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Exposure assessment using high spatial resolution hyperspectral (HSRH) imagery

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Abstract. This special issue reports the findings of a specialist workshop held in the summer of 2000, in Ann Arbor, Michigan. This introduction provides background information on HSRH imagery, briefly describes the major ways in which remote sensing data have been used previously for exposure assessment, presents the salient findings of the workshop, and places the papers resulting from the workshop within the context of these findings. It concludes with a description of a ground-truthed, HSRH data set that was used by several of the researchers to evaluate and compare their methods.

Key words: Hyperspectral imagery, spatial analysis, exposure assessment, resolution

JEL classification: I10, C89, C00

1 Introduction

This special issue of the Journal of Geographical Systems seeks to provide a framework for the use and application of high spatial resolution hyperspectral (HSRH) imagery in exposure assessment. Despite the potential benefits expected from data with increased spatial and spectral precision, to date HSRH imagery has seldom been applied to assess human health risks for infectious diseases or to environmental hazards and toxic materials. In part, this lack of application can be explained by the newness of the technology – researchers are unfamiliar with the data product and are not

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sure of how to use it in their studies. HSRH imagery can be very different from its lower resolution counterparts, and it requires new approaches to collecting data; new methods and analysis tools suited to the extraordinary size of the images; as well as new ways of thinking that exploit both the spatial and spectral dimensions. Although the techniques classically used for data collection and analysis of lower-resolution remote sensing imagery can be used for HSRH imagery, these standard approaches do not adequately address either the challenges or the potentials created by this remarkable new technology.

2 Changes in remote sensing technology

Remote sensing devices carried on satellites (e.g. Landsat) and airplanes (e.g. AVIRIS) may be classified based on their spatial and spectral resolution. We define high spatial resolution images as having resolutions of less than 5 m, an order of magnitude improvement over historical satellite imagery, which resolves pixels at scales of 10–80 m. Fourteen high spatial resolution satellites should be launched over the next 3 years, 9 of which will be commercially owned and operated (Ustin and Costick 2000).

The new generation of high resolution satellites such as IKONOS can produce images of the earth's surface at ground resolutions as small as 1 m. At 1 m resolution, cars can be differentiated from trucks, individual houses can be identified, and previously inaccessible areas of the earth's surface can be mapped in detail for the first time in history. Not only does this allow better resolution of features on the ground, but it will also create an exponential growth in the size of data sets that requires a revolution in the handling and analysis of spatial information.

Just as high spatial resolution data remarkably enhance our ability to differentiate features based on variations in shape and texture, so hyperspectral data provide order of magnitude improvements in our ability to differentiate features that reflect or emit radiation at slightly different wavelengths. We define hyperspectral imagery as having data for 64 or more bands of electromagnetic radiation for each pixel, with each band representing the reflected or emitted light over a narrow spectral region. The number of spectral bands recorded on existing multiband satellite sensors is generally 4–8, a much lower number than the 64–256 bands recorded by the 5 hyperspectral satellites planned for launch over the next few years.

Hyperspectral data are radically different from multiband data. A single band of multiband data senses across a large range of spectral reflectance (e.g. all green light) and therefore picks up signals from a variety of objects that reflect in that range (e.g. most vegetation). This spectral resolution makes it difficult to impossible to identify specific features (e.g. individual species) in a given pixel. In contrast, the large number of narrow bandwidths in hyperspectral data allows accurate classification of objects by detecting subtle differences measured across narrow spectral ranges. Furthermore, if data exist on the reflectance properties of a specific feature, then a pixel can sometimes be spectrally "unmixed" to sense objects that make up as little as 2–4% of the total pixel area (see Aspinall et al. 2002 in this special issue for an overview of spectral analysis techniques).

We are at the beginning of the high spatial resolution, hyperspectral world. Historically, both high spatial resolution and hyperspectral data have only been collected from airplanes and coverage was limited to areas and dates accessible to aircraft. With 14 high spatial resolution satellites and 5 hyperspectral satellites (3 of which are high spatial resolution), there will be global coverage available. We thus stand on the cusp of a new age defined by high resolution, hyperspectral data of extraordinary accuracy and precision. The widespread availability of these data will radically change how we document, monitor, and model our environment and has profound implications for exposure assessment.

To afford a framework for understanding these implications, this introduction provides a brief overview of how remote sensing has been used in the past for exposure assessment. We then identify expected benefits of the new HSRH imagery and the means to realize those benefits as identified by participants at the workshop.

