MAPPING OAK WILT IN TEXAS

Wendy Cooley and Amuche Ezeilo

EES 5053

December, 2006.

Introduction

Oak wilt, *Ceratocystis fagacearum*, is a serious fungal disease that affects oak trees primarily in Texas and the Northeastern part of the United States (Figure 1). It has attacked oak trees in many counties across Texas. Central Texas has been the hardest hit with thousands of oaks lost over the past 20 years (Figure 2) (TFS).

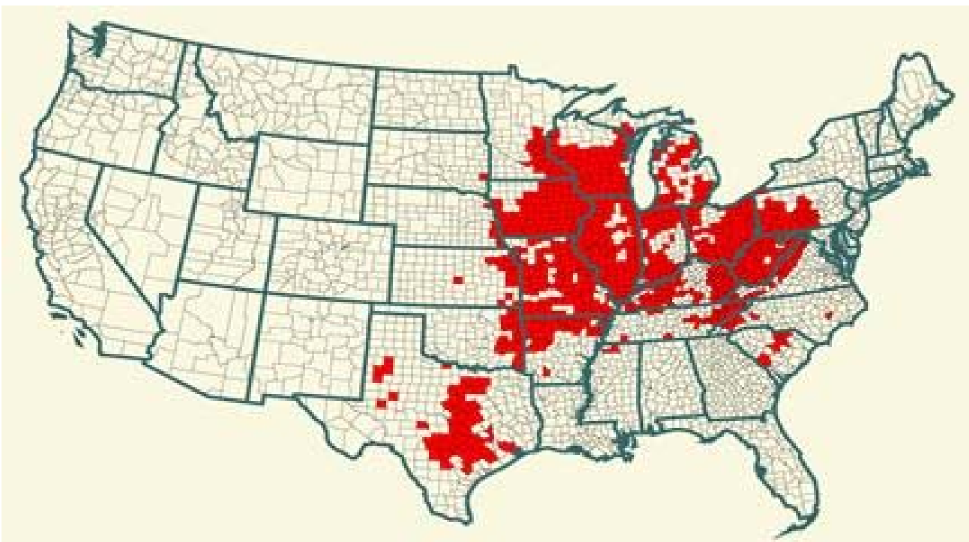


Figure 1. 2005 Oak wilt distribution map in the United States (USDA Forest Service)

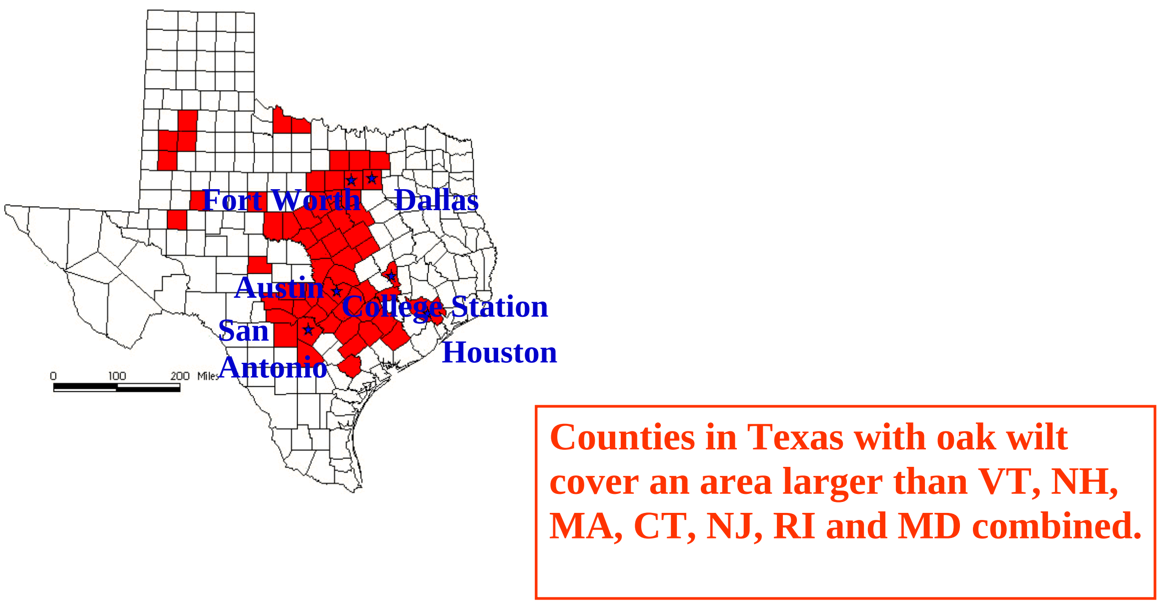


Figure 2. Oak wilt coverage in Texas (The Texas Forest Service)

