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Studying the Relationship between Mud/Salt Flat Habitat and Shorebird Abundance at Two Wetland Areas using Landsat

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STUDYING THE RELATIONSHIP BETWEEN MUD/SALT FLAT HABITAT

AND SHOREBIRD ABUNDACE AT TWO WETLAND

AREAS USING LANDSAT

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ABSTRACT

The objective of this project was to determine the degree and direction of association between the amount of mud/salt flat area and shorebird abundance during spring and early summer. This study used Landsat 5 to indirectly measure mudflat and salt flat areas at two wetland complexes within Kansas over a period of several years (1991-2008). These measurements were compared to shorebird surveys conducted by several individuals at both Quivira National Wildlife Refuge and Cheyenne Bottoms Wildlife Area. A correlation analysis showed that significant relationships exist between mud/salt flat area and the abundance of certain shorebird species. Correlation coefficients for individual species differed between Cheyenne Bottoms and Quivira. Statistically significant positive relationships to mudflats exist with species of Long-billed Dowitcher, Greater & Lesser Yellowlegs, and Dunlin at Cheyenne Bottoms Wildlife Area. Several species of Plover and species of Greater Yellowlegs, Pectoral Sandpiper, and Stilt Sandpiper show statistically positive relationships to salt flats at Quivira. The amount of area these land cover types take up within a wetland are contributing factors to avian abundance during spring and early summer.

ACKNOWLEDGMENTS

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

INTRODUCTION

Many characteristics define wetlands as different from any other habitat type and wetlands also provide exclusive ecosystem services (Cowardin et al., 1979). Wetlands act as stop-over sites for migrating birds, provide habitat for flora and fauna, recharge underground aquifers, and aid the improvement of regional water quality (Groom et al., 2006). Direct human use of wetland areas include commercial hunting and fishing, medicines, and irrigation (Groom et al., 2006). The United States Fish and Wildlife Service (USFWS) and state controlled wildlife and parks divisions are both funded to manage and/or protect wetland areas for both direct and indirect uses (USFWS 2010).

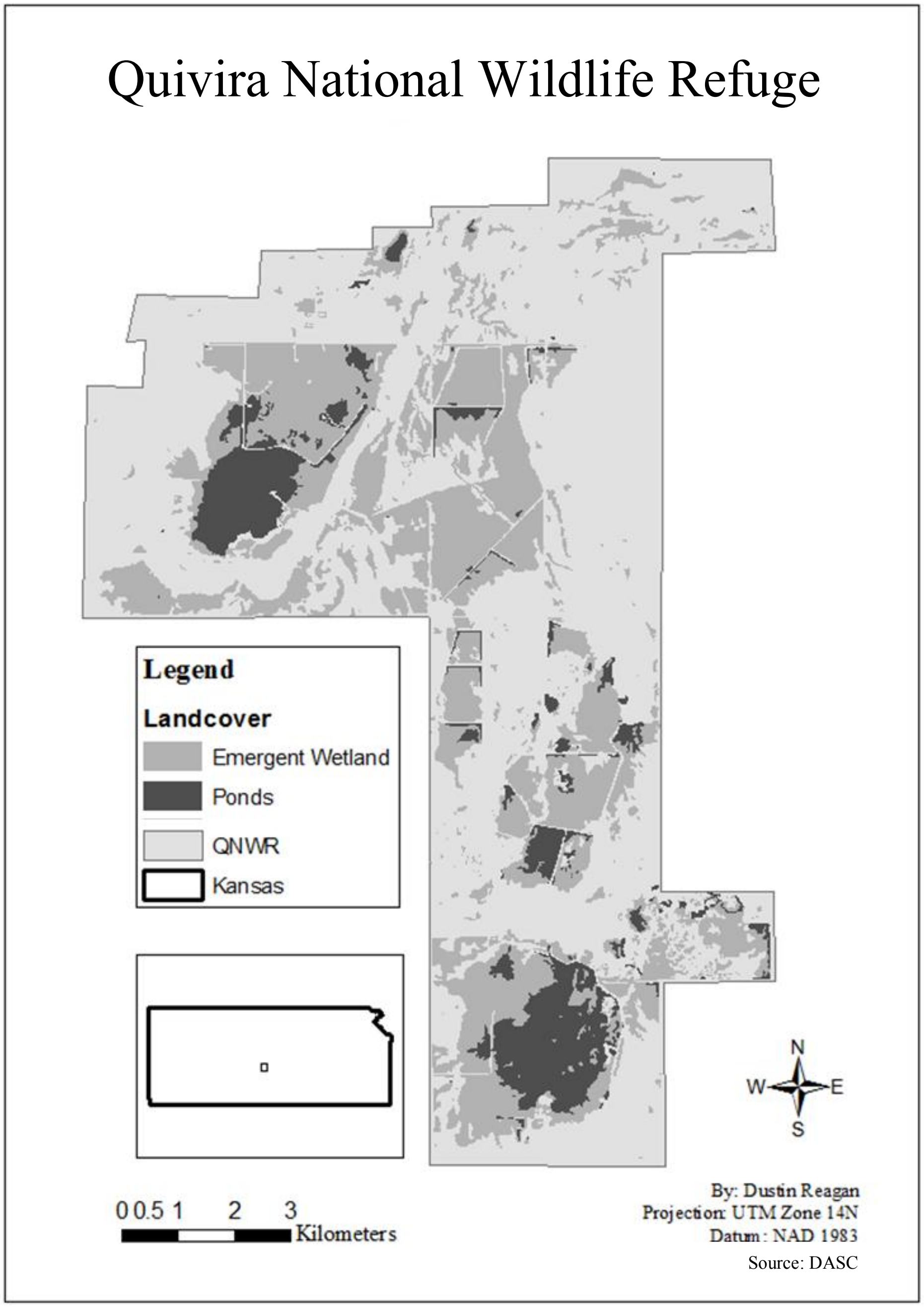
The Cowardin system (Cowardin et al., 1979) defines wetlands based on at least one of the following conditions: (1) the substrate is predominantly un-drained hydric soil; (2) the substrate is not soil and is saturated or covered by shallow water at some time during the growing season of each year; and (3) at least periodically, the site supports predominantly hydrophytic vegetation. Wetlands are dynamic ecosystems because the characteristics defining them (soil moisture, inundation, vegetation, and fauna) vary temporally and spatially (Wright and Gallant, 2007). Variability is even more substantial in semi-arid areas where extreme changes are present between the wet and dry season (Schmid et al., 2005). Many anthropogenic activities such as agricultural and urban development have caused a significant loss of wetlands (Syphard & Garcia, 2001). Over the last 200 years, it is estimated that at least 50% of wetland areas have been destroyed within the contiguous United States (Dahl 1990).

Many wetlands in the central United States lie in the middle of avian migration routes from Canada to South America and act as an important stop-over site for many bird species (Brown et al., 2001). Many of these migrating species belong to the Order Charadriiformes. The Suborder Charadrii includes what commonly are known as shorebirds, which are small to medium-sized birds that have slim, probing bills and relatively long legs (Gill 1995). Shorebirds have distinct foraging behaviors and primarily use their bills to probe in mud or sand to feed on prey items from the surface of the ground (Gill 1995). The amount of mud/shallow water habitat within a wetland area has a direct effect on the amount shorebirds present (Skagen & Knopf, 1994, a). Mud/shallow water habitat can change rapidly and during migratory periods, transitory populations of shorebirds respond to this resource opportunistically rather than exhibiting strong annual site fidelity (Skagen & Knopf, 1994, a). Birds that exploit unpredictable resources in temporally dynamic wetlands might rely on behaviors such as opportunistic use or colonization behavior rather than fidelity to specific wetland sites (Colwell & Oring 1988).

