A Pilot Study: Using knowledge-based classification to identify springs in a portion of the Sewickley Creek Basin, Pennsylvania

A PROJECT REPORT SUBMITTED TO THE COLLEGE OF ARTS AND SCIENCES OF WEST VIRGINIA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN GEOLOGY

By

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Abstract

A rule-based classification of thermal and ancillary data was developed to investigate the potential of an automated approach, to identify springs potentially associated with mine drainage. The study site is the Greensburg, PA 1:24,000 USGS topographic quadrangle, approximately 25 miles southeast of Pittsburgh, PA. Twenty six flight lines of two-band (3-5 and 8-12 µm) thermal imagery over the study site were provided by the US Department of Energy, National Energy Technology Laboratory (NETL), Pittsburgh, Pennsylvania. Additional coverages used included a 30 m USGS digital elevation model (DEM), a vector file of the Pittsburgh coal seam subcrop, and a vector coverage of the springs and other water bodies that were identified by NETL and field-checked for water quality. The thermal data was imported into ERDAS Imagine, subset, mosaiced and radiometrically normalized using the overlap portions of each flight line. Limited radiometric resolution in the 3-5 µm band of two flight lines degraded the quality of the resulting mosaic for that band. Four rules were used to process the data: (1) a DN value of greater than 130 DN for the 8-12 µm band, (2) a distance of greater than 5 meters from building roofs as identified from a multispectral classification of the thermal data, (3) a location in a locally relatively low elevation site, and (4) near Pittsburgh Coal subcrop. A comparison of the results from the rule based classification with the NETL data suggest that errors of omissions were 36% (4 out of 11 springs). Errors of commission were more extensive, though they could not be quantified. Radiometric normalization of the thermal bands appears to be a crucial issue in the quality of such automated methods. A higher resolution DEM would be useful, but the 30 meter DEM was surprisingly effective, despite the coarse scale.
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Introduction

Since the beginning of commercial coal mining in the United States, environmental problems have plagued the industry. One particularly pervasive problem is mine drainage, which is a result of degradation of surface or groundwater as a consequence of mining. Mine drainage often has high iron content, and may also be acidic due to the oxidation of sulfides often found in coal and associated sulfide bearing rocks by oxygenated waters (Robbins et al., 1996). Acid mine drainage-impacted streams are characterized by a pH less than 4, a lack of aquatic life, and yellow, orange, and red precipitates that coat streambeds. Mine drainage from thousands of coalmines has contaminated more than 3,000 miles of streams and associated ground waters in Pennsylvania alone (Figure1; USGS, 2002).

Due to the large area over which mine drainage sources are found, the detection and monitoring of these sites is very labor intensive. Remote sensing is therefore a potentially valuable tool for surveying mine drainage sites because it provides a systematic method for mapping large areas. Mine drainage, like other groundwater, tends to be warmer than surface water during the cooler months of the year. Mine drainage is thus potentially detectable using thermal sensors, especially during the predawn hours when the thermal contrast is greatest. However, determining whether mine drainage is present and the chemistry of the water requires field checking.
Figure 1. Impact of mine drainage on the streams of Pennsylvania. The brown streams indicate reaches where no fish are present, the green streams indicate reaches where some fish are present (USGS, 2002).
A significant issue for remote sensing of mine drainage sources is that springs are not the only warm feature in pre-dawn thermal imagery. Even an expert interpreter may struggle to differentiate springs from other warm objects, such as small fires, exhaust fans and buildings. Manual interpretation is both subjective and time consuming. These problems suggest that computer-based classification of thermal and ancillary data may provide a more efficient, systematic and objective method for automating the mapping of springs and other ground water seepage.

**Literature Review**

**Remote Sensing of Springs**

Thermal infrared imagery has been used to identify and assess surface and groundwater in large areas where conventional field techniques can be time-consuming or impractical (Banks, 1996). The use of thermal infrared imagery for detection of groundwater seeps, as well as numerous other environmental applications, is increasing.

