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Translation of remote sensing data into weed management decisions

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Remote sensing and associated spatial technologies provide tremendous opportunity to enhance weed management and improve–protect the environment through judicious use of the most efficacious control methods for a given site. They can also be invaluable assets for detection of invasions, assessment of infestation levels, monitoring rate of spread, and determining the efficacy of mitigation efforts for weed management. In combination with other technologies such as global positioning systems and geographic information systems, sampling strategies can be devised to efficiently determine the location of weed populations in agricultural and wildland situations. Maps created from remote sensing or sampling (or both) allow site-specific weed management of only the areas requiring corrective action. Potential benefits to the land managers and the ecosystem as a whole will come from reductions in inputs, reduced environmental liability from the detrimental effects of applying control measures to entire areas, crop yield increases through better management decisions, and early detection and effective management of invading species. Improvements in spatial and spectral resolution, temporal frequency, image turnaround time, and cost of image acquisition, combined with the realization of the value of the data, are enhancing the acceptance and usage of remote sensing technologies. However, remote sensing will be best used by providing accurate, site-specific data that can be converted into information used by decision support systems (DSSs). Advances in these DSSs, and their ability to incorporate remote sensing data, have been rapid and widespread in the past 10 yr. As a result, federal management and research agencies, academic institutions, and private entities have collectively developed efforts to use this information in monitoring and management efforts for invasive species in western rangelands, aquatic ecosystems and forestry, and site-specific weed management in agronomics.

Key words: Decision support systems, invasive species, spatial technologies.

Remote sensing technologies are powerful tools made stronger when integrated into agronomic and natural resource management decision making. Remote sensing data come in a variety of forms, from ground-based sensors mounted on tractors or other equipment, to aerial imaging systems, to data collected from satellite platforms. For the purposes of this article, however, ground-based remote sensing will not be a part of the discussion. Remote sensing offers many new capabilities in a wide variety of applications, including environmental monitoring, site-specific management (SSM), and detection of changes in land cover, vegetation stress, and land use patterns. The ability to detect subtle changes in vegetation characteristics makes remote sensing an attractive tool for detecting weed infestations in wildlands and in determining the size and location of weed patches in agronomic production systems. This article will discuss the concepts behind remote sensing applications in weed detection and management, the challenges that are faced in developing decision support systems (DSSs) that use remote sensing information, practical examples of how this is being done, and future needs.

The concept behind SSM is to identify, analyze, and manage site-specific spatial and temporal variability within fields to achieve optimum profitability, sustainability, and environmental protection (Robert et al. 1994). Based on the concept of SSM, the power of remote sensing information lies in the ability to make within-field observations, determine crop growth, and manage fields based on current conditions that may be overlooked using current on-the-ground methods of visual scouting and crop production decisions. Another force that can spur the acceptance of new technology is public perception of agriculture as causing environmental contamination and the new technology ameliorating the problem. The increased scrutiny producers face comes from environmental advocacy groups and government regulatory agencies. The ongoing review of agrichemicals under the Food Quality Protection Act (U.S. EPA 1999) may jeopardize the use of much-needed crop protection pesticides by limiting or restricting the current usage patterns of labeled pesticides. Runoff of sediment and pesticides from agricultural operations will soon be regulated by total maximum daily loads that are allowed in our streams and rivers (Chen et al. 1999; Federal Register 2000). These government regulations and public perceptions mean producers must further justify the application of pesticides and fertilizers. These factors, along with rising production costs and flat commodity prices, are the driving forces making producers seriously evaluate SSM and technological advances such as remote sensing.

Managers of rangelands, national parks and other govern-

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ment-owned landholdings, lakes and rivers, and privately held natural resource areas face tremendous challenges in managing weeds, particularly those considered invasive. For purposes of this article, invasive weeds are those plants that are not native to the location and have warranted some type of governmental action in attempts to detect, monitor, and manage the species. Invasive weeds have been classified as the second most pressing problem in natural areas; habitat destruction is the only greater threat (Randall 1996). Westbrook (1998) estimated that 2,100 ha of western lands were being lost daily to invasion of species such as leafy spurge (*Euphorbia esula* L.) and yellow starthistle (*Centaurea solstitialis* L.). The sheer magnitude of the areas involved coupled with inaccessibility and rough terrain makes early detection of invasive plants challenging and the value of remote sensing for detection purposes obvious.

Opportunities to use remote sensing information are at an all-time high. Reasons for this are many. Computing power continues to increase dramatically each year, and processing data takes only minutes now compared with days a few years ago. The availability and accuracy of global positioning systems (GPS) make accurate georeferencing of both the imagery and SSM possible. Software products that provide advanced geographic information system (GIS) features can now extract information from imagery and convert it into easily translated formats for SSM. Sensor systems, both aerial and satellite, are now readily available. The widespread availability of broadband internet allows rapid delivery of remote sensing imagery files, thus enabling production of site-specific map products before the weeds are too large or the infestation level has changed so much that the imagery is of little value. Finally, the cost of components, both remote sensing data products and SSM hardware and software, has decreased dramatically over the past few years.

