EXTENDING A PROTOTYPE KNOWLEDGE- AND OBJECT-BASED IMAGE ANALYSIS MODEL TO COARSER SPATIAL RESOLUTION IMAGERY: AN EXAMPLE FROM THE MISSOURI RIVER

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ABSTRACT:

A prototype knowledge- and object-based image analysis model was developed to inventory and map least tern and piping plover habitat on the Missouri River, USA. The model has been used to inventory the state of sandbars annually for 4 segments of the Missouri River since 2006 using QuickBird imagery. Interpretation of the state of sandbars is difficult when images for the segment are acquired at different river stages and different states of vegetation phenology and canopy cover. Concurrent QuickBird and RapidEye images were classified using the model and the spatial correspondence of classes in the land cover and sandbar maps were analysed for the spatial extent of the images and at nest locations for both bird species. Omission and commission errors were low for unvegetated land cover classes used for nesting by both bird species and for land cover types with continuous vegetation cover and water. Errors were larger for land cover classes characterized by a mixture of sand and vegetation. Sandbar classification decisions are made using information on land cover class proportions and disagreement between sandbar classes was resolved using fuzzy membership possibilities. Regression analysis of area for a paired sample of 47 sandbars indicated an average positive bias, 1.15 ha, for RapidEye that did not vary with sandbar size. RapidEye has potential to reduce temporal uncertainty about least tern and piping plover habitat but would not be suitable for mapping sandbar erosion, and characterization of sandbar shapes or vegetation patches at fine spatial resolution.

1. INTRODUCTION

In their natural state, riverscapes consist of a dynamic mosaic of habitats as a result of the interactions of fluvial action (erosion, deposition, transport, transformation, and connectivity) and successional phenomena (Ward et al., 2002). Dams profoundly affect the flow regime, water-temperature regime, and the sediment regime of rivers (Jacobson et al., 2009). The endangered least tern (*Sternula antillarum*) and threatened piping plover (*Charadrius melodus*) nest on unvegetated and sparsely vegetated sandbars and have been impacted by the suppression of habitat dynamics on the regulated Missouri River (U.S. Fish and Wildlife Service, 2003). Knowledge about habitat selection of least terns and piping plovers at the riverscape scale much less than at the nest site scale (Sherfy et al., 2012). A precursor to gaining knowledge of habitat selection at the riverscape scale is the ability to map and describe habitats at large extents.

A prototype knowledge- and object-based image analysis model was developed to inventory and map the terrestrial habitat of the Missouri River, USA, with an emphasis on emergent sandbars used by the least tern and piping plover (Strong, unpublished). The model has been used to inventory the state of sandbars annually for 4 segments of the Upper Missouri River since 2006 using very high spatial resolution (0.36 m^2) multispectral Quickbird (QB) imagery (Digital Globe, Longmont, CO).

With only one QB satellite in orbit, multiple dates of imagery have generally been required to obtain complete coverage of the spatial extent of a river segment. Interpretation of the state of sandbars for a river segment is difficult when images for the segment are acquired at different river stages and different states of vegetation phenology and canopy cover. In August 2008, the RapidEye (RE) constellation of 5 high spatial resolution (36 m^2) multispectral satellites was placed in orbit (RapidEye AG, Brandenburg an der Havel, Germany). RE imagery has the potential to improve the temporal characterization of emergent sandbars but at a reduction in the spatial characterization of sandbars. In this paper, I describe extension of the model to the analysis of RE imagery and present results from a comparison of land cover and emergent sandbar maps produced from QB imagery and concurrent RE imagery.

2. DATA AND METHODS

2.1 Study Areas

Three study areas along the Missouri River were defined by overlap of the spatial extent of QB or WorldView2 (WV2) imagery with RE imagery acquired on the same date and nearly concurrently (RE ~ 30 minutes after QB/WV2) (Fig. 1). On 30 May 2009, QB and RE images were acquired for 4.2 km of the Missouri River at the headwaters of Lewis and Clark Lake. The Lewis and Clark study area (hereafter LC) is located at the downstream edge of a large delta composed of many islands with continuous wetland vegetation that provide no nesting habitat for least terns and piping plovers. In December 2008, the U.S. Army Corps of Engineers (CORPS) completed construction of two sandbars from dredged materials to provide habitat for both bird species.

