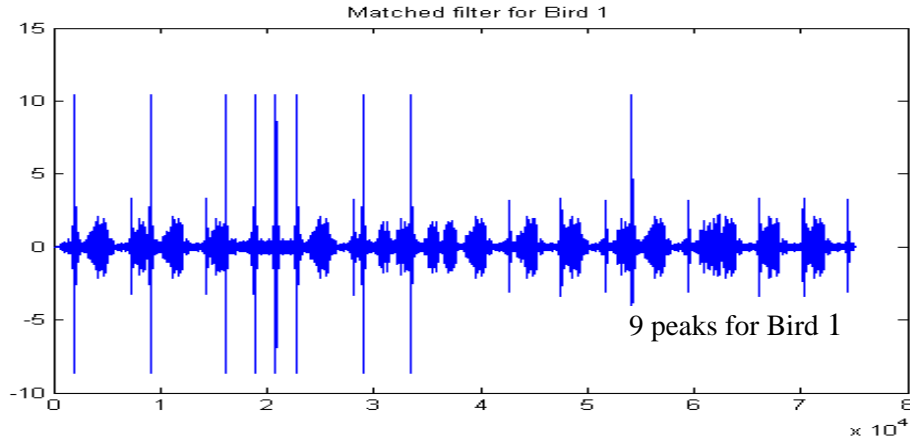
Test signal: test = [b1; b3; b4; b1; b3; b4; b1; b2; b1; b1; b1; b3; b1; b4; b2; b4; b1; b4; b2; b4; b2; b2; b3; b2; b3; b3; b2; b4; b1; b3; b2; b4; b4; b3; b3; b3]

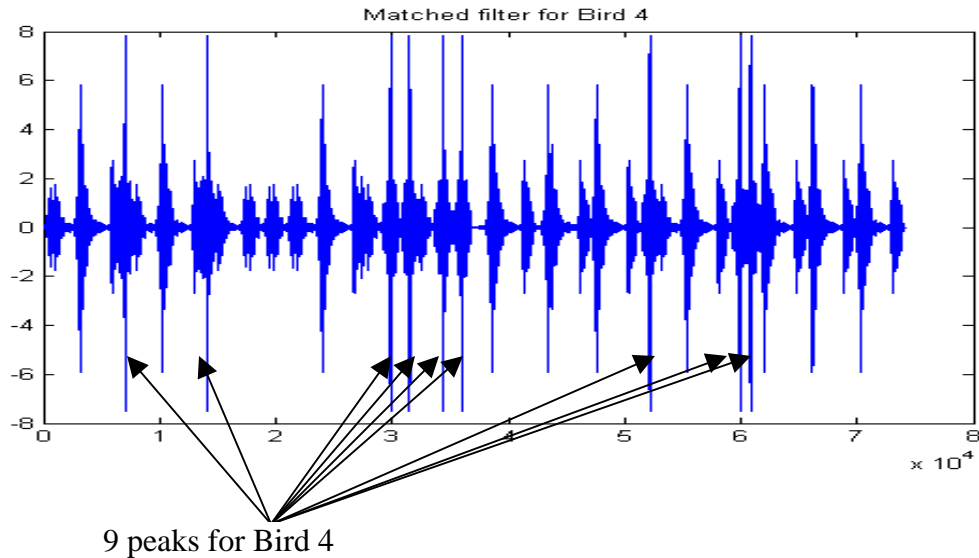
Note: b1 (Bird 1) = 9 times; b2 (Bird 2) = 8 times, b3 (Bird 3) = 10 times, b4 (Bird 4) = 9 times.



A matched filter is designed for each individual bird. When the individual bird signal passes through the matched filter, it recognizes and outputs with a peak of high amplitude.

Below is the matched filter output with high peaks for Bird 1, Bird 2, Bird 3 and Bird 4.





A **count** program detects the number of times individual bird sounds in the given signal which is determined by its threshold. Here are the results after execution, which correlates with the test signal.

Bird 1 = 9 times, Bird 2 = 8 times, Bird 3 = 10 times, Bird 4 = 9 times

## 2. Pattern Analysis of 1000 Acoustic Sensors (Stratified Random Sampling)

### Steps involved

- Stratified random distribution of 1000 sensors using ERDAS Imagine. The output is a (x, y) coordinate system of 1000 points proportionate to the seven class percentages namely Urban, Agriculture, Rangeland, Forest, Water, Wetland and Barren land
- Export the points to an Excel spreadsheet and rearrange class wise
- Import the points into R statistical package and perform F-hat and G-hat point pattern techniques to identify whether the arrangement is clustered, random, or regular

### Point Pattern Analysis

A point pattern is a dataset consisting of a series of point locations. The data are coordinates of events. They exhibit whether a pattern in general is random, clustered or regularly arranged. A first order effect relates to variation in the mean value of the process in space. It measures a large or global scale in general. A second order involves interrelationship between number of events of pairs in small area next to each other. It measures a local or small scale.

The technique employed is Nearest Neighbor Distances, G-hat and F-hat. The two types of nearest neighbor distances are Event – Event distance, W; Point –Event distance, X. The formula for G-hat and L-hat are given as

$$G\text{-hat}(w) = \#(w_i \leq w) / n$$

$$F\text{-hat}(w) = \#(x_i \leq w) / n$$

Where w or x is an arbitrary distance, # (blah) = number of nearest neighbor events within w(x), n (m) = events (random points) in R statistical package.



Interpretation of G-hat: If the G-hat plot is very steep in the early part of range before flattening out, then indication would be an observed high probability of short as opposed to long nearest neighbor distances which suggests it's clustered due to inter-event attraction. If it climbs up very steeply in the later part of its range then it suggests inter-event repulsion or regularity.

Interpretation of F-hat: If the F-hat plot has gentle increase in the early part of range before flattening out, then indication would be an observed high probability of long as opposed to short nearest neighbor distances which suggests its regularity. If it rises up gently in the later part of its range then it suggests it is clustered.