Applications and Benefits—Agronomic Weed Management

Basic economic principles dictate that the cost of the service must be less than the value obtained from using the service. If a direct increase in net return is not observed, the benefits of remote sensing may be obscured, even if they still exist. To maximize the potential benefits offered by remote sensing, an infrastructure such as those proposed by Moran et al. (1997) or Brown (2000) will provide a logical and orderly path to transfer remote sensing information by means of the images to the producer. Once the data are collected, a specialist will correct for factors such as sun angle and atmospheric effects to calibrate the data, georeference each pixel to ensure consistency in the location of information, and analyze the images for spectral characteristics or changes that can be attributed to specific events, e.g., crop stress caused by poor fertility, drought, and pest infestation (ideally, this entire process would be automated to remove time constraints from specialist processing). The images will be passed to the consultant for recommendations to be made, after which SSM action will be initiated (Moran et al. 1997). The potential of remote sensing lies in its ability to provide qualitative and quantitative information (Servilla 1998). Moran et al. (1997) separated the information that can be obtained by remote sensing into three categories. Seasonally variable information includes factors such as soil moisture, insect and weed infestations, and disease incidence and severity. Seasonally stable information includes growth factors such as soil type and topography that remain relatively constant over years and need not be continually monitored. The third category is a combination of the above two. It involves circumstances in which the variability in crop growth is not obvious and may result from a combination of seasonally variable and seasonally stable factors.

A scenario of the benefits that remote sensing may provide (before planting through harvest) follows. Early images of bare ground taken before planting and displaying differences in soil reflectance may provide useful information regarding surface features such as drainage and soil moisture (Estes et al. 1997; John 1992), texture (King et al. 1994), surface residue (Powell et al. 2003), organic matter (Varvel et al. 1999), iron oxides (Coleman and Montgomery 1987), calcium carbonate (Leone et al. 1995), and compaction (Burrough et al. 1985). Using a GIS, early-season aerial images can be linked to light detection and ranging (LIDAR) data or digital elevation models and soil series maps to determine elevation, slope, and aspect (Pilesjo et al. 2000). This process may illustrate the need for within-field remedial actions such as land-forming operations or additional soil amendments to transform less productive areas into higher yielding areas. It may also enable the planning actions for the establishment of soil management zones for sampling and aid in determining fertilizer and seeding rates (Campanella and Seal 2000; Sassenrath-Cole et al. 1998).

In-season image collection provides information concerning crop growth, vigor, and biomass (Thenkabail et al. 2000; Wiegand et al. 1991). Images also provide visual indications on the severity and extent to which crops are affected by weed infestations (Garegnani et al. 2000; Medlin et al. 2000; Menges et al. 1985), disease problems (Blazquez and Edwards 1986; Manzer and Cooper 1967; Safir et al. 1972), nutrient deficiencies (Jackson et al. 1980; Walburg et al. 1982), insect infestations (Fitzgerald et al. 2000; Hart and Myers 1968; Heald et al. 1972; Sudbrink et al. 2000; Willers et al. 1999), and areas under drought stress (Carlson et al. 1971; Penuelas et al. 1994; Tucker 1980). Georeferenced maps of the affected areas could be generated to allow site-specific application of agrichemicals to avoid further yield loss. The input of remote sensing data and ancillary data into DSSs will improve management decision making based on incorporating several parameters observed within a field at a certain point in time (Barnes et al. 1998). Collectively, multiple uses of the same imagery should benefit weed management, thereby spreading cost of imagery over multiple decisions and justifying their use for weed patch identification and development of herbicide application maps for SSM of weeds.

Applications and Benefits—Invasive Plant Management

An absolute priority for invasive plant management is the early detection and rapid response to these invasions (Westbrook 2003). Typically, natural resource managers and volunteers are scouting to identify areas with new invasions and respond with control practices. Given the size of the area and often rough terrain, early detection and rapid response is difficult, if not impossible, with ground-based scouting.

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Remote sensing can readily detect changes in vegetation type and identify outbreaks of invasive plant species from surrounding native vegetation. These have included common St. Johnswort (*Hypericum perforatum* L.) (Lass et al. 1996), yellow hawkweed (*Hieracium pratense* Tausch) (Carson et al. 1995), and false broomweed (*Ericameria austrotexana* M. Johnst.) (Anderson et al. 1999). Hirano et al. (2003) used remote sensing data to detect small stands of latherleaf [*Colubrina asiatica* (L.) Brongn.] in the Florida Everglades. Successful detection typically is tied to reflectance properties of the invasive plant species at specific phenological stages in contrast to the surrounding environment (Everitt and Deloach 1990).