In the 1970s thermal infrared imagery was used in an attempt to identify shallow aquifers. Cartwright (1968a, b, 1970, 1971, 1974), using the assumptions of a constant temperature aquifer and steady state heat flow between the aquifer and the land surface, estimated the approximate depth and extent of aquifers in glacial terrain by the variation in soil temperatures at 1-m depths. In a similar study, Chase (1969) found radiometrically cool areas on thermal infrared imagery corresponded with areas of shallow groundwater. Myers and Moore (1972) demonstrated a correlation between radiometric temperature and both aquifer thickness and depth for shallow (1.5-4.5 meter) aquifers. However, Huntley (1978) disputed these prior studies because they failed to
consider evaporative cooling related to soil moisture, and asserted that it is not possible to estimate the groundwater depth directly from thermal infrared imagery.

In recent years, thermal remote sensing has benefited from the development of digital systems, which have replaced the early analogue sensors. These modern systems tend to have a higher radiometric resolution, and sometimes multiple bands. For example, modern digital scanners such as the Thermal Infrared Multispectral Scanner (TIMS) can differentiate variations of 0.1° C or less. TIMS has been used to locate ground-water discharge zones in surface water over two military ordnance disposal facilities at the Edgewood Area of Aberdeen Proving Ground, Maryland (Banks, 1996).

Recently, the US Department of Energy (US DOE) National Energy Technology Laboratory (NETL) has successfully used thermal imagery for identifying springs, many of which are associated with mine drainage. The NETL analysis is based on a combination of manual interpretation and limited automated analysis of single flight lines, in which complex relationships and associations are used by an expert interpreter to identify likely target areas (J. Sams, 2002, personal communication).

**Knowledge Based Classification**

An alternative approach to manual image interpretation is a knowledge based classification, also known as an expert system. An expert system has been defined as a computer program that handles complex, real-world problems and attempts to solve problems by reasoning like an expert (Skidmore, 1989). Most expert classifiers are implemented through a hierarchy of rules. A rule is a list of conditional statements that determine the informational component of hypotheses. Multiple rules and hypotheses
can be linked together into a hierarchy that describes a final set of target informational classes or terminal hypotheses. One implementation of an expert system for remotely sensed data is the ERDAS Imagine Expert Classifier (ERDAS, 1999). The Expert Classifier has two components: the Knowledge Engineer and the Knowledge Classifier. The Knowledge Engineer provides an expert, who has knowledge of the data and the application, with the tools to identify the variables, rules, and output classes of interest and create the hierarchical decision tree (ERDAS, 1999). The Knowledge Classifier is the interface for applying the knowledge base to create a classification (ERDAS, 1999).

Advantages of knowledge based systems include their flexibility with regard to diverse data sources, such as aerial photographs, DEMs, and multispectral imagery (Skidmore, 1989), and the wide range of potential applications, for example, resource mapping, and the detections of oil spills or land mines (Stefanov et al., 2001). There are, however, problems associated with expert systems. Firstly, according to Schowengerdt (1989), a significant problem for all expert systems is the acquisition of appropriate knowledge. For detection of springs, knowledge of appropriate image processing techniques and factors that influence the development of springs is required. A second problem, the knowledge acquisition bottleneck (Huang and Jensen, 1997), is a consequence of the inability of most experts to formulate their knowledge in a form sufficiently systematic, correct, and complete for quantitative use in a computer application.

**Purpose**

The purpose of this study was to investigate the feasibility of using an expert system to identify springs from thermal imagery and ancillary data. The focus of this research is
the development of the expert system rule and their evaluation—with less emphasis placed on the accuracy of the final classification. A pilot project was undertaken in the Sewickly Creek basin, Pennsylvania, using thermal data acquired by US Department of Energy National Energy Technology Lab (NETL). Three tasks were carried out to complete the project.