On 19 June 2009, QB and RE images were acquired for a 36.0 km reach downstream from Garrison Dam. The QB imagery had a small amount of clouds and the area of clouds and cloud shadows were excluded from the analysis. The Garrison 2009 study area (hereafter GAR09) has experienced bed degradation following closure of the dam and consists of an alternating series of narrow and wider reaches with islands, sandbars, and floodplains occurring primarily in the wider reaches above and below the confluence of the Knife River.

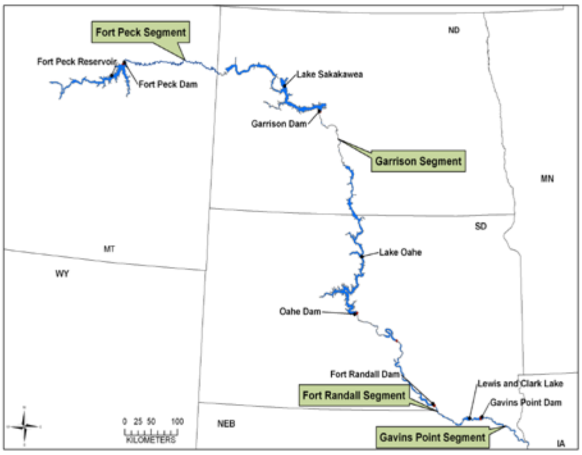

Fig. 1. Locations of four segments of the Missouri River where remote sensing is used to inventory least tern and piping plover habitat. Study areas in this paper are located in the Garrison segment and at the downstream end of the Fort Randall Segment.

On 8 June 2010, WV2 and RE images were acquired for 105.7 km portion of the Garrison segment from 1960 river mile 1361.4 to the headwaters of Lake Oahe (hereafter GAR10). The WV2 imagery provided coverage of the full spatial extent from Garrison Dam to the headwaters of Lake Oahe which was the first time in 7 attempts since 2006 to acquire QB or WV2 imagery for the Garrison segment that complete coverage could be acquired on a single date. The RE imagery had a small amount of clouds and the area of clouds and cloud shadows were excluded from the analysis. The river is wider in this segment of the river than in the upstream portion of the river and islands, sandbars, and floodplains are more abundant.

2.2 Satellite Imagery

The prototype model was developed using QB imagery. QB has blue, green, red, and near infrared spectral bands at 5.8 m^2 spatial resolution at nadir and a panchromatic band with 0.36 m^2 spatial resolution. The 4 corresponding spectral bands from WV2 and RE images were used for the analysis. The spatial resolution for WV2 is 4 m^2 and 0.25 m^2 for the panchromatic band. The spatial resolution for RE spectral bands is 36 m^2 and RE does not have a panchromatic band. Image specifications for all sources were 16-bit data, cubic convolution resampling, and off-nadir view angle <15 degrees.

Four pre-processing steps were applied to the imagery. The first process was conversion of the relative digital numbers for the 4 spectral bands to surface reflectance factors using the Standardized Reflectance Factor Index procedure (SRFI.sml) available in MicroImages Map and Image Processing System software (Paris, 2005). The method uses the image histogram and a physically based model to estimate coefficients characterizing atmospheric path radiance and transmission processes. The second process was pan-sharpening of the four reflectance factor images using the panchromatic band (Zhang, 2004). Images were orthorectified and QB, WV2, and RE images were resampled to 0.36 m^2, 0.25 m^2, 36 m^2 spatial resolutions, respectively. In the remainder of this paper, I will not distinguish between QB and WV2 imagery, and refer to both image sources as QB. The fourth process was the calculation of a perpendicular vegetation index as the distance from a bare sand line estimated for each image from a bivariate display of the near infrared reflectance and the red reflectance (Qi et al., 1994).

2.3 A Prototype Knowledge- and Object-Based Model

A prototype knowledge- and object-based model to inventory and map habitat for least terns and piping plovers on the Missouri River was developed using QB imagery in eCognition Developer (ED) (eCognition, 2012). The knowledge base was organized in a class hierarchy in ED. The knowledge base for this model consisted of a list of classes at each of 3 levels (landforms, sandbars, land cover), rules for discriminating among the classes, and fuzzy set procedures to evaluate the strength of evidence for each class and make classification decisions (Robinson, 2003).

