COMPUTER AIDED STATISTICAL ANALYSIS OF SATELLITE SENSOR DATA CROSS-CALIBRATION

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ABSTRACT

The space borne Moderate Resolution Imaging Spectroradiometer (MODIS) instrument was designed as the leading edge of global observation technology. The MODIS instrument and later follow-on satellite sensors (e.g., NPP, VIIRS) represent the best technology for further observations of global change, land use/land cover change, and for global mapping. However, the value of MODIS data for these applications has been limited because of its short history. The satellite sensor that serves as the precursor to MODIS is the Advanced Very High Resolution Radiometer (AVHRR). The USGS National Center for Earth Resource Observation and Science (EROS) has an archive of AVHRR data covering the conterminous United States dating from 1989 to the present.

Using the year 2003 where we have data from both sensors, we investigated a method to transform the heritage AVHRR data to a form useful for comparison with the MODIS data. This will allow for comparative studies, such as climate and environmental change, which require the long history of AVHRR data with the current and future data supplied by MODIS.

We have found that a simple linear regression does not appear to provide an accurate transform between the sensors. In addition, it has been observed that divisions by land type, position in the season, and geographical area need to be addressed for accurate comparisons. Within the data, we have seen some obvious problems with heteroskedasticity, and suspect that the data could be cross-sectional in nature to account for the reported variance.

INTRODUCTION

The use of remote sensing has continued to increase over the past decade as increasingly advanced technology becomes available to give more accurate measurements and faster evaluation times of current seasonal data. One of the most widely used sets of data from remote sensing sensors has been the Normalized Difference Vegetation Index (NDVI). NDVI is routinely calculated using the visible and near infrared light spectrum acquired by satellite sensor data. Until recently, the data has been collected using the NOAA Advanced Very High Resolution Radiometer (AVHRR) series satellites. As these satellites have begun to age, a new set of sensors have been created to give better measurements and higher resolutions. The sensor that will be used to replace AVHRR is the Visible/Infrared Imager/Radiometer Suite (VIIRS). While this sensor has not been put into production yet, the VIIRS sensor will be very similar to the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) sensor.

Many studies have used the long history of NDVI data that has been collected from the AVHRR sensor [11], [10], [9], [17], and [19]. A number of these studies have used the almost twenty years worth of sensor data to monitor changes in both vegetation and a variety of land surface properties. Being able to understand how current AVHRR derived NDVI and current and future sensor derived NDVI data relate is crucial to being able to allow future long term trend analysis studies to continue.

PROJECT BACKGROUND

Background

A small number of studies have previously compared observed and simulated MODIS and AVHRR data ([1], [4], [5], [8], [13], [18]), which have provided varied results, mainly in support of high correlation values between cross sensor evaluations. Gitelson, et. al, shows that MODIS NDVI values are slightly greater than those from AVHRR in simulated data from the red and near infrared (NIR) bands [3]. In addition, Gallo et. al ([4], [5]) both found that MODIS NDVI data has shown good agreement with other sensor NDVI data when properly corrected for water vapor, ozone, Rayleigh scattering, and other atmospheric conditions in a manner discussed by [12] and [16]. There is evidence that there is a poor correlation between the NOAA-14 AVHRR satellite and the MODIS Terra sensor [2]. However, while the NOAA-14 and NOAA-15 satellite showed poor correlation, the NOAA-16 satellite has a slightly adjusted range of bands that are used to determine NDVI, which should allow for a better correlation [18].

Many of the studies have used simulated data rather than actual data in order to avoid the atmospheric and other sensor based problems that exist within satellite image data. The majority of these studies have found that there is a strong linear relationship between the two sensors. In particular, Steven et. al has noted that the reflectance for spectral band effects can be corrected to approximately a value of plus or minus 0.02 [13]. To deal with the effects of satellite images that simulated data does not factor in, it appears that topography, solar angles, and viewing angles have a contribution to the differences between satellite data [13]. One problem with the data is the problem of geo-registration (not being able to accurately map the data to the same locations) [18]. Further, AVHRR and MODIS NDVI values can vary with land cover type, simply by observation of the data sets, and noted that correctional algorithms should take the land cover differences into account [4].

Initial Hypothesis

The initial regressions were created under the hypothesis that the differences between the AVHRR and MODIS sensors were a result of the general differences between sensors, including spectral band differences and time of day, as well as the contamination based on clouds. It was also believed that there may be a general link between sensor differences among different types of land cover classes. Under some brief exploration of data sets, our hypothesis shifted to include some type of correction for approximate time of season.

Comparison Data Setup

Our study compares four satellite sensors. Two satellites, N16 and N17, use the AVHRR sensor; the other two satellites, AQUA and TERRA, use the MODIS sensor. We use a piece-wise linear regression technique to compare the data from these sensors.

We classify the data by land cover type and the 16-day composite observation number. The land cover type was determined from the adjusted 1992 NLCD land cover map [19]. The land cover classes we use are: *deciduous forest, evergreen forest, mixed forest, grassland and herbaceous, shrub land, row crops, small grains, pasture and hay, residential and commercial, water and ice,* and the generic *other*. This study extends Gallo's work, which examined the first nine classes, as water and ice have many notable problems with NDVI values being artificially low [5]. In addition, the land cover classified as the "other" category defines too broad of a region to be useful in making an accurate evaluation.

The compilations of the data sets were done in two ways. The first was to use a pixel to pixel comparison using images of the US. In total the comparison used 13,251,843 points per composite, which was divided into the eleven land type groupings. While this comparison is ideal in the comparison of data, a number of issues, such as accuracy problems with the land type map, geo-registration problems, as well as artificially low data point values due to image contamination, led to the use of the second data set aggregation. The second compilation of the data set used 20km by 20km sample sites located around the United States where the contents of the sample is 80% or greater of one land type. Each sample was averaged, using only the pixels that according to the modified NLCD land type map were of the dominant land type. The averaging also removed the effects of cloud- and water-masked pixels.

One issue within the data set is that the N16 satellite began to fail midway through the 2003 data year (at image observation number 16), resulting in an incomplete year of data for comparison between the four different satellites. In the regression analysis, all depictions of N16 are used through the last good date of N16 to gain full value of the regression values. Unfortunately, due to the failure, there is only a limited amount of data between N16 and the Aqua satellites. The 2003 data year was chosen as it provides the greatest amount of data between N16 and Aqua allowing for the maximum number of data comparisons in one season.

Running Regressions

In order to use the statistical package SAS, each land cover type was divided into a separate file that was ordered by seasonal composite image number. These groupings from each image were then sequentially linked together to allow for data evaluation.

The particular regressions that were run were simple ordinary least squares first order linear regressions. Under our initial hypothesis, the differences between the two data sets were dependent on the differences between the sensors, which should affect all data equally and should be easily corrected based on some simple linear regression. In addition, some work completed by Kevin Gallo at the National Center for EROS suggested that there may be explainable differences between land cover types [5]. Following this, we divided the data into nine divisions, using the modified NLCD map and omitting the water and bare rock/sand/clay land covers. As we worked further into the project, it became apparent that the inability to accurately geo-register the satellite images pixels to the correct latitude and longitude position was creating problems with regressions analysis. To solve this, another program was used to extract sample areas with large coverage of the desired land cover class and average a twenty by twenty pixel area.

We then ran regressions in SAS and the open source program Gretl according to the seasonal observation number on all of the data set combinations, as well as doing an inclusive land type regression dismissing the observation number on all sample sites. The observation numbers discussed in the article refer to the time offset from the beginning of the year based on 23 composite observations in one year. No corrections were done in the techniques to solve problems with heteroskedasticity and no correlation problems appeared in the data sets.

DATA RESULTS

The results from the regressions have shown to be very troublesome in some areas of the data. As a general rule, land types one and three (deciduous and mixed forests) were the most troublesome of the nine evaluated land cover classes. In addition, there appears to be a seasonal trend that is portrayed in the adjusted R^2 as well as the coefficient and the intercept. It should also be noted that as the NDVI values increase and reach the peak of the growing season, usually in the middle of the season around observations 10-12, there is a greater chance for large NDVI deviations between satellites to occur. In evaluation of the R^2 on all combinations, running a regression on all 16-day composite samples of the same land type resulted in R^2 values between .7 and .95 in addition to matching the hypothesized sign and approximate value of the coefficient.