Identification of potential infestations of invasive plants can then be used to initiate ground-based observation methods. Management crews can use georeferenced maps to navigate to the identified sites to determine if the species is present, its occupancy and density of infestation, and appropriate management–eradication efforts.

Spatial resolution is a key factor in the detectability of invasive plant populations. Early detection, which is critical to rapid response, requires identification of small patches, which can be difficult with low spatial resolution sensors that have the capability of covering large areas. These limitations will be discussed in more detail in the next section.

Limitations

Limitations of remote sensing information and optimal parameters for remote sensing data have been suggested by several authors (Moran et al. 1997; Robert 1997; Thenkabail et al. 2000). Reoccurring topics have been spatial resolution, spectral resolution, temporal frequency, and processing time for the images. Current technology and recent advances have overcome some of the limitations. A review of current and future satellite-based imagery and their respective capabilities has been provided by Moran et al. (1997).

The degree of spatial resolution needed is dependent on the task of interest (Moran et al. 1997). The optimal spatial resolution that has been recommended for agricultural applications such as crop monitoring is 2 to 4 m (Moran 2000). A pixel size of 2 m would allow for management units on the order of 10 m (Moran 2000). Other applications such as early-season crop growth assessment, weed and insect monitoring, and fertilizer application monitoring would require finer resolution (< 2 m), dependent on the size of the mapping unit or detection of edges of certain anomalies that is required. At present, multispectral imagery with 4-m spatial resolution has been achieved with satellites. Airplane-mounted sensors can provide finer spatial resolution by varying the flight altitude and provide the convenience of capturing images on demand (Lamb et al. 1999; Rew et al. 2001). Aerial multispectral sensors are routinely used to obtain 0.5- to 1-m spatial resolution (Medlin et al. 2000). Figure 1 demonstrates the observable difference between 0.5- and 1.0-m resolution for some 4- by 4-m weed plots. This resolution has been sufficient for weed detection in some agronomic situations, but weed patches must be of a density to be detectable or individual weeds must be large enough to be detected.

Conversely, remote sensing applications in invasive plant management have often used spatial resolutions of 20 to 200 m (Everitt and Deloach 1990). This has been largely determined by the satellite imagery available for these large geographic areas and the ability to process the large data sets over these areas. As new satellite systems are becoming available with higher spatial resolution, new opportunities may arise for using remote sensing information to detect small, new outbreaks of invasive plants. However, an associated limitation of these data sets is the costs involved; commercial imagery covering a broad area with a revisit frequency sufficient to detect new infestations is currently cost prohibitive. Aerial imagery has proven useful for detecting very small infestations of invasive plants (e.g., Carson et al. 1995); however, these systems do not have the ability to cover large geographic areas within a reasonable time period or cost. One potential mechanism to use this type of imagery would be for model prediction of most probable infestation points, with high-resolution surveillance of only these high-probability sites. This will be discussed more in Decision Support Systems.

The choice of spectral resolution and bands to include in the sensor is primarily dependent on the variable of interest. Spectral resolution refers to the amount of the electromagnetic spectrum that is detected and is usually given as a range of wavelengths. The term "band" refers to the width and specific location within the electromagnetic spectrum. Broadband and narrowband vegetation indices have been used to monitor various crop parameters that are often good indicators of crop yield (Bartlett et al. 1998; Shibayama and Akiyama 1991; Thenkabail et al. 1995; Wiegand and Richardson 1990). An example of this would be use of the normalized difference vegetation index (NDVI) to estimate crop biomass at a given point in the growing season and correlating this with yield or yield potential. The drawback for the use of broadband indices has been the loss of information that can be acquired using narrowbands (Blackburn 1998). Recently, Thenkabail et al. (2000) recommended specifications for a 12-band sensor with relatively narrowbands for optimum biophysical determination of crop stress and yield estimation.

The revisit interval or temporal frequency required for remotely sensed images is largely determined by the critical growth stages of the weed, weed growth rate, and weed size to be detected, and cost of the imagery. The ability to acquire images on demand, weather permitting, is being overcome with the successful launch of each new satellite. Satellite platforms currently can acquire images every 2 to 7 d by means of off-nadir viewing capabilities (Moran 2000), although the turnaround time for image acquisition and delivery may still be too slow to be practical for weed management. Within the next 10 yr, another 50 satellites are expected (Moran 2000). This will further enhance data collection capabilities and allow imagery acquisition when weather conditions are favorable. An alternative that is being more successfully used is the use of aerial imagery. Aerial acquisitions allow image collection on demand and also allow much higher spatial resolution. Limitations to this technology, however, are for the relatively small area coverage and at least in some instances the higher per-area cost (Moran 2000).

