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Remote Imaging Applied to Schistosomiasis Control:
The Anning River Project

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Introduction

The use of satellite imaging to remotely detect areas of high risk for transmission of infectious disease is an appealing prospect for large-scale monitoring of these diseases. The detection of large-scale environmental determinants of disease risk, often called landscape epidemiology, has been motivated by several authors (Pavlovsky 1966; Meade et al. 1988). The basic notion is that large-scale factors such as population density, air temperature, hydrological conditions, soil type, and vegetation can determine in a coarse fashion the local conditions contributing to disease vector abundance and human contact with disease agents. These large-scale factors can often be remotely detected by sensors or cameras mounted on satellite or aircraft platforms and can thus be used in a predictive model to mark high risk areas of transmission and to target control or monitoring efforts. A review of satellite technologies for this purpose was recently presented by Washino and Wood (1994) and Hay (1997) and Hay et al. (1997).

To:AST

In China, there is currently concern about the establishment and spread of infectious diseases, including malaria and schistosomiasis, in the area along the Yangtze upstream of the Three Gorges Dam which is now under construction. Our group has been working with parasitologists from the Sichuan Institute of Parasitic Disease (SIPD) responsible for schistosomiasis monitoring and control in the area of the dam. The profound ecological and social changes that will take place as the dam is being constructed and when it is completed may create new habitat for the snail species central to the cycling of the disease, as well as new relationships between humans, domestic animals and the aquatic environment. The size of the lake that will be created behind the dam and the difficulty of access to this mountainous area make remote sensing technology an attractive adjunct to land based surveillance of these changes as the lake fills and the dam goes into operation.

As a means of exploring the use of remote sensing in the context of schistosomiasis control prior to the completion of the Three Gorges Dam, we have been studying a region where the disease is endemic, where ground based data sets on its prevalence and on snail habitat exist, and which is of a scale suitable for study using remote sensing. With the assistance of our colleagues in the SIPD, we have focused on the area along the Anning River in the Daliang mountainous area of southwestern Sichuan province. This region includes villages studied in our earlier work.

Remote sensing has been demonstrated to be a viable means of identifying habitat for vectors of other diseases. The potential efficacy for using remote sensing to determine high-risk areas of malaria transmission was recently illustrated (Beck et al. 1994; 1997). Two types of Anopheline mosquito habitat, unmanaged pastures and transitional swamps, were shown to be detectable based on classification of Landsat Thematic Mapper (TM) data. That research was an extension of previous work which focused on the identification of high and low Anopheline-producing rice fields (Wood et al. 1991). Landsat TM data have also been used to map land cover to study landscape correlates of Lyme disease (Dister et al. 1993). In that study disease data and landscape classifications were overlaid to look for land cover correlates to disease risk.

Several studies have implied that remote sensing could be a useful tool for schistosomiasis monitoring. Cross and Bailey (1984) and Cross et al. (1984) showed a correlation between local temperature variation and prevalence rate. Malone et al.(1994) showed that historical prevalence data correlated well with remotely detectable geographic features. Both of these studies take a different approach from the Anopheline studies in that they demonstrated a correlation between disease and ecological factors, whereas the malaria vector studies by Beck et al. (1994; 1997) and Wood et al. (1991), remotely sense habitat correlates of the vector known to be the disease agent.

In the current study we ask if the second approach is applicable to detecting spatial variations in the vector population which transmits the parasite causing schistosomiasis japonicum, the Asian form of schistosomiasis. The disease is vectored by an amphibious snail, *Oncomelania hupensis*. A recent preliminary study by the SIPD used Advanced

Very High Resolution Radiometer (AVHRR) data to identify snail habitat (Li et al. 1990). In the current analysis we use higher resolution Landsat TM data to look for correlations with detailed ground based snail ecology surveys. If surveyed snail habitats correlate with the satellite data, there is the potential to use remote sensing to monitor large and remote areas in the region of the dam, and to identify areas at high risk of transmission.