Based on the initial hypothesis, a linear regression was chosen to be the first model structure. It was estimated that the intercept should occur between -0.2 and 0.2, with a positive slope. The data would be piece-wise as well, allowing for slope changes between 16-day composites. However, in the plotting of the data without separation for observation number, it became apparent that using either a squared regression or a higher polynomial function may offer more explanation between the combinations of sensors. The plots presented in the next section of the paper also offer some other insights into potential differential factors in the data as well.

Common Features

The following basic plot charts were created using pairs of sensors (with MODIS sensor on the vertical axis, and the AVHRR sensor on the horizontal access). The plots were done according to the dataset and the land cover type number. A general trend is evident in most of these plots. In examining all data points together, there is a definite general data comparison line; however, there is also a large amount of deviation from the regression line as shown in figure 1.

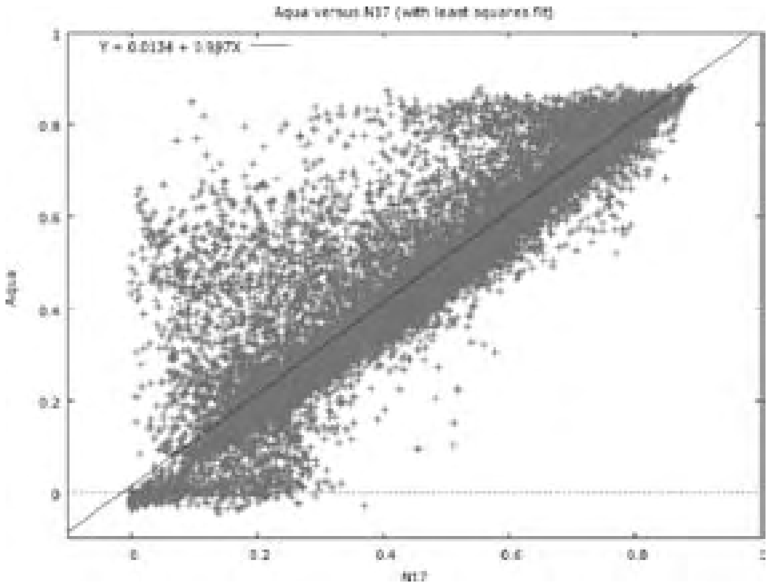

Figure 1. All land cover and observations. Notice the general trend line evident in the data. However, there is also a great deal of scatter. While a regression offers a relatively high R2, the amount of variation limits the ability of the regression to explain the sensor differences by combining all observations together.

In simply separating the data into forest and non-forest, the data shows characteristics based on land cover. In general, there is a "floor" on all data derived from the non-forest land areas, and a "ceiling" on all forest land areas. The differences can be seen in figure 2 and figure 3. In addition to identifying which land cover in general has the "floor" and "ceiling" effects, the data also has a considerably smaller amount of variation, due to specifying the forest and non-forest samples. This ability to improve our results by splitting the data suggests that there could be further gain from analyzing the different land cover types separately. Examining the data plots, it also is interesting to see that even though the regression lines plotted over the data points are different, if we could remove the problem areas of the data, it may be seen that the other factors such as seasonality may be involved in determining the makeup of the general comparison of the data calibration. To begin breaking apart these data sets, these simple relations were first broken into the nine land cover classes to be evaluated separately.

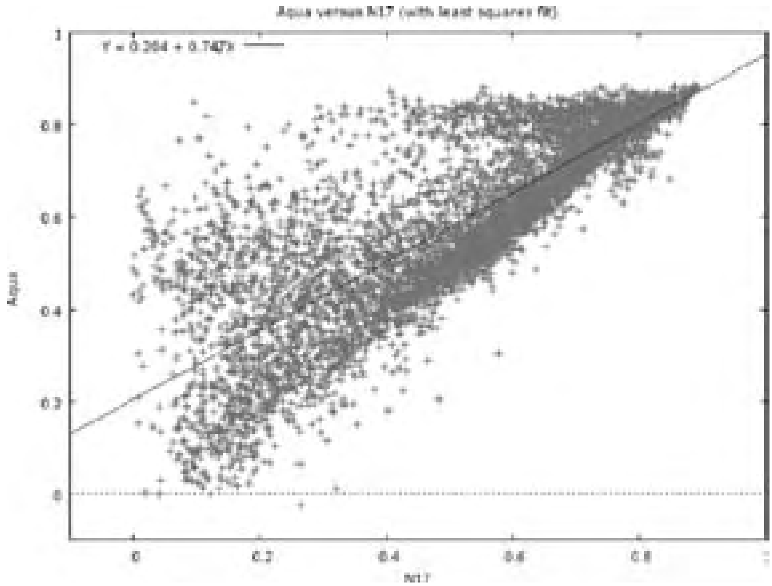

Figure 2. All forest land cover, all observations, with the ceiling effect visible, but the floor effect missing, suggesting that the lower saturation level on the MODIS based sensor exists in the non-forest land cover. We also note that the non-scattered and non ceiling saturated data represents a very similar data plot to the non-forest land covers. This suggests that there may be other common factors to these two data sets, such as seasonality which should be accounted for.

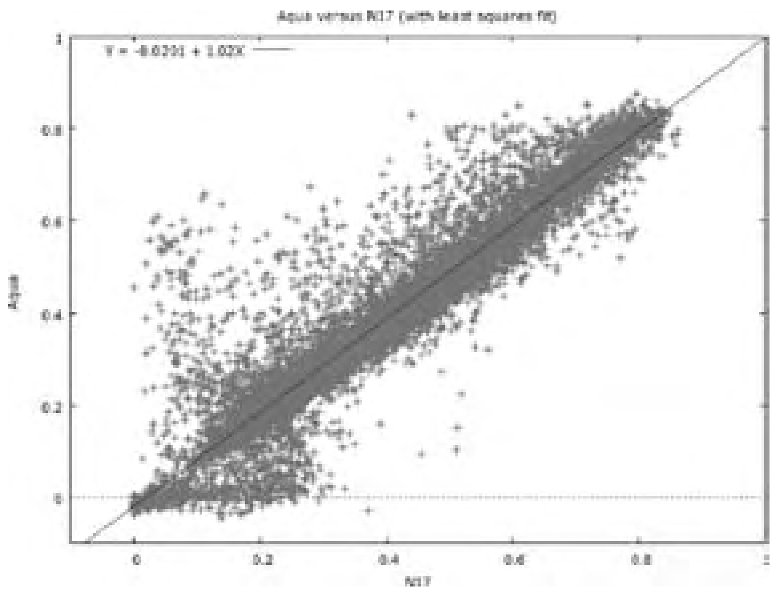

Figure 3. All Non-forest land covers for all observations. Notice the floor effect is present, but the ceiling effect is missing from this data. We notice especially that while a floor effect exists heavily on the MODIS sensor at the 0 NDVI level, it also exists on the AVHRR sensor around the 0.2 NDVI level. We also note the similar characteristics as noted on Figure 3-2.

Growing and Non-Growing Season

Deciduous Forest

In the Deciduous Forest land cover class, as shown in figure 4, a distinct discontinuity in the data values appeared. In the lower ranges of AVHRR (under 0.4 NDVI), there is a large scatter of the MODIS points from 0 NDVI to 0.7 NDVI. However, there also appears to be a strong relationship of the sensors between 0.35 NDVI to 0.6 NDVI in the AVHRR sensor and 0.37 NDVI to 0.63 NDVI in the MODIS sensor. However, at 0.6 NDVI in AVHRR and 0.7 NDVI in MODIS there appears to be a discontinuity. It also appears that there is a "ceiling effect" occurring at 0.9 NDVI on the MODIS sensor. Looking at figure 4, it becomes clear that there are two separate regions, a lower region with a typical slope and an upper region with a less steep slope.