C. fagacearum is a vascular disease that develops in the outer sapwood of a tree. A vascular disease means that the fungus is found in the vascular tissues of the water conducting vessels referred to as the xylem. The fungus disables the xylem in susceptible trees and plugs these vessels up, greatly reducing the water flow in a tree. Due to a lack of water, the tree will begin to wilt and often times die (TFS).

All oak trees are vulnerable to this fungal disease but Red oaks are more susceptible than the White oaks (Waitt, 2006). Live oaks, *Quercus fusiformis* and *Quercus virginia,* are specifically vulnerable due to their growth form and their abundance. These trees tend to grow in large motts or dense groups. The roots of these grouped live oaks are all interconnected through grafting of the roots (Waitt, 2006). Therefore, it is easy for one tree to pass the disease to others within the mott. Live oaks will usually die in three months to a year. Red oaks, on the other hand, usually die within two week to several months (TFS).

There are two ways in which *C. fagacearum* can be spread. One method of transmission, mentioned earlier, is through root grafts. Root grafts not only occur between live oaks within motts but can also include grafting between live oaks and red oaks within these motts. If one tree becomes infected, all nearby healthy trees then become infected as well (O'Brien et al). Another method of transmission is through an insect vector. The Nitidulid Beetle is the primary vector for over land spreading of oak wilt (O'Brien et al). Fungal mats produced in the bark of Red oaks emit an odor that attracts sap feeding beetles in the Nitidulidae family as well as other insects like Oak Bark Beetles (Rexrode et al). These beetles carry the fungal spores on their bodies from the spore mat to a healthy oak. The beetle then visits a fresh wound of the healthy oak to feed on the sap and, thus, spreads the fungal spores to that once healthy tree (TFS, 2006).

There is no known cure for oak wilt. However, prevention is the key to maintaining healthy trees. Early detection and rapid removal of infected trees including breaking grafted roots is the most important prevention (Rexrode et al). One should also avoid injuring trees. Fresh wounds on healthy oak trees can be visited by beetles carrying the oak wilt spores. Thus, infecting healthy trees. Injuring trees can be through many different avenues like construction, pruning, or damage from severe storms. When these wounds cannot be avoided, paint them with commercial tree wound dressing immediately after the damage has occurred. Cutting deep trenches around infected centers also help control the spread of oak wilt (O'Brien et al, 2006).

The Texas Forest Service has started an Oak Wilt Suppression Project to detect oak wilt centers. Aerial survey flights are conducted annually over 59 counties to locate possible oak wilt centers. These centers are then confirmed on the ground (Cameron et al,). Using remote sensing to classify possible oak wilt centers from aerial photographs will provide the Texas Forest Service and the USDA Forest Service with one more tool to fight this devastating arboreal disease.

AIM

The aim of this project is early detection of areas of oak wilt in Kerr County, Texas. We also propose to classify and map these areas, using ENVI techniques. A comparison of the results of the various classifications would also be done. This is to enable easier monitoring and control of the disease (rsl.gis.umn.edu) for the Texas Forest Service and other interested parties.

METHODS

We used 1 meter orthophotos of 2004 to classify oak wilt centers in Kerr County. This involved the use of color infrared technology. We performed both unsupervised and supervised classifications using methods available in ENVI, the aim being to determine which method(s) is (are) best at classifying Oak Wilt. Supervised classification involves two basic steps:

1. The specification of on-screen training areas by delineating regions of interest based upon forest color. These would be areas of forest which we judged to be healthy or to be in one of several stages of disease or death. This was determined by reference to previous works (see Table 1).

DISPLAY COLOR	***STATUS OF FOREST AREA***
DARK RED	HEALTHY
LIGHT-RED TO GRAYISH MAGENTA	EARLY/MODERATE DISEASE
FAINT GRAYISH-MAGNETA	SEVERELY AFFECTED
GRAYISH	DEAD

Table 1. Classification table (From Everitt et al, 1999).

2. The spectral information within these training areas was then put through a maximum likelihood classification technique to determine the probabilities of each pixel belonging to each of the training areas, and therefore, in each of the disease classifications.