The current problem is different from that of detecting malaria vectors since the vector habitat for *O. hupensis* is usually a micro-environment which is itself not detectable using most remote sensing data because of their course spatial resolution. However, micro-environmental conditions may be affected by larger scale factors including local vegetation type and surrounding crops, fertilizer usage, and water and temperature patterns. These factors will cause local changes in the environment, which in turn will influence the remote sensing signal. Further, the other two schistosomiasis studies found correlations between large-scale phenomena and disease rates implying that something can be seen at this scale. The question addressed at present is whether or not remote sensing data of local areas can be accurately classified, based on large-scale environmental factors, as being suitable for these vector snails or not, and thus be at high risk for transmission.

Methods

To address this issue our group conducted a study in the Anning River Valley in southwestern Sichuan Province. The Anning River Valley is a high mountain valley at an elevation of about 1500 meters. This is primarily an agricultural area with irrigated farming of rice, corn, wheat, and a variety of vegetables and some export crops. The valley is also a highly endemic area for schistosomiasis japonica. The remote sensing data used was from the Landsat TM sensor. The ground data indicating suitable snail habitat were point observations from one environment type and classified as habitat or non-habitat. Suitability was determined by the presence of young or reproducing snails *vs.* no young or reproducing snails. Few locations are found with only adult snails present, presumably because snails leave unsuitable locations or die.

A large-scale snail monitoring effort was conducted in 1994 by the Xichang County Anti-endemic Station (XCAS). The station is responsible for monitoring and controlling human schistosomiasis infection and vector snail ecology in the seventeen-township middle section of the Anning River Valley. Snail surveys were performed throughout the area in townships where the human incidence exceeded 10%. Snail surveillance was done in June. We chose this section of the river valley as our study area in order to take advantage of this existing surveillance data. The study area extends from Lizhou township in the north to Hexi township in the south, and covers about 45 km of the river valley around Xichang City. A map of the area showing these reference points is shown in Figure 1.
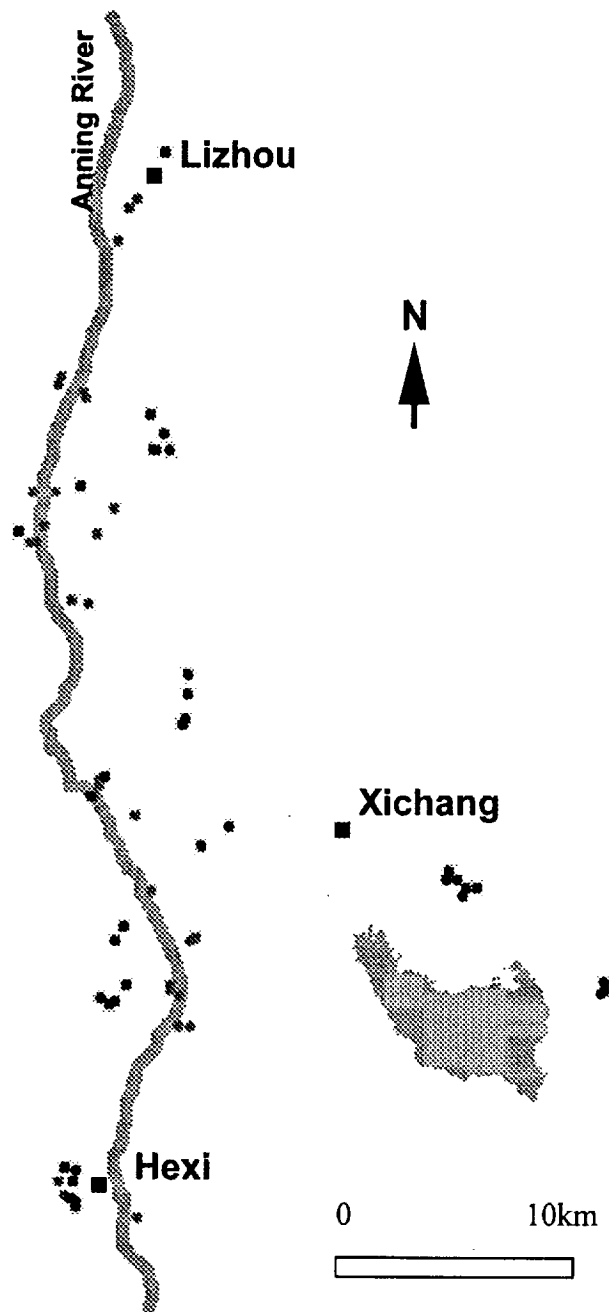
Figure 1: Map of the Anning River Valley Study Area. Non-habitat sites are shown as gray pixels. Snail habitat sites are shown in black pixels.