The time a producer or resource manager can afford to wait on processed, ready-to-use imagery is determined by

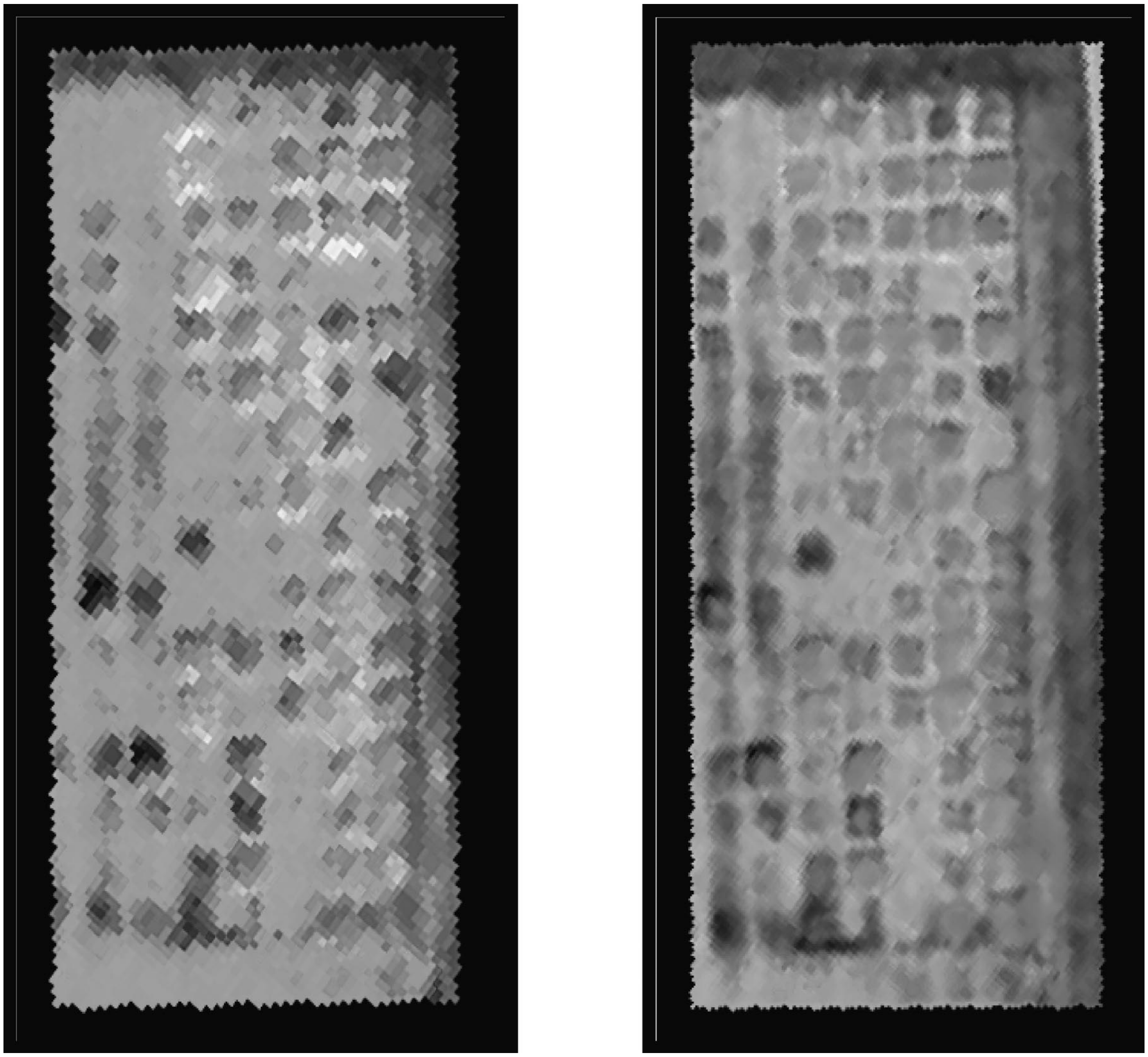

FIGURE 1. Aerial multispectral imagery at 1.0-m (left) and 0.5-m (right) spatial resolution of 4- by 4-m weed plots. Imagery is a false color composite.

the amount of time that will result in the image having no or little consequence to the decision to be made and the implementation of that decision. Once imagery is acquired, turnaround time is based on the amount of time required to process and deliver the final product to the user, whether that be a raw image file, a georeferenced vegetation index, or a digital map prescribing a specific corrective treatment. The general consensus on turnaround time required by the crop producer is between 24 and 72 h for in-season crop management decisions (Anderson et al. 1999). The amount of time estimated to produce finalized imagery is 20 to 24 h for aircraft-based imagery and 16 h for satellite-based imagery (Moran et al. 1997). Although detection of invasive species in wildlands is also time critical, the timing of detection is usually not considered as demanding as agronomic applications, on the order of weeks rather than hours or days. The time required for processing will ultimately depend on the desired product and automation of the image processing. Currently, reported processing time for satellite imagery ranges from as little as 15 min to 24 h after acquisition (Fritz 1996; Servilla 1998). The development of complex algorithms allowing automated processing is being researched by academia and the remote sensing industry to circumvent delays in data delivery.