3 Previous applications of remote sensing to exposure assessment

3.1 Remote sensing, habitat identification, and vector-borne diseases

Remote sensing plays an important role in environmental exposure assessment at both regional and local scales (see Kitron 1998 and the papers in Hay et al. 2000 for the current state of the art). Spatial analysis of satellite images supports classification of vegetation and forest types to identify habitats suitable for the vectors of Lyme, Malaria, onchocerciasis, Lacrosse encephalitis and other diseases (Richards 1993; Kitron et al. 1994, 1997; Kitron 1997). Such analyses have led directly to health interventions to eradicate the vector and/or disrupt its life cycle, including but not limited to habitat modification, targeting of preventative treatment programs, and pesticide applications.

The classification and improved understanding of habitat types and habitat changes also contributes to the analysis and assessment of emerging diseases. Classification and spatial analysis of vegetation and soil types using existing multiband remotely sensed images presently supports habitat quantification and assessment of change due to anthropogenic activities, climatic variability, and climate change (reviewed in Beck et al. 2000). For example, two research projects on hantavirus (Boone et al. 2000, Glass et al. 2000) used Landsat Thematic Mapper imagery along with field samples and other data to track risk factors for hantavirus pulmonary syndrome.

3.2 Remote sensing and contaminant exposure

Remote sensing technology has been used in the past to document contaminants associated with mining and agriculture. Airborne hyperspectral imaging is currently used by the mining industry to guide exploration, leveraging its ability to identify rock types and soil mineral content. Hyperspectral technology is also already used to assess potential exposure to heavy metals. Using AVIRIS data (224 bands, 20 m pixel), the USGS mapped assemblages of acid-generating minerals at the California Gulch superfund site in Leadville, Colorado (Swayze et al. 1996). These assemblages are associated with different heavy metals and provide a tool for documenting potential for exposure to contaminants: for example, oxidation of the pyritic assemblage found by Swayze et al. (1996) releases lead, arsenic, cadmium, silver and zinc.

Remote sensing and image classification resolves crop types and are already used for assessing pesticide exposure (Pers. Comm. J. Nuckols), which is strongly associated with agricultural practices and crop types. For example, the US incidence of non-Hodgkin's lymphoma (NHL) has increased markedly in the last 25 years (Ward et al. 1996) due in part, but not entirely, to exposure to agricultural pesticides (Zahm et al. 1993).

3.3 The workshop

It was in the context of rapidly changing remote sensing technology and present uses of remote sensing for exposure assessment that BioMedware, with funding from the NIEHS, convened a meeting in August, 2000 of some of the nation's top experts in risk assessment, environmental analysis, geographic information science, and spatial analysis (Table 1). The goal of this meeting was to identify problems and opportunities in risk assessment using high-spatial resolution hyperspectral imagery. Over the course of 2 days, these specialists identified significant opportunities as well as the obstacles that must be overcome (see http://www.biomedware.com/pages/HRH_conference/hrhagenda.html for the meeting agenda). The specialists addressed the following topic areas in HSRH image analysis:

- techniques needed to identify environmental hazards and their locations;
- spatial methods to quantify heterogeneity, patches, and patterns;
- statistical techniques for assessing significance of spatial patterns;
- spatial modeling techniques for assessing exposure;
- prototype applications expected to identify unique benefits of HSRH imagery in exposure assessment.

We've organized this special issue around three topic areas identified by the specialists as bearing special merit. These are:

1. *HSRH data collection and image processing requires new approaches*. Collecting ground truth data and processing HSRH imagery is not remote sensing "business as usual." These data sets are unique for many reasons not limited to their extraordinary size and resolution.
2. *HSRH has the potential to significantly enhance environmental mapping and modeling applications for exposure assessment*. HSRH imagery is expected to make unique contributions that will significantly advance our understanding of health-environment relationships. These contributions will arise from our enhanced ability to map the landscape and conduct change analysis and from the results of modeling using these rich data sets.
3. *HSRH analysis and modeling require new, spatially explicit tools*. To realize these contributions requires new, spatially explicit techniques that exploit the high spatial and spectral resolution of the images. One of the

Table 1. Participants in the August, 2000 BioMedware workshop on high resolution hyperspectral imagery in exposure assessment