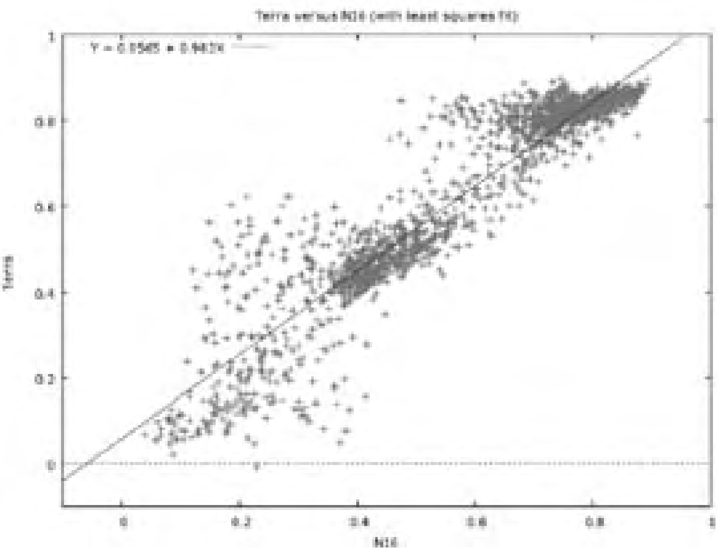

Figure 4. Deciduous Forest N17 vs. Terra – All Observations. Two separate regions appear in the data plot of the deciduous forest land cover. The lower portion has a great deal of scatter on the AVHRR sensor from 0.1 to 0.4 NDVI, while the MODIS sensor has a ceiling effect around a 0.9 NDVI. The R^2 for the regression is 0.88, which may be artificially boosted due to the large number of samples used for the regression.

This occurrence could suggest that there may be an additional dimension that needs to be accounted for, such as geographic region. However, under further analysis, we see that the data is broken into at least two of sections, as can be seen in figure 5 and figure 6. These figures show that simply breaking the image into parts of the growing season result in greater grouping of the data. However, in breaking the data into these two groups, the models have a relatively low explanation factor, with an R^2 of approximately 0.78 for the off-growing season and 0.34 for the growing season. This is a large drop considering the full deciduous forest model R^2 is approximately 0.88.

In figure 5 there is also ambiguity between the two sensors in the N16 0.1 to 0.3 NDVI ranges. In examining the individual plots from the data, these values are caused by Observations 2, 3, and 21 of the given year. This could be possibly explained with respect to snow and ice reflection, as well as cloud shadows or other sky clarity and atmospheric issues that have not been detected and accounted for in the cloud or snow mask.

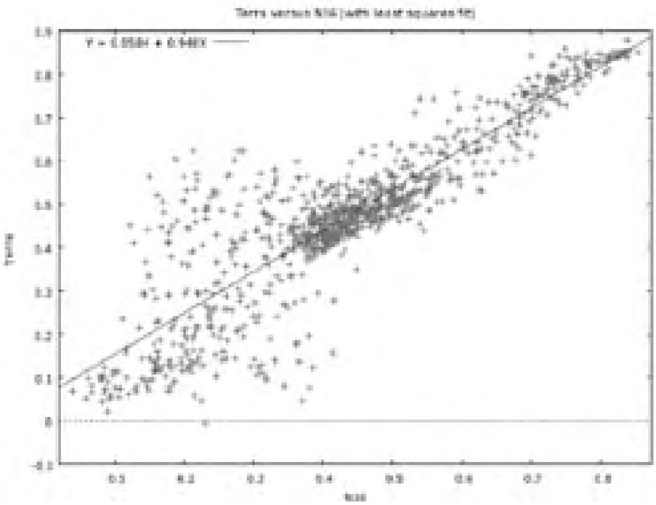

Figure 5. Deciduous Forest Observations 1-9. These observations make up the non-growing season. It is easily noticeable that the regression follows a regression line that has a reasonable slope and intercept. Interestingly below 0.4 NDVI there is a great deal of variation between the two sensors. However, above 0.4 NDVI, there appears to be a well behaved data correlation.

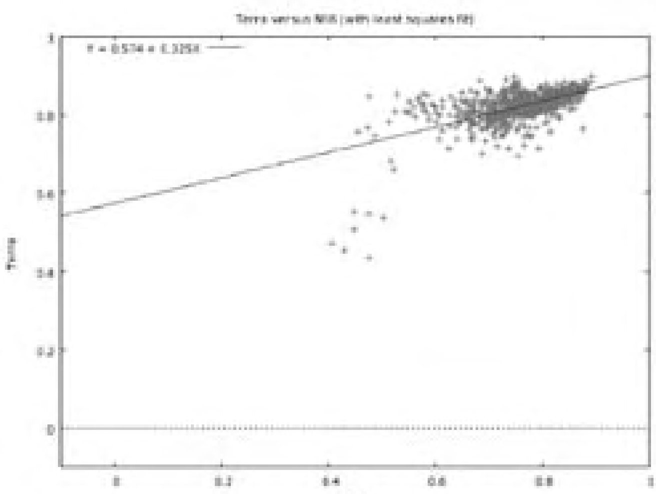

Figure 6. Deciduous Forest Observation 10-16. The growing season for the deciduous forest appears to be a much higher regression combination, possibly due to a sensor saturation with the MODIS NDVI calculation. There also appears to be a set of points that are considerable outliers that may be a result of mis-classified data points of low-NDVI growing seasons.

The explanation of this reduction could also be in part due to the number of observations used in each regression model. Since there are close to 2000 points in the full regression, the R^2 is artificially boosted, giving an inflated value which will decrease when reducing the number of observations in a set.

Evergreen Forest

The evergreen forest did not appear to have a distinct break, as seen in the deciduous forest. However, it did become apparent that there is a greater variation between the data points as well as possibly a quadratic relationship. It is interesting to note that the N17 sensor combined with either MODIS sensor had a smaller root mean squared error (RMSE) as well as having a higher R^2. The most noticeable difference between the N17 and Terra comparison is the scattering of data points above the main concentration, as seen in figure 7.

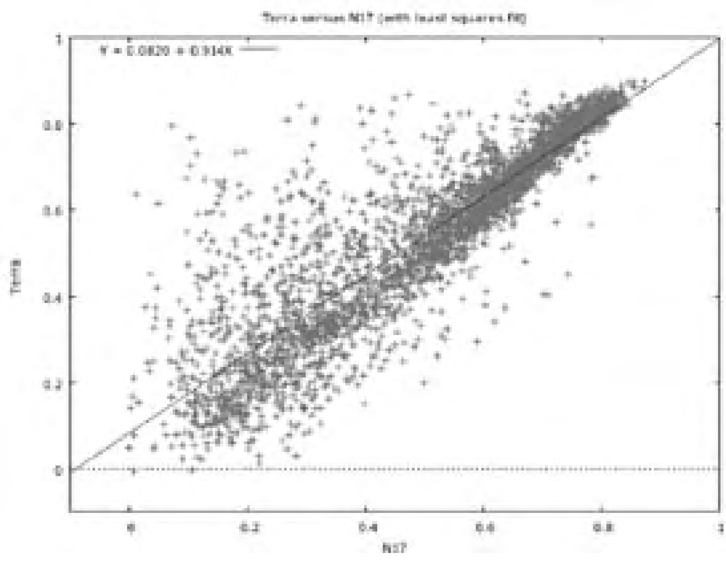

Figure 7. Notice the higher polynomial curve shape of the concentrated data points. In addition, a peculiar trend showing more variation on the high Terra, low N17 side than on the opposite side.

In breaking this image apart, we see two distinct time regions. Observations 1-9 and 19-23, which has a larger standard error (0.015), lower R^2 (0.657) and show the non-uniform parts of the graph (figure 8). Observations 10-18 however have a nice distribution and offer a high R^2 (0.888) and an even lower standard error (0.009) (figure 9).

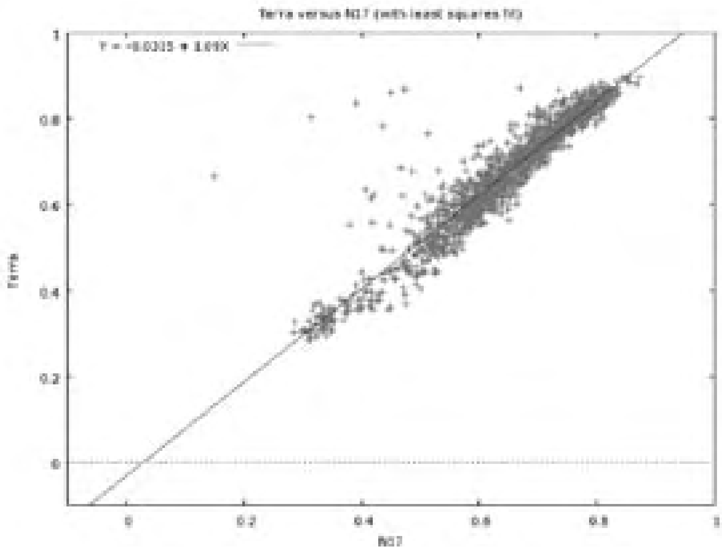

Figure 8. Evergreen Forest Observations 10-18 ***The growing season for this forest appears to be well behaved and have little residual data points with large variations. There are a few samples with low NDVI values on the AVHRR sensor, however, the split to the growing season offers a great deal of explaination between the two sensors.***