Another limitation with remote sensing is that rapid advancements in technology render equipment and software obsolete in a short period of time. Even if equipment still performs the desired functions, it may no longer be supported by the company it was purchased from, whether due to mergers or companies going out of business (Lowenberg-DeBoer 1999). Thus, the end user may be frustrated at the rate of change in technology, which can discourage the adoption of the technology as a whole. This is not unusual with new, evolving technologies; however, it has been widely recognized as a major limitation in the adoption of remote sensing (Johannsen et al. 2000).

Economic Aspects

Economic considerations concerning remote sensing and agriculture have been explored by several authors (Moran 2000; Moran et al. 1997; Robert 1997). The use of remote sensing in agriculture boils down to the cost of the technology and the value or benefits that it returns. For producer

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interest in remote sensing to increase, it must be proven that the technology produces a positive return on investment. Remote sensing as a risk management tool is based on the notion that better information will allow knowledgeable decisions to be made and better crop management will occur (Lowenberg-DeBoer 1999). Benefits that would be instantly recognized by growers would include occasions where previsual injury detection from pests, fertilizer misapplication, or drainage problems could be identified and treated before traditional crop scouting techniques would have identified them. Benefits such as these are difficult to price but no doubt would be easily recognized by the producer. Another benefit that can be highlighted would be the automation of digital recordkeeping, tracking numerous farm activities, and recording agrichemical applications (date, time, and specific locations) for both recordkeeping and regulatory compliance documentation.

The current costs, product packaging, and restrictions for obtaining satellite imagery can be obtained from various image providers on the internet (e.g., http://www.earthscan.com, http://www.agricast.com, http://www.spaceimaging.com). As more satellites are successfully launched and aerial imaging companies are established, competition between companies will reduce the price of imagery and simultaneously the ability to collect images in a timely manner will improve. The actual cost of imagery is hard to interpret because of volume buying, pricing, separate pricing schemes for images not already on hand, and differences in software and processing fees charged by each company. Below are some relative prices obtained from the above internet sites. Earthscan offers 4-m spatial resolution (multispectral) or 1-m spatial resolution (panchromatic) IKONOS imagery. One year of access with no additional requirements can be purchased for \$95/image or \$1.01 ha^{-1}. Purchasing sixteen 568-ha images lowers the price to \$62 per image or \$0.67 ha^{-1} (for current pricing structure, see http://www.spaceimaging.com). The software to analyze images must be bought at an additional charge; in many instances this is not a nominal cost. However, in some instances the software may be part of the package purchased by the end user. AgriCast offers 5-m panchromatic and 20-m multispectral imagery covering 60 m^2 per image. Panchromatic imagery can be purchased for \$250 in stock or \$350 not currently in stock. Multispectral imagery costs are \$300 in stock or \$450 out of stock plus \$48 shipping and handling plus a \$635 processing fee per quad (approximately 160 km^2). Imagery acquired from airplane-mounted sensors is more difficult to price and is mostly dependent on the total area covered and spatial resolution. Image acquisition costs from the 1999 WHIPP program using the NEOS (Near Earth Observation System) system were \$0.07 to \$0.22 ha^{-1} (Holmberg 2000).

The value of remotely sensed data is based on the amount of information that can be obtained from the images. Imagery cost factors include frequency of acquisition required by the producer, rapidity of delivery, spatial resolution, spectral resolution, and processing costs. These costs will most likely decrease over time because of competition among imagery providers. As production areas adopt remote sensing, cost sharing of imagery may be obtained by consultants, cooperatives, and producers joining together to purchase different dates of imagery during the production season. Additional costs incurred by the producer, consultant, cooperative, or service provider may include upgrading computer hard drive space to store large amounts of data or finding companies offering storage space for sale.