Plotting G-hat against F-hat with theoretical line will help in determining the pattern of point's distribution on the data set. If G-hat and F-hat are in the same line of theoretical line then it is random distribution. If G-hat is above F-hat then it is clustered distribution. If F-hat is above G-hat then it is regular distribution.

### Sensor distribution in Muskegon Watershed for 1000 points in all the seven classes

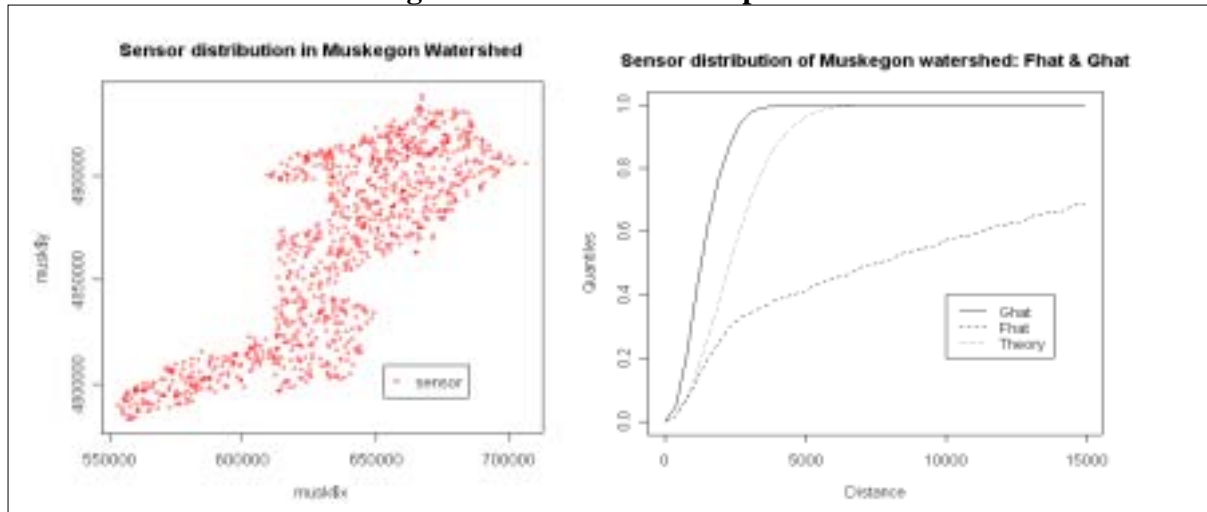


Figure 5: Sensor distribution and F-hat & G-hat plots

The plot of G-hat and F-hat suggests that the pattern of distribution of sensors is clustered since G-hat is above the theoretical line and F-hat is below theoretical line. G-hat steeply increases to a distance of 3500 meters and then flattens out. This indicates inter-event attraction at closer distances. F-hat increases very gently to a distance of 2500 meters and then increases gently further. This again indicates clustering of the 1000 points (sensors). This is because the distribution of the classes is not regular which in turn makes the points to get arranged in the desired classes thereby making the arrangement cluster than random.

Next we take sensor distribution in each of the 7 classes and analyze the pattern of distribution whether it is clustered, random or regular. The table below gives the number of sensors in each of the 7 classes proportionally arranged depending on the histogram value which can be interpreted as the percentage of the individual classes.

| Class | Histogram | Land Cover  | Sensor |
|-------|-----------|-------------|--------|
| 1     | 289002    | Urban       | 37     |
| 2     | 1423836   | Agriculture | 181    |
| 3     | 1249005   | Rangeland   | 159    |
| 4     | 3183018   | Forest      | 405    |
| 5     | 319494    | Water       | 41     |
| 6     | 1373815   | Wetland     | 175    |
| 7     | 20821     | Barren Land | 2      |

### Sensor distribution in Muskegon Watershed for Class 1 (Urban) with 37 sensors

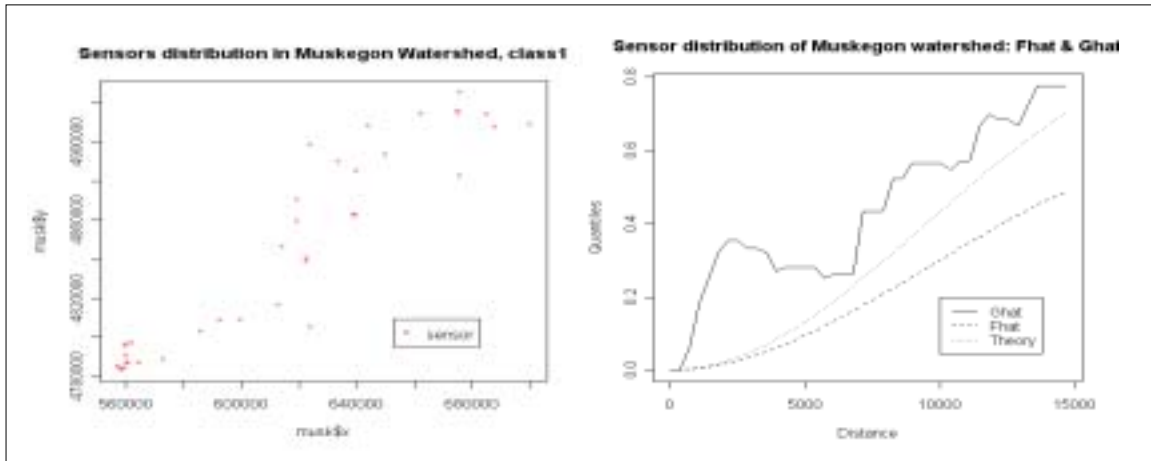


Figure 6: Sensor distribution and F-hat & G-hat plots for Class 1

The plot of G-hat and F-hat suggests that the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat steeply rises up to a distance of 2500 meters then falls down and rises again abruptly and so on. F-hat has very gentle increase and rises slowly which again indicates the spatial arrangement is clustered. This is because of the few samples points for the large area and also the spatial arrangement of the urban class which is irregular.