Two Landsat TM scenes (one Spring April 7, 1994, and one Fall October 16, 1994) were obtained for the region. Both images were free of cloud cover over the area of interest, and each represents a distinct agricultural season. The major crops during these times are rice and corn in summer-fall and wheat and beans in the winter-spring season.

Ground data on the locations of snail colonies was obtained from the XCAS's 1994 snail surveys (this is being supplemented with density information). During 10 days in the middle of June, 1997, our group with the help of the local authorities and the head of the XCAS visited townships and recorded the geographic locations of the 1994 surveillance data. Collection sites were located with a Trimble Pro XL global positioning system to allow for correlation with the remote sensing data. Three base stations were established and positioned with respect to a known surveyed control point at the peak of the Lushan mountain south east of Xichang city. All data points were differentially corrected to the base station locations to provide positioning accuracy in the 1-5 m range.

Collection sites were located in 14 townships throughout the study area. Townships were chosen based on availability of 1994 data or if there was historical knowledge of apparently stable snail habitat or non-habitat. Three environment types exist in the study area: irrigated farming in the river plain, terraced rice culture at the base of the hills, and mountain streams areas higher in the mountains. The three habitat types are structurally different with distinct local ecologies. In light of this, the study was limited to one type of environment, irrigated farming areas in the river plain, for which there was an abundance of ground/field data (and travel was more convenient). Snail habitat in the river plain area is limited to irrigation and drainage ditches and the boundaries of fields. This resulted in a total of 103 data points (55 classified as habitat and 48 as non-habitat).

Image processing was performed using PCIWORKS image processing software. Before data analysis, the images were geometrically corrected and registered using 11 ground control points taken throughout the river valley. Points used for referencing the image to a world coordinate system were large structures easily seen on the image, such as the corners of the Xichang airport runway, large intersections and an isolated paved village compound. The 103 ground/field data points were located on the image. Each snail habitat and non-habitat site was specified as a 3 × 3 pixel area surrounding the site location as determined in the field by GPS measurements.

After geographic correction, a preliminary supervised maximum likelihood classification was performed using all TM channels from both dates. The 55 habitat and 48 non-habitat areas were used both to train the classification algorithm and assess the accuracy of the classification. The results of this accuracy assessment are presented in the next section.

Realizing that the accuracy of our preliminary classification was inadequate, we next employed a two-tiered analysis approach. The first step of this approach employed an unsupervised classification method called Isodata clustering to break up snail habitat and non-habitat classes into subclasses. The Isodata algorithm is an iterative process whereby the pixels of the image are grouped into clusters based on an examination of their

multispectral brightness values. Pixels grouped into the same cluster are similar with respect to their spectral properties. The Isodata algorithm was first applied to those pixels corresponding to snail habitat sites. The algorithm was used to split the pixels into 5 separate clusters. These 5 snail habitat clusters may correspond to different micro-habitats which are all suitable for snails. The Isodata algorithm was then run using the non-habitat sites to produce 5 non-habitat clusters. The spectral distributions for each of these 10 clusters were determined and used to perform the second part (i.e., supervised maximum likelihood classification) of this two-tiered analysis.

Results

The result of the preliminary supervised classification using all TM bands from the spring and fall images is presented in Table 1. For the 55 snail habitat sites, there was good classification accuracy, with 89.3% of the pixels being classified correctly. However, for the non-habitat sites there was a large number of misclassified pixels, with only 52.3% of the pixels being accurately classified as non-habitat. 3.4% of the pixels corresponding to snail habitat sites and 8.8% of the pixels corresponding to non-habitat sites were unclassified.

The result of the two-tiered classification is presented in Table 2. For the pixels corresponding to 55 snail habitat sites, 3.6% were unclassified. Of the remaining 96.4%, 90.3% of the pixels were correctly classified as snail habitat. For the pixels corresponding to 48 non-habitat sites, 4.2% were unclassified. Of the remaining 95.8%, 86.6% of the pixels were correctly classified as non-habitat. A classification matrix showing the percentages of each cluster for both types of habitat is presented in Table 3.