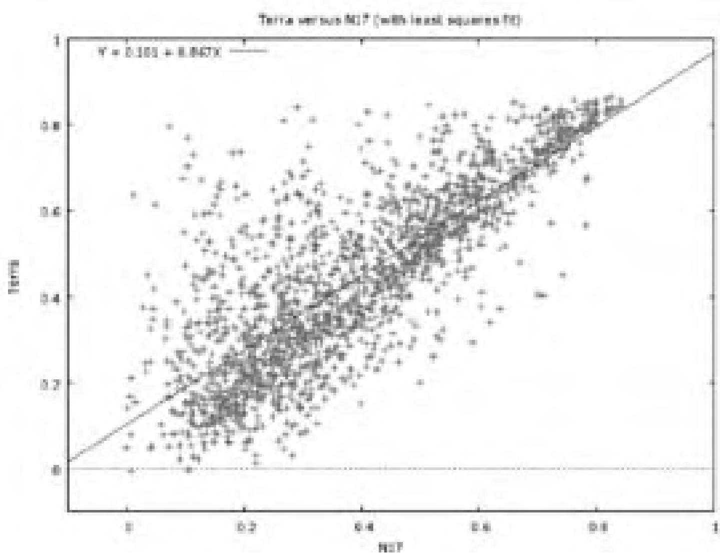

Figure 9. Evergreen Forest Observations 1-9 and 19-23. The non-growing season in comparison to the growing season has a greater variation. It is obvious that there is something that occurs in the early and late part of the season which needs to be accounted for. This could be a result of residual clouds not detected by the CLAVR cloud mask, or other atmospheric contamination or snow and ice contamination.

Mixed Forest

The mixed forest is difficult due to a relative lack of data points. In the N17 vs. MODIS, there were approximately 550 data points, and 367 points in the N16 vs. MODIS comparison. The N16 vs. MODIS comparisons were fairly straightforward. The N17 vs. MODIS comparisons (Figure 10), however, resulted in a similar effect as the evergreen forest observations 10-18 (figure 9). The overall data plot shown in Figure 10 appears to be a cross between the characteristics of both the deciduous forest, with a discontinuous regression, and the increased scatter found within the evergreen forest. With the smaller amount of data, the problems could simply be a result of a lack of data observations to successfully determine the variations from the actual data points.

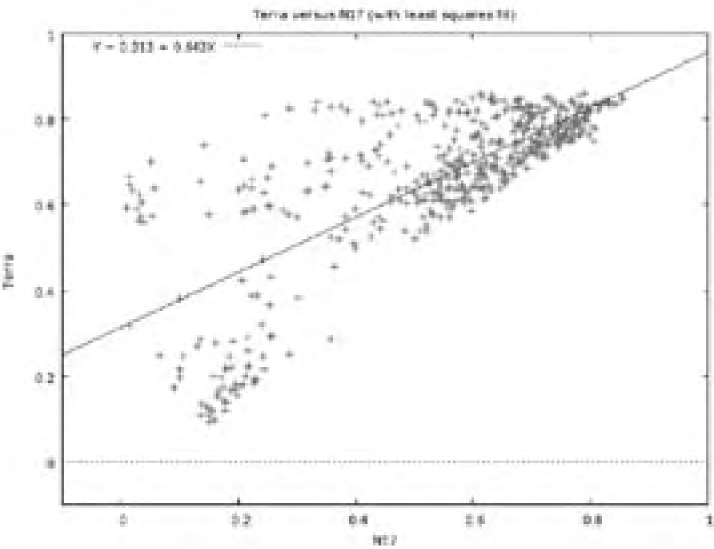

Figure 10. Mixed Forest all observations. This land cover has features which appear to be a cross between the deciduous and evergreen forest land cover classes. Due to the relative lack of data points, it is difficult to derive any solid deductions on this data set.

Grasslands / Herbaceous

The Grasslands land cover type offers another problem. In all of the samples, it appears that at low levels of NDVI, the MODIS sensor measures NDVI at approximately 0, but the AVHRR sensor shows a scattered range between 0 and 0.2. This could be due to snow and clouds (as the difference is occurring at very low levels of NDVI), typically found during winter months.

The low levels can be seen by combining observations 1 through 6 and 19 through 23. As depicted in Figure 11, the floor effect occurs in the off-season. While there is still a considerable amount of good data points in this particular non-growing season, there is a significant problem with these off-growing season observations. The resulting growing season then lacks any floor effect and has minimized scatter (figure 12).

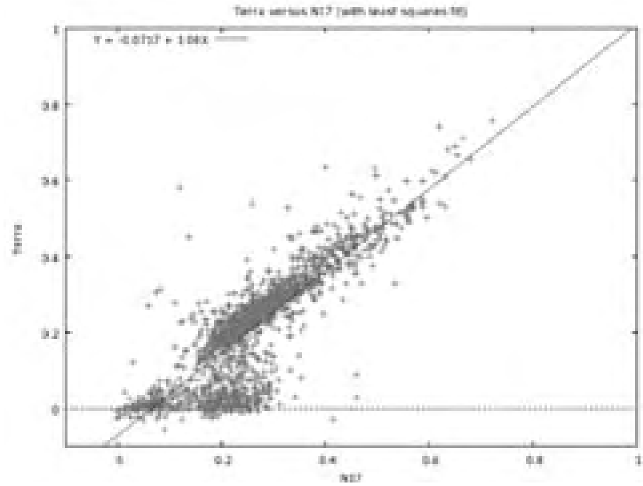

Figure 11. Grasslands/Herbaceous Non-Growing Season Observations 1-6 and 19-23. The off-growing season of the grasslands contains a large floor on MODIS values that range from 0 to 0.4 NDVI (based on AVHRR), which may be a result of snow, clouds, or other atmospheric contamination. The upper regions of the data are well-behaved, and follow a regression line relatively well.

Evaluating the standard ordinary least squares method, it was observed that the floor effect, occurring within the non-growing portion of the season, has an R^2 of .687 while the growing season has an R^2 of .912. This offers a promising method for correcting off-season and on-season data with a great improvement for the growing season as the R^2 of the entire season for the fourth land cover is .852.

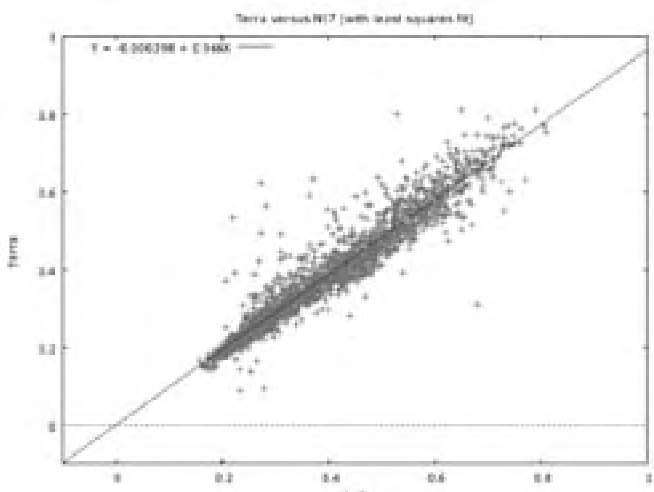

Figure 12. Grasslands/Herbaceous Growing Season Observations 7-18. The growing season of the grassland offers a promising comparison between the two sensors, as the data plot follows the regression line relatively closely, having an R^2 of 0.92.

Shrub land

Similar to the other non-forest land cover classes, the data has relatively little data scatter. Without any time-of-year separation to the data, the regression has a relatively high R^2 at 0.88 (figure 13). However, the shrub land does not clearly separate into a season and off-season. While the same floor is visible within the data to a smaller degree, the primary contributors are the first four observations.