1. The remotely sensed and ancillary data were imported into ERDAS Imagine, subsetted, and mosaiced.

2. Four main sets of rules were established to identify springs based on their relative radiant temperature, relative topographic position, proximity to the Pittsburgh Coal Seam, and multispectral thermal classification.

3. The success of the study was evaluated both qualitatively and quantitatively. For the qualitative analysis, the general feasibility of the expert system approach for mapping springs that may be sources of mine drainage was evaluated. For the quantitative analysis, the number of springs identified by fieldwork by NETL was compared to the results of the expert system.

**Study Area**

The study area comprises the majority of the Greensburg, Pennsylvania 1:24,000 7.5 minute USGS topographic quadrangle (Figure 2). The study area includes part of Sewickly Creek, a tributary to the Youghiogheny River (Figure 3), and is located approximately 40 kilometers (25 miles) southeast of Pittsburgh.

The study area has a long history of coal exploitation, with mining of coal in the Youghiogheny valley documented from the early 1800s. During the late 1800s coking became one of the primary industries in the Youghiogheny River Basin, and during the
Figure 2. Greensburg, PA 1:24,000 7.5 minute USGS topographic quadrangle. The yellow-outlined area is the approximate extent of all 26 thermal flight lines. The yellow line is the approximate location of Little Sewickly Creek.
Figure 3. Location of Youghiogheny River Basin in Pennsylvania, Maryland, and West Virginia (Sams et al., 2000).
time period between 1860-1919 western Pennsylvania was the world leader in bituminous coal mining and steel production. Since the 1940s the coal production in the Youghiogheny basin has been decreasing, and the economics of the region is now increasingly dependent on recreation (Sams et al., 2001). Mine drainage from abandoned mine sites is the single biggest source of surface water contamination in Pennsylvania (Pennsylvania DEP, 1998), and the lower Youghiogheny alone has approximately 147 Abandoned Mine Lands (AML), 67 of them in the Sewickley Creek basin (Figure 4).
Figure 4. The known locations of abandoned mine sites and coal and non-coal bearing rock strata in the Youghiogheny River Basin (Sams et al., 2000). The boxed area is the approximate location of the study area.
Methods

Data Acquisition

The Greensburg Quadrangle, which defines the study area for this research project, is a part of a larger project conducted by the Clean Water Team of NETL, Pittsburgh, Pennsylvania. The thermal data were acquired by the US DOE Remote Sensing Laboratory in Las Vegas, NV, with a Daedalus AADS1268 multispectral scanner, fitted with a dual thermal infrared detector (3-5 µm and 8-12 µm). The 3-5 µm band is located within the range of the peak energy radiant emission of objects with temperatures ranging from 330 to 730° C. By comparison, the 8-12 µm band is within the range of peak energy emission of objects ranging in temperature from –20 to 100° C. Thus the 8-12 µm band is likely to have a better signal to noise ratio than the 3-5 µm band for differentiating springs from other natural surfaces. Nevertheless, the shorter wavelength thermal band, when used in combination with the 8-12 µm band, is potentially valuable for differentiating objects based on radiant emissivity differences, rather than simply temperature differences.

The sensor was mounted on an aircraft flown at an altitude of 1,300 feet above ground level in the predawn hours. The nominal pixel size is 1 meter, with a 0.1° C nominal radiometric resolution. The imagery was geometrically preprocessed using data from a Geometric Correction System coupled to the scanner which, when combined with further georeferencing by NETL, produced a relative locational accuracy of approximately 5-7 meters.
Twenty-six thermal flight lines covering the study site were provided by NETL in ER-Mapper format. Extensive image analysis to identify potential springs was carried out by NETL, and the results were field checked, including identifying springs and measuring the quality of water (Table 1, Figure 5). ArcInfo coverage of the resulting spring data base was provided by NETL. Additional ancillary data provided by NETL includes a 30 meter digital elevation model (DEM), and 1 meter USGS digital orthophoto quarter quadrangles (DOQQ’s).
<table>
<thead>
<tr>
<th>ID</th>
<th>HYDRO COND</th>
<th>SITE TYPE</th>
<th>PH</th>
<th>CONDUC</th>
<th>FLOW RATE</th>
<th>USED IN ANALYSIS</th>
<th>IDENTIFIED BY EXPERT SYSTEM</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>Low</td>
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<td>240 ppm</td>
<td>Medium</td>
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</tr>
<tr>
<td>7</td>
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<td>SPG</td>
<td></td>
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<td>Yes</td>
</tr>
<tr>
<td>8</td>
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<td>SPG</td>
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<td>High</td>
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<tr>
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<td>MDS</td>
<td>7.8</td>
<td>490 ppm</td>
<td>Very Low</td>
<td>Yes</td>
<td>Yes</td>
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</table>