The 4 classes at the landform level are water, islands, floodplain, and terrace and valley walls. Islands are defined as objects within the high river banks surrounded by water. At this level, the island class contains sandbars and vegetated islands. Floodplains are objects within the high river banks not surrounded by water. Depending on river stage, islands can coalesce with floodplain and some areas on the floodplain can become islands. The terrace and valley walls class is used for objects outside the high river banks.

The land cover level has the finest spatial resolution objects. The same land cover classes are possible on islands and floodplains. The 15 land cover classes include 4 classes used by least terns and piping plovers, a low canopy cover class representing a transitional habitat where increases in vegetation cover begin to limit use for nesting by the birds, a moderate canopy cover class with low biomass and vegetation height found on lower elevations of sandbars that can be important foraging areas for piping plovers, and 9 vegetated herbaceous-, shrub-, and tree-dominated classes that are not used by the birds. The 4 classes used by least terns and piping plovers are named (1) dry sand, (2) dry sand sparseveg, (3) wet sand, and (4) wet sand sparseveg. The dry sand and wet sand classes represent the endpoints on a gradient of sand moisture. The use of unvegetated and sparsely vegetated classes attempts to represent small differences in vegetation canopy cover that are important to the birds but are difficult to detect remotely. The 9 vegetated classes are ordered along an ordinal scale of increasing amounts of vegetation canopy cover and structure. For these analyses the 9 vegetated classes were pooled into a single class.

Each land cover class is described by fuzzy membership functions representing the characteristic response of a class on 3 dimensions. The 3 dimensions are a brightness or albedo dimension, a vegetation canopy cover dimension, and a texture dimension. The rules are combined using the geometric mean to calculate an overall membership possibility for a class.

The third level is termed the sandbar level and is located between the other 2 levels. Island and floodplain objects at the landform level are classified into one of 10 sandbar, island, and floodplain classes from analysis of their land cover composition. The classes include 3 sandbar classes (dry sandbar, wet dominated sandbar, or wet sandbar) which represent a gradient in security from nest inundation and 2 island classes (herb shrub island, woodland island) which identify environments with the potential for increased presence of predators and equivalent classes on floodplains rather than sandbars or islands. Four variables are used to summarize the land cover composition of sandbars: (1) the proportion of bare or sparsely vegetated substrate, (2) the proportion of bare or sparsely vegetated substrates that are dry, (3) the proportion of herb and shrub land cover, and (4) the proportion of tree land cover. Classification decisions for classes at the sandbar level are based on fuzzy membership functions for the 4 summary variables and the rules are combined using the geometric mean to calculate an overall membership possibility for a class.

Procedural knowledge in ED is organized in a process tree. The first process is multi-resolution segmentation of the reflectance images using a scale parameter of 100, a shape parameter of 0.1, and a compactness parameter 0.2 to create a fine-scale segmentation of the image. The procedure then uses an iterative application of classification, remove objects, merge region, grow region, and manual editing processes to create and classify objects at the 3 levels. In the current implementation of the model, vegetated land cover classes are aggregated in the final stage of production and fuzzy membership possibilities are deleted in the distributed product.

2.4 Extending the Prototype Model

The only change to the prototype model to extend its use with RE imagery was a change in the value of the scale parameter in the multi-resolution segmentation process in the ED process tree. For RE imagery the value of the scale parameter was changed from 100 to 50. The value of the scale parameter for RE imagery was determined in an iterative, trial and evaluation process of a range of values with the evaluation criteria being the creation of homogeneous land cover objects on emergent sandbars. No changes were made to the class hierarchy.

2.5 Comparison of Land Cover and Sandbar Maps

Three analyses were performed to compare the land cover and sandbar maps created using QB and RE in addition to examination of simple summaries of the area of land cover and sandbar classes for each study area. Summary statistics for a study area can mask differences in the spatial distribution of the classes. To analyze the spatial correspondence of the maps, a geometric intersection of the maps was created using ArcMap and the resulting map was analyzed using a contingency table analysis. The contingency table approach identifies the relationship between the 2 kinds of errors in maps: omission and commission. Because the prototype model was developed using QB and QB has 100x greater spatial resolution, the QB maps are considered here as “truth” for the purpose of describing the differences between the maps using the terminology developed for accuracy assessment of thematic maps. Producer agreement (1 – omission error) can be described as the probability of being correct given the QB class and user agreement (1- commission error) as the probability of being correct given the RE class. Crisp and fuzzy agreements were calculated. Crisp agreement occurred when the QB and RE class for a polygon in the intersect map agreed. Fuzzy agreement occurred when the crisp class according to QB and RE for a polygon in the intersect map disagreed but either QB or RE had a non-zero fuzzy membership value for the class of the other sensor.