ENVI unsupervised methods were also used to classify Oak Wilt. These involved subjecting the map information to various statistical classification techniques that involve no person's a priori knowledge of the actual situation on the ground. The two methods available in ENVI are K-Means clustering and Isodata.

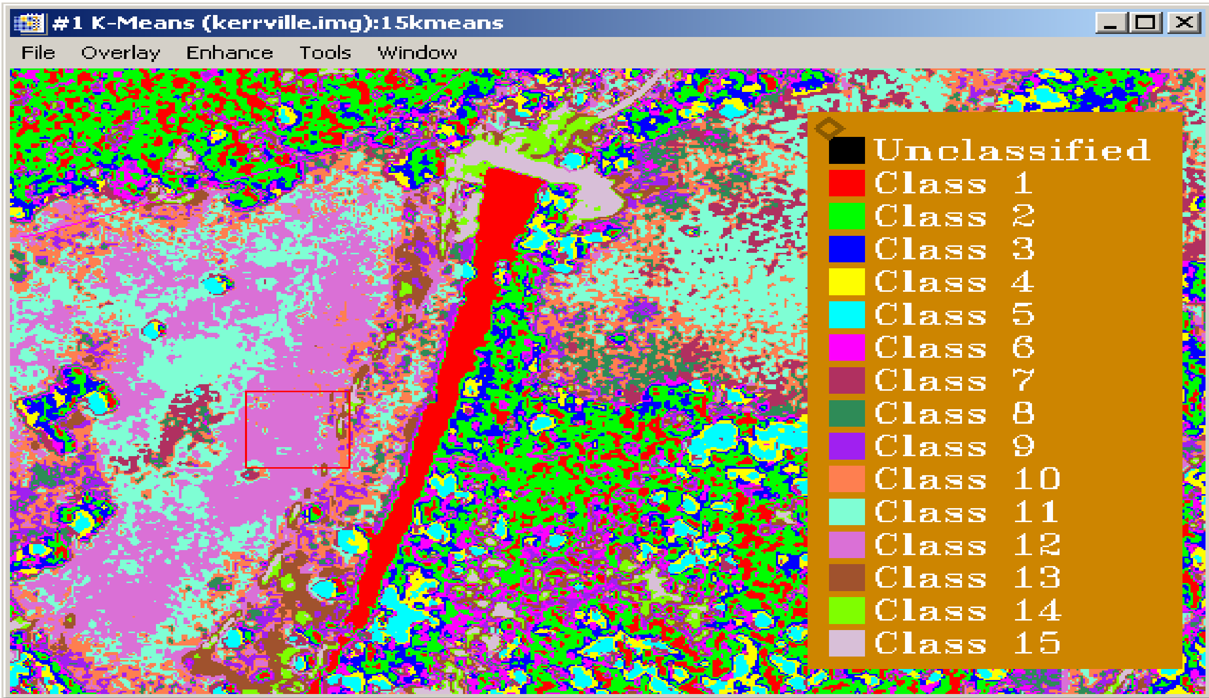
Both K-means and Isodata have starting values that have to be first selected. This can influence the outcome of the classification. Both methods first have an arbitrary initial cluster value assigned. Each pixel is then classified to the closest cluster. Then, a new cluster mean vector is calculated based on all pixels in one cluster. These steps are repeated until the change in iterations is small. The K-Means Clustering analysis requires the analyst to select the number of clusters, which we selected at 15. The technique then arbitrarily locates this number and iteratively repositions them until optimum separation is achieved (Univ. of Lethbridge).

The Isodata (Iterative Self-Organizing Data Analysis) goes further by splitting and merging the clusters. This technique repeatedly performs the entire classification and recalculates statistics. Self-organizing refers to way in which it locates inherent data clusters. The minimum spectral distance formula is used to form clusters (Univ. of Lethbridge). The means shift with each iteration until either a maximum number of iterations is achieved, or a maximum percentage of unchanged pixels has been reached between 2 iterations (Univ of Lethbridge). We selected three iterations for this method, and 10 classes were produced.