Initial indications from simulated data sets and large on-farm tests are promising with respect to cost savings obtained because of better weed management decisions provided by remote sensing information. Like many variables affecting production yields, weeds occur in aggregated patches rather than being uniformly distributed across fields (Cardina et al. 1997; Marshall 1988; Thornton et al. 1991). Calculated cost savings using site-specific herbicide applications (SSHA) ranged from \$96.24 ha^{-1} to \$104.76 ha^{-1} in soybean (Medlin and Shaw 2000). Scouting based on sampling at a 10-m grid size resulted in an increased net gain of \$77.17 compared with a 20-m grid-sampling scheme. The difference was reduced to a \$19.84 net gain in soybean (Medlin and Shaw 2000). Similar findings have been calculated by Garegnani et al. (2000) for Maryland soybean fields. Imagery indicated that only 32 ha of a 60-ha field needed treatment for weeds. Applications to the entire field were subsequently made, costing \$80.03 ha^{-1}. Had the 32 ha been treated, a cost savings of \$36.85 ha^{-1} would have been realized. Brown and Steckler (1995) cut herbicide usage 40% by using a system based on images and GIS-based weed distribution maps to apply varying herbicide rates and mixtures. SSHA for controlling wild oat (*Avena fatua* L.) in spring wheat (*Triticum aestivum* L.) led to decreased herbicide use and thus lower production costs (Maxwell and Colliver 1995). Felton et al. (1991) reported savings of \$16.95 ha^{-1} (Australian) for controlling annual weeds on fallow land with SSHA instead of broadcast herbicide applications (BHA). Lindquist et al. (1998) compared SSHA with BHA to manage three weeds, velvetleaf (*Abutilon theophrasti* Medik.), pigweed species (*Amarathus* spp.), and foxtail species (*Setaria* spp.), and reported a \$10 ha^{-1} higher economic return with SSHA. However, they based their economic returns on hypothetical herbicide treatments capable of controlling all three weeds equally well. In most of these instances, increased costs for SSHA were not included in the calculation because the equipment to apply these SSHA was still experimental in nature.

Decision Support Systems

Agriculture and natural resource managers work with many pieces of knowledge. Some of these are descriptive, characterizing the past, present, or future state of the resource being managed. Other bits of information are procedural in nature, specifying how to accomplish various tasks. In addition to information and procedures, a manager may use reasoning knowledge toward making a decision. This third type of knowledge indicates that certain conclusions are valid under specific circumstances. Resource managers may make decisions individually or decisions may be distributed, involving the combined and coordinated efforts of many. Both individual and distributed decision making can be supported by knowledge-based systems that facilitate, expand, or enhance a manager's ability to work with one or more kinds of knowledge called DSSs (Holsapple and Whinston 1996). DSSs are now defined as interactive computer-based tools used by decision makers to help answer questions, solve problems, and support or refute conclusions.

Many DSSs are designed for individual decision support. However, the most active research areas in DSSs are those that directly support distributed decision making at the group, organization, and interorganization levels. DSSs also differ with respect to the types of knowledge they manage. The majority of conventional DSSs have been devised to help manage descriptive and procedural knowledge. In contrast, a new class of artificially intelligent DSSs is concerned mainly with the representation and processing of reasoning knowledge (Holsapple and Whinston 1996).

Developing accurate and effective DSSs for weed management has long been recognized as a primary goal for land managers and weed scientists. These can be in a simple form, such as software that indicates whether a herbicide is recommended based on weed threshold concepts (e.g., Rankins et al. 1998). More complex DSSs would incorporate herbicide efficacy and environmental impact, weed competitiveness, ecological principles of weed propagule movement and ecosystem dynamics, and the impact of other variables such as micro- and macroclimate, soil factors, and topography (Cardina et al. 1997). Outputs from such a DSS will vary but may be a site-specific map for herbicide applications in a field based on all these factors and principles, or a georeferenced map with the probable location of invasive plants, or the predicted location of highest probability of initial invasion. Remote sensing can play a key role in the development of these advanced DSSs. Remote sensing data can provide information on weed location, vulnerable ecosystems, high-resolution topography, soil characteristics, habitats most suitable for invasion, and effect of management practices on weed control or eradication efforts.

Examples—Remote Sensing in DSSs

Mississippi Herbicide Application Decision Support System

Mississippi Herbicide Application Decision Support System (MS-HADSS) and its predecessor MSU-HERB are yield loss prediction and herbicide recommendation models currently available to Mississippi soybean producers and were developed through adaptations of the HERB software from North Carolina State University (Wilkerson et al. 1991). Adaptations in the competitive indices and efficacy ratings improved the utility of HERB for Mississippi production conditions in soybean (Rankins et al. 1998); subsequent adjustments have been made in cotton as well (Rankins et al. 2003). However, these yield loss prediction models assume uniform and random distributions of weed populations, whereas weeds usually occur in patches in most agronomic fields (Auld and Tisdell 1988; Brain and Cousens 1990). Generally, these patchy distributions result in overestimated yield losses (Auld and Tisdell 1988). Within-patch variability may also affect yield loss prediction, but to a lesser degree (Thornton et al. 1991). MS-HADSS could ideally be used for recommending herbicides strictly for areas with weed infestations above the economic threshold. A herbicide applicator attached to a GPS could then be used to apply those herbicides. This system would reduce herbicide inputs in weed-free areas and improve herbicide recommendations within weed patches.