Two wetland areas in Kansas; Quivira National Wildlife Refuge (QNWR) and Cheyenne Bottoms Wildlife Area (CBWA), are key resource areas for many land-based migrating birds, including those of the Order Charadriiformes (Castro et al., 1990). The value of these areas is recognized and both are designated “Wetlands of International Importance” by the Ramsar Convention on Wetlands (Kostecke et al., 2004).

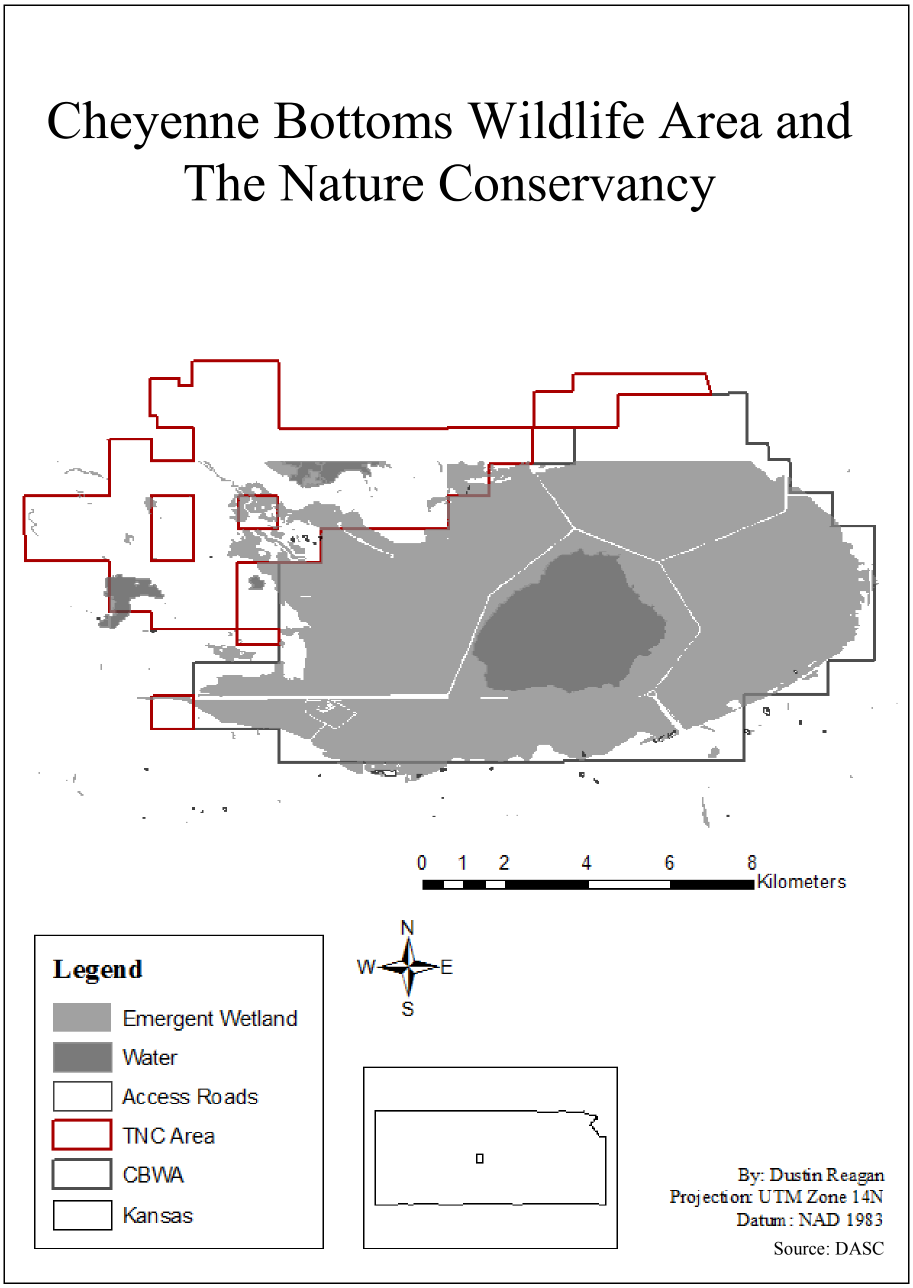
Quivira National Wildlife Refuge is located in south-central Kansas in Stafford County and is an 88 km^2 refuge managed by the United States Fish and Wildlife Service (USFWS) (Figure 1). Along with precipitation and groundwater discharge, Rattlesnake Creek supplies the wetland complex with fresh water throughout the year. Over thirty water units ranging from 1 to 600 hectares are supplied by this drainage. QNWR is a saline environment and includes salt flats on its landscape. Primary wetland vegetation within the area includes the genera *Spartina, Typha, Juncus, Carex*, and *Distichlis* (Skagen & Knopf, 1994, a). The blend of varied plant communities and the presence of the Big and Little Salt Marshes attract shorebirds that winter in South and Central America (Skagen & Knopf, 1994, b). There have been 39 species of the Order Charadriiformes have been observed at QNWR (Hands, 2008).

Figure 1. Map of Quivira National Wildlife Refuge in Stafford County Kansas.



Cheyenne Bottom is a large structurally controlled internally drained wetland. The basin itself is approximately 9.5 km in width and 13 km long and encompasses an area of approximately 165 km^2. Three creeks, Blood, Walnut, and Deception creek, enter the basin and provide flow to the bottoms. Furthermore, the Arkansas River provides water from a canal on the southwest side of CBWA (USFWS 2010). Over 320 species of birds have been identified at Cheyenne Bottoms Wildlife Area (Hoffman 1987). Cheyenne Bottoms is especially important to approximately 500,000 shorebirds that use the reserve annually (Kindscher et al., 2004). Two agencies own the land encompassing this wetland complex. The Cheyenne Bottoms Wildlife Area (CBWA) managed and owned by the Kansas Department of Wildlife, Parks and Tourism (KDWPT), another smaller plot of the Cheyenne Bottoms Preserve is owned by The Nature Conservancy. The CBWA encompasses a 79 km^2 area and uses active management practices which move water between pools via dikes, canals, and pumping stations (Figure 2). In early April at least two pools are drained to provide mud-flat habitat for migrating shorebirds and to promote vegetation growth providing food for waterfowl in the fall; these pools are then re-watered in July and August depending on water availability (USFWS 2010). The Nature Conservancy owns 28 km^2 with a primary objective of re-establishing natural hydrology and plant communities within this area (Figure 2) (Kindscher et al., 2004).

Figure 2. Map of Cheyenne Bottoms Wildlife Area and The Nature Conservancy in Barton County Kansas.



Management strategies for both CBWA and QNWR include practices that manage for either mudflat or salt flat habitat respectively (USFWS 2010, Skagen and Knopf, 1994, a). However, these areas differ in hydrology, habitat type and availability, and controlling agencies USFWS and KDWPT, respectively. Hunting is much more prevalent at CBWA than at QNWR and management strategies focus heavily on direct usage at CBWA (USFWS 2010). Although these differences exist, this research will define both areas as reserves with shorebirds and mud/salt flat habitat area functioning as indirect rather than direct values to the environment.

Objective and Hypothesis

The objective of this thesis is to determine the degree and direction of association between shorebird abundance and mud/salt flat area. The hypothesis is that the area of mud/salt flat habitat is a factor influencing shorebird abundance during the spring and early summer at two wetland areas in Kansas. The null hypothesis is that there is no association between mud/ salt flat area and shorebird abundance.