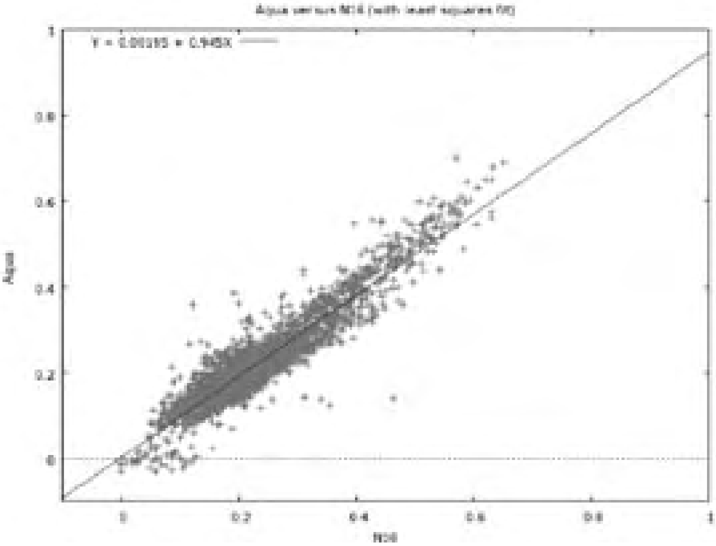

Figure 13. Shrub land: Total Season Observations 1 – 16. The shrub land is difficult to divide into a season and non-season data set. There is relatively little variation between the two sensors, and the small floor that appears on the MODIS sensor is barely recognizable.

One possible way to better explain these data would be to employ a piece-wise regression technique. Basically, instead of only splitting the data by growing- and non-growing season, this technique groups the data by composite observation number. These smaller data sets are then evaluated in a linear regression technique with the hopes of avoiding any problems that exist due to changes in conditions as a result of different time different sun angle, and other factors that occur with different times of the year. These individual regressions can then be examined to see if any pattern exists of if there exist condition changes between growing and non-growing times of the year.

In examining the piece-wise regressions, we find no clear observable pattern of the data. By examining the intercept of the regression line, we can observe trends for both within- and outside the growing season. As shown in table 1, the later observations within the growing season (periods 11-16) tend to have a similar intercept. Evaluation of these six periods in the later growing season (figure 14) reveals a more uniform data set compared to the whole growing season (figure 15). An R2 of 0.93 shows that this smaller period correlates better..

It is difficult to create an explanation for the change in behavior of this land cover. However, because of the small number of observations (just over 60 per time period), it is possible that there may not be completely accurate representations due to water vapor or other factors that may occur at more frequently at certain times of the year, which are adjusted by the MODIS sensor but not by the AVHRR sensor.

Table 1. Shrub land: Slope-Intercept Table sorted by Intercept. This table is an example of the intercepts and slopes obtained using a piece-wise regression. While the R^2 on all of these regressions was low, it was largely due to a lack of data points. By examining the intercepts and slopes, we can pick out observations that are approximately from the same time, which we would expect may have a common seasonal shape.

OBSERVATION	INTERCEPT	SLOPE
12	-0.51	1.04
13	-0.0661	1.08
16	-0.062	1.07
14	-0.0429	1.03
11	-0.0392	1.07
15	-0.0371	0.987
3	-0.0207	1.12
1	0.002	1.07
8	0.0038	1.01
7	0.00875	0.96
2	0.0105	0.996
4	0.0116	1.02
9	0.0121	0.942
6	0.0163	0.936
5	0.0219	0.974
10	0.0243	0.908

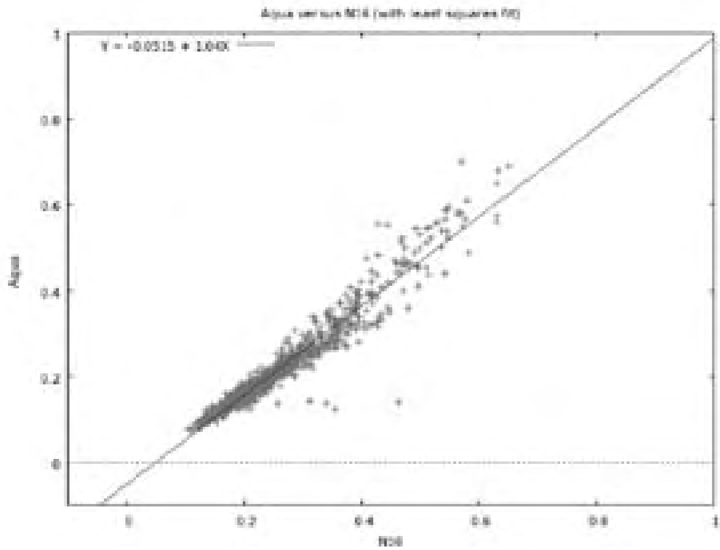

***Figure 14. Shrub land: Late Growing Season 11-16.** Using a piece-wise regression technique, we found a set of observations that appear to have a relatively close fit together. Since we were using all late growing-season observations, it may be possible that the correlation between data points may also have a factor dealing with green-up or green-down parts of the growing-season.*

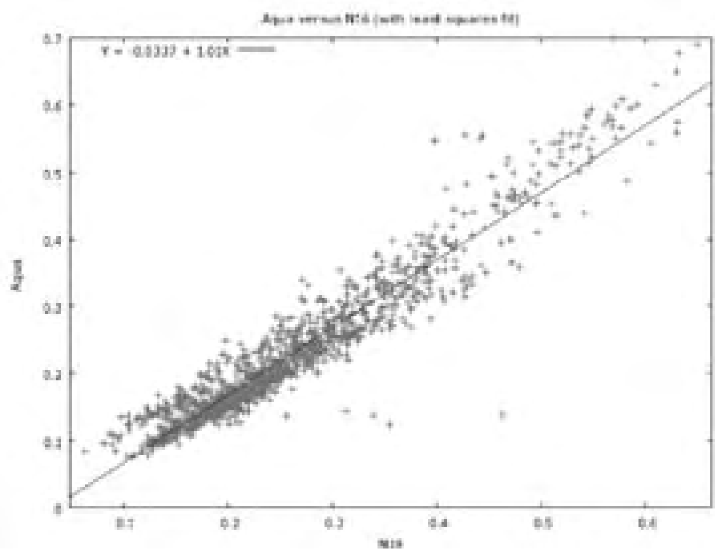

***Figure 15. Shrub land: Growing Season 9– 16.** Compariablly to the late growing season, this shows a "dual" set of data points. However, this may also be impacted by different seasonality dates, depending on where the data point is located.*

The off season (figure 16) also should be noted as having a similar R^2 (0.91) to the complete growing season. However, as shown in table 1, there is not a clear pattern showing the lead-up to the season. Instead what we see is a range of intercepts from 0.002 to 0.0243. This variation along with the variation of slopes suggests that there are some other factors involved other than time of season.

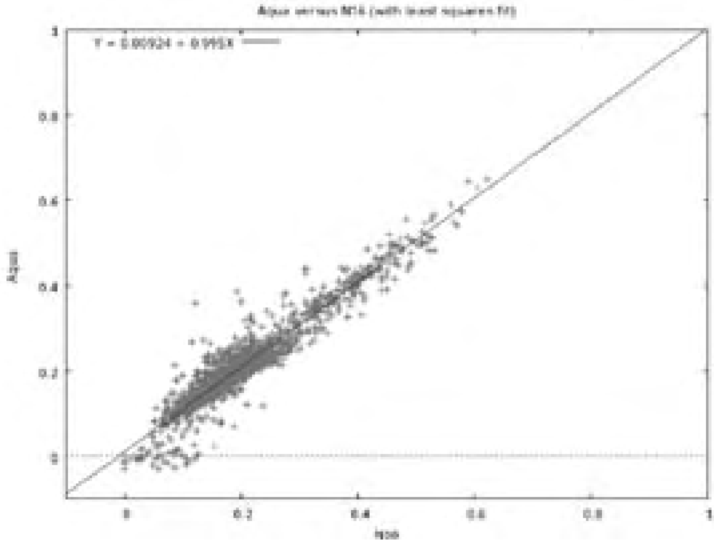

Figure 16. Shrub land: Non-Growing 1-8. The non-growing season is held to a minimal variation, however, it does have a small floor on the MODIS NDVI values, as well as have a slight spread between the 0.1 NDVI AVHRR and 0.35 NDVI AVHRR. This suggests that there may be other factors that lead into the explaination other than growing/non-growing season evaluation.

Row Crops

Row Crops typically attain higher levels of NDVI during the growing season, but otherwise behave similarly to the other non-forest land cover types. While these values do not exhibit the same drastic ceiling behavior found in the forest land covers, it is possible that this effect could be observed during years of extremely high growth.

Figure 17 illustrates two areas of concern. The first is the floor values that occur along with the high amount of scatter in the lower NDVI range. The second concern is that the data appears to be related under a higher order polynomial. While these areas lower the regression explanation, the R^2 maintains itself above 0.91.