The resulting classification for the Anning Valley is shown in Figure 2. A 5 x 5 pixel mode filter was applied to the image for presentation. The mode filter is primarily used to clean up thematic maps for presentation purposes by it grouping together areas that are predominantly snail habitat or non-habitat. In particular, for each 5 x 5 pixel area, the predominant class is assigned to all pixels in the area.
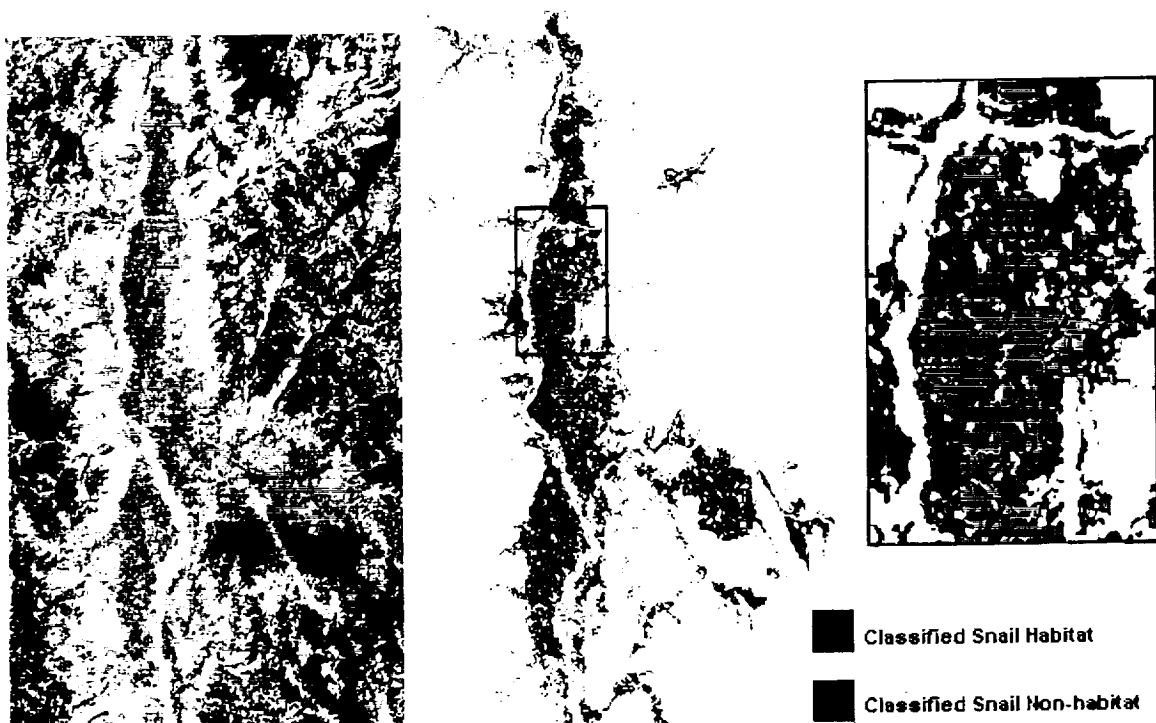
Figure 2: Three panels showing (from left) (a) Landsat TM of Anning river valley, (b) classification of habitat using Isodata and maximum likelihood algorithms, and (c) enlargement of valley floor showing mixed habitat.

Table 1: Results of Preliminary Maximum Likelihood Classification of Snail habitat and Non-habitat Sites.

	Total # Pixels	% Uncl. Pixels	% Classified as Snail habitat	% Classified as Non-habitat
48 Non-habitat Sites	432	8.8	38.9	52.3
55 Snail habitat Sites	495	3.4	89.3	7.3

Table 2: Results of Two-tiered analysis using Isodata and Maximum Likelihood Classification algorithms.