METHODS

General Approach

The approach of this thesis was to apply a supervised classification procedure that quantifies mudflat and salt flat area (km^2) from Landsat imagery at CBWA and QNWR. These calculated areas were compared to shorebird surveys conducted at these reserves to determine the degree and direction of association between individual species, and the amount of mud/salt flat land cover type. Correlation results were obtained by performing statistical tests and corrections including the Pearson Product Moment Correlation, Bonferonni correction, and correction for attenuation.

Basis for Hypothesis

It has been demonstrated that shorebirds respond to mud/salt flat habitat opportunistically (Colwell & Oring 1988). However, many other factors including local and regional weather, topology, and overall wetland status contribute to the quantity of shorebirds present at these reserves (USFWS 2010). The amount or area of mud/salt flat habitat limits the quantity of individual shorebirds that can utilize this resource with respect to their body size and foraging needs. The carrying capacity of these reserves varies from year to year due to fluctuations in water availability, vegetation, insect availability, and mud/salt flat habitat. However, the amount of mud/salt flat area defines a large portion of this carrying capacity because mud/salt flats are critical habitat for shorebirds and describes part of the overall health of the wetland (USFWS 2010). Studies have shown that landscape level habitat measures can explain abundance and diversity of animals (Naugle et al., 1999). For example, Robbins et al. (1989) found that relative abundances of breeding birds in the Middle Atlantic States were related to forest area and patch isolation. This study seeks to exploit a similar relationship to mud/salt flat habitat and describe its association as a factor influencing shorebird abundance.

Data Used

This study utilized two datasets. One dataset consists of avian bird count data collected by Helen Hands. This dataset is in Excel format and consists of bird count observations from both wetland reserves. These counts were conducted by several individuals including; Helen Hands, O Lin, and Donna Allen, volunteers from the International Shorebird Survey ISS, and many others (Hands, 2008). Only bird count data with known locations of shorebird surveys and a single observation technique were selected for the study. Observations collected by Helen Hands at CBWA and O Lin and Donna Allen at QNWR were used for this study while several other counts were discarded for reasons addressed later in this paper. A second dataset consists of Landsat imagery collected from the Global Visualization Viewer (GLOVIS), a data collection portal operated by the United Stated Geological Survey (USGS). Landsat imagery from several years was not available for study due to cloud cover. Samples were considered valid when criteria for the shorebird count dataset were met and corresponded with a date that a cloud free Landsat image was available. Furthermore, the use of imagery and bird count data varied between both QNWR and CBWA, so dates chosen for analysis vary between reserves.

Remote Sensing of Wetland Areas

Traditionally, aerial photographs have been used to monitor changes in wetland resources (Coppin et al., 2004). This method can be time consuming and resource intensive (Ozesmi & Bauer, 2002). Furthermore, change detection by visual photograph interpretation is subject to human error, and replicating interpretations can prove difficult and inconsistent (Coppin et al., 2004). Methods combining remote sensing and other ancillary information can be useful for examining large areas for wetland monitoring (Ozesmi & Bauer, 2002). Wetland mapping by means of remote sensing has been performed since the launch of ERTS-1, the first satellite of the Landsat MSS series, in the 1970s (Töyrä & Pietroniro, 2005). Other space-born sensors such as Landsat, Satellite Probatoire d'Observation de la Terra (SPOT), and Indian Remote Sensing Satellite (IRS) have been successfully used to monitor wetlands (Baker et al., 2007). The archive of data provided by satellites can prove useful in identifying change in wetland areas over time (Ozesmi et al., 2002). Repeat coverage allows wetlands to be temporally monitored and the digital format of the data is easily integrated into GIS (Ozesmi et al., 2002). Other ancillary data such as hydric soil maps, national wetland inventory maps, and digital elevation models can be combined with remote sensing techniques to produce accurate wetland maps. Although satellite imagery is extremely useful, it has some limitations. The spatial resolution of remotely sensed satellite imagery (20-30m) produces difficulty in identifying narrow or small wetlands (Ozesmi et al., 2002). The availability of data from the Landsat satellite archive can limit analysis with respect to area and time. In addition, images containing cloud cover can prevent the use of optimal dates for wetland mapping (Ozesmi et al., 2002).

Imagery Processing

Processing of the imagery was conducted to obtain an acceptable representation of where and when the surveys were performed. CBWA Landsat scenes were masked to the extent of the state-owned wildlife area and do not include the land that is owned by The Nature Conservancy. Although the counts conducted by Helen Hands were opportunistic and routes differed between observations, the majority of the observations were performed within the state–owned area and primarily done so via the access roads surrounding the reserve (Helen Hands Personal Communication, Feb. 2013). Masking the imagery to the state-owned area gave a reasonable representation of where the birds were counted. Many of the counts conducted at QNWR encompassed the entire refuge and were primarily conducted from the access roads within the reserve (Helen Hands & Rachel Laubhan, Personal Communication, Feb. 2013). Imagery collected from QNWR that corresponded to O Lin and Donna Allen observations were masked according to the seven survey areas defined by their dataset. Masking the imagery allowed for information to be obtained from where the shorebirds were observed and counted. Imagery from both CBWA and QNWR were temporally filtered to represent two time periods. Imagery collected from March and April were combined into a category to represent a two month interval during the spring, and imagery collected from May and June were combined into a category to represent a two month interval during late-spring to summer.

Classification Procedure and Spectral Angle Mapper (SAM)

The software program Environment for Visualizing Images (ENVI) extracts spectra from individual or groups of pixels and computes statistics for regions of similar composition. The collected spectra, known as end-members, are imported into algorithms to classify similar spectral regions within an image. The Spectral Angle Mapper (SAM) is a classification algorithm that defines the spectral similarity between given reference spectra and the spectra found in each pixel (Kruse et al., 1993). This algorithm calculates the angle between end-member collection spectra and pixel spectra treating them as vectors in a dimensional space defined by the number of bands in an image (Hunter & Power, 2002). In the case of Landsat, seven bands define a seven dimensional space of which spectral means are compared. A threshold value expresses the maximum acceptable angle for separation between the pixel vector and the end-member spectrum vector (Petropoulos et al., 2010). This threshold value is adjusted on an iterative basis and has been shown to increase classification accuracy (Petropoulos et al., 2010). The SAM algorithm is a single, consistent procedure that can be applied to multiple images to classify spectrally similar pixels related to the end-member collection data.

Using multiple Landsat images, training end-members were collected and placed into a spectral library. Training data collection pixels from the imagery were selected based on criteria from visual interpretation of several true color, false color, and tasseled cap transformed images (Figure 3). A tasseled cap transformation outputs an image based on the characteristics of brightness, greenness, and wetness (BGW) (Baker et al., 2007). Different band combinations were necessary for identifying differing moisture characteristics and the presence or absence of vegetation. The spectral library contained several end-members relating to three land cover classes; open water, mudflats, and salt flats (Figure 4). A default threshold value of 0.1 was defined for water and mudflat end-members. A threshold value of 0.25 was defined for the salt flat end-member. The value of 0.25 was obtained by running several iterative classifications by using different threshold values to determine the best possible classification of salt flat area based on visual interpretation. The salt flat end-member was extracted from imagery of QNWR because this land cover type only exists at that location and not at CBWA. The SAM classification algorithm was performed on the masked Landsat imagery. Pixels that exhibited an angle larger than the specified threshold level were left unclassified by the algorithm and placed in an "Other" category. This category contained pixels representing anything other than mudflats, salt flats, or open water areas. This included the other land cover types present at the reserves such as grassland, trees, and emergent vegetation (Houts 2006).

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Figure 3. Image of CBWA and examples of different band combinations used to select end-member collection data from visual interpretation.