Expert	Title and affiliation	Expertise
Richard Aspinall, Ph.D.	Professor & Director, Geographic Information and Analysis Center, Montana State University	GIS, spatial analysis, error propagation and uncertainty assessment.
Dan Brown, Ph.D.	Associate Professor, School of Natural Resources & Environment, Univ. of Michigan	Image analysis, remote sensing, pattern detection on multispectral images
Leah Estberg, DVM, Ph.D.	Senior Scientist, BioMedware, Inc.	Epidemiology, cluster surveillance
Pierre Goovaerts, Ph.D.	Assistant Professor, Dept. of Civil & Environ. Engineering, University of Michigan	Geostatistics, stochastic simulation; environmental modeling
Dunrie Greiling, Ph.D.	Research Associate, BioMedware Inc.	GIS, invasive species
Dan Griffith, Ph.D.	Professor, Department of Geography, Syracuse University	Spatial autocorrelation modeling of very large data sets
Geoff Jacquez, Ph.D.	President, BioMedware, Inc.	GIS and health, spatial analysis
Uriel Kitron, Ph.D.	Professor and Chair, Division of Epidemiology and Preventive Medicine, University of Illinois	Spatial analysis of vector-borne diseases; using remote sensing, GPS, and GIS
Francesco Lagona, Ph.D.	Assistant Professor, University Roma Tre, Dept. of Social Sciences	Spatial statistics, environmental statistics, multivariate analysis
Richard Levenson, M.D.	Technical Director, Biomedical Systems, Cambridge Research and Instrumentation, Ltd.	Biomedical hyperspectral imaging
W. A. Marcus, Ph.D.	Associate Professor, Department of Geography, University of Oregon	Remote sensing & assessment of trace metal fate using hyperspectral imagery.
Susan Maruca, M.S.	Senior Research Associate, BioMedware, Inc.	Spatial analysis, boundary analysis, statistical algorithms
Jignesh Patel, Ph.D.	Assistant Professor, Department of Computer Science, The University of Michigan	Computer Science; design of RDBMS for large, multivariate, spatial databases.
Mark Wilson, Ph.D.	Professor, Departments of Biology and Epidemiology, The University of Michigan	Exposure assessment from remotely sensed images; spatial epidemiology

opportunities deemed most significant is the use of high spatial resolution to identify local-scale variation in variables directly related to risk.

In the following sections we briefly describe each of these themes and outline how papers in this special issue relate to each.

4 New procedures for data collection, handling and processing

The collection and processing of HSRH ground-truth and image data requires users to address a number of issues that are familiar to remote sensing researchers, ranging from collection of appropriate ground truth data to calibration and removal of error from the imagery to validation of classification results. At the same time, however, the data collection and image processing for HSRH mapping and analysis are substantially different. There is the obstacle of having to store, process and deliver data volumes several orders of magnitude larger than would be required for coarse resolution, multispectral data of the same geographic area. Beyond this obvious obstacle, however, lie a number of less obvious problems that result from: the difficulty of acquiring HSRH data; the geometric and calibration constraints imposed by the fine spatial and spectral resolution of the data; and problems in applying classical validation techniques when the imagery may map the environment with greater accuracy than can be obtained by field crews. Investigators looking to use HSRH data therefore need to be aware that the field investigations and subsequent data processing may be significantly different from “business as usual.”

In this issue, Aspinall et al. (2002) provide an overview of key considerations in working with HSRH data collection and processing. They point out that even the acquisition of HSRH imagery is hindered by the small number of sensors that are presently available, by the intense competition for their services, by cost, and by the difficulties involved in coordinating brief periods of sensor availability with weather, field teams, and environmental conditions (e.g., vegetative stage) required for the analysis. As we write this, there are very few commercial hyperspectral sensors available for hire. In contrast, 10–80 m resolution multispectral data for many parts of the world are available via the internet.

If HSRH data are available, the user should be aware that hyperspectral sensors collect light from very narrow bandwidths, which means that the amount of energy reaching the sensors is very small. This light generates variations in voltage that are measured by the instrument and recorded as a reflectance signal. Because the voltage variations are so small, the instruments must be sensitive to exceedingly small variations in voltage, which in turn means that tiny electrical surges or miscalibrations can cause the recorded data to be significantly in error. Instrument operators and data users alike therefore must pay close attention to instrument calibration.