**LEGEND:**

Acid Mine Drainage = RED

Springs = BLUE

Not identified = PURPLE

Table 1. Springs identified by NETL fieldwork and image analysis
Figure 5. The field-checked locations of the springs overlayed onto the Greensburg, PA 1:24000 7.5 minute USGS topographic quadrangle. The yellow-boxed area illustrates the outline of all 26-subsetted flight lines.
Subsetting

The digital processing for this project was carried out in ERDAS Imagine; therefore, each flight line was first imported into the Imagine format (Figure 6). The flight line was then subsetted to cover only the area within the Greensburg USGS 7.5 minute topographic map.

Mosaicing

The mosaicing of images was performed using the Imagine Mosaic tool. The purpose of creating a mosaic is to create one large image in which all flight lines are seamlessly combined (ERDAS, 1999; Figures 7 & 8). A major problem with combining the 26 flight lines is that the digital numbers (DN values) of objects often vary when imaged in different flight lines (Figure 9). This may be a result of a combination of real changes in the temperature of these objects, a drift in the sensor’s detectors, or possibly changes in the instrument’s gain and bias. To allow global analysis of the mosaic, it is important that these radiometric differences between flight lines be minimized.

Two forms of mosaicing the thermal flight lines were analyzed for this project. Firstly, the mosaic was created without radiometric normalization (Figures 7 & 8). For the second approach, one flight line was chosen as a reference image. The adjacent images are then normalized so that the pixels in the overlapping region have a similar statistical distribution. This procedure is iterated with the successive adjacent flight lines, until all the images have been normalized. Following the normalization, the images are then combined (Figures 10 & 11). For both the mosaics with and without normalization,
the images were joined at the middle of the overlap interval, with the outside overlap region of each line discarded. In some cases, however, aircraft drift and roll made it necessary to adjust manually the cutline where the two images join, to ensure that no data gaps were produced.

**Rules**

It was initially planned to implement the rule based classification using the ERDAS Expert System because of its powerful tools, clear structure and effective visualization of the overall rules. However, it quickly became clear that the ERDAS Expert System was too slow for the large size of the data set used in this project. A possible cause of the relative slowness of the Expert System is that it records the decision path associated with each output pixel, which necessitates the creation of large temporary files. The decision path data is potentially useful for adjusting the rules to increase the system’s accuracy.

As an alternative to the Expert System, Imagine Spatial Models (ERDAS, 1999) were used to create the rules. The Imagine Spatial Modeler is a powerful scripting language that uses linked icons to characterize the processing flow. One advantage of using this approach for implementing the rules is that a sequence of Spatial Models can be created, thus facilitating the analysis and adjustment of the rules based on interim processing steps.