### Sensor distribution in Muskegon Watershed for Class 2 (Agriculture) with 181 sensors

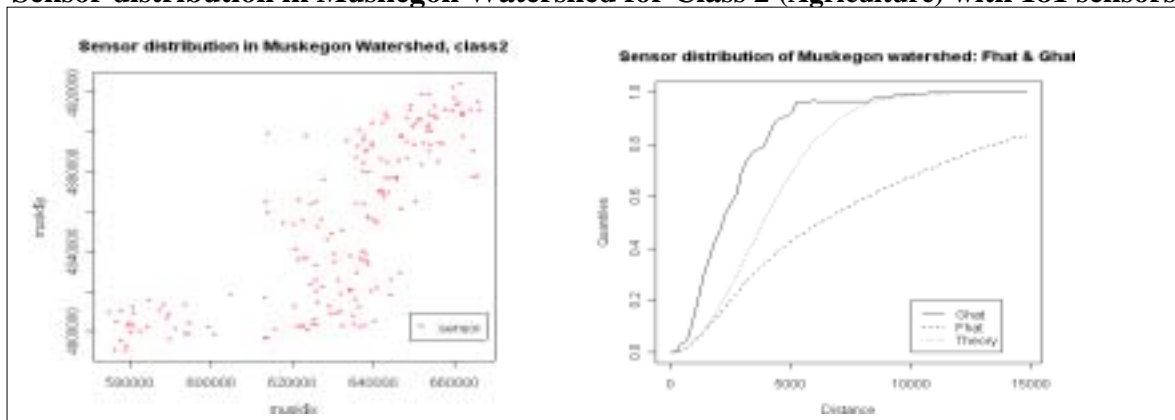


Figure 7: Sensor distribution and F-hat & G-hat plots for Class 2

The plot of G-hat and F-hat for class2 (agriculture) suggests that the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat very steeply rises up to 4000 meters with slight abrupt and then flattens out. This indicates inter even attraction at closer distances. The abrupt is less because the percentage area of agriculture is greater and relatively more number of sensors. F-hat increases gently which again indicates the distribution of points is clustered.

### Sensor distribution in Muskegon Watershed for Class 3 (Rangeland) with 159 sensors

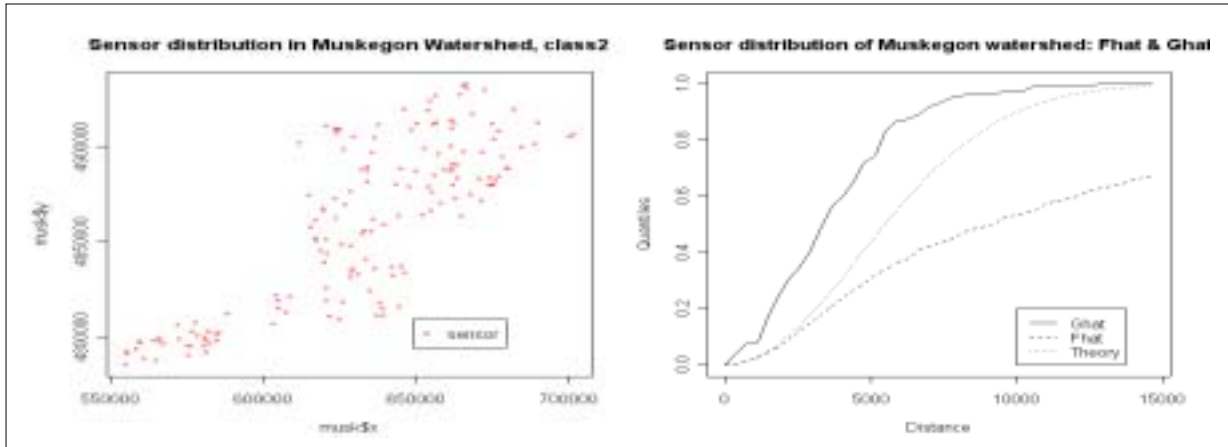


Figure 8: Sensor distribution and F-hat & G-hat plots for Class 3

For class 3, rangeland with 159 sensors the distribution is again clustered similar to agriculture. This is because of the sparse distribution of rangeland. This causes the sensors to fall in groups of clusters though the distribution is stratified random. Even the plot of G-hat and F-hat suggests that the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat rises steeply up to 5000 meters with slight abrupt and then flattens out. This indicates inter even attraction at closer distances. F-hat increases gently which indicates its again clustering.