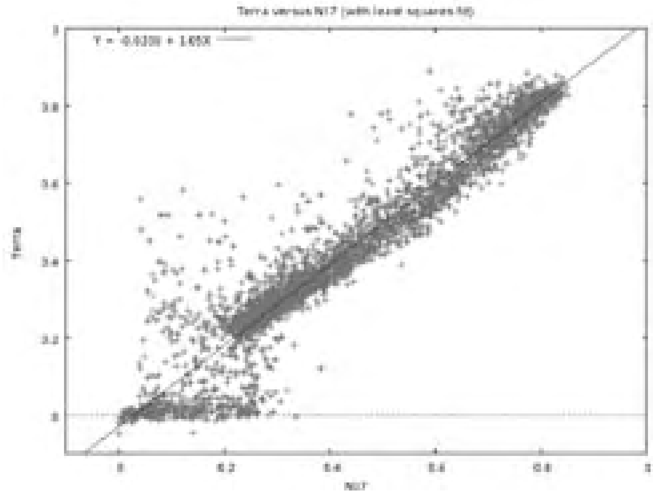

Figure 17. Row Crops: Entire Season. The row crop land cover has a unique in that it achieves high NDVI levels, as well as low NDVI levels. While it is not extremely obvious, there does appear to be a slight saturation level, as well as a quadratic shape to the data. Also noticeable is the floor, as well as the low NDVI level scatter.

Breaking the season into the growing and non-growing sections, there is clearly a correlation again to the floor effect and the non-growing part of the season. In addition, most of the scatter occurs in the non-growing part of the season, as shown in figure 18. Due to the scatter of the comparison, as well as the floor effect of the MODIS sensor, the R^2 measures a 0.68 for this off-season data.

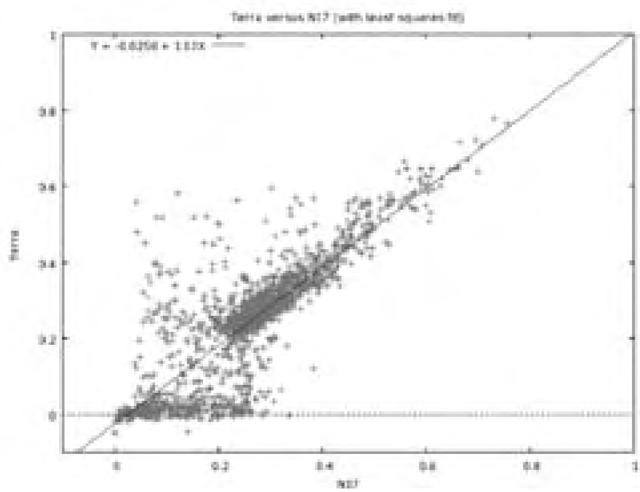

Figure 18. Row Crops: Non-Growing Season: Observations 1 - 8 and 20 – 23. By using the non-growing season, we are able to extract the scatter as well as the floor of the MODIS samples. There are a few higher NDVI values, which may be a result of misclassifications or early growing seasons. Floor values have been shown to be removed by the addition of a snow mask (not shown), and improved the regression R^2 above the 0.68 from the non-snow masked regression.

The growing season for the row crops also has an interesting feature. The data appears to have a non-linear correlation. The data would suggest that a higher order polynomial function may be needed to model the data points. In addition, the data also appears to have a slight ceiling effect, which could also be contributing to the need for a polynomial function. Figure 19 shows the data with a simple linear regression. While it is possible that a higher polynomial function should be used, the regression does have a rather high rate of explanation (R^2 = 0.92). In addition, the possibility of using piece-wise regression, as discussed in a later section, eliminates the need for the higher order function.

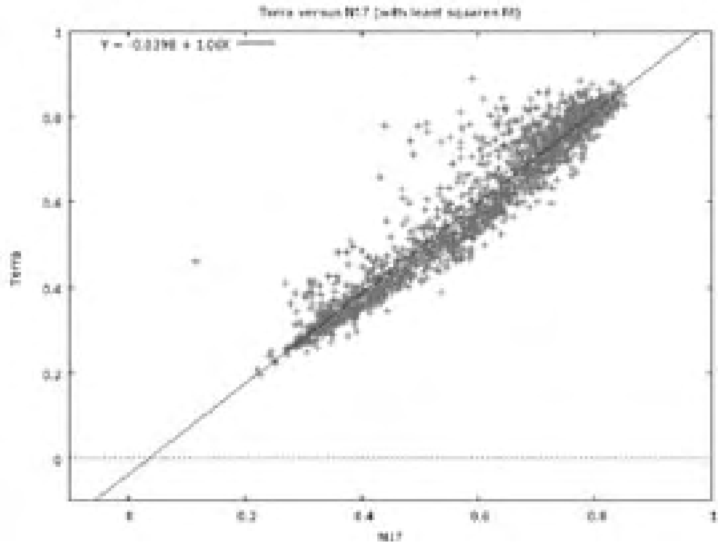

Figure 19. Row Crops: Growing Season: Observations 9- 19. The row crop growing season appears to have a slight ceiling saturation from the MODIS data, as well as a quadratic shape to the data. This may be in part due to differences within seasonal characteristics; however, the linear regression has a relatively high R^2 of 0.92.

Small Grains

The last three land cover types provide interesting attributes. Similar to row crops, a slight higher order polynomial function appears in the data comparison. Figure 20 shows a linear regression over the entire season for the small grains, producing an R^2 of 0.93, which is one of the highest regression values we have been observed in this study. However, compared to the other land cover classes, we have relatively few observations, only 775 data points for the entire season.

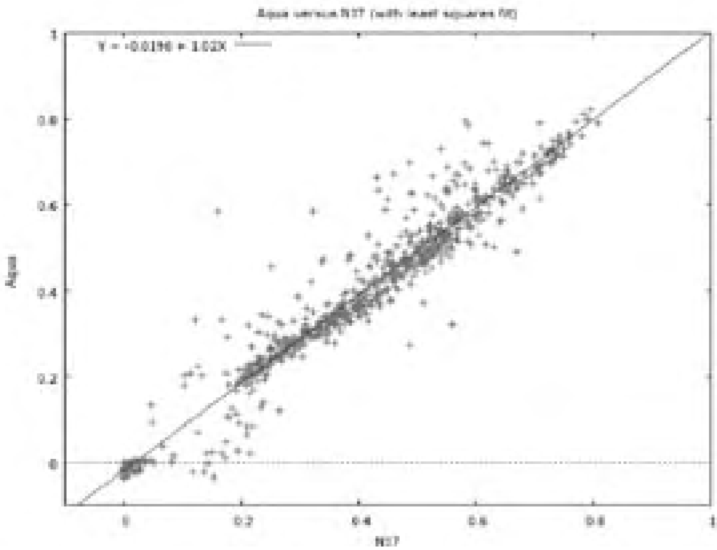

Figure 20. Small Grains: Entire Season. The small grains regressions are limited severely by the number of data samples available. In addition, it is difficult to determine a seasonal difference clearly by observation of the data. This is in part due to the wide variety of crops that are planted, which have seasons that overlap, and start very early in the year. As a result, the seasonal characteristics depend largely on what type of small grain is being observed.

Because of the relatively good linear fit to the data, it was difficult to divide the data into any clear separation based on observations. However, in order to eliminate the floor effect data, observations 6 through 19 were separated and compared with an R^2 of 0.91 (figure 21) and the remaining observations (figure 22) had an R^2 of 0.91.

One possible explanation for the relatively similar data comparison throughout the entire season could be the length of the season for small grains. Because small grains have an earlier growing season and have varied lengths of seasons, depending on area, it may be difficult to accurately separate the growing/non-growing season.

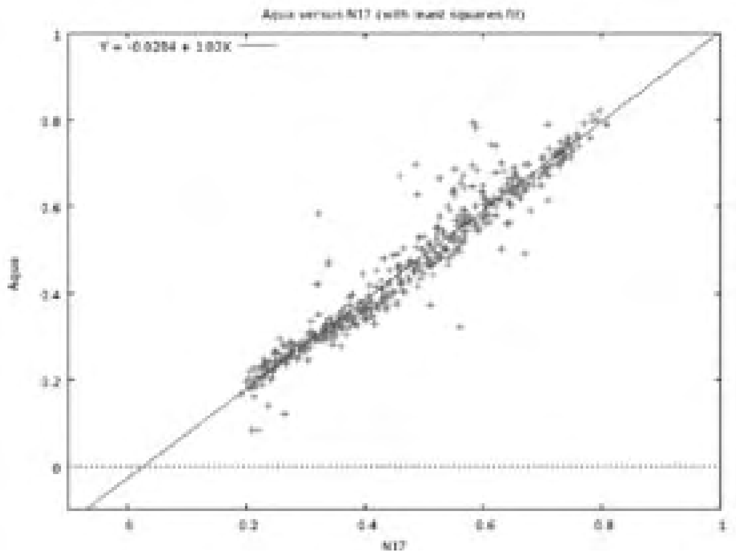

Figure 21. Small Grains: Growing Season: Observations 6 – 19. Creating a growing season portion of the data lowers the R^2 value from 0.93 to 0.91, due to the reduction in the number of data points. There is a small amount of variation in the upper NDVI values; however, in general it forms a relatively good linear regression line.