	Total # Pixels	% Uncl. Pixels	% Classified within Snail habitat Clusters	% Classified within Non-habitat Clusters
48 Non-habitat Sites	432	4.2	12.6	83
55 Snail habitat Sites	495	3.6	87.1	9.2

Table 3: Percentage of pixels classified by cluster for snail habitat and non-habitat sites.

			Snail habitat Clusters					Non-habitat Clusters				
	Total # Pixels	% Uncl. Pixels	% c1	% c2	% c3	% c4	% c5	% c6	% c7	% c8	% c9	% c10
48 Non-habitat Sites	432	4.2	6.9	3.7	0.2	1.6	0.2	28.9	9.0	18.3	11.8	15.0
55 Snail habitat Sites	495	3.6	31.3	23.6	8.5	17.6	6.1	4.8	0.0	4.0	0.0	0.4

Discussion

Despite the fact that we limited our analysis to only those sites that were in the irrigated farming areas located in the river plain, there was a great deal of variability within the snail habitat and non-habitat sites. This was observed visually in the field as well as in the distributions of the spectral data. Our preliminary classifications ignored this variability by lumping all of the habitat sites together and all of the non-habitat sites together to train the classification. As a result the snail habitat class included many of the non-snail sites, while the non-habitat class did not classify enough of the non-snail sites. This poor classification may be due to the existence of multiple micro-environments/habitats within the irrigated farming environment which each have distinct spectral properties. Hence, the terms "snail habitat" and "non-habitat" encompass distinctly different micro-environments which support, or do not support snails, respectively. Therefore, when either snail habitat or non-habitat is considered as a whole, it appears to be quite variable.

In the two-tiered approach, we solved the problem of multiple micro-environments by using the Isodata algorithm to effectively separate the highly variable habitats into "relatively pure", less variable clusters before performing supervised classification. This was not based on field observation, but rather, the spectral data was used to create these clusters. The choice to create five habitat clusters, and five non-habitat clusters is not explained in detail, because these numbers were chosen somewhat arbitrarily. However, the high classification accuracy indicates that such numbers are not unreasonable. It will not be hard to fine-tune the number of clusters by looking at the variability and separability between signatures.

In addition to refining the number of clusters, we are also working on reducing the number of bands used to only those that add information to the classification. Once we have reduced the classification down to the key bands, we hope to develop an understanding of what the clusters correspond to in the field.

Future Work

Validation Study

In our current work we assessed the accuracy of the classification only at the locations of the training sites. This may have resulted in artificially high accuracies. This summer we plan to revisit the Anning River valley to validate our two-tiered analysis with a rigorous field study. We intend to obtain spring and fall Landsat TM images from a more recent year than 1994 to repeat the two-tiered classification. This more recent classification would be validated in the field. In the past, however, we have had problems obtaining clear images for this region. If more recent images are not available, we will perform our validation based on our current classification of 1994 data.

Field sites will be chosen by randomly sampling single pixel locations within the classified image. The sampling will be stratified across image classes. (Recall in the

preliminary analysis that 5 image classes each were statistically attributable to snail and non-snail sites.) Each sampled pixel corresponds to geographical coordinates of a site where field data will be collected. Balancing sample size considerations with the practical implications of navigating in rice fields using GPS, approximately 100 sites will be visited (50 for snail habitat and 50 for non-habitat). At each site, a snail survey will be conducted in the surrounding 30 m × 30 m area according to the standardized sampling protocol employed in Sichuan. The snail survey data will be used to assess the accuracy of the classification map for overall misclassification, misclassification by class, and misclassification by site.

The work described thus far is useful in validating the model at the level of individual pixels. In many cases it is more useful to validate classifications at a much larger scale. Our eventual goal is to extend this work to monitoring potential snail habitat formation throughout the Three Gorges Dam area. This is a much larger area where policy makers assigning resources for control and research would require knowledge of the degree to which villages and townships have snail habitat. With this in mind, our second goal is to validate our classification at different regional levels. Since at a larger scale it is difficult to carry out field studies, we will rely on the knowledge from anti-endemic monitoring stations which routinely monitor snails with coarse surveys around villages of high endemicity. We propose to acquire aerial photographs of the Anning River valley. With the assistance of the regional anti-endemic agency, areas on the photographs will be mapped out which correspond to snail habitat and non-habitat. Estimates will be made on the amount of snail habitat within each area. These areas will be compared with corresponding areas in the Landsat classification map, and a similarity statistic will be computed. This statistic will not weigh heavily on individual pixel misclassifications, but will indicate whether or not the majority of the region is classified similarly by both methods.