A second analysis compared the QB and RE land cover and sandbar maps for the location of least tern and piping plover nests observed by CORPS bird survey field crews using contingency table analysis and visual inspection of the maps. A third analysis compared the areas of QB and RE sandbars for a paired sample of 47 sandbars where birds were observed nesting from GAR10.

3. RESULTS AND DISCUSSION

3.1 Land Cover

Generally, the area of land cover classes were similar between the two image sources for each of the study areas (Fig. 2). Differences in the areas of a land cover class within a study area can often be explained by confusion between two similar land cover classes. For example, at LC the magnitude of the positive difference in area for dry sand was similar to the magnitude of a negative difference for wet sand.

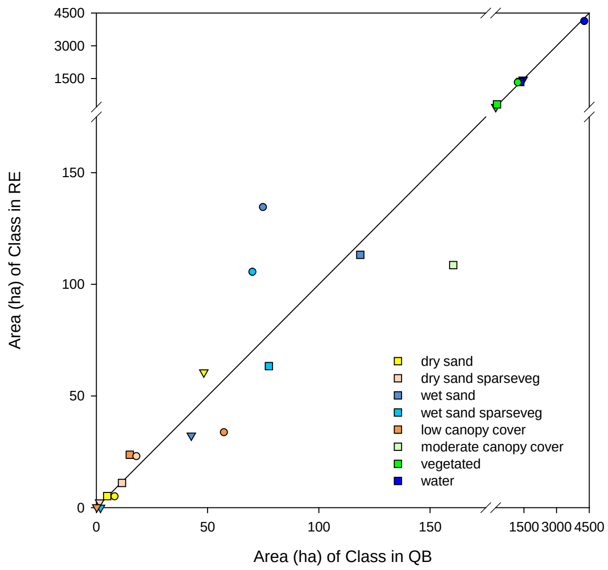

Fig. 2. Areas of land cover classes from simple area summaries of land cover maps for the three study areas. Land cover classes are represented by colors and study areas by symbols. Study areas symbols are: GAR10 =circle, GAR09 = square, LC =triangle. Note the break in x- and y-axis scales.

The increase in agreement from crisp to fuzzy agreements varied among land cover classes and study area (Fig. 3). The largest increases using fuzzy agreement occurred for dry sand at all of the study areas and for wet sand at the LC study area. The majority of wet sand at the LC study area was in the interior portion of the 2 constructed sandbars while most of the wet sand at GAR09 and GAR10 was along the perimeter of sandbars. Water accounted for 17% and 24% of the omission errors for QB wet sand at GAR09 and GAR10, respectively, and only 3% at LC.

Producer and user agreements were the largest for the dry sand, wet sand, vegetated, and water land cover classes at all study areas. Lower agreements were observed for the dry and wet sand sparseveg classes, the low canopy cover class, and the moderate canopy cover class. The classes in the latter group are characterized by a mixture of sand and vegetation. The cover and spatial patterns of sand and vegetation, how it is captured by the different spatial resolutions of the QB and RE and the segmentation process, may explain the lower agreements for these classes.