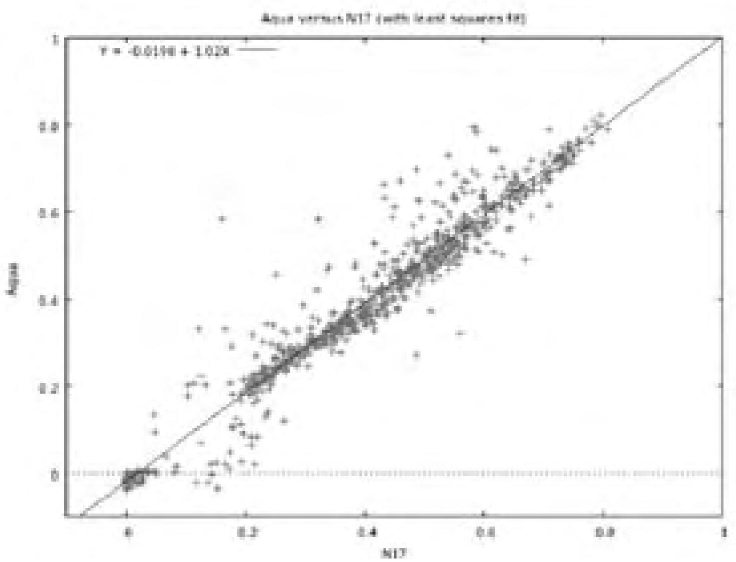

Figure 22. Small Grains: Non-Growing Season: Observations 1-5 and 20-23. The non-growing season is much like the growing season, except for an additional floor that occurs around 0 NDVI. The 0.91 R^2 is the same as the growing season, with a similar range of NDVI values. This in large part is due to the near continuous growing season offered by different types of small grains. As a result, the extremely low values may only last for a short time, suggesting that there is a much smaller non-growing season that what has been depicted.

Pasture Hay

Compared to the row crop and small grain land cover, pasture hay has a greatly reduced correlation between the sensors. Using the first 16 observations, due to N16 sensor failure, figure 23 shows a set of data with a wider spread along with a small set of floor pixels with a limited amount of pixels that fall below 0.2 NDVI. The R^2 for all pasture hay pixels over the sixteen good observations is 0.81.

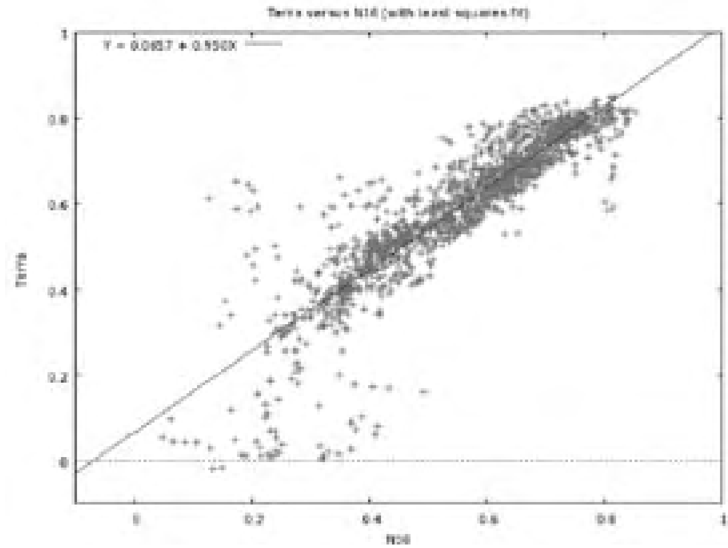

Figure 23. Pasture Hay: Entire Season: Observations 1 – 16. The pasture/hay has greatly reduced explaination by linear regression compared to the previous land cover classes. There is a much larger scatter range, as well a more extreme set of floor values that exist. In addition, there appears to be some type of non-linear regression involved with the heaviest part of the data plot.

By dividing the data into the respective parts of the season, we see a drop in the R^2 values to 0.71 for the non-growing season (figure 24) and 0.75 for the growing season (figure 25). While the regression has a lower R^2 value, noting visually that there is not a great deal of difference between the three regressions suggests that the entire season R^2 value was artificially inflated due to the number of data points used.

Also, in figure 24, the NDVI values reach almost the same levels as the growing season. This may be in part due to the geographic location of the data points. Examining the location of the sample sites, the pasture hay land cover class primarily runs along the Mississippi river, in a north-to-south fashion. This land cover type has a considerable amount of the sample locations derived from the southern part of the U.S., where growth levels do not typically fall to extremely low levels. This could result in high levels of NDVI during the non-growing season.

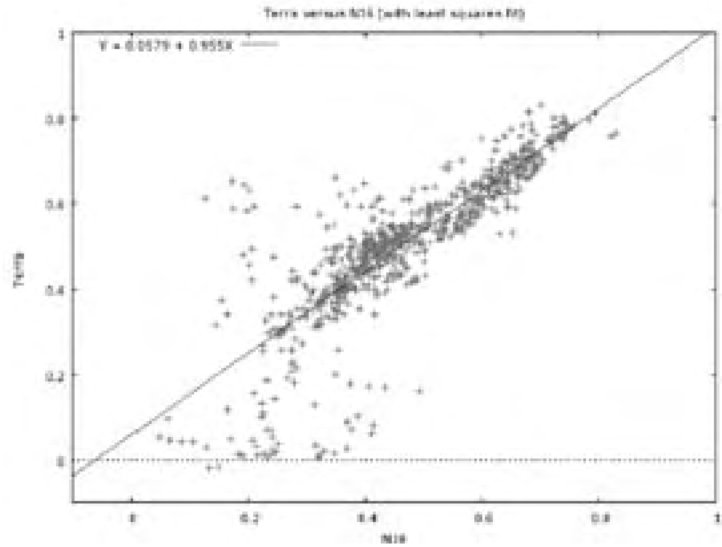

Figure 24. Pasture Hay: Non-Growing Season: Observations 1-8 . The non-growing season has a relatively high NDVI value. This may be in large part due to the southern geographic location of the data points. We also expect that because of the geographic location differences between the sample locations, the growing seasons may need to be divided in a much more careful manner specific to the geographic location.

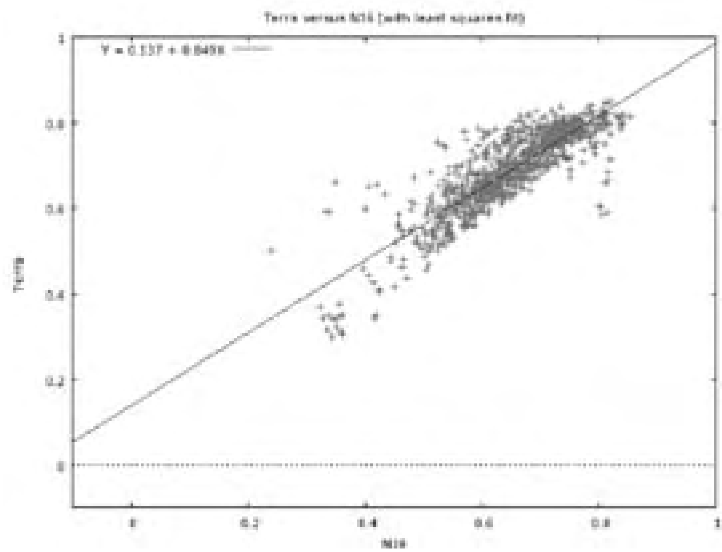

Figure 25. Pasture Hay: Growing Season: Observations 8 – 16. The growing season has a much less scattered appearance than its non-growing counterpart. This is largely due to all locations having a high NDVI value. While the R^2 of 0.75 suggests that there are other factors involved in the regression, in examining the difference between the non-growing season, we see that a closer look at starting and ending dates of the season are important.