Once HSRH imagery is acquired, its fine spatial resolution makes coregistration of field data and imagery exceedingly difficult. When pixels are as small as 1 m, then an error of only 0.5 m in field coordinates can lead to incorrect overlays of image data on to field data (e.g., incorrectly overlaying a several meter square wetland site where mosquitoes might breed onto an adjacent rock face pixel). Incorrect coregistration of this type leads to mis-identification of features on the ground and negates much of the potential of HSRH imagery. The need for high precision coregistration suggests that alternative approaches to coregistering imagery and field maps should be developed and used, an issue discussed by Aspinall (2002), Aspinall et al. (2002) and Marcus (2002) in this issue.

Assuming that HSRH data are available and that field data can be coregistered to the image, then atmospheric corrections may be necessary, depending on the application. This is a procedure enabled by the many spectral bands, some of which cover the atmospheric absorption wavelengths and thus provide a basis for estimating atmospheric moisture content and subsequent attenuation of light reaching the sensor (see Aspinall 2002 and Aspinall et al. 2002, in this issue).

Finally, field teams may not be able to map environmental features with the same detail provided by HSRH imagery, at least not in a way that allows the field map and imagery to be precisely coregistered. This raises the thorny problem of how to verify image-based classifications and maps, since the images may be more accurate over broad areas than a ground-based field map ever could be. In this volume, Aspinall and Marcus discuss how this dilemma poses a serious challenge to accepted methods for accuracy assessment and suggest that new approaches are required for evaluating HSRH maps and modeling results.

5 Potential for new contributions to mapping and exposure analysis

Workshop participants identified a wide range of new contributions to exposure assessment and the environmental health sciences that might arise from HSRH image analysis. The variety of thinking on how HSRH data might contribute to exposure assessment is captured in two overview perspectives presented in this special issue. Wilson (2002) presents the perspective of an infectious disease epidemiologist and ecologist, and describes how the potential for the spread and resurgence of emerging and vector-borne diseases may be elucidated from high spatial resolution and hyperspectral imagery. He also speculates on how forecasts such as risk maps might be improved using the new imagery. Aspinall (2002) writes on how the framework being formulated by the University Consortium for Geographic Information Science provides a structure for working with HSRH imagery. This structure includes thoughts on ways to make the imagery accessible to other researcher and stakeholders, suggested improvements in image processing, and recommendations on research required to advance hyper-spectral analysis beyond the status quo procedures used for multispectral imagery.

At a more specific level, workshop participants focused on two major contributions that they expect to arise out HSRH imagery: improved mapping and innovative analysis and modeling. The rationale for focusing on these themes and the papers associated with them are discussed in the following sections.

5.1 Improved habitat mapping

It was clear to all workshop participants that improved mapping is one of the major contributions that will derive from HSRH imagery. Although previous research has demonstrated potential applications and benefits of remote sensing imagery in exposure assessment, the coarse spatial resolution of these instruments has precluded documentation of fine spatial scale variability. And exposure, of course, occurs on both regional and local spatial scales, with many of the biotic interactions that mediate vector-borne and infectious diseases occurring at scales of less than 10 m. For vector-borne diseases, local variation in habitat suitability is driven by microclimate and by small-scale differences in soil and vegetation; vectors are small and experience the world on local scales. High spatial resolution data thus has the potential to significantly enhance our understanding of how these microscale processes relate to exposure and the spread of diseases.

For example, recent advances in our ability to identify pathogens, infectious agents and their vectors at the molecular level; and to identify the immunological basis of host response, have substantially enhanced our understanding of the transmission and epidemiology of infectious diseases. But how these factors relate to spatial variability in biotic and ecological systems is still only poorly understood. While low spatial resolution, multispectral images quantify broad-scale spatial variation in biotic systems, they cannot document microhabitat characteristics at the 10 m scale or smaller, a problem solved by the new high resolution technology.

Similarly, much of the spatial heterogeneity in non-biological exposures occurs locally. Consider heavy metals. Large variability in stream sediment heavy metal content is found at fine spatial scales, with up to 50% variation in mean values occurring at distances of only 1–5 m in both rural (Ladd et al. 1998) and urban (Rhoads and Cahill 1999) settings. In terrestrial settings, metal concentrations in soils can vary by 3 orders of magnitude over distances of 2 m or less (Stoughton and Marcus 2000). An understanding of both regional and small scale variability in environmental hazards is thus essential for exposure assessment. High spatial resolution imagery provides the capability to fully document both regional and small scale variability that is so critical for exposure assessment.