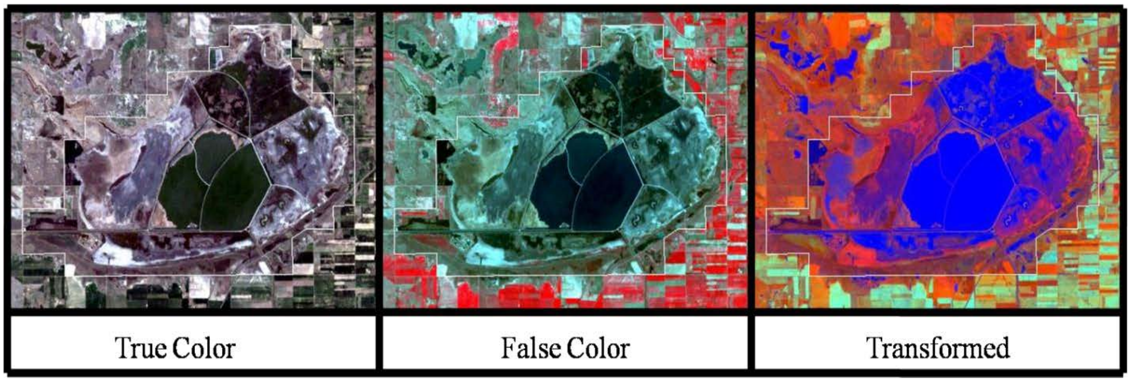
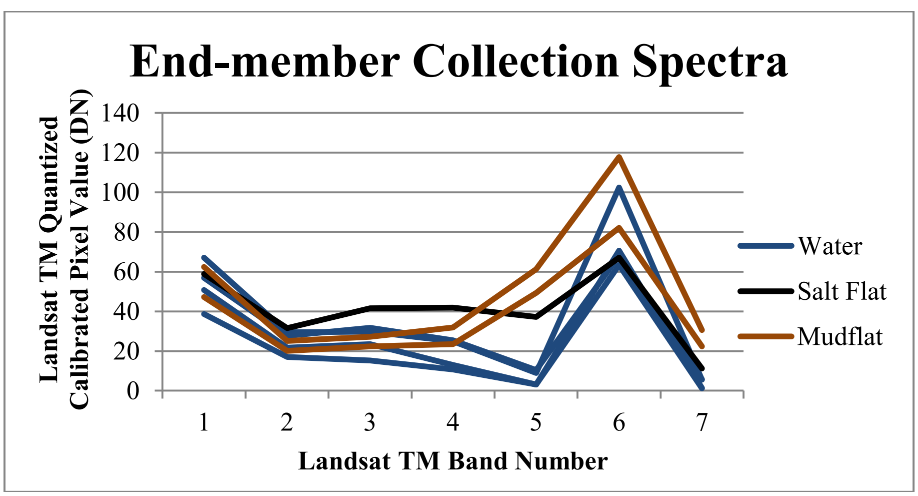


Figure 4. End-member collection spectral signatures used to classify three land cover types; mud flats, water, and salt flats.



Accuracy Assessment

Accuracy assessments were conducted for both classification procedures relating to CBWA and QNWR. With the addition of the salt flat end-member used at QNWR, it was necessary to perform a separate accuracy assessment relating to the salt flat land cover classification. The evaluation of classifications regarding the salt flat spectral library was aided by a detailed vegetation map produced by the USFWS in 2008. This map is in shapefile format and has attribute information relating to both land cover type and the date that it was observed in the field. Mapped land cover polygons were then extracted based on attribute information relating to specific categories. Further extraction was accomplished by cross referencing the date that the land cover was observed in the field with available Landsat scenes. Land cover polygons were discarded if the observation date did not fall within one week before or week after the Landsat scene acquisition. Discarding polygons was performed because wetlands are highly variable and can change in short periods of time (Syphard & Garcia, 2001). These Landsat scenes were then classified by using the same spectral library used for QNWR and applied to the SAM algorithm. The classified images were imported into ENVI and masked to the polygons extracted from the USFWS shapefile. The classified pixels were counted within and outside the polygons to generate an error matrix defining user and producer accuracies.

Classification accuracies also were determined for the CBWA spectral library. Two land cover maps were used for the assessment. One map was produced during a two week period in July, 2001 by the Bureau of Reclamation, and another was produced in June 2005 by Houts (2006). Using ArcGis Software, both maps were georeferenced to the Landsat imagery and projected to UTM Zone 14N. The land cover areas identified as mud flat and open water areas were digitized and polygon shapefiles were created to exhibit the land cover areas. Both Landsat scenes acquired during the time the two maps were produced are useable and have minimal cloud cover. These scenes were downloaded and classified by using the CBWA spectral library and the SAM classification algorithm. The classified images were then masked to the digitized polygons and the numbers of pixels for each category were counted within and outside the polygons. From these counts a matrix was generated by combining both assessments and relates to user and producer accuracies.