Urban

The urban land, consisting of commercial, industrial and residential areas, has a limited number of data points available for comparison. Due in part to the lack of data points, it was difficult to find any explanation between the sets of data. A general explanation line between the sensor data appears to form within the data; however, there is a great deal of scatter that could possibly be explained by the differences in latitude and longitude of the data areas. The entire season regression (figure 26) only had a 0.67 R^2; however, it is obvious that other factors are influencing the data. One possible factor could be the differences between geographic locations, as this was not considered in the study. This may be an important factor and a possible area for further study of how different locations will be affected by the differences of light reflection.

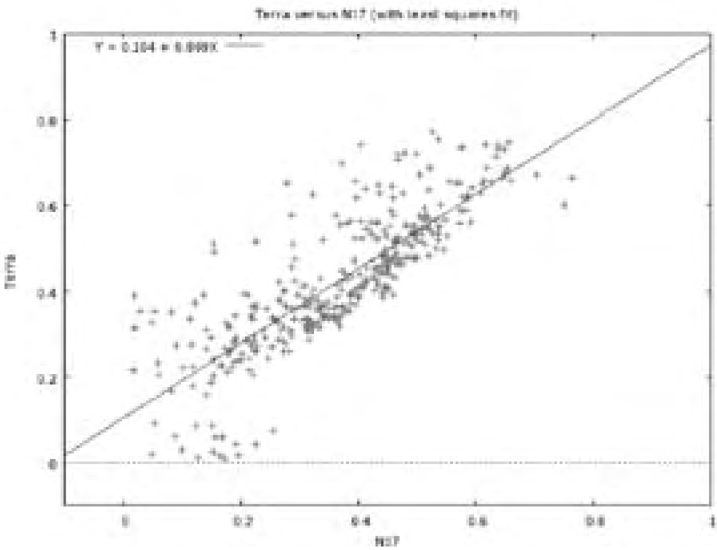

Figure 26. Urban: Entire Season. The Urban land cover suffers from three problems. The first problem is a lack of data sample sites, resulting in semi-visible regressions. The second problem is that the urban sample areas are scattered around the U.S. and have different lengths of growing seasons. The third complication is that the urban land cover is known to be problematic within a growing year due to the wide range variety of areas classified as urban.

Especially in the urban areas, there is very limited ability of separating out the scatter among different observations. However, there does appear to be a correlation between a few lower floor values and the off-growing season. Figure 27 shows the observations during the growing season. Overall, this collection of data points had a R^2 of 0.47, which is significantly lower than the entire season. However, as was stated earlier, while there is less explanation, the higher R^2 value could simply be due to more observations.

Figure 28, shows the non-growing season part of the year, with a R^2 value of 0.54. Surprisingly, in this case, the off-growing season has a better regression than the growing season. This could potentially be due to more data points; however, it may also be a result of atmospheric conditions, such as smog or water vapor, which if one sensor does not correct for, could show greater reductions, since smog and water vapor tend to be more prevalent during the summer months, causing reduced correlation.

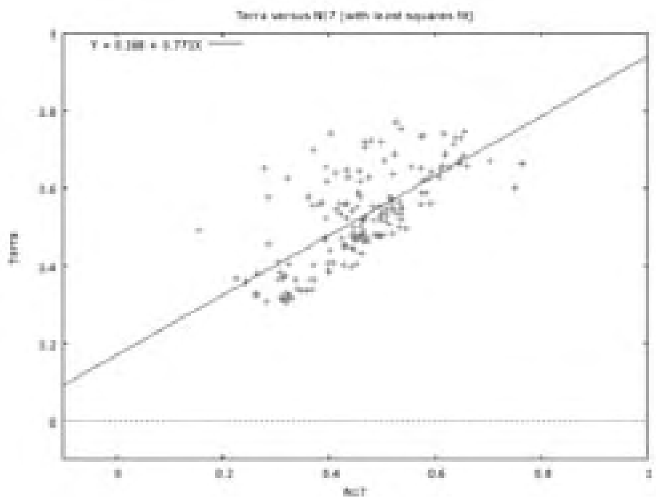

Figure 27. Urban: Growing Season: Observations 9-19. Aside from eliminating the lower NDVI values, very little is gained from the separation into a typical growing/non-growing season set of data.

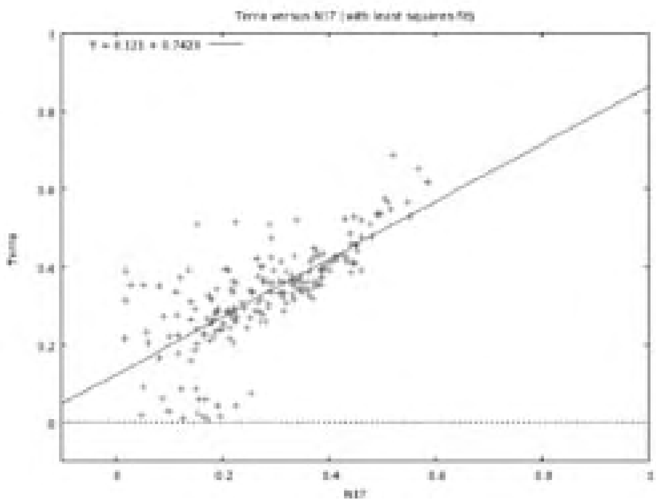

Figure 28. Urban: Non-Growing Season Observations 1 - 8 and 20 – 23. We notice a floor on both sensors; however, due to the lack of data points, it is difficult to show how great of an impact the floor values have. In addition, there is extensive scattering, suggesting that some other factors must be in play.

Specific Satellite Features

Between each of the different satellite sensors, there are a few unique features. In general, the N17 satellite tended to have a greater spread of the data points over the N16 satellite. This tended to make the N16 regressions a bit cleaner and gave better explanation between the sensors. However, due to the limited data from the N16 satellite, N17 data was primarily used for demonstration purposes due to the complete 2003 data set.

Another consideration when evaluating the data sets is to examine the cross calibration of the different satellites. While this was not a focus of this paper, it was interesting to note that while in general the sensors have limited variation, the variation between satellites increase in a similar pattern as the calibration between the AVHRR and MODIS comparisons. This increase was not of a similar magnitude, yet, the comparisons did note a difference in variation in growing and non-growing parts of the season.

For an example of the evaluation, a comparison of the Aqua and Terra satellites is considered for the Evergreen Forest Land Cover Type. In figure 32, the non-growing season is displayed, with a R^2 of 0.79. However, this can be compared with figure 33, which shows a much tighter data set, that has a R^2 value of 0.97. While this does not match up to the variation change of the AVHRR to MODIS regression, it does show that the analysis of these sensors is based on more than a sensor mis-calibration, and there are other factors that could be influencing the data.

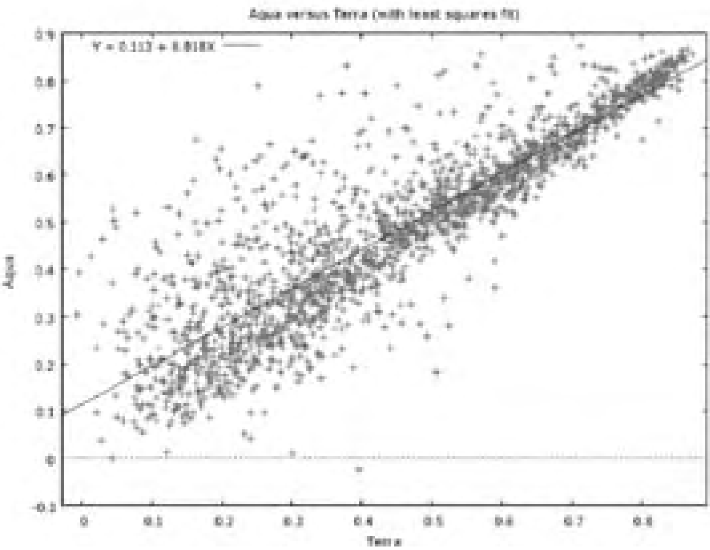

Figure 29. Aqua vs. Terra: Observations 1-8 and 19-23. Despite these two satellites being of the same sensor type, there is a considerable amount of scatter between the data points. Differences between these two sensors may include cloud problems, atmospheric contaminations, as well as the sun angle due to the time of day that the over-pass of the satellite occurred. While these were not considered in the scope of this project, we note