Four sets of rules were developed: a thermal threshold to identify the warmest objects based on the radiant temperature in the 8-12 µm band, a location not immediately adjacent to a building, a relatively low topographic elevation determined from a comparison of a pixel to the average of its neighbors, and a location close to the
Pittsburgh Coal subcrop region (Table 2). The development of the rules, and their relative value in identifying springs is discussed further in the Rules section of the

*Results and Discussion.*
Figure 6. All 26 flight lines, 8-12 µm band, before subsetting, mosaicing, and normalization.
Figure 7. All 26 flight lines, 3-5 µm band, subsetted, mosaiced, without normalization.
Figure 8. All 26 flight lines, 8-12 µm, mosaiced without normalization.
Figure 9. The yellow box illustrates the variation in DN values (8-12 \( \mu \text{m} \) band) of the same object across flight lines after mosaicing and before normalization.
Figure 10. All 26 flight lines, 3-5 mm, subsetted, mosaiced, and radiometrically normalized.
Figure 11. All 26 flight lines, 8-12 µm, subsetted, mosaiced, and radiometrically normalized.
Evaluation of the knowledge based classification results

The success of this project was measured quantitatively by comparing the number and location of springs identified in the field to those flagged by the expert system (Table 1). The same data set was used to develop the expert system and to test its accuracy. This will result in a slightly over-optimistic estimate of the classification accuracy, but the number of springs identified in the study site is not large enough to divide into separate development and testing groups.

Of the 20 spring locations identified in the study area by NETL, only 11 could be clearly identified with specific thermal anomalies through a visual analysis of the imagery. The reason for the difficulty in identifying the remaining nine springs on the imagery may be because of the relative spatial uncertainty of the thermal image or the geometric rectification, especially in overlap regions. Although in some cases it may have been possible to identify nearby probable locations of springs, it was decided to exclude those points from the analysis, rather than to adjust the locations of the field data. This is because moving the field locations may introduce false confidence in the Expert System results. Furthermore the primary aim of the quantitative evaluation was to identify what springs the Expert System was overlooking (errors of omission), rather than focusing on errors of commission. In fact, it was not possible to evaluate errors of commission quantitatively, because it could not be assumed that the NETL data was 100% complete.
Results and discussion

Mosaicing

Mosaicing without normalization produced an image dominated by the differences in radiometric values between flight lines (Figures 7 & 8), and was not found to be useful. This result was expected, because NETL had already found that it was necessary to analyze each flight line separately due to the radiometric differences (Sams, 2002, personal communication).

The radiometric normalization based on the overlap regions produced mixed results. For the 8-12 µm band, radiometric differences between the majority of the flight lines are not apparent, although there is a general brightening towards the southern end of the mosaic, and some residual banding in the middle of the mosaic (Figure 11). For the 3-5 µm band, the results were less successful (Figure 10). Flight lines 12 and 13 near the middle of the mosaic had a very low radiometric range, as well as a pronounced variation in DN value with view angle. Because the radiometric normalization is iterative across the images, radiometric problems in any one flight line will be propagated onto adjacent images. Thus, for the 3-5 µm band, all the flight lines to the south of the problem lines have a low radiometric range and are not useful.

Rules

The first of the four rules (Table 2) was based on thermal properties of springs, which are generally warmer than surface water in this predawn imagery. The application of a minimum threshold of 130 DN for the 8-12 µm band was found to produce the
optimal segregation of the springs identified by the NETL fieldwork from the rest of the image. However, this threshold does not exclude many other warm features, such as
### Table 2. Summary of Expert System Rules

<table>
<thead>
<tr>
<th>HYPOTHESIS</th>
<th>RULE</th>
<th>COVERAGE USED</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Relatively warm</td>
<td>8 – 12 μm band ≥ 130 DN</td>
<td>8 – 12 μm thermal band</td>
</tr>
<tr>
<td>2 Not associated with heat loss from the buildings</td>
<td>&gt; 5 meters from pixels classified on roofs</td>
<td>3 – 5 μm and 8 – 12 μm thermal band</td>
</tr>
<tr>
<td>3 Locally low topographic site</td>
<td>Pixel value &lt; average of neighboring pixels ≤ 5 pixels from central pixel</td>
<td>30 m USGS DEM</td>
</tr>
<tr>
<td>4 Areas underlain by the Pittsburgh Coal Seam</td>
<td>Within the Pittsburgh Coal outcrop area or a 1km buffer</td>
<td>Pittsburgh Coal vector coverage</td>
</tr>
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exhaust fans on rooftops and heat escaping from windows. Therefore the use of the thermal threshold alone results in an excessive number of errors of commission (false positives).