### Sensor distribution of Muskegon Watershed for Class 4 (Forest) with 405 sensors

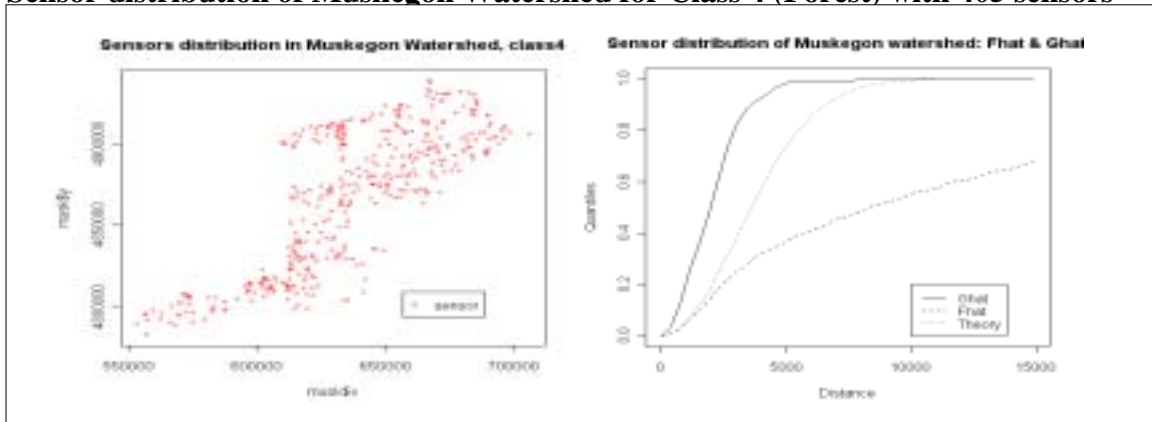


Figure 9: Sensor distribution and F-hat & G-hat plots for Class 4

The plot of G-hat and F-hat for Class 4 is smooth because of the number of sensors being more in number since a large percentage of the watershed area is covered by forest. Again the plot of G-hat and F-hat shows the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat increases up to 4500 meters steeply and then flattens out. This is an indication of inter even attraction at closer distances. F-hat increases slowly which again indicates that the sensors distribution is clustered.

### Sensor distribution of Muskegon Watershed for Class 5 (Water) with 42 sensors

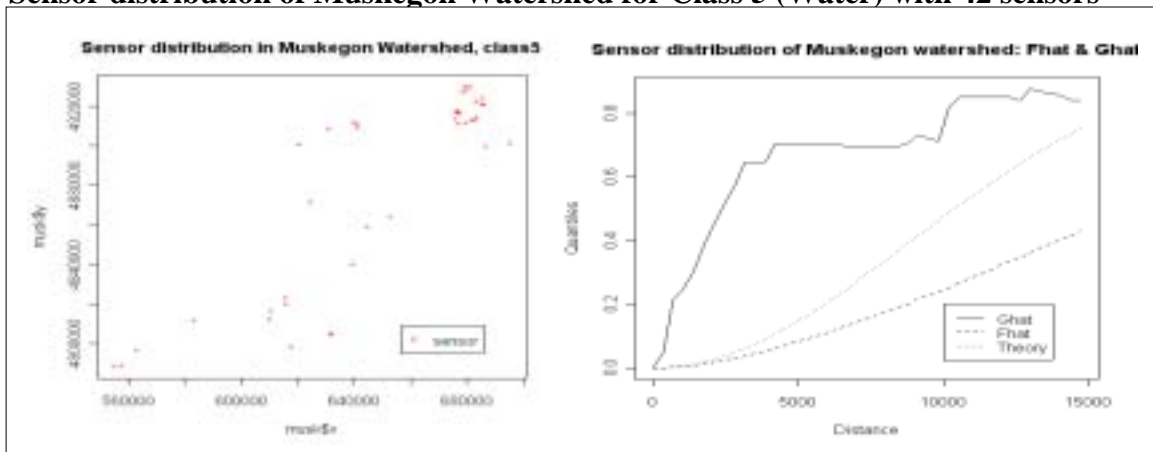


Figure 10: Sensor distribution and F-hat & G-hat plots for Class 5

For class 5, water with 42 sensors the distribution is again clustered since water bodies are present mostly on the northern part of the watershed. Again the plot of G-hat and F-hat shows the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat steeply rises up to 4000 meters and then flattens out. This indicates inter even attraction at closer distances. Its very abrupt since the percentage of area and the number of sensors assigned are relatively few. F-hat increases gently which indicates that the sensors distribution is again clustered.

### Sensor distribution of Muskegon Watershed for Class 6 (Wetland) with 172 sensors

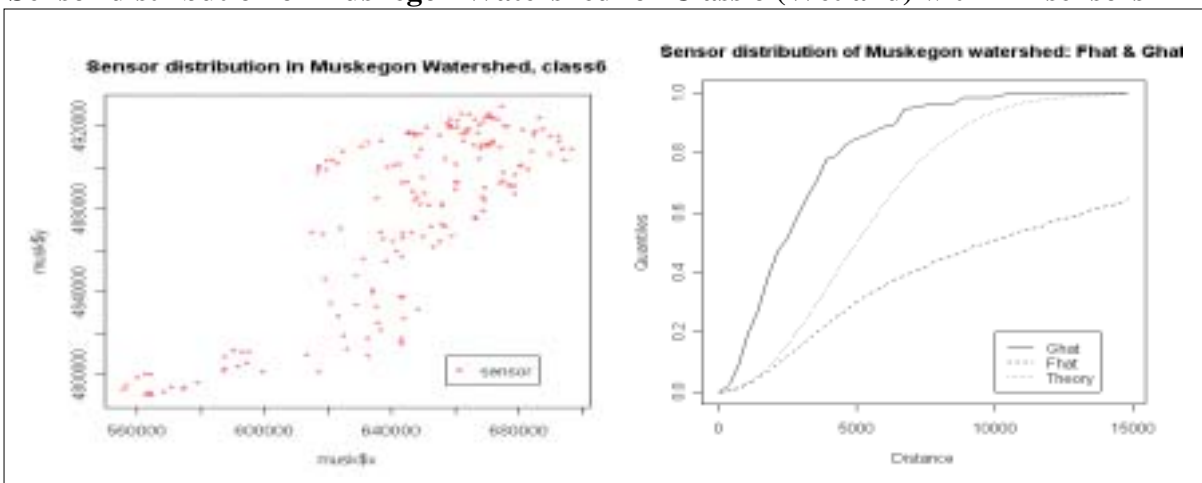


Figure 11: Sensor distribution and F-hat & G-hat plots for Class 6

The plot of G-hat and F-hat for Class 6 is smooth because of the number of sensors being more in number as wetland area covers good part of the Muskegon River Watershed. Again the plot of G-hat and F-hat shows the pattern of distribution of sensors is clustered since G-hat is above theoretical line and F-hat is below theoretical line. G-hat rises steeply up to 4800 meters and then flattens out. This indicates inter even attraction at closer distances. F-hat increases gently which indicates the distribution of sensors is again clustered.