High spatial resolution alone, however, may not provide sufficient resolving capability in many circumstances. Hyperspectral resolution supports detailed classification of habitat variation that simply is not possible with 8 or fewer bands. For example, Wright et al. (2000) found that 1-m, 4-band imagery was incapable of distinguishing microhabitats such as riffles and pools in which metals preferentially are deposited. Similarly, Marcus et al. (in press) could not distinguish woody debris, a key microhabitat in riparian areas, from other vegetation and substrate, even though they had 1-m multiband imagery. In both cases, high spatial resolution alone was not enough to classify the key habitats of interest and the authors felt that improved spectral resolution would have provided better results.

In this issue, Marcus (2002) tests the ability of 1-m resolution hyperspectral imagery to map stream microhabitats. He finds that the combination of high spatial and high spectral resolution significantly exceeds the performance of multispectral, 1-m resolution data and, in fact, may map the stream habitats with greater accuracy than the field teams that were on the ground. The Marcus paper also provides an example of classical, spectrally-based analysis that can be compared to the results from new, spatially driven algorithms using data from the same study area and presented by Goovaerts (2002), Griffith (2002), Lagona (2002), and Maruca and Jacquez (2002) in this volume.

5.2 Analysis and modeling

HSRH data will tremendously enhance our ability to model spatial systems and to analyze cause and effect relationships by providing accurate mapping of sources and driving factors at local spatial scales; by enabling investigators to statistically explore and link the complex web of local to regional scale phenomena controlling exposure; and by providing powerful data bases that can drive spatial and temporal modeling of exposure at multiple scales. For example, the ability to identify homogeneous patches in 'real time' will support the construction and validation of predictive spatial models such as those used in compartmental analysis (Jacquez 1999). In addition, the ability to identify geographic boundaries at local scales should allow us to better relate fine-scale spatial processes to their environmental outcomes. Finally, frequent flyovers will make possible accurate assessment of environmental change, allowing us to monitor and model time-dependent environmental exposures with unprecedented frequency, accuracy and on unprecedented spatial scales. The potential contributions from modeling and analysis are evaluated by Wilson (2002) and Aspinall (2002) in their overviews of potential HSRH applications and by other authors in this issue who look at new, spatially explicit modeling approaches, as is discussed below.

6 New analysis tools: Spatially explicit techniques

All natural and anthropogenic processes are imbedded in geographic space. The need for spatially explicit techniques is clear whenever the spatial resolution of the data is sufficient to resolve spatial and spatio-temporal patterns that emerge from the underlying processes. It thus seems reasonable to expect that spatially explicit analysis techniques, when applied to HSRH imagery, might help identify local- as well as large-scale features important to infectious disease and hazardous material exposure assessment, including but not limited to vector microhabitat and the spatial distribution of surface heavy metal assemblages. These methods will need to exploit both the spectral and spatial dimensions of the data, and are expected to include new techniques for spatially explicit classification, pattern recognition, field-object transformation, field-based modeling, multivariate autoregressive techniques, improved geostatistical methods, and novel approaches of Exploratory Spatial Data Analysis that support inferential statistics. Although many of these techniques already exist, their application in the context of massive HSRH data sets requires new algorithms and software. Two categories of approaches to this problem are represented in this special issue.

The first category of approaches extends existing spatial analysis methods such as geostatistics, autoregressive modeling, and inferential statistics to large multivariate raster data sets. In this issue Goovaerts (2002) incorporates spatial coordinates into supervised classification using geostatistics. This novel application of the geostatistical paradigm uses spatial dependencies, as modeled by the semivariogram, to construct landscape classifications that incorporate location-based information. He compares and contrasts spectral-only classifications, spectral and spatial-based classifications and primarily spatial classifications. Griffith (2002) approaches the problem from the tradition of spatial autoregressive models. He develops techniques for modeling spatial dependence in high spatial resolution hyperspectral datasets. This problem is non-trivial because of the enormous size of the images, and Griffith develops a novel approach for estimating autoregressive parameters. Lagona (2002) relies on the field-based formulation and the representation of large imagery as Markov random fields. To incorporate spatial relationships he presents techniques for specifying adjacencies in very large Markov random fields. Rogerson (2002) is concerned with the detection of change on very large images. Given two HSRH images, one taken at t and the other at time $t + \Delta t$, how does one detect changes in the images or in the features detected on those images? Here change may be defined as (1) a change in the value of a pixel's set of attributes, (2) change in a pixel's class, (assuming classification has been accomplished) or (3) change in the spatial arrangement of the classes. Rogerson is concerned with specifying change detection thresholds that may be used to make probabilistic statements regarding the extent of change. To varying extents, these papers build on existing traditions of spatial analysis such as geostatistics, autoregressive modeling and change detection.