Rule two was developed from the observation that a major source of false positives is heat loss from buildings, particularly windows, and to a lesser extent, exhaust vents. A preliminary analysis of a two band thermal false color composite suggested that that although buildings had a wide range of apparent radiant temperatures, the building roofs tended to have distinctive colors, suggesting that they have characteristic emissivity patterns. Unlike temperature, which is a transient property of an object, emissivity is an inherent physical property of a material, and can be used for classification just as optical reflectivity is used in standard image classification. Thermal emissivity can in fact be calculated from thermal reflectivity by the formula: 1- reflectivity.

It was therefore postulated that the false positives associated with buildings could be reduced by suppressing apparent thermal anomalies in close proximity to building roofs. A maximum likelihood multispectral classification (Lillesand and Kieffer, 2000) was carried out on the two-band thermal data. This multispectral classification draws on both the first and second order statistics of the spectral classes. One limitation of the maximum likelihood classifier is that it is a relative classifier, thus although only roofs were of interest, it was necessary to collect signatures for the following spectral classes: roofs, roads, water, bushes, and fields.

As previously discussed, the radiometric normalization of the 3-5 μm band had a significant artifact, causing the classification of the southern half of the mosaic to differ from the northern half (Figure 12). Therefore, it was necessary to classify the image in
Figure 12. Multispectral classification, by means of a maximum likelihood classifier, of all 26 flight lines in a single pass. Note the change in classification pattern associated with flight lines 12 and 13.
two sections, because the class signatures from the southern part of the image (flight lines 12-26) were not comparable to those in the north (flight lines 1-11). A qualitative comparison of the separately classified mosaic sections (Figure 13) and the single combined classification (Figure 12) suggests that processing the data in two sections reduced these problems significantly.

Thermal anomalies that are immediately adjacent to buildings were identified by buffering the spectrally classified roof class out to a distance of 5 meters, and suppressing any of the thermal anomalies in this region that would otherwise be classified as potential springs due to exceeding the thermal threshold.

The first two rules, including the thermal threshold applied to the 8-12 µm band, and the suppression of building related false positives, were implement with an ERDAS Spatial Model (Figure 14). The resulting image (Figure 15) includes only a small number of potential spring pixels, but this still has too many false positives.

The third rule was developed from the relative topographic location, inferred from the DEM. The DEM is a potentially useful coverage for the automated analysis of springs, because when the water table intersects the ground surface, a spring or seep typically results. Therefore, sites that are relatively low topographically are more likely to be spring locations. However, the definition of a low site has to be locally determined, because the water table elevation tends to be influenced by the local topography.

The DEM available for the study site has a grid cell of 30 m, and was initially assumed to be too coarse to capture the topographic variation that controls groundwater flow. Nevertheless, a qualitative analysis suggested that the DEM did give sufficient
Figure 13. Multispectral classification, by means of a maximum likelihood classifier of all flight lines, with classification applied to lines 1-11 and 12-26.
Figure 14. Roof buffer rule and threshold rule.
Figure 15. The output from the model shown in figure 14. Potential thermal anomalies remaining after elimination of pixels near roof tops are shown in shades of gray.
resolution, at least to capture the major topographic features (Figure 16), to be incorporated into the model.

Locally low elevations were identified using an Imagine Spatial Model, which compares each pixel to the average of the surrounding pixels (Figure 17). Only those pixels that were lower than the average of the surrounding pixels were regarded as potential spring locations (Figure 18). The radius of the zone of the surrounding pixels was arbitrarily chosen as 5 pixels (150 meters). A sensitivity analysis indicated, however, that changing this radius by 1-2 pixels produced very similar results, suggesting that for this landscape the results are not particularly sensitive to the size of the local neighborhood.