### Sensor distribution of Muskegon Watershed for Class 7 (Barren land) with 2 sensors

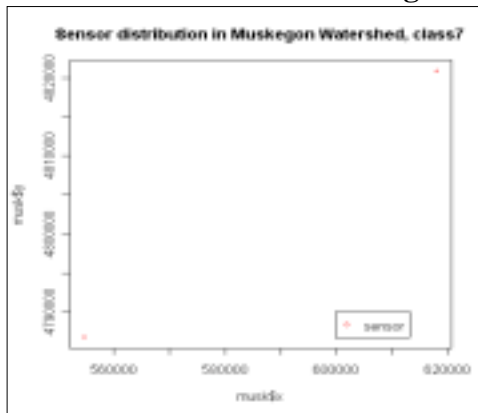


Fig 12: Sensor distribution for Class 7

Class 7, barren land has only two sensors. This is because of the negligible presence of barren land in Muskegon River Watershed area in the corners. There can be no distribution because of two points which is very less for characterizing a distribution.

### 3. Regular Spatial Arrangement of 10, 25, 50, 75, 100, 500 and 1000 Sensors in Muskegon Watershed

In regular spatial arrangement of sensor network, we distribute 'n' number of sensors which arrange in a regular pattern in the given area.

The steps involved are

- Creation of a shape file of the outer boundary which is a single polygon of the total area using GIS tools
- Regular spatial distribution of 'n' points for the given area in statistical package
- The number of points varies from 10, 25, 50, 75, 100, 500 and 1000 for our study area
- Overlay of the classes shape file with the regular points generated using GIS tools
- Study of the spatial distribution and the classes covered given the number of points at different scales

### Regular spatial arrangement of 10 sensors (11 sensors)

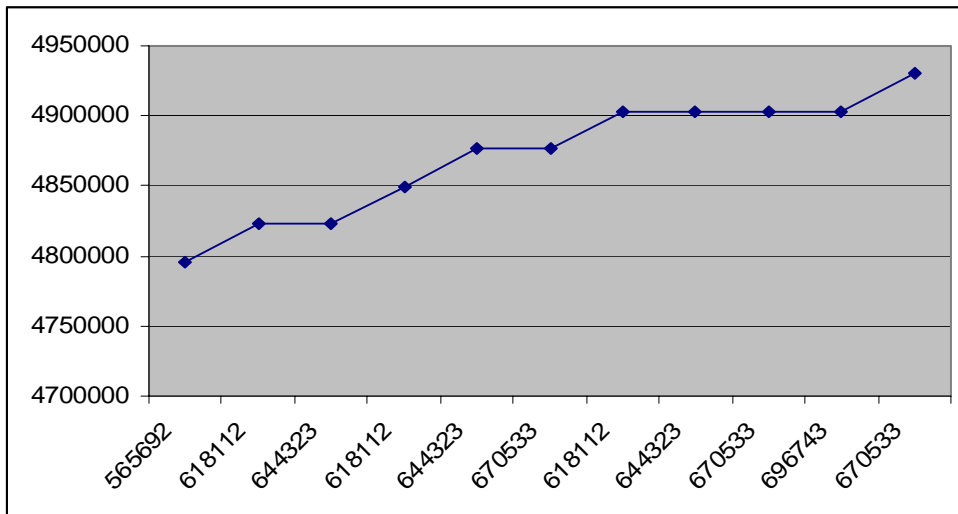
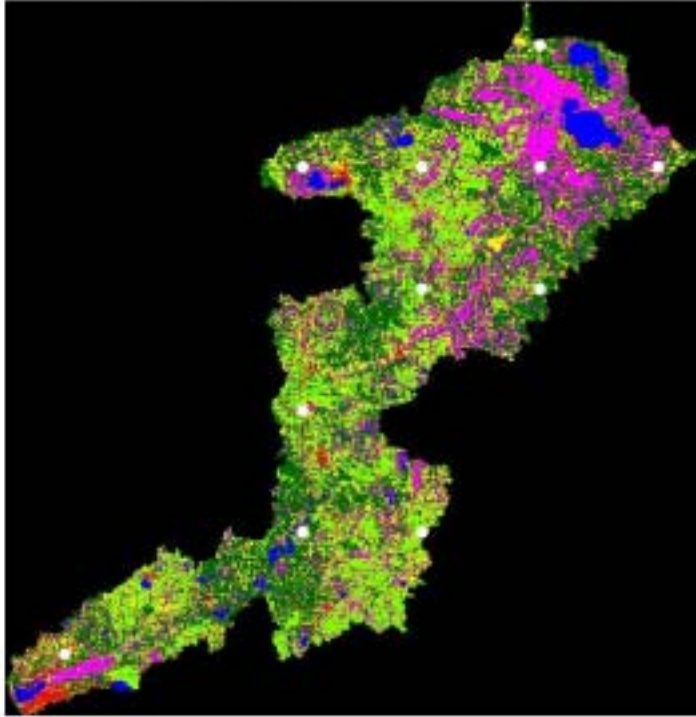


Fig 13: Regular spatial distribution of 10 sensors and their coordinates

When 10 sensors are distributed on a regular grid the arrangement of sensors covers most of the classes except water bodies which are missed. This is because of the spatial arrangement of the sensors is regular, where land cover types are not. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 26211 units. Though 10 sensors are expected to arrange regularly the program automatically adjusts to 11 sensors for better regular spatial distribution.