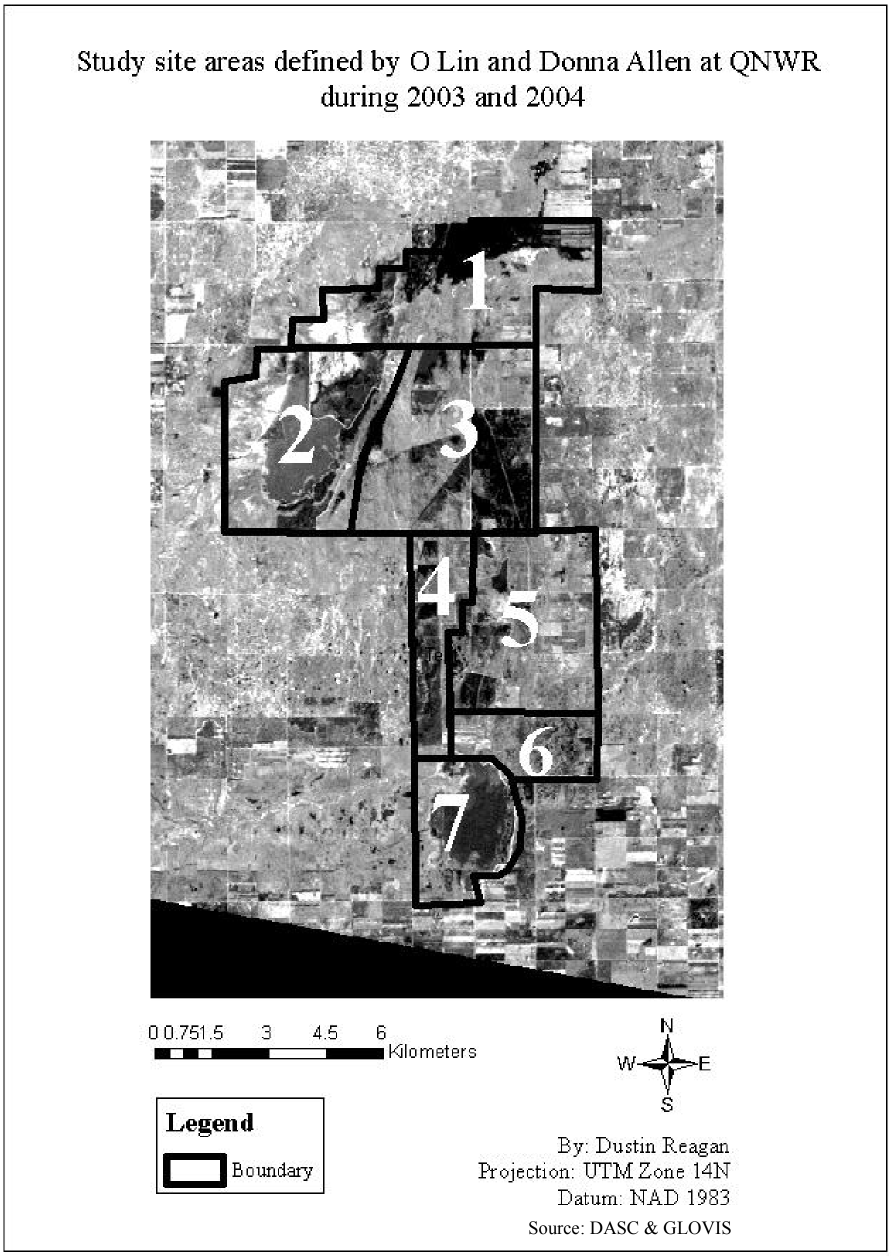
Shorebird Data Processing

All of the shorebird data was temporally filtered to represent the time periods outlined by the Landsat imagery collection date. Shorebird data collected from March and April were combined into a category to represent a two month interval during the spring, and data collected from May and June were combined into a category to represent a two month interval during late-spring to summer. A two month time interval allows for the imagery and shorebird datasets to be combined temporally into two defined time periods of spring and late-spring summer. Wetlands are areas of high variability (Syphard & Garcia, 2001). However, Landsat collects imagery from an area every sixteen days, and many images are unusable due to cloud cover. Several individual years were left un-sampled due to imagery availability. A two month time interval allows for reasonable amount of Landsat scenes to be used while controlling some aspects of temporal variability in mud/salt flat area within the reserves.

The sampling method of bird count data differed between reserves due to the several different observing techniques used throughout the years. The counts for CBWA were conducted by two primary observers. Edward Martinez conducted counts from 1976 to 1993 and Helen Hands conducted counts from 1994 to 2008. Only data collected by Helen Hands was used for analysis of CBWA. This is partly due to the consistency a single observer can provide. Survey estimates differed greatly between Helen Hands and Ed Martinez (Hands, 2008). Furthermore, minimal Landsat scenes were available when Ed Martinez was conducting surveys 1979-1993. The Helen Hands dataset was filtered to represent the total amount of shorebirds counted within both two month time intervals from 1994 to 2008. Any two month sample that contained less than three surveys was discarded from the analysis to remove any underestimate bias (Hands, 2008).

The counts obtained at QNWR had far more individual observers than that of CBWA. Furthermore, the observation techniques involving where and how the birds were counted differed between observers (Hands, 2008). One observation dataset was chosen for analysis and included the counts from surveys conducted by O Lin and Donna Allen during 2003 and 2004. This dataset was used in the analysis because their study included the entire reserve and divided their counts into seven separate areas increasing the spatial resolution of the data (Figure 5). Since the researchers were consistent with the number of observations made per two month interval (3), removal of data because of underestimate bias was not necessary. The O Lin and Donna Allen data were filtered to represent both the total and maximum number of shorebirds counted within both two month time periods of March-April and May-June from 2003 to 2004.

Figure 5. Map of Quivira Nation al Wildlife Refuge in Stafford County, Kansas relating to O Lin and Donna Allen observations from 2003-2004. (Hands, 2008). The map is divided into seven zones that outline the observation areas.



Sample collection

Once the Landsat imagery was masked and classified and the shorebird datasets were processed, samples were taken of both variables defining two month time intervals. Samples were considered valid when Landsat imagery and shorebird data were available within either two month time interval. Sixteen samples were taken from CBWA data defining a period from 1994-2008. Eight samples were taken from the March-April time interval, and eight samples were taken from the May-June time interval. The number of shorebird observations taken within both intervals varied, but no sample had fewer than three observations per interval and none had greater than five observations per interval. Twenty eight total samples from four two month time intervals were taken from QNWR data defining a period from 2003-2004. Seven samples were measured per two month time interval and were taken from the seven units defined by O Lin and Donna Allen. All data contained three observations per unit per interval.

Statistical Testing

The observed variables were tested to obtain Pearson product moment correlation coefficients relating the independent variable of shorebird abundance to the dependent variable of mud/salt flat area. The Pearson product moment correlation coefficient r describes the linear relation between two metric variables (Kornbrot 2005). The r statistic is a measure of association and does not imply causality in either direction (Kornbrot 2005). The Pearson test requires two assumptions; a bivariate normal distribution and a linear relation (Kornbrot 2005). Values of r are compared to the t-distribution to test against the null hypothesis that there is no association between variables (Kornbrot 2005). The p-value output from comparison to the t-distribution gives the probability of committing a type I error; namely rejecting the null hypothesis when it is in fact true (Rice 1989).

A Bonferonni correction is warranted because multiple tests were performed within this a study (Dunn 1974). If no adjustments are made for the number of tests, a group wide type I error rate cannot be controlled (Rice 1989). The Bonferroni equation adjusts the significance based on the original confidence level (95%) by dividing the original confidence by the number of tests performed (Dunn 1974).

The interest of this research is the relationship between shorebird abundance and mud/salt flat area as they exist without any observation error. If there were no errors in the collection of both the mud/salt flat measurements and shorebird count observations, the Pearson correlation coefficients would be sufficient evidence to describe the relationship. However, data collection techniques allow only for empirical observations and include measurement error. This error attenuates the magnitude of correlation between variables and lack of perfect reliability within a measurement produces a downward bias in the observed correlation (Muchinsky 1996). Therefore, when there are errors in empirical data collection, the actual correlation is greater than the observed relationship. An equation was used to compensate for this attenuation and correct for imperfect accuracies of observed variables. ρ_{xy}, the corrected validity coefficient, is obtained by dividing the obtained Pearson coefficient r_{xy} by the square root of the reliability of the independent variable r_{xx} (Muchinsky 1996). This correction has certain assumptions; (1) The correction cannot make a test more predictive then it actually is (Nunnally 1978), (2) Corrected coefficients cannot be directly compared with uncorrected coefficients (Muchinsky 1996), and (3) Coefficients corrected for attenuation cannot be subjected to statistical hypothesis testing (Magnusson 1967).

$$\rho_{xy} = \frac{r_{xy}}{\sqrt{(r_{xx})}} \qquad (1)$$

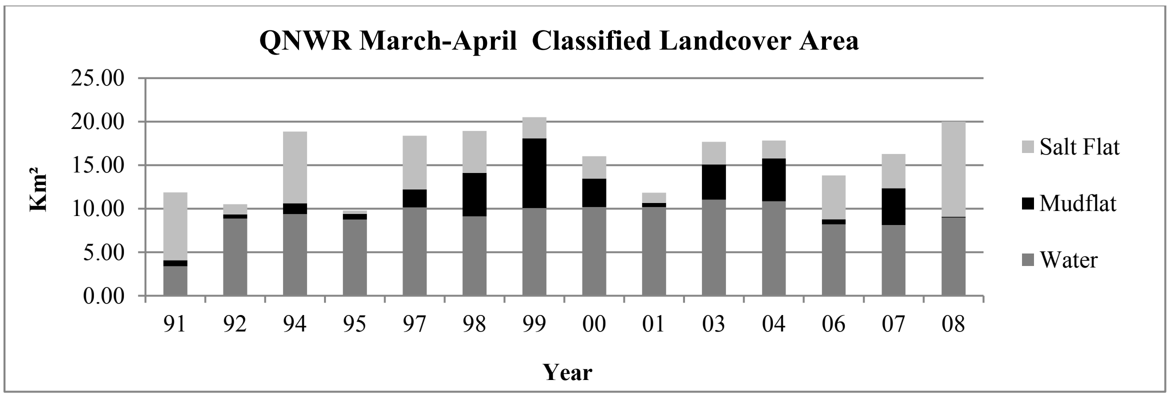
The shorebird observations were assumed to have no error. Assuming anything other than perfect reliability could correct for attenuation that was not present (Muchinski 1996). The reliability of the mud/salt flat variable is measureable from the accuracy assessment of the classification algorithm. Therefore, correction for attenuation was performed by using a single correction method to account for measurement error in the independent variable of mud/salt flat area. The reliability was obtained from the producer accuracy of the mud/salt flat class and output a measure of reliability based on the classification output.