The second approach seeks to create new methods specifically suited to HSRH imagery. This requires computationally fast techniques founded on constructs from Geographic Information Science such as field-object transforms to accomplish both data reduction and pattern recognition simultaneously. This new way of thinking about this problem is represented in this issue by Maruca and Jacquez (2002), who present statistical tests for assessing the correspondence between two spatial segmentations. For hyperspectral imagery, one segmentation might be a spatially explicit landscape classification, while the second might be ground-truthed landscape classes. After developing the technique, Maruca and Jacquez apply it to the Yellowstone imagery data to determine whether stream microhabitats (e.g. riffles, eddy drop zones) can be mapped effectively with the new algorithm.

7 The test data

In this special issue, papers by Goovaerts (2002), Griffith (2002), Lagona (2002), Marcus (2002), and Maruca and Jacquez (2002) use data collected as part of a Yellowstone Ecosystem Studies project funded through the NASA EOCAP (Earth Observing Commercial Applications Program) program of Stennis Space Flight Center, Mississippi. In addition, many of the comments on the collection, processing and use of HSRH data in this overview article and in the articles by Aspinall (2002) and Aspinall et al. (2002) derive from lessons learned from collecting and working with the Yellowstone data set.

The Yellowstone HSRH data were collected in August of 1999 using procedures described in detail by Marcus et al. (2000). The data were collected using the Probe1 sensor, which is a commercially available imaging spectrometer owned by Earth Search Systems, Inc. and built by Integrated Spectronics of Sydney Australia. Probe1 is a 128-spectral channel cross track scanner with four 32-element linear detector arrays (one Si and three InSb). Liquid nitrogen is used to cool the InSb detectors. There are four dispersive grating spectrometers that cover the 0.4–2.5 μm range, with gaps at 1.4 and 1.9 μm in channels of approximately 15 nm width. Images are 512 pixels wide, with the image length determined by the length of the flight line. The 5 m resolution data used by Griffith (2002) and Lagona (2002) in this volume