### Regular spatial arrangement of 50 sensors (49 sensors)

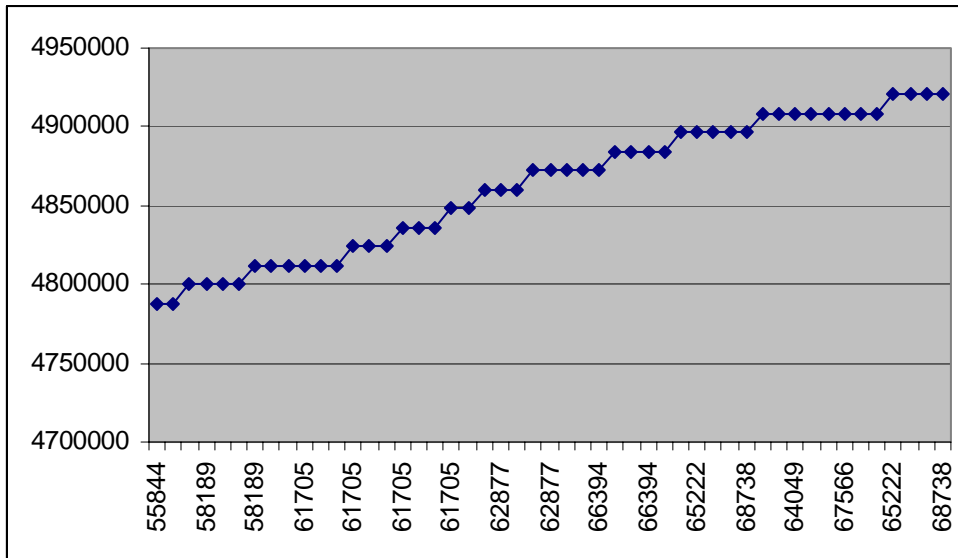
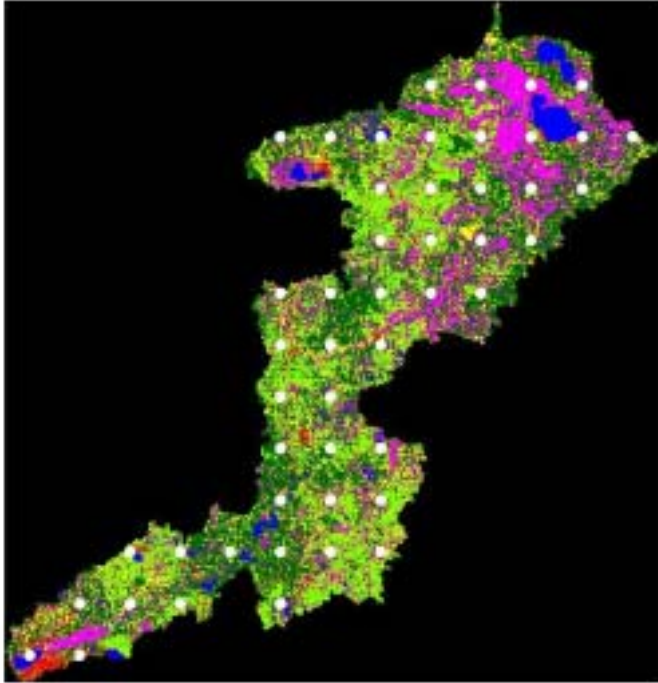


Fig 15: Regular spatial distribution of 50 sensors and their coordinates

When the number of sensors is increased to 50 almost all the classes are covered. Above is the arrangement when 50 sensors are placed. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 11722 units. Though 50 sensors are expected to arrange regularly the program automatically adjusts to 49 sensors for better regular spatial distribution.



### Regular spatial arrangement of 75 sensors (79 sensors)

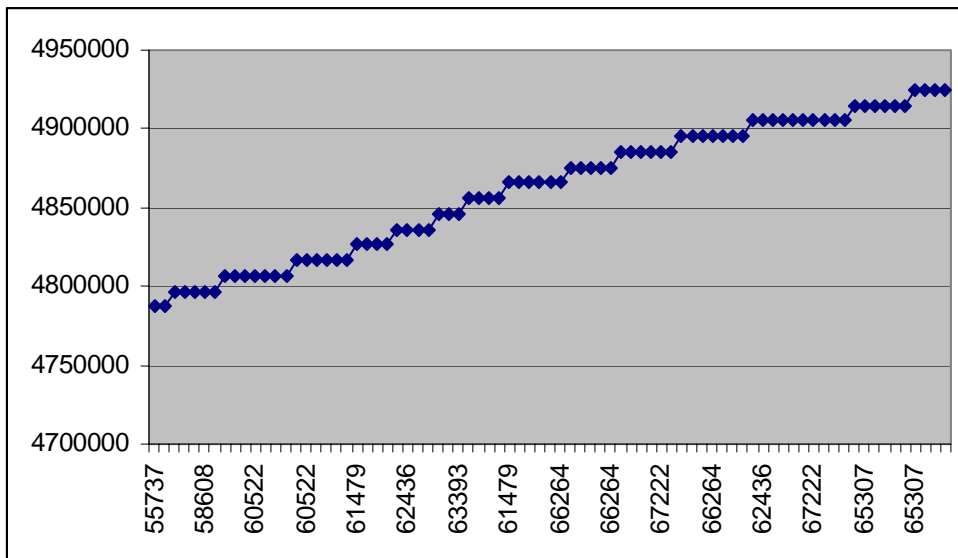


Fig 16: Regular spatial distribution of 75 sensors and their coordinates

When the number of sensors is increased to 75 almost all the classes are covered. Above is the arrangement when 75 sensors are placed. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 9571 units. Though 75 sensors are expected to arrange regularly the program automatically adjusts to 79 sensors for better regular spatial distribution.