MS-HADSS was developed for recommending herbicide inputs based on field averages of weed populations. However, it can also be used for SSHA with some modifications. Early work by Medlin et al. (2000) ran MS-HADSS on the weed populations from each grid cell and then composited the herbicide recommendations into a single map. More recently, work in Mississippi and North Carolina has evaluated modifications to the software to automate the process of generating SSHA maps (Givens et al. 2004; Price et al. 2003). Inputs for MS-HADSS use have been evaluated on the basis of grid sampling patterns (Medlin et al. 2000), weed patch perimeter tracing with a GPS unit, and remote sensing imagery (Easley et al. 2004). According to Easley et al. (2004), the only viable means of providing weed patch information is remote sensing imagery; perimeter tracing is often inaccurate, and grid sampling is a labor-intensive and an expensive undertaking.

In recent years, the use of herbicide-resistant crops has provided alternative weed management options for producers. Glyphosate-resistant soybean offer producers less costly weed control programs (Delannay et al. 1995) and have the potential to improve productivity and profitability for growers (Griffin et al. 1994). Currently, research is underway to evaluate the economic benefits of SSHA in glyphosate-resistant soybean. A glyphosate-resistant soybean management system often greatly simplifies the decision process for herbicide selection; more often than not it is a spray glyphosate vs. do not spray decision rather than a selection of which herbicide and use rate among dozens of options. Figure 2 illustrates a glyphosate application map for a field near Brooksville, MS, in 2001 and 2002 based on multispectral imagery used to identify weed patches in the soybean field. In these two situations, MS-HADSS recommended that approximately 50% of the field needed to be treated with a herbicide each year; the remainder of the field contained either no weeds or below-threshold populations.

Several additional steps must now be taken to accept spatially variable inputs and generate SSHA recommendations from MS-HADSS. New algorithms or imaging capabilities must be developed that can better identify species, groups of species, or noncrop plant patches in a field. The software must also be rewritten to accept inputs from multiple sources used to identify weed populations and automate the process of generating SSHA maps that can be used by an onboard computer system coupled with the appropriate sprayer technologies.

Weed Detection at Harvest

Real-world applications of remote sensing technologies have become commonplace in agriculture and natural resource management. An excellent example of this is a private company established in 2002 based on the premise of spectral changes in green vegetation as a basis for crop management. This company first began its focus on insect management in cotton (*Gossypium hirsutum* L.) based on an understanding of insect ecology in relation to cotton growth. Many cotton insect pests are attracted to the most vigorously growing portions of a cotton field (Willers et al. 1999). Remote sensing imagery can easily identify these portions of the field because of an increase in the absorption of red and near-infrared portions of the spectrum. Cotton scouts can then be directed to sampling locations based on a stratified sampling procedure in which the highest probability locations can be sampled first, and if no insects are detected at

FIGURE 2. Maps developed for site-specific application of glyphosate in soybean based on weed populations in 2001 and 2002.

these points then no further sampling is needed. If insects are found, their location and population are recorded with GPS and additional strata are sampled to determine the portions of the field containing threshold-level insect populations. The data on insect populations are uploaded onto the company server and, based on user-established criteria, variable-rate insecticide recommendation maps are provided back to the producer or consultant. These maps are uploaded into the spraying system (aerial or ground), and only the portions of the field needing treatment are sprayed with the insecticide (http://www.gointime.com). A strength of this system is that image processing has been completely automated, while at the same time the user can customize the output easily and without having to have extensive training in either remote sensing or GIS software. The company expanded its product line in 2003 to include variable rate cotton growth regulator and defoliant applications (M. Seal, personal communication). These applications were based on the variability in NDVI, a measure of plant vigor derived by ratioing the green and red bands from a multispectral sensor. In 2004, the company also expanded their product line to include preharvest weed control. Difficult-to-control perennial weeds in cotton such as redvine (*Brunnichia ovata* L.) in cotton are best controlled with systemic herbicides applied in the fall (Shaw and Mack 1991). In cotton, this would be after a defoliant application (defoliating the cotton, but not the weed), but before harvest, so that maximum redvine leaf area would be available to intercept the herbicide and translocate it to the roots. The NDVI after a cotton defoliant application is an excellent and highly accurate means of identifying the portions of the field that still contained green weeds, and SSHA maps can be developed in the same manner as those for insecticide applications as described above. Thus, in this example remote sensing data are used in a DSS to direct applications to weed and insect infestations, thereby reducing cost substantially and reducing pesticide load into the environment.