RESULTS

Classification Results

Both reserves exhibited land cover variability from year to year. The amount of water, mud flat, salt flat areas fluctuate over time (Figures 6 & 7). Analysis shows that the amount of mudflat area decreases at QNWR as summer continues, this loss is contrasted by a gain to the "other" category which includes other land cover types within the reserves such as grassland, trees, and emergent vegetation (Skagen & Knopf, 1994, a). At QNWR, data collected showed an average of 88% mudflat loss from the March-April to the May-June time period. Furthermore, the salt flat class exhibited an average loss of 27.8%. It is also evident that CBWA was essentially dry during spring migration during 2006.

Figure 6. Classified land cover area by year for Quivira National Wildlife Refuge in Stafford County, Kansas. Bar graphs depict QNWR classified land cover areas for each sample image applied to the Spectral Angle Mapper. Land cover data from 2003 and 2004 were merged with O Lin and Allen shorebird data.



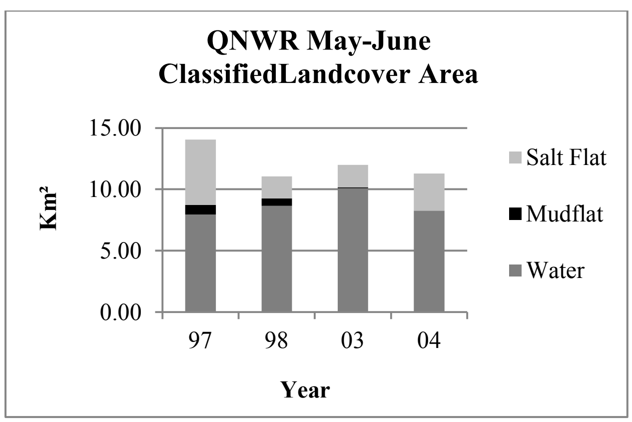
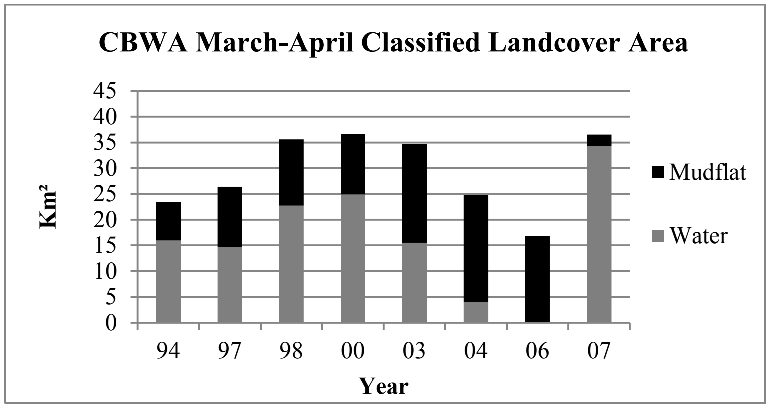
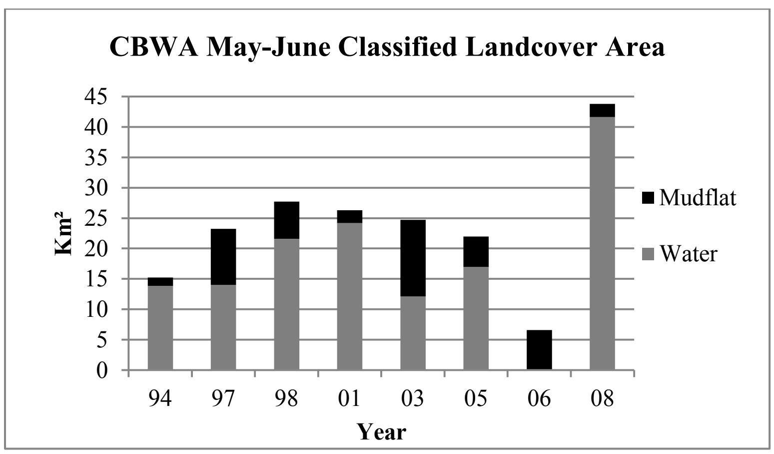


Figure 7. Classified land cover area by year for Cheyenne Bottoms Wildlife Area in Barton County, Kansas. Bar graphs depict CBWA classified land cover areas for each sample image applied to the Spectral Angle Mapper.





Classification Accuracy

CBWA Accuracy

The overall accuracy of the classification procedure used for CBWA is 73.8% with 79.4% user and 73.4% producer accuracies (Table 1). The highest individual class performance is that of the water class with 94.4% user and 84.1% producer accuracies.

The mudflat classification exhibits the lowest performance with 41.7% user and 52.0% producer accuracies. The overall classification has a higher user accuracy meaning the procedure has a high propensity to commission pixels into the correct categories. The lower producer accuracy shows that the procedure is more likely to omit pixels belonging to correct categories. However, the opposite is true of the mudflat class individually. A 41.8% user performance is mainly due to the over commission of mudflat pixels into the other category. A 52.0% producer performance is due to the omission of several pixels that should have been classified as mudflats but were classified other instead.

Table 1. Error matrix for CBWA classification procedure. Combination of accuracies attained from two land cover maps produced by Mike Houts in 2005 (Houts 2006) and from the Bureau of Reclamation in 2001 (TM# 8260-02-04).

	Water	Mudflat	Other	Total	Producer Accuracy
Water	24609	509	4132	29250	84.1%
Mudflat	579	12435	10877	23891	52.0%
Other	876	16838	93634	111348	84.1%
Total	26064	29782	108643		
User Accuracy	94.4%	41.8%	86.2%		
				Commission (User) Accuracy	79.4%
				Omission (Producer) Accuracy	73.4%
				Overall Accuracy	73.8%

QNWR Accuracy

The performance assessment for QNWR was evaluated only by the accuracy of the Salt Flat classification and excluded the water, mudflat, and other classes. This was done for two reasons. First, the only difference between procedures was the addition of the salt flat spectral end-member to the QNWR classification. Since the other end-members are the same it is assumed that the performance attained from the CBWA classification is similar to that of the QNWR classification for these categories. Second, there was no mudflat land cover defined within the shapefile that the USFWS provided. Without the mudflat class it is impossible to measure the performance of the entire procedure.

The salt flat category has an overall performance of 43.1% with 46.0% user and 40.2% producer accuracies. The low user performance is due to the procedure classifying areas that were salt flats into the water category. The low producer accuracy is due to the procedure classifying areas that were salt flats into the water and other categories. Although no data were collected from the mudflat user performance, it was possible to measure the accuracy because the procedure fully classified the salt flat pixels into either the water or salt flat category.

Variability of Spectral Signatures

The training end-member spectral signatures exhibit variability between and within land cover classes. The highest variability between end-members exists within Landsat bands five and six or short wavelength infrared and thermal infrared, respectively. The variability within the thermal band width can be attributed to varying degrees of temperature during the time of end-member collection. Since multiple images were sampled and classified partly in respect to their thermal signature, the differences in temperature at the time of image collection are attributing a source error within the classifications. Landsat band 5 or short wave infrared can be used to determine differing moisture content of land cover (Joo-Hyung et al., 2002). The differing amounts of moisture content within the mudflat and salt flat signatures are contributing to the variance between them. Mudflats are highly variable in regards to moisture content (Joo-Hyung et al., 2002). The highly variable nature of mudflat and salt flat signatures in respect to moisture content are affecting classification accuracies.