Classification Using Remote Sensing Data and Supplemental Ecological Data

Once we have verified our classification approach we intend to study the degree to which additional ground data might improve the classification accuracy. According to SIPD (1995), the ecological correlates of *O. hupensis* snail habitat in Sichuan include the existence of certain vegetation types, size and density of irrigation ditches, proximity of agricultural field edges, wet lowland areas, and soil moisture, type and quality, and local temperature. Some of this information, such as soil type is readily available at a coarse scale across the Anning valley. Other kinds of information such as vegetation type and coverage will be collected during the randomized validation study. Local temperature variation is difficult to measure because of the size of the area. However, mean local temperature at several points throughout the valley should be available.

The aforementioned ground data is measured on several different scales, and with varying reliabilities. For example soil type is a nominal variable and percent vegetation coverage, a bounded, interval variable. Because traditional remote sensing image analysis algorithms such as the maximum likelihood classifier and minimum distance classifier

cannot be used to process nominal and ordinal data, we will analyze this additional ground data using several non-traditional techniques: CART (Breiman et al. 1984), logit regression (Chung et al. 1991), evidential reasoning (Wang et al. 1994; Gong 1996) and artificial neural algorithms (Gong 1996). Each of these algorithms can handle all the different levels of measurements and have proven useful in classification tasks where similar issues existed. In particular, when mapping 4 geological types in Northern Canada using Landsat TM data, gravity anomaly, Potassium radiometric and aeromagnetic data, Gong (1996) obtained high classification accuracies using evidential reasoning and neural networks. The data in that study had different spatial qualities, and all the data other than the remote sensing data are essentially point-based sample data. They had to be resampled through spatial interpolation in order for use with the Landsat TM data. When mapping 29 ecological classes in Alberta, Canada using forest species, crown closure and size and digital elevation data, (Gong 1996) assessed the potential of neural networks. Forest species data is of nominal measurement scale. The experience gained in these other studies will prove useful in this proposed analysis.

Developing an ecological interpretation of the classification algorithms is central to being able to extrapolate the use of the algorithm to different areas. From the perspective of the RS information, the key will be to develop a physically based interpretation of the classification data for identifying the underlying ecological factors being sensed. In order to accomplish this, we will address several potential problems. One problem is that the remote sensing data come from different areas, each subject to different surface properties and atmospheric irradiance. Since we will select images from clear sky conditions, we will employ a simple atmospheric correction algorithm developed for correcting the molecular and aerosol effects that dominate the clear sky condition (Forster 1984; Liang et al. 1997). Because the snail habitat areas used in this study are located in relatively flat areas, the effect of illumination variation and shadowing can be safely ignored. Another potential problem is that the spectral signal of a pixel in each band carries spectral contributions from various surface cover types within approximately a pixel. We will use multivariate piecewise regression algorithms to investigate the relationship between various surface cover conditions combined with the modification by surface topography and the spectral values from various snail habitat and non-snail habitat sample areas. Statistical regression algorithms will be useful in revealing the dominant factors that cause the spectral differences between snail habitat and non-habitat areas. The results from such quantitative studies will help verify and improve our understanding of the ecological conditions for the habitat of different snail subspecies. Furthermore, the analysis results will help us in developing snail habitat indicators based primarily on spectral properties and the derivatives such as landscape features obtained from remotely sensed data.

Other Image Sources and the Identification of Landscape Features Relating to Disease

The work described thus far has focused on locating snail habitat. There are locations where snails exist, however, no disease transmission occurs. It is unclear why this is the case. It is clear, however that on a local scale infection intensity and disease prevalence

are related to the relationships between people, animals, and snails, as they may be mediated by landscape features. These landscape features include crop type, the nature and density of irrigation in villages, and the proximity and density of settlements. In addition, topographical features such as slope and aspect determine the flow of water channels, which in may influence the transmission of disease. Therefore, it is of considerable interest to determine if topographical or landscape features that can be determined remotely are correlates of transmission, for such information would further inform remote surveillance programs for prioritizing locations within the Three Gorges region for intensive ground investigation. To investigate these questions, higher resolution images than those from Landsat TM would be necessary.