RESULTS

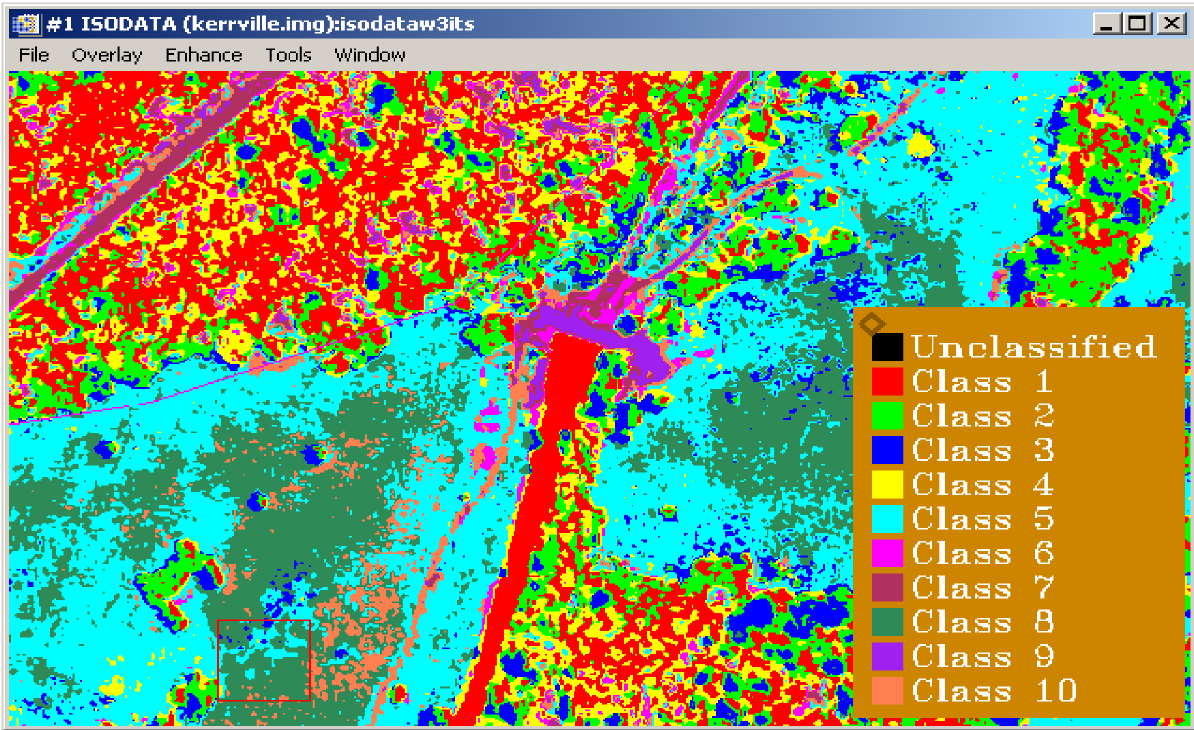
Methods proposed above were performed and comparisons were made by observing various linked images of each classification and orthophoto. Figures below illustrate the three methods used by highlighting a sample area. We then determined the visual relative best fit of each classification to the data.

K-Means


#1 K-Means (kerrville.img):15kmeans
File Overlay Enhance Tools Window
Unclassified
Class 1
Class 2
Class 3
Class 4
Class 5
Class 6
Class 7
Class 8
Class 9
Class 10
Class 11
Class 12
Class 13
Class 14
Class 15