The final rule was based on the geology, because only springs associated with mine drainage are of interest in this study, and mine locations are inherently geologically determined. Unfortunately, only the Pittsburgh Coal subcrop information (Figure 19) was available for the study site, although additional coals seems were probably mined. Nevertheless, because this study is a pilot project, it was decided to include the geology information in the analysis to demonstrate how such data might be used. In addition, it was observed that the majority of acid producing springs recorded in the NETL field based coverage are found near the Pittsburgh Coal subcrop region.

The vector coverage of the Pittsburgh Coal subcrop was rasterized, using Imagine’s Vector to Raster tool. The Pittsburgh Coal subcrop area was extended with a Spatial Model (Figure 20) that buffered the subcrop regions by 1 kilometer, because springs may occur some distance from the mined areas. The resulting image is shown in (Figure 21).
Figure 16. The 30 meter USGS DEM
Figure 17. The model for the DEM to identify relative low elevations.
Figure 18. Locally low elevations identified with DEM model (Figure 17) applies to the DEM (Figure 16).
Figure 19. Pittsburgh Coal subcrop areas, major streams and springs location. The blue areas are the Pittsburgh coal seam within the Greensburg quad. The dots are the location of the springs; the yellow are neutral discharges and the blue are acidic discharges. The black outlines are the stream locations.
EITHER 1 IF ( SEARCH ( $n1_vrptcoal2 , $n4_Integer , 1) < 101 ) OR 0 Otherwise

Figure 20. The model for the 1km buffer around the Pittsburgh Coal subcrop region.
Figure 21.  The results of the model shown in Figure 20. The white area is the coal subcrop region with a 1km buffer.
The last Spatial Model (Figure 22) combines the four separate coverages: thermal anomalies, local topographically low regions, Pittsburgh subcrop and adjacent regions, and areas that are not adjacent to roof tops. The output represents pixels most likely to represent springs that may represent mine drainage (Figure 23).
Figure 22. The final model for identifying springs and seeps. The output of this model is an image of all the objects that meet the criteria of the thermal DN threshold, coal buffer, roof buffer, and elevation.
Figure 23. The results of the expert system model shown in figure 22.
Evaluation of the knowledge based classification results

Table 1 lists the 20 springs identified in the NETL field data. Of the 11 springs that were used in the accuracy analysis, seven were identified by the Expert System. This corresponds to 36% omission errors. The four springs that were misclassified were springs 1, 3, 12, and 14. The buffering of pixels classified as roofs eliminated spring 1. Spring 12 was eliminated by the Pittsburgh Coal subcrop rule. Springs 3 and 14 were eliminated by the combination of all the rules together.

As discussed in the Methods section, it is not possible to evaluate commission errors quantitatively. However, a qualitative evaluation suggests that there are still significant errors of commission. One source of the errors of commission relates to the first rule, that of the thermal threshold. Although the 8-12 µm band is considerably less noisy than the 3-5 µm band, it does suffer from some scan-angle related variations in radiometric values, making the average DN values on the edges of images slightly different from those of the central part of the image. Unfortunately, although the mosaicing eliminates some of the edge pixels, it does use the edge pixels for radiometric normalization. Therefore, methods that reduce the scan angle variations in radiometric values may increase the overall accuracy.

Conclusions

This study produced an automated classification system to identify springs based on remotely sensed thermal and ancillary data. The errors of omission for the Expert System were found to be 36% (4 out of 11 springs). This number was lower than
expected, although it should be emphasized that although errors of commission could not be quantified, they do appear to be significant. Errors of commission, however, are less costly than errors of omission, because it is easier for a human analyst to screen out incorrectly flagged pixels, than to go back through the entire image searching for potential springs that have been missed.