Shorebird Abundance and Mud/Salt Flat Area

Pearson and Corrected attenuated correlation coefficients were calculated for CBWA and QNWR describing the relationship between mud/salt flat area and species specific shorebird abundance. (Tables 2 & 3). Pearson and corrected coefficients relating to total shorebird numbers are greater at QNWR (r = 0.34) then at CBWA (r = 0.20). The strongest calculated relationship to mudflats at CBWA is evident in the species of Long-billed Dowitcher (*Limnodromus scolopaceus*) with a significant Pearson value (0.71) and a corrected coefficient of (0.99). The Black-necked Stilt, (*Himantopus mexicanus*), American Avocet (*Recurvirostra americana*), Undifferentiated Sandpipers, and the small gleaner guild all have significant Pearson values to salt flats at QNWR. These species also had corrected correlations that were (1.00). Species exhibit differing strengths of relationships to either mudflat or salt flat areas. The large probing guild has a greater relationship to mudflats at CBWA, the small gleaning guild shows a stronger relationship to salt flats at QNWR.

Table 2. Correlation coefficients from CBWA data. ρ_{xy} is the corrected correlation coefficient and r is the Pearson value. Values in bold indicate statistical significance at 95% confidence and asterisks denote statistically significant values after Bonferroni correction.

Common Name	Pearson Value (r)	ρ_{xy} (Mudflat)	Total Shorebirds
Black-bellied Plover	-0.34	-0.47	245
American Golden-Plover	0.03	0.04	10
Snowy Plover	0.17	0.23	220
Semipalmated Plover	-0.03	-0.04	268
Piping Plover	-0.18	-0.25	61
Killdeer	-0.04	-0.06	1479
Black-necked Stilt	0.13	0.18	118
American Avocet	0.46	0.64	3791
Greater Yellowlegs	***0.66**	0.92	**487**
Lesser Yellowlegs	**0.50**	0.69	**918**
Willet	-0.03	0.02	36
Spotted Sandpiper	-0.32	-0.35	82
Hudsonian Godwit	0.03	0.04	5777
Marbled Godwit	0.21	0.29	11
Ruddy Turnstone	0.04	0.06	58
Sanderling	-0.13	-0.18	151
Semipalmated Sandpiper	0.18	0.25	6506
Western Sandpiper	0.44	0.61	216
Least Sandpiper	-0.09	-0.12	399
White-rumped Sandpiper	-0.19	-0.26	15480
Baird’s Sandpiper	0.41	0.57	10321
Pectoral Sandpiper	0.20	0.28	203
Dunlin	***0.55**	0.76	**44**
Stilt Sandpiper	-0.43	-0.59	16493
Long-billed Dowitcher	***0.71**	0.99	**54004**
Common Snipe	-0.13	-0.18	309
Wilson’s Phalarope	-0.18	-0.25	57185
Red -necked Phalarope	-0.35	-0.49	38
Large Gleaner Guild	-0.15	-0.21	65274
Large Prober Guild	***0.57**	0.80	**76797**
Small Gleaner Guild	-0.15	-0.21	2303
Small Prober Guild	0.16	0.22	194095
Undiferentiated Sandpiper	0.15	0.20	160978
Unknown Species	0.14	0.20	57004
Total Shorebirds	0.20	0.28	399410

Table 3. Correlation coefficients from QNWR data. ρ_{xy} is the corrected correlation coefficient and r is the Pearson value. Values in bold indicate statistical significance at 95% confidence and asterisks denote statistically significant values after Bonferroni correction.

Common Name	Pearson Value (r)	ρ_{xy} (Salt flat)	Total Shorebirds
Black-bellied Plover	0.26	0.41	11
American Golden-Plover	***0.43**	0.68	**32**
Snowy Plover	***0.56**	0.88	**193**
Semipalmated Plover	***0.59**	0.93	**179**
Killdeer	***0.57**	0.90	**613**
Black-necked Stilt	***0.71**	1.00	**369**
American Avocet	***0.67**	1.00	**258**
Greater Yellowlegs	***0.56**	0.89	**512**
Lesser Yellowlegs	0.26	0.41	163
Spotted Sandpiper	0.28	0.44	58
Hudsonian Godwit	0.11	0.18	13
Semipalmated Sandpiper	0.22	0.34	450
Least Sandpiper	0.32	0.51	83
White-rumped Sandpiper	-0.02	-0.03	2326
Baird's Sandpiper	0.26	0.41	1313
Pectoral Sandpiper	**0.38**	0.60	**13**
Stilt Sandpiper	***0.39**	0.61	**268**
Long-billed Dowitcher	-0.02	-0.03	641
Wilson's Phalarope	0.29	0.45	5545
Large Gleaner Guild	0.34	0.53	6595
Large Prober Guild	0.16	0.25	941
Small Gleaner Guild	***0.74**	1.00	**1032**
Small Prober Guild	0.20	0.32	4920
Undiferentiated Sandpiper	***0.64**	1.00	**741**
Unknown Species	0.13	0.21	2391
Total Shorebirds	0.34	0.54	16200

CONCLUSIONS

The hypothesis of this study is that the amount of mud/salt flat area at CBWA and QNWR is a contributing factor of shorebird abundance during spring and early summer. Evidence from the research suggests the hypothesis holds true for certain species of shorebirds. The use of Landsat and the SAM algorithm estimated both CBWA and QNWR land cover variability. Estimating the amount of mud/salt flat area on a semi-annual basis has allowed for inferences to be made about which species of shorebirds are influenced by the amount of this habitat during nesting and stopover selection in the spring and early summer. Accuracies of the classification procedure introduced varying degrees of uncertainty in the measurement of the independent variable. This source of error attenuates the data as to decrease the observed correlation (Muchinsky 1996). All corrected values are estimates of the true correlation and are all greater than the observed Pearson values. In accordance with (Muchinsky 1996), statistical significance is determined from the Pearson correlation values but not from corrected values.

At CBWA, four species of shorebirds show statistically significant positive relationships to observed mudflat area. Two of these species, the Long-billed Dowitcher (*Limnodromus scolopaceus*) and Dunlin (*Calidris alpina*) have similar foraging behaviors and are shallow water feeders (Millicent, 1984). These animals forage and probe along mudflats in a “sewing machine” like motion picking invertebrates, particularly chironomids, out of wet mud or shallow water (Millicent, 1984). These types of species showed the greatest relationship to mudflats at CBWA and the analysis agrees in part with their foraging behavior. Greater Yellowlegs (*Tringa melanoleuca*) and Lesser Yellowlegs (*Tringa flavipes*) both feed on aquatic invertebrates and small fish by sweeping their bills through the water column and by visual pecking (Robert & McNeil, 1989). The correlation to mudflat areas partially agrees with what is known about their foraging behavior and diet of invertebrates does agree with the relationship (Robert & McNeil, 1989).

At QNWR, several species showed statistical significance to observed salt flat area. Similar to CBWA, shorebirds that exhibited a sweeping foraging style showed significant relationships. The American Avocet (*Recurvirostra americana*) Greater

Yellowlegs were both significant. Several species of Plover (*Charadriidae*) showed significant relationships to salt flat areas including the Snowy Plover *Charadrius nivosus,* Semipalmated Plover (*Charadrius semipalmatus*), and American Golden Plover (*Pluvialis dominica*). Many species nest at QNWR including the American Avocet, Black-necked Stilt (*Himantopus mexicana*), Killdeer (*Charadrius vociferous*), and Snowy Plover (Fellows et al., 2001). The nesting behavior of these animals on salt flats at QNWR is contributing to the significant correlations in these species. The Wilson's Phalarope (*Phalaropus tricolor*) is the most abundant species at QNWR (Hands 2008). However, the correlation is not significant with a Pearson value of (0.29). The foraging behavior of this animal does not require mud or salt flats as these species wade and spin circles in the water to dig up prey (Colwell & Jehl Jr., 1994).