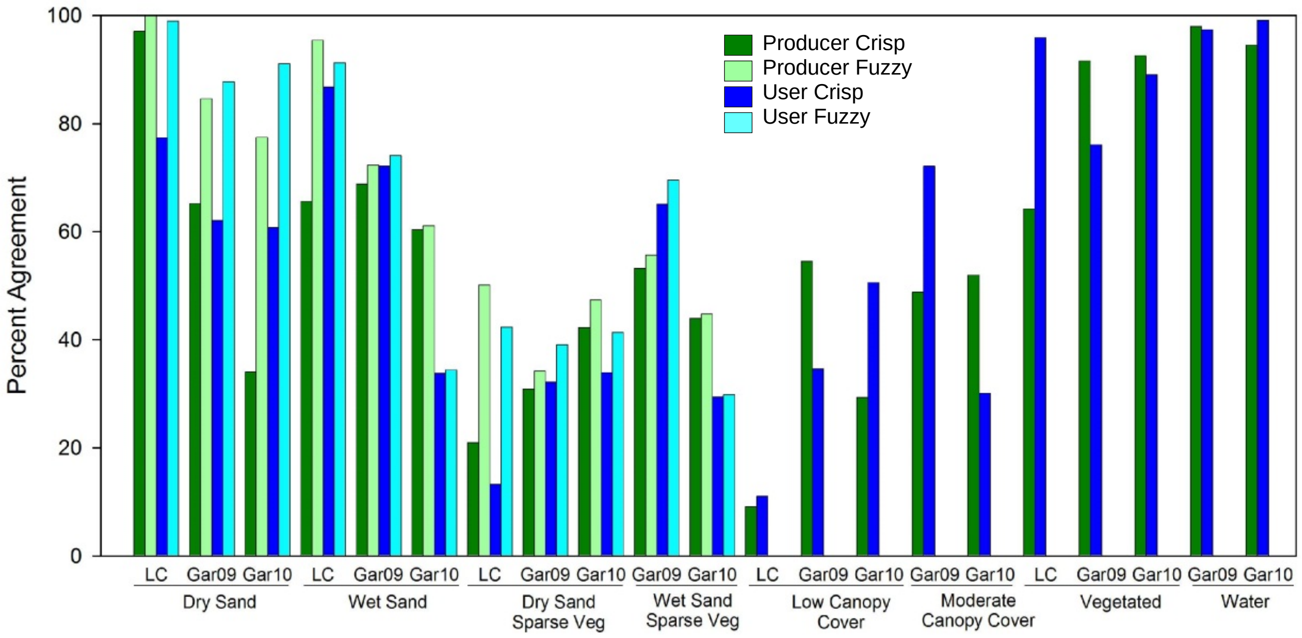

Fig. 3. Producer and user agreement for land cover classes calculated from a contingency table analysis of a feature class created from the intersection of the QB/WV2 and the RE land cover maps.

The RE low canopy cover class accounted for 6% and 11% of QB dry sand, and 48% and 34% of QB dry sand sparse veg at GAR09 and GAR10, respectively. For all four of the QB unvegetated and sparsely vegetated land cover classes the RE vegetated class accounted for less than 5% of a QB class for all study areas and errors were greater for the sparsely vegetated classes than the bare substrate classes at all study areas. Fig. 4 shows the land cover classification by QB and by RE for a herb shrub island at GAR10 and illustrates the confusion between the dry sand sparse veg and the low canopy cover class.

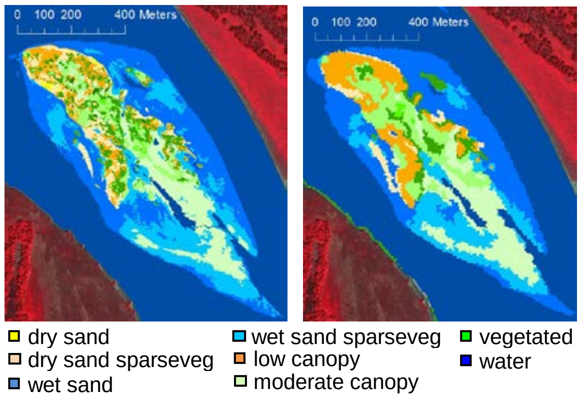

Fig. 4. Example of land cover maps from QB and RE imagery. QB map is on the left and RE map is on the right. The aggregated vegetated land cover class used for analyses in this paper includes multiple shades of green in the land cover maps.

3.2 Sandbars

Generally, the areas of sandbar classes were similar between the two image sources for each of the study areas (Fig 5). Differences in the areas of a sandbar class within a study area can often be explained by confusion between 2 similar sandbar classes and often can be resolved using fuzzy membership possibilities.