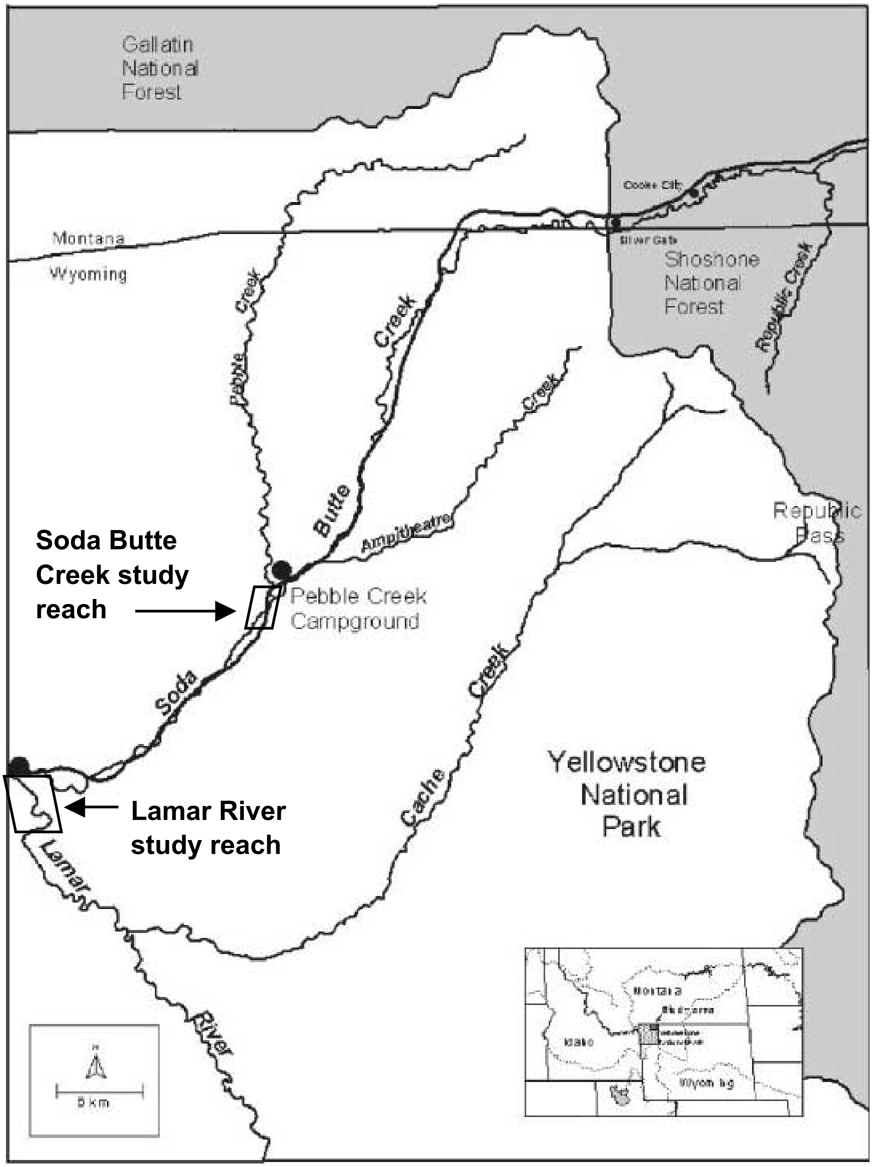

Fig. 1. Locations where HSRH imagery used in this special issue were collected in August, 1999. Maruca and Jacquez (2002) use 1 m data from the Soda Butte Creek study reach. Goovaerts (2002) and Marcus (2002) use 1 m imagery and Griffith (2002) and Lagona (2002) use 5 m imagery from the Lamar River reach

was collected with the Probe1 operated on a stabilized camera mount in a twin engine Cessna 320. The 1-m data used by Goovaerts (2002), Marcus (2002), and Maruca and Jacquez (2002) was collected by mounting the Probe1 on an A-Star Aerospatiale helicopter which was flown at slow speed at low elevations. The instrument suffered a number of operation problems as a result of being deployed on the non-standard helicopter platform, some of which are described in this volume by Aspinall et al. (2002). Readers should contact the authors of this volume before undertaking helicopter-based HSRH data collection.

The Yellowstone data were collected as part of a study evaluating the potential of HSRH imagery for mapping of in-stream and riparian habitats (Marcus et al. 2000). Data were collected over the Lamar River and Soda Butte Creek within Yellowstone National Park (Fig. 1). At the time of the overflights, both streams had clear conditions. Bed sediments in the channels range from gravels to small cobbles and depths range up to 1.6 m. Channel widths range from approx. 5–50 m. A variety of in-stream habitats are present as described by Ladd et al. (1998) and Marcus (2002).

One meter imagery was collected over cloud-free portions of the streams on August 3, 1999 and 5 m imagery was collected on August 25, 1999. Imagery was downloaded and printed out as true color images within 3–24 h of the over flights. Ground truth teams mapped key features directly to the high spatial resolution print outs, insuring precise coregistration of field maps and image data. These field maps were later digitized as point and vector layers that could be overlaid onto the imagery for training and ground truthing purposes.

8 Order of papers

The papers are loosely organized thematically. We begin with Aspinall, Marcus and Boardman (2002), who focus on point (1), that HSRH data collection and image processing require new approaches. Given our focus on exposure assessment, we then follow with Wilson (2002), who addresses point (2), that HSRH data has the potential to significantly enhance environmental mapping and modeling applications for exposure assessment. The bulk of the papers focus on point (3), that HSRH analysis and modeling require new, spatially explicit tools. Drawing on a variety of disciplines, almost all of these develop applications using the Yellowstone data set. We close with an overview from a GIScience perspective that provides a research agenda for the future of HSRH imagery in exposure assessment (Aspinall 2002).

References

Aspinall RJ, Marcus WA, Boardman J (2002) Considerations in collecting, processing, and analyzing high spatial resolution and hyperspectral images in analyses and forcasts. (In this issue). *Journal of Geographical Systems* 4:15–29

Aspinall RJ (2002) A geographic information science perspective on hyperspectral remote sensing. (In this issue). *Journal of Geographical Systems* 4:127–140