Comparing the results of the observations found at both reserves has the potential for error. CBWA was sampled a total of ten individual years yet has less spatial resolution whereas the QNWR was sampled only two years yet has a greater spatial resolution. The conclusions and correlations retained in regards to CBWA reflect relationships based on the mudflat area within the entire reserve. This gives information regarding CBWA use over time as a whole to migrating species. The conclusions from the QNWR data reflect a smaller time period (2003-2004) and give more spatially detailed observations (7 sub-areas) of where the birds might occur preferentially or nest within QNWR.

Although this is the case, this research has shown that individual species display different correlation coefficients to each reserves land cover types. The large difference between reserves is evident in the species of Long-billed Dowitcher, which is a very common migrant through Kansas (Skagen and Knopf, 1994, b). This species abundance has a statistically significant Pearson correlation to mudflats at CBWA (0.71) whereas the Pearson correlation to salt flats at QNWR is (-0.02). The Long-billed Dowitcher is more common at CBWA than at QNWR (Hands, 2008). Another large disparity is also evident in the species of Stilt Sandpiper (*Calidris himantopus*). The Stilt Sandpiper shows a significant Pearson value (0.39) at QNWR where a negative Pearson value (-0.43) was obtained at CBWA. The Stilt Sandpiper and Long-billed Dowitcher have similar foraging behaviors and diet (Baldassarre & Fischer, 1984). Both species utilize CBWA and QNWR heavily during spring migration (Fellows et al., 2000), yet their correlation coefficients between the reserves differ greatly. The reason for this is currently unknown. However, Stilt Sandpipers migrate thousands of miles along a narrow corridor whereas Long Billed Dowitcher migration is intermediate but widespread (Skagen et al., 1999). Stilt Sandpipers have a gradual migration pattern and do not arrive at Kansas latitudes until late April and the beginning of May (Skagen et al., 1999). The surveys conducted at CBWA obtained higher Stilt Sandpiper abundances in the May-June time interval whereas lower abundances were obtained from observations during the March-April time period. The differing times of arrival between Stilt Sandpipers and Long-billed Dowitchers are affecting the correlation coefficients.

Many species of plover show significant relationships to salt flats at QNWR but had low coefficients to mudflats at CBWA. Many species of plover are known to utilize salt flat areas for migration and nesting purposes (Fellows et al., 2000). These correlations suggest that the difference between mud and salt flat habitat types are contributing to separate abundances found within both reserves. Other species including the American Avocet also nest in saline environments (Fellows et al., 2000).

Differences in the use of mudflat and salt flat land cover types by various shorebirds are evident within this study. Preferential nesting of several species at QNWR accounts for the higher correlations at this reserve than at CBWA. Other differences in saline concentration between the reserves have a potential impact on the invertebrate ecology within these areas (Andrei et al., 2008). This research suggests that difference in mudflat and salt flats habitat type attributes to the differing correlations found between both CBWA and QNWR.

DISCUSSION

Classification accuracies are 40-50% for both CBWA and QNWR mud/salt flat classifications, and slight varying degrees of water content were not able to be defined. For example, wet mud/salt, dry mud/salt, and extremely shallow water are all considered to be one mud/salt flat land cover type. Increasing the imagery spatial resolution or the use of hyperspectral sensors could prove useful in differentiating types of mud/salt flats. This differentiation was not achieved from the current classification procedure and is affecting the correlations found at CBWA and QNWR.

Sample collection was limited due to the temporal resolutions of both the Landsat imagery and shorebird data. Merging these two datasets required a two month sample time frame. If the time frame was reduced, the amount of samples available for collection would be reduced dramatically. Furthermore, equal sampling from each time interval would not have been possible with a reduction in the time frame. The two-month interval is a period where many species abundances peak and decline, sometimes within two weeks to a month (Hands 2008). This issue was unable to be corrected due to the availability of Landsat imagery and is introducing an unknown degree of error in the analysis. Combining both two month time intervals into correlation analysis was also necessary. If only one time interval was used; March-April for example, the sample size is reduced by half and although some of the correlations increase, the degrees of freedom reduce and less statistical significant relationships exist. The sampling method chosen allowed for the maximum amount of samples to be measured given the constraints of observer consistency and availability of Landsat imagery.

The acquisition of Landsat imagery combined with the SAM classification procedure could prove useful in the future to measure shorebird habitat on a landscape scale. Improving the classification procedure could help identify critical mud/salt flat habitat over large areas within the Central Flyway. Identifying this habitat and understanding its use by shorebirds might allow for management strategies to adapt accordingly and to create ample mud/salt flat habitat for migrating and nesting shorebirds.

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Appendix 1. Common and Scientific name of all Shorebird Species listed referenced to the American Ornithologists Union.

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Common Name	**Scientific Name**
Black-bellied Plover	*Pluvialis squatarola*
American Golden-Plover	*Pluvialis dominica*
Snowy Plover	*Charadrius nivosus*
Semipalmated Plover	*Charadrius semipalmatus*
Piping Plover	*Charadrius melodus*
Killdeer	*Charadrius vociferus*
Black-necked Stilt	*Himantopus mexicanus*
American Avocet	*Recurvirostra americana*
Greater Yellowlegs	*Tringa melanoleuca*
Lesser Yellowlegs	*Tringa flavipes*
Willet	*Tringa semipalmata*
Spotted Sandpiper	*Actitis macularius*
Hudsonian Godwit	*Limosa haemastica*
Marbled Godwit	*Limosa fedoa*
Ruddy Turnstone	*Arenaria interpres*
Sanderling	*Calidris alba*
Semipalmated Sandpiper	*Calidris pusilla*
Western Sandpiper	*Calidris mauri*
Least Sandpiper	*Calidris minutilla*
White-rumped Sandpiper	*Calidris fuscicollis*
Baird's Sandpiper	*Calidris bairdii*
Pectoral Sandpiper	*Calidris melanotos*
Dunlin	*Calidris alpina*
Stilt Sandpiper	*Calidris himantopus*
Long-billed Dowitcher	*Limnodromus scolopaceus*
Common Snipe	*Gallinago gallinago*
Wilson's Phalarope	*Phalaropus tricolor*
Red-necked Phalarope	*Phalaropus lobatus*

Appendix 2: List of ".tar" file names of cloud free Landsat 5 imagery available from GLOVIS website. All files contain imagery from Path 29, Row 33.

LT50290331994093XXX02.tar	4/3/1994
LT50290331994141XXX02.tar	5/21/1994
LT50290331995096AAA01.tar	4/6/1995
LT50290331997117AAA03.tar	4/27/1997
LT50290331997133XXX03.tar	5/13/1997
LT50290331998104XXX02.tar	4/14/1998
LT50290332000110XXX02.tar	4/20/2000
LT50290332003102LGS01.tar	4/12/2003
LT50290332003150LGS01.tar	5/30/2003
LT50290332004089PAC02.tar	3/30/2004
LT50290332004152PAC02.tar	6/1/2004
LT50290332005091PAC01.tar	4/1/2005
LT50290332006110PAC01.tar	4/20/2006
LT50290332006142PAC01.tar	5/22/2006
LT50290332007097PAC01.tar	4/7/2007
LT50290332008084PAC01.tar	3/25/2008
LTF0290332008163PAC01.tar	6/12/2008