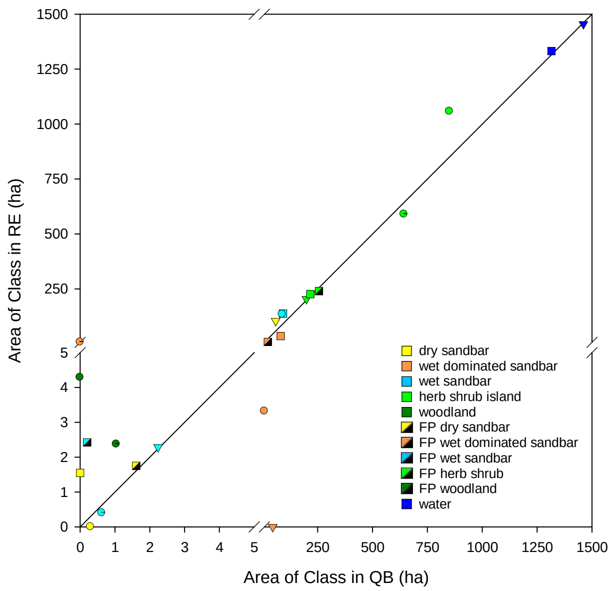

Fig. 5. Areas of sandbar classes from simple area summaries of sandbar maps for 3 study areas. Sandbar classes are represented by colors and study areas by symbols. Study areas symbols are: GAR10 =circle, GAR09 = square, LC =triangle. Area of water for GAR10 (QB =4300 ha, RE=4094.7 ha) is excluded for scale reasons. Note the break in x- and y-axis scales.

The difference between crisp and fuzzy agreements varied among sandbar classes with some classes showing little change and other classes significant change (Fig. 6). For three cases, fuzzy agreement resulted in a change from accuracies of 0 (a sandbar class is missing from one of the sandbar maps) to accuracies approaching 100%. One such case was the dry sandbar class at GAR10. The RE sandbar map did not contain a dry sandbar class. However, a RE wet dominated sandbar was mapped at the location of the only QB dry sandbar which

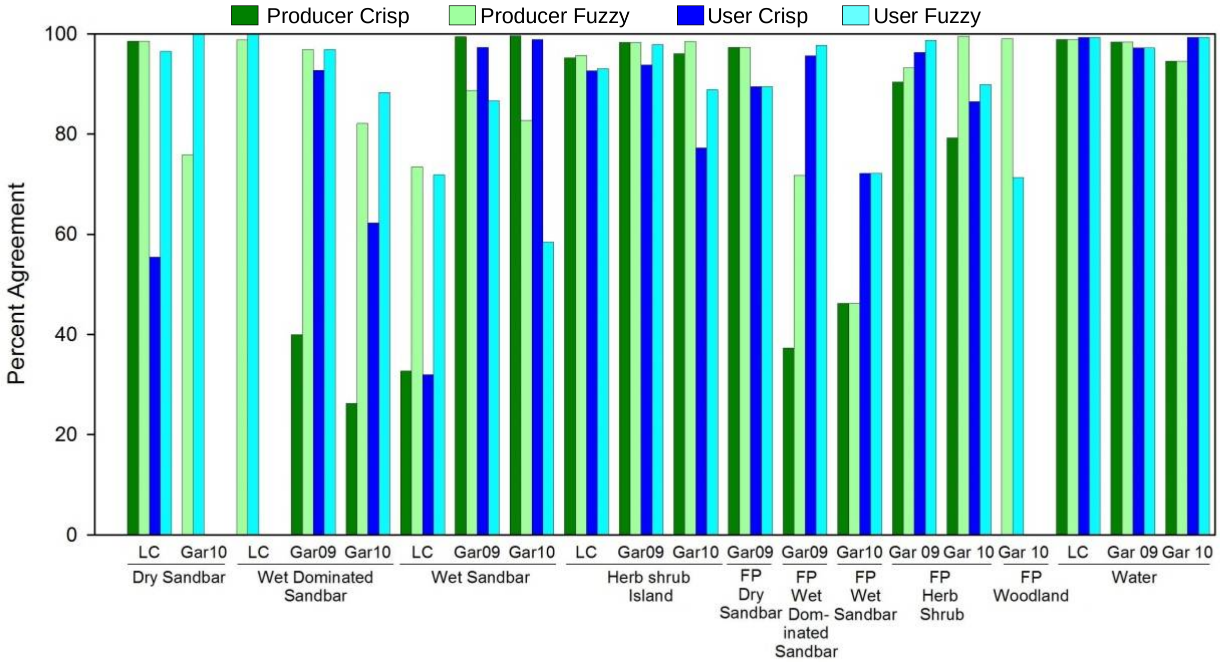

Fig. 6. Producer and user agreement for sandbar classes calculated from a contingency table analysis of a feature class created from the intersection of the QB and the RE sandbar maps.