The mosaicing of the 26 flight lines of thermal imagery was performed to enable the classification of the entire area simultaneously, instead of classifying each line separately. However, along with the mosaicing, it is necessary to apply a radiometric normalization to suppress the large variations in DN values between flight lines. The normalization using the overlap regions was not very successful for the 3-5 µm band, and necessitated that the multispectral classification be carried out in two sections. The 3-5 µm band of lines 12 and 13 was severely degraded, and thus even if alternative normalization strategies had been used, the area covered by these flight lines would remain poorly classified. Normalization of the 8-12 µm band produced a more uniform result, but some residual variation in DN values was still evident. Further research in reducing the artifacts in the thermal imagery could be useful in improving the results of the automated classification and in setting the thermal threshold that determines potential anomalies.

The knowledge based system was implemented using the Imagine Spatial Modeler. The Spatial Modeler was chosen because of its power, flexibility, and speed. This was crucial for this study, which used a very large data set. However, in the long term, especially with additional development in computing power, the Imagine Expert
System will be a preferable platform for such knowledge based systems, because of the more structured environment.

Four basic sets of rules were established for the classification. The first rule was based on a minimum 8-12 \( \mu \text{m} \) band threshold that identified potential thermal anomalies. However, springs were not the only warm objects that exceeded the threshold, and therefore all the remaining rules were developed to try to reduce these errors of commission. It is therefore significant that if a more effective radiometric normalization had been applied, fewer errors of commission would need to be corrected in the subsequent rules. This again emphasizes the importance of the mosaicing and normalization process as discussed above.

Heat loss from buildings, especially windows and vents, was identified as a particularly common source of errors of commission. Therefore the multispectral classification of the two band thermal data was used to identify roofs. This classification was plagued by errors introduced by the radiometric normalization, especially in the 3-5 \( \mu \text{m} \) band. Processing this data in two sections partly overcame these problems, but the results are still rather noisy. An alternative therefore maybe to use high resolution daytime satellite imagery, such as QuickBird data, which has a nominal pixel size of 2.4 meters for 4 band multispectral imagery. This spatial resolution may be sufficient to identify building roofs. However, in order to exploit such ancillary data, it may be necessary to improve the quality of the geometric rectification of the thermal data.

The digital elevation data was found to be useful in characterizing the landscape, despite the relatively large pixel size of 30 meters. Nearly all the springs observed in the field by NETL were associated with elevations that were lower than the surrounding
regions, defined by a 150 meter radius. An improved high resolution DEM, along with more sophisticated analysis techniques, might make it possible to improve the topographic analysis further. A higher resolution DEM could potentially be obtained by interpolation from the digitized contours of the 1:24,000 USGS topographic quadrangle. A much more expensive, but very high quality, DEM could be obtained from specially acquired lidar data. Lidar data would also be useful in providing orthorectification of the thermal imagery. Furthermore, small-footprint, high sample density lidar data could be yet another way identifying buildings, though it would require the development of customized object recognition software.

The fourth rule was based on proximity to the Pittsburgh Coal Seam. Although other coal seems were likely mined in this area, most of the acid producing seeps were found close to the Pittsburgh coal seem. Therefore, this coverage was included in the classification. Nevertheless, for future analyses it would be important to include subcrop information for all coal seems mined in an area. Ideally, the structural contours of the coal seems should be digitized, so that in regions of steep topography, or structurally complex geology, areas where the coal is too deep to mine could be excluded. Mine maps would be particularly useful, however, digitizing such data can be very time-consuming.

In summary, the knowledge based system produced good results. The advantages of the knowledge based computer classification is that it is systematic, objective, relatively quick, and can easily be extended to include new coverages as they become available. Limiting factors include problems with normalization and geometric rectification of the thermal data, the spatial resolution of the DEM, and the incomplete
coverage of the coal seam data. Errors of omission were low (36%), but errors of commission were numerous. However, errors of commission are less costly than errors of omission, because manual screening of flagged pixels can eliminate many errors of commission. By contrast, errors of omission are more troublesome because very extensive checking through the original data is required to identify them.
References