We propose to analyze the relationships between a variety of landscape features in areas of known snail habitat with the level of disease prevalence using both ground and RS data. Snail habitat and density will be predicted using data collected as part of the validation fieldwork described above. We intend to obtain prevalence data at approximately 20 villages throughout the valley where data is available from the local anti-endemic authority. Landscape features, such as crop type, the nature and density of irrigation in villages, proximity and density of settlements, and topographic slope and aspect will then be analyzed to investigate the relationship of these landscape features to estimates of disease prevalence treated as a continuous variable.

After determining the degree to which different landscape and topographical features relate to disease prevalence, we will then evaluate how remote sensing techniques can be used to identify these features. Without using remote sensing, landscape features such as the structure, location and density of human settlements, locations of roads and even details of irrigation are obtainable in a variety of ways. For established areas, good maps are usually available and these can be digitized. But for working on a regional scale, map-based information is labor intensive to obtain and prone to errors at several stages during digitization. In the new settlements within the Three Gorges area such information will not be available for some time. Locations of settlements can be obtained with a GPS in the same way that habitat sites are located, or they could be identified from imagery. Detailed landscape information such as the proximity of field edges or density of irrigation ditches is more difficult to obtain. Such data is problematic for this study and its inclusion will depend upon the ease of obtaining the data.

As an example, ditch density estimates can be obtained in several ways. An estimate at a village scale can be obtained from the anti-endemic authority during the field studies. A more objective estimate could be obtained by digitizing maps from the local Irrigation Bureau and spatially aggregating the information to add them to the analysis. The average density of irrigation ditches of various widths could be calculated at spatial aggregates comparable to the size of the 3 × 3 pixel (90 m × 90 m) aggregates used in the original classification described above. Because of the labor involved in working with detailed maps on this scale, this is the least attractive method.

Presently there are two types of satellite imagery that can be used for obtaining topographical features: 10 m resolution SPOT HRV-PAN imagery and 6.25 m IRS-1D imagery (resampled to 5 m). With these high resolution satellite data, we can obtain topographic features through automatic processing of stereo pairs of these images (images taken from different view angles of the same region). This is accomplished by digital photogrammetry (Saleh et al. 1994). Digital photogrammetry is a promising tool for mapping plain and valley bottom areas that are of interest to this study. Such capability has been developed rapidly for 10-20 years and now is mature enough to extract digital surface elevation from aerial photographs and satellite imagery. With digital photogrammetry applied to high resolution stereo-imagery, one can extract both the horizontal and vertical coordinates for any point in either stereo image producing a highly accurate three-dimensional digital surface model (DSM). Our previous experience with monitoring the change of hardwood rangeland in California indicates that better than 2-3 m accuracies in both the horizontal and vertical directions are possible with 1 m resolution imagery (Lee 1997; Mostafa et al. 1997). From a DSM landscape features like slope, aspect , and concaveness or convexity of areas are easily extracted. At Berkeley, we have expertise in digital photogrammetry and the necessary professional software packages for processing this data (e.g., virtuoZo from Jetway Inc., and OrthEngine from PCI Inc.).

In the next couple of years, we will have available, not only improved spectral imaging capabilities such as the MODIS with 36 spectral bands, but also improved spatial resolution from commercial satellites, such as the approximate 1 m resolution capabilities of Space Imaging and Earth Watch. Both improved spectral imaging and higher resolution data will allow us to better identify landscape features. With 1-5 m resolution satellite data, ditches of varying widths and types, edges of agricultural fields, coverage of vegetation, surface roughness, land-cover and land-use patterns and the exact spread of villages can all be extracted with improved accuracy. In particular, we will explore the use of linear feature extraction algorithms and the gradient profile modeling algorithm (Wang 1993). The gradient profile modeling algorithm has been used successfully in drainage and road network extraction (Gong et al. 1997) with remote sensing imagery of different spatial resolution varying from 1.6 m to 30 m.

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