Beck LR, Lobitz BM, Wood BL (2000) Remote sensing and human health: New sensors and new opportunities. *Emerging Infectious Diseases* 6:217–226
Boone JD et al (2000) Remote sensing and geographic information systems: Charting Sin Nombre virus infections in Deer mice. *Emerging Infectious Diseases* 6:248–258
Glass GE et al (2000) Using remotely sensed data to identify areas at risk for Hantavirus pulmonary syndrome. *Emerging Infectious Diseases* 6:238–247
Goovaerts P (2002) Geostatistical incorporation of spatial coordinates into supervised classification of hyperspectral data. (In this issue). *Journal of Geographical Systems* 4:99–111
Griffith D (2002) Modeling spatial dependence in high spatial resolution hyperspectral datasets. (In this issue). *Journal of Geographical Systems* 4:43–51
Hay SI, Randolph SE, Rogers DJ (Eds) Remote sensing and geographical information systems in epidemiology, *Advances in Parasitology*, Vol 47, Academic Press. 351 pp
Jacquez JA (1999) Modeling with compartments. Ann Arbor, MI, BioMedware Press
Kitron U (1997) Spatial analysis of the distribution of Lyme disease in Wisconsin. *American Journal Epidemiology* 145(6):558–566
Kitron U (1998) Spatial tools (GIS, GPS, remote sensing and spatial statistics) for landscape ecology and epidemiology of vector-borne diseases. *J Med Entomology* 35:435–445
Kitron U, Pener H et al (1994) Geographic information system in malaria surveillance: mosquito breeding and imported cases in Israel, 1992. *Am J Tropical Med Hygiene* 50:550–556
Kitron U, Michael J et al (1997) Spatial analysis of the distribution of LaCrosse encephalitis in Illinois. *Am J Tropical Med Hygiene* 57:469–475
Lagona T (2002) Adjacency selection in Markov random fields for high spatial resolution hyperspectral data. (In this issue). *Journal of Geographical Systems* 4:53–68
Ladd S, Marcus WA, Cherry S (1998) Trace metal segregation within morphologic units. *Environ Geol Water Sci* 27:1–12
Marcus WA (2002) Mapping of stream microhabitats with high spatial resolution hyperspectral imagery. (In this issue). *Journal of Geographical Systems* 4:113–126
Marcus WA, Crabtree R, Aspinall RJ, Boardman JW, Despain D, Minshall W, Peel J (2000) *Validation of high-resolution hyperspectral data for stream and riparian habitat analysis*. NASA EOCAP Final Phase 2 Annual Report. Stennis Space Flight Center, MS 128 p
Marcus WA, Marston RA, Colvard CR, Jr, Gray RD (2002) Mapping the spatial and temporal distributions of large woody debris in rivers of the Greater Yellowstone Ecosystem, U.S.A. *Geomorphology* (in press)
Maruca SL, Jacquez GM (2002) Area-based tests for association between spatial patterns. (In this issue). *Journal of Geographical Systems* 4:69–83
Richards FO (1993) Uses of geographic information systems in control programs for onchocerciasis in Guatemala. *Bull Pan Am Health Organization* 27:52–55
Rhoads BL, Cahill, R (1999) Geomorphological assessment of sediment contamination in an urban stream system. *Applied Geochem* 14:459–483
Rogerson P (2002) Change detection thresholds for remotely sensed images. (In this issue). *Journal of Geographical Systems* 4:85–97
Stoughton J, Marcus WA (2000) The persistent impacts of trace metals from mining on grass communities along Soda Butte Creek, Yellowstone National Park. *Environ Management* 25:305–320
Swayze GA, Clark RN et al (1996) Mapping acid-generating minerals at the California gulch superfund site in Leadville, Colorado using imaging spectroscopy. *6th Annual JPL Airborne Earth Science Workshop*, USGS.
Ustin SL, Costick L (2000) Multispectral remote sensing over semi-arid landscapes for resource managment. In: Hill MJ, Aspinall RJ (eds) *Spatial information for land use management*. Gordon and Breach. Chapt 7
Ward MH, Mark SD et al (1996) Drinking water nitrate and the risk of non-Hodgkin's lymphoma. *Epidemiology* 7(5):465–471
Wilson M (2002) Emerging and vector-borne diseases: role of high spatial resolution and hyperspectral images in analyses and forecasts. (In this issue). *Journal of Geographical Systems* 4:31–42

Wright A, Marcus WA, Aspinall RJ (2000) Evaluation of multispectral, fine scale digital imagery as a tool for mapping stream morphology. *Geomorphology* 33:107–120

Zahm SH, Weisenburger DD et al (1993) The role of agricultural pesticide use in the development of non-hodgkin's lymphoma in women. *Arch Environ Health* 48(5):353–358