has a fuzzy membership possibility for wet dominated sandbar. With fuzzy agreement, the producer agreement for QB dry sandbar at GAR10 was 76%, with RE water accounting for a 24% omission error for QB dry sandbar. The fuzzy user agreement for RE dry sandbar was 100%. Similar situations occurred for QB wet dominated sandbar and a RE dry sandbar at LC and QB floodplain woodland and RE floodplain herb shrub at GAR10.

For wet sandbars at GAR09 and GAR10, producer and user agreement decreased from crisp to fuzzy as the RE wet sandbar objects were allocated to alternative QB sandbar classes based on fuzzy membership possibilities. Taking the maximum of either crisp or fuzzy agreement as the measure of producer or user agreement, most sandbar classes had agreements near and above 90% and producer and user agreements for a sandbar class were similar.

3.3 Nest Locations

At LC in 2009, 231 bird nests were observed by CORPS bird survey crews on the 2 constructed sandbars both of which were classified by RE as dry sandbar and by QB as one dry sandbar and one wet dominated sandbar with a fuzzy membership possibility for dry sandbar. Using crisp agreement 87% of the nest locations were classified as the same land cover class by QB and RE and dry sand was the land cover at 95% of those nests. Using fuzzy agreement 97% of the nest locations were classified as the same land cover class by QB and RE with 193 nests occurring on dry sand, 30 nests on wet sand, 7 nests on dry sand sparse veg, and 1 nest in low canopy cover according to QB.

At GAR09, 47 bird nests were observed on 5 sandbar objects as follows: wet sandbar (n=7 nests), wet dominated sandbar (n=26), 2 floodplain herb shrub objects (n=3, n=1), where QB and RE sandbar classifications agreed, and on 1 QB wet dominated sandbar (n=10) with fuzzy membership possibility for wet sandbar mapped as a RE wet sandbar. Using fuzzy agreement 70% of the nest locations were classified as the same land cover class by QB and RE. One nest location classified as QB dry sand and RE vegetated appeared to be the result of a poor segmentation of the RE image. At 15 nest locations classified by RE as low canopy cover, 8 locations were omission errors for QB dry sand sparseveg, 2 for QB wet sand sparseveg, and 1 for QB dry sand. Four of the nest locations were classified as low canopy cover by QB and RE. Two nest locations were classified as vegetated by RE and moderate canopy cover and vegetated by QB.

At GAR10, 229 nests were observed and according to QB, 222 nests were observed on 58 sandbars and 12 nests were located on water. According to RE 222 nests were observed on 53 sandbars and 7 nests on water. Most of the nest locations where the QB sandbar map was water were water omission errors by RE that occurred along perimeters of the RE sandbars. However, at 2 locations, inspection of the imagery revealed a more complex relationship between omission and commission errors for land cover and sandbar maps (Fig. 7). Using fuzzy agreement, QB and RE sandbar classifications agreed for all sandbars except one classified as FP wet sand dominated by RE and wet sandbar by QB due to RE not detecting a small river channel separating the sandbar from the floodplain. Using fuzzy agreement, 86% of the nest locations were classified as the same land cover class by QB and RE. Confusion between adjacent unvegetated and sparsely vegetated land cover classes that could not be resolved using fuzzy membership accounted for 5% of the nest locations. Water omission and commission errors accounted for 5% of the nest locations. The remaining 3% of disagreement consisted of confusion of low canopy cover and moderate canopy cover classes with other land cover classes.

A regression of RE area on the QB area for a paired sample of 47 sandbars that ranged in size from 0.2 to 18 ha, with 75% of the observations less than 2.8 ha in size, had an intercept of 1.16 (se=0.55) and a slope of 1.08 (se=0.11). The intercept was different from 0 (t_{45}=2.12, p=0.04) and the slope was not different from 1 (t_{45}=0.71, p=0.48). This suggests an average positive bias of 1.16 ha in the RE area that did not vary with sandbar size for this sample. A constant bias provides further support that RE may be satisfactory for area estimation if classification errors can be accounted for.