### Regular spatial arrangement of 100 sensors (105 sensors)

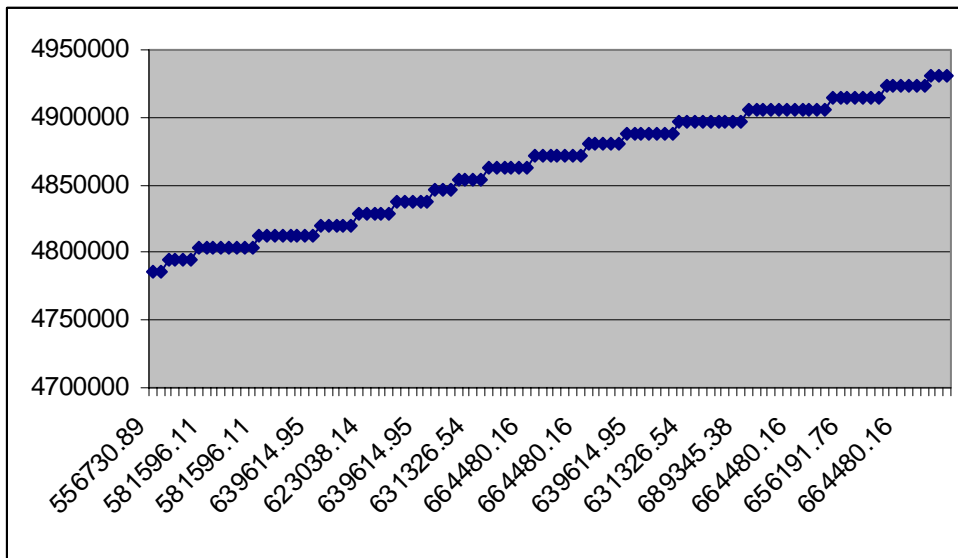
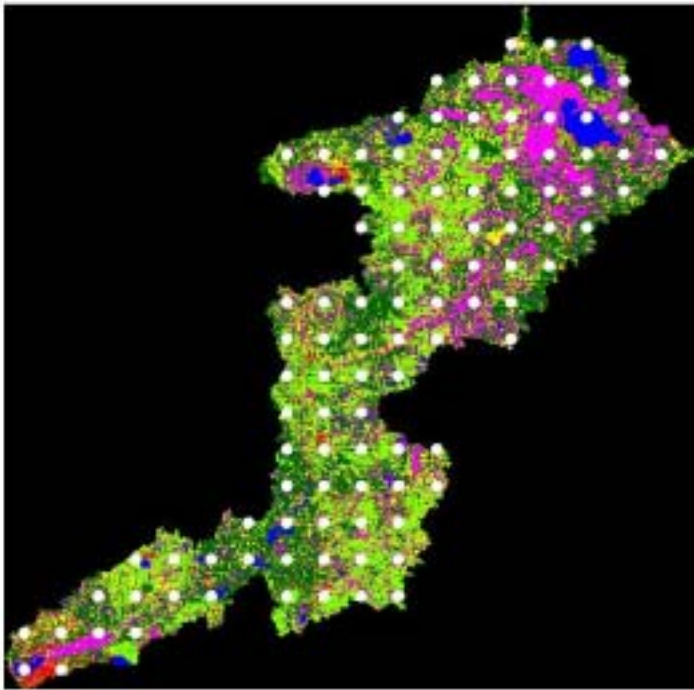


Fig 17: Regular spatial distribution of 100 sensors and their coordinates  
When the number of sensors is increased to 100 all the land use classes include at least 1 sensor location. Above is the arrangement when 100 sensors are placed. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 8288 units. Though 100 sensors are expected to arrange regularly the program automatically adjusts to 105 sensors for better regular spatial distribution.

### Regular spatial arrangement of 500 sensors (504 sensors)

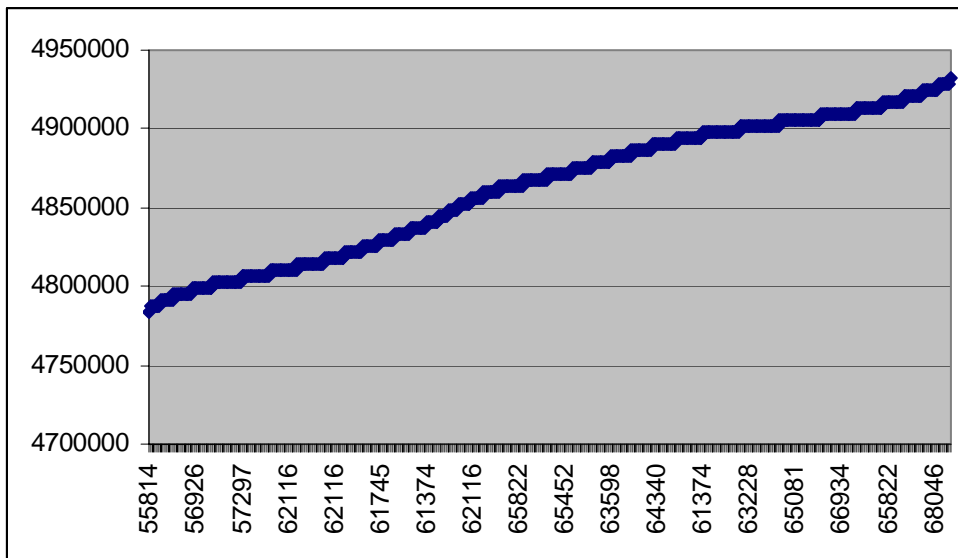


Fig 18: Regular spatial distribution of 500 sensors and their coordinates

When the number of sensors is increased to 500 almost all the classes are covered. Above is the arrangement when 500 sensors are placed. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 3707 units. Though 500 sensors are expected to arrange regularly the program automatically adjusts to 504 sensors for better regular spatial distribution.