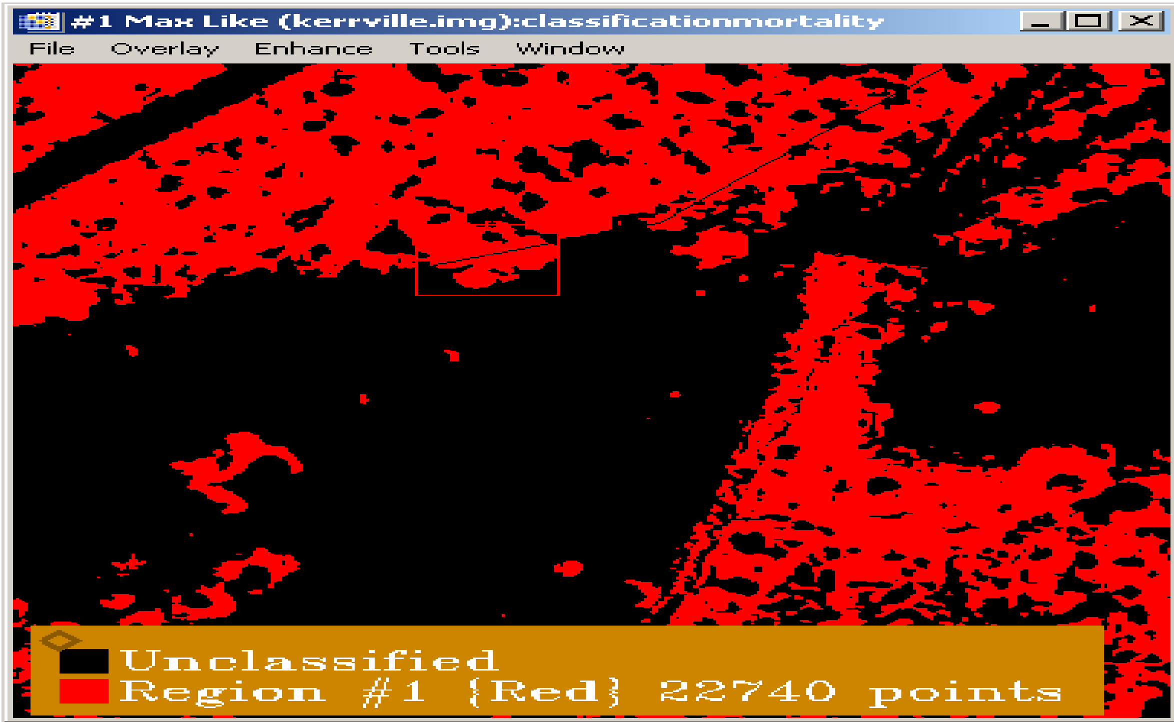

#2 (R:R (R (Resize (R:naip_1-1_1c_s_tx265_2004_1.sid):kerrville.img):kerrville.img),...
File Overlay Enhance Tools Window

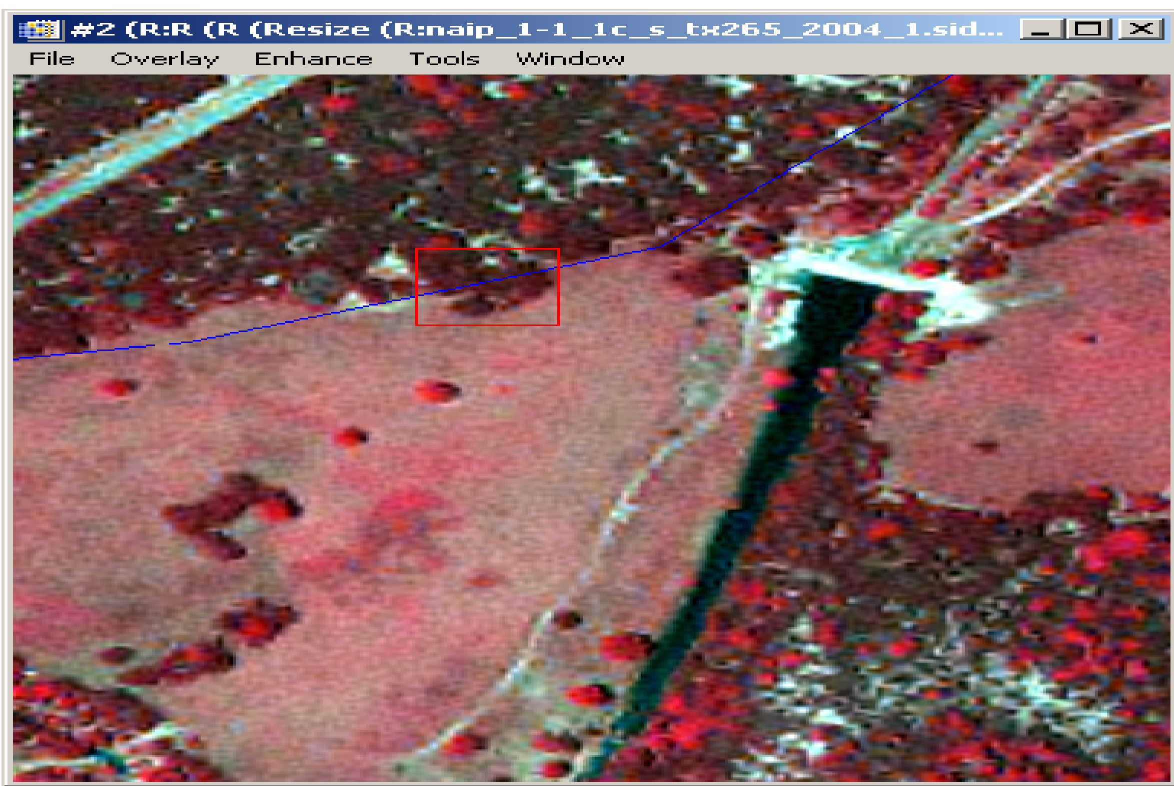
ISODATA


#1 ISODATA (kerrville.img):isodataw3its
File Overlay Enhance Tools Window
Unclassified
Class 1
Class 2
Class 3
Class 4
Class 5
Class 6
Class 7
Class 8
Class 9
Class 10