National Invasive Species Forecasting System

During the past 10 yr, the impact of invasive weeds on wildlands and aquatic habitats has been recognized nationally. A number of federal agencies, including the U.S. Department of Agriculture, U.S. Geological Survey, U.S. Environmental Protection Agency, National Park Service, U.S. Forest Service, and numerous state agencies, conservation groups, and private landholders must manage the devastating effects on habitats from these invaders. At the recent Invasive Plants in Natural and Managed Systems Conference (November, 2003) many of the presenters called for enhanced detection and monitoring capabilities for invasive plants and integration of these capabilities into systems that can aid in the decision process for management strategies. In response to the threat of invasive plant species, the U.S. Geological Survey and the National Aeronautical and Space Administration have signed a joint Memorandum of Understanding to collaboratively develop a National Invasive Species Forecasting System (Schnase et al. 2003; Sheffner 2003). The focus of this effort is to protect U.S. Department of Interior landholdings from invasive plants. It is based on an approach of predictive modeling of suspect sites of invasion based on ecological modeling and habitat identification. Remote sensing data are used to determine land cover characteristics for habitat identification. In addition, remote sensing data are used for spectral characterization of specific species, groups of species, or associations of species, thus improving the ability to detect infestations and dominant vegetative cover. Not only are spectral differences at a specific date used but temporal changes are being assessed to determine detectability of specific species based on their phenological changes.

Future Needs

From a weed science perspective, the tremendous challenge is the need for research in weed and ecosystem biology and ecology. A great deal of research has been published in this regard; however, it has often highlighted how much there is yet to understand. Ecological forecasting of sites of invasion and rapidity and direction of spread of introduced plant species requires a detailed understanding of the impacts that climate, topography, soil, and anthropomorphic factors have on plant introduction and movement. Regarding SSM of weeds in agronomic systems, research in weed biology and ecology again is a critical need, simply at a different scale. The ability to predictively model weed presence and population dynamics in a field based on previous history, microclimate, topography, soil factors, agronomic cultural practices, and remote sensing data will substantially enhance our ability to manage weeds on a site-specific basis.

In the near future, remote sensing information should be used as a management assistance tool and not as a stand-alone, problem-solving tool. Many of the limitations that hindered the use of remote sensing in the 1970s are being overcome by recent advances in technology. Issues concerning the various types of resolution are being resolved with each technological advance, also allowing for the timely delivery of information to the resource manager (Johannsen et al. 2000). The ability to use remote sensing data in a DSS that enables an agricultural or natural resource manager to apply corrective measures on a site-specific basis is opening up new opportunities and creating demand for remote sensing information. This is increasing interest from companies in developing more remote sensing products. Success of remote sensing for weed management decisions will depend on satellites delivering images when needed and be supplemented by airplane-mounted sensors when weather interferes with satellite imagery acquisition. Cost of imagery can often be shared or used for multiple purposes; in an agricultural setting it may be in the form of multiple producers buying imagery or a single producer buying imagery for weed and insect management and crop growth regulation; in an invasive plant scenario multiple state and federal agencies may be interested in the image. However, these collaborative purchases must be sought and encouraged.

The development of a knowledgeable workforce able to accurately and correctly interpret imagery is also critical for the use and acceptance of remote sensing. This pertains to those manipulating the imagery beginning with its acquisition all the way through the transfer of the imagery to the end user in a usable, reliable, and understandable format. To aid this process, standardization of image processing throughout the industry would be useful. One such example is the development of the cropland anomaly classification system (Carter and Johannsen 2000). Algorithms to transform the data into SSHA maps will enable rapid processing and thus speed the decision-making and corrective action process. Such standardization will require cooperation among the industry and research community. Remote sensing imagery is not currently a stand-alone product, and must be used with a priori knowledge of production practices and current conditions when interpreting imagery (Barnes et al. 1998; Johannsen et al. 2000). In the future, continued research will optimize the bands used in the construction of sensors. The addition of new satellites will further enhance the capture of images in a timely manner to meet the needs of agriculture. In addition to standardizing image processing, the university system would also be providing a knowledgeable workforce to fill the needs of a growing industry. Ultimately, widespread adoption will require a seamless, near real-time conversion of raw data into information readily understood by the end user or transferred directly to equipment used to manage weed infestations (or both). However, remote sensing will be best used by providing accurate, site-specific data that can be converted into information used by a DSS to aid agricultural and natural resource managers in an operational setting. Advances in these DSSs, and their ability to incorporate remote sensing data, have been rapid and widespread in the past 10 yr. However, further development of DSSs also represents the greatest area of need for the implementation of remote sensing in weed management systems. The goal of remote sensing should be conversion of data into management information in time for it to have benefit.

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