### Regular spatial arrangement of 1000 sensors (999 sensors)

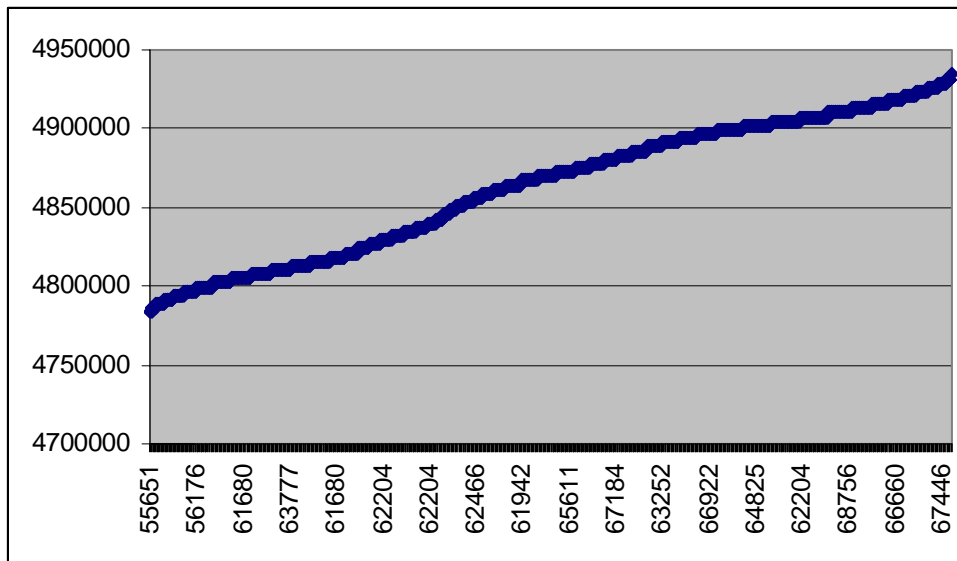
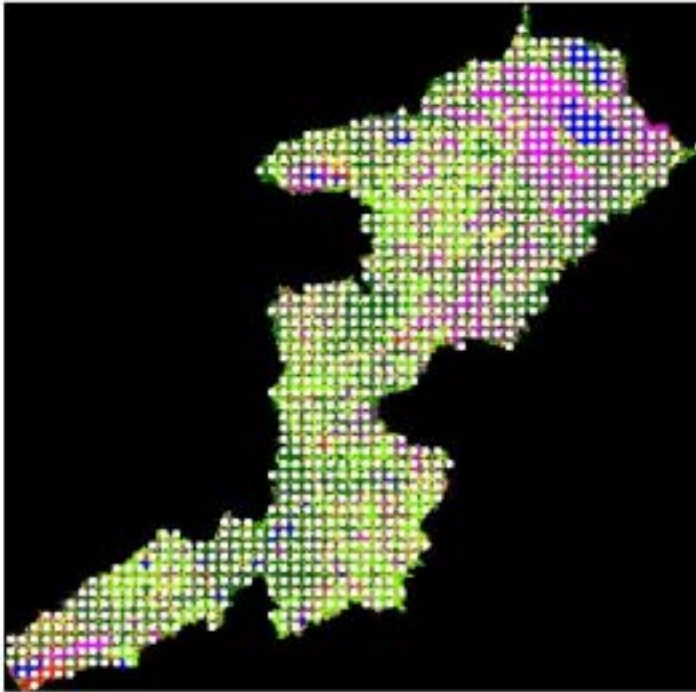


Fig 19: Regular spatial distribution of 1000 sensors and their coordinates  
When the number of sensors is increased to 1000 the classes are covered. Above is the arrangement when 1000 sensors are placed. The coordinates of the individual sensors are known to place the sensors if needed. The spatial resolution of the grid is 2621 units. Though 1000 sensors are expected to arrange regularly the program automatically adjusts to 999 sensors for better regular spatial distribution.

Depending on the number of sensors placed we find that as the number of sensors increases the classes covered also increases. We find that the grid spacing proportionately reduces as the number of sensors is increased. Also when we assign 10 sensors or more the arrangement of sensors is rounded to the closest value to make the arrangement spatially regular.

#### **Software & tools used**

ArcView, ArcMap, R, ERDAS, Matlab, Excel

### **III. CONCLUSION**

Acoustic data analysis determines the species presence and their number. As the number of birds in the library increases, preprocessing and threshold of each species determines the accuracy of the output. A constraint faced is the challenge to get used to both the acoustic signals and engineering aspect to identify individual species. It was a challenging and integrated approach by engineers, geographers and environmentalists.

Stratified random sampling of sensors was done using ERDAS Imagine. The constraint was difficult in finding appropriate software to conduct this analysis. Though the sampling was random the arrangement of sensors was clustered. This is because of the distribution of different classes in Muskegon River Watershed area is random and thus most of the sensors fall into that specific area tend to arrange clustered.

Regular arrangement of sensors was done using statistical software and analyzed in ArcView. Depending on the number of sensors, we can determine whether the sensors fall in all the classes or not. As the number of sensors is increased all the classes are covered. Here the challenge is finding the optimal number of sensors to be placed since the spatial distribution of classes is not and cannot be regular. Another advantage in the spatial distribution of sensors in regular format, though the number of sensors given is 10, 25, 50 and so on it automatically distributes regularly by adding or subtracting few additional sensors. Depending on the requirements and affordability the optimal distribution of sensors can be analyzed. When large areas are taken for spatial analysis, there is a level uncertainty of the dataset. Feasible approaches to calculate the uncertainty can be performed through various forms of kriging using the uncertainty models to develop the map of the likely phenomenon, given the available information (Shi W., Goodchild M.F., & Fisher P.F., 1999).

Our next steps are to determine a balance between a regular spatial distribution of sensors network and at the same time include all the classes. The data gathered through these sensors are analyzed to detect environmental change. Presently this is performed through the existing sensors network. We also need to design effective acoustic sensors.

Thus for further advancement the potential multi-disciplinary research issues are

1. Spatial distribution of acoustic sensors – Geographer research
2. Spatial data analysis – Geographers, environmentalists & engineers research
3. Design of acoustic sensors – Engineering research

We hope this work is a first step towards better understanding the spatial distribution of biodiversity to help people make better decisions about preserving global biodiversity.

## **Acknowledgements**

We thank Brian Napoletano, who is completing his Masters in Entomology at Michigan State University, for his assistance on acoustics. We thank Ranjeet John who is completing his Masters in Geography for assisting with Muskegon Watershed data.

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