Fig. 7. Example of complex relationship between omission and commission errors for land cover and sandbar maps from QB and RE. Yellow and red polygons are 10 wet sand land cover objects mapped using QB. Yellow polygons are 2 wet sandbar objects mapped using QB. The 8 red polygons had areas less than 0.05 ha minimum map unit used to create sandbar maps. White polygon is a composite of wet sand land cover objects and the wet sandbar object mapped by RE whose spatial extents included the 10 wet sand land cover objects mapped by QB and areas of shallow water- submerged sand (commission errors).

4. SUMMARY AND CONCLUSIONS

The primary motivation for this study was a desire to reduce uncertainty in emergent sandbar area due to images for a river segment being acquired on different dates with different discharges. Thus the hypothesized benefits of RE imagery will depend on the ability to acquire imagery at the desired times and over shorter temporal windows.

Fuzzy producer and user agreements for dry sand and wet sand land cover classes were higher in early successional environments (constructed sandbars at LC) than in later successional environments at GAR09 and GAR10 where dry sand occurs in smaller patches interspersed with vegetation. Omission and commission errors were largest for land cover classes that are mixtures of sand and vegetation and generally occur among adjacent classes along a gradient of vegetation amount.

Confusion between the dry sand sparseveg and low canopy cover classes was high and resulted in a readily observable visual difference in the land cover maps. The most significant errors from the perspective of least tern and piping plover habitat, e.g., confusion between dry sand and vegetated classes, occurred at borders and ecotones of land cover classes.

Sandbar classification decisions are made using information on land cover proportions. Differences in sandbar classifications between QB and RE could often be resolved using fuzzy membership possibilities for sandbars. Confusion with water along the perimeter of sandbars was the main source of error remaining at the sandbar level after using fuzzy agreement. Analysis of area for a paired sample of sandbars at GAR10 indicated an average positive, but constant area bias, in RE estimates of sandbar area. The coarse spatial resolution of RE is responsible for this bias and RE would not be suitable for mapping sandbar erosion and characterization of sandbar shapes or vegetation patches at fine spatial resolution.

The conversion of image relative digital numbers to surface reflectance factors, high spectral contrast information classes, segmentation of images into relatively homogenous objects, and analysis of these objects are believed to be the primary factors that allowed the model to be successfully extended to coarser spatial resolution imagery.

REFERENCES

eCognition, 2012. eCognition Developer 8.7.1 User Guide, Trimble Germany GmbH, Munich, Germany.

Jacobson, R. B., Blevins, D.W., and Bitner, C.J., 2009. Sediment regime constraints on river restoration – an example from the Lower Missouri River. In: James, L.A., Rathburn, S.L., and Whittecar, G.R., eds., Management and Restoration of Fluvial Systems with Broad Historical Changes and Human Impacts. Geological Society of America Special Paper 451, pp. 1-22.

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H., and Sorooshian, S., 1994. A modified soil adjusted vegetation index. Remote Sens. Environ. 48, pp. 119-126.

Paris, J., 2005. Surface reflectance images. http://www.microimages.com/downloads/FAQsByJack.htm FAQ B. Surface Reflectance Images – SRFI.sml (accessed 3 March 2012)

Robinson, V.B., 2003. A perspective on the fundamentals of fuzzy sets and their use in geographic information systems. Transactions in GIS 7(1), pp.3-30.

Sherfy, M.H., Stucker, J.H., and Buhl, D.A., 2012. Selection of nest-site habitat by interior least terns in relation to sandbar construction. J. Wildlife Manage. 76(2), pp. 363-371.

U.S. Fish and Wildlife Service 2003. Amendment to the 2000 Biological Opinion on the Operation of the Missouri River Main Stem Reservoir System, Operation and Maintenance of the Missouri River Bank Stabilization and Navigation Project, and Operation of the Kansas River Reservoir System, 308 p. http://www.moriverrecovery.org/mrrp/f?p=136:6:898764753284718::NO 2003 Amend.BiOp (accessed 3 March 2012).

Ward, J.V., Tockner, K., Arscott, D.B., Claret, C., 2002. Riverine landscape diversity. Freshwater Biology 47, pp. 517-539.

Zhang, Y., 2004. Understanding Image Fusion. Photogrammetric Engineering and Remote Sensing 70(6), pp. 657-661.

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