#2 (R:R (R (Resize (R:naip_1-1_1c_s_tx265_2004_1.sid):kerrville.img):kerrville.img),G:G (G (Resi...
File Overlay Enhance Tools Window
#2 (R:R (R (Resize (R:naip_1-1_1c_s_tx265_2004_1.sid):kerrville.img):kerrville.i

Maximum Likelihood





CONCLUSION

In conclusion, after visual comparisons, the supervised maximum likelihood classification seems to best classify the data, followed by the unsupervised Isodata classification, and then thirdly came the unsupervised K-Means classification. However, no methods could separate water from diseased vegetation.

Both the unsupervised K-means and Isodata did not prove to be the best at classifying the diseased trees in the sample area. This could be due to a number of different reasons. Starting values had to be selected for both methods. This can have an impact of the outcome of the data. Both number of clusters and iterations were arbitrarily selected without prior experience in unsupervised classification techniques. With more experience in both these techniques, the results could have been different and possibly more useful. Also, neither one of these methods could distinguish the water from the diseased vegetation. Perhaps more classes could have better distinguished the water from the diseased tree canopy.

The supervised classification technique proved to be more useful than the unsupervised classification methods used for this project. Only the diseased areas were selected for classification. When compared to the original aerial image, the classified areas closely matched the diseased dark vegetative area on the aerial. This was predetermined to be areas of infection and disease. This method worked best because regions of interest (ROI) were delineated in areas determined to be diseased. Once these areas were chosen, the computer applied these ROI'S to the rest of the image. From visual analysis, most of the red area is diseased forest. However, this method also included some of the water as diseased area. For this method, a masked ROI or separate class could have been used to separate the water from the diseased forest.

In summary, maximum likelihood supervised classification worked best. This is due to the amount of classified regions needed for this project (only one, diseased forest) and due to the fact that the areas of diseased forest can be selected through drawing regions of interest. K-means and Isodata did not prove to be useful. This could be due to the number of classes assigned at the beginning of the analysis. Neither one of these unsupervised methods could distinguish the water from diseased areas. The supervised classification also did not differentiate water from the diseased forest in most areas. A masked ROI or separate class could have corrected this problem. All in all, supervised classification is the best method for mapping oak wilt in central Texas.

References

1. C. Rexrode, D. Brown, 2006, Oak Wilt. Forest Leaflet and Disease Leaflet 29. U.S. Department of Agriculture Forest Service

2. D. Waitt, 2006, Texas Oak Wilt Information Partnership [On-line]. Available WWW: http://www.texasoakwilt.org

3. J.G. O'Brien, M.E. Mielke, D. Starkey, J. Juzwik, 2006, How To Identify, Prevent, and Control Oak Wilt [On-line]. Available WWW: http://www.na.fs.fed.us

4. J.H. Everitt, D.E. Escobar, D.N. Appel, W.G. Riggs, M.R. Davis, 1999, Using airborne digital imagery for detecting oak wilt disease. Plant disease, 83:66, 502-505,

5. Oak Wilt Specialist Certification Workshop: Identification and Management of Oak Wilt in Texas. 2006. Texas Forest Service.

6. R.S. Cameron, R.F. Billings, 2006. The Texas Oak Wilt Suppression Project-Development, Implementation, and Progress to Date. Oak Wilt Specialist Certification Workshop: Texas Forest Service.

7. Wilson, Dan A, 2005, Recent advances in the control of oak wilt in the United States, Plant Pathology Journal. 4(2): 177-191.

8. http://rsl.gis.umn.edu/

9. University of Lethbridge. Spring 2003. Geography 4725. Dr. C. Coburn. Laboratory 4. classes.uleth.ca/200601/geog4753a/lab/Geog**4725**-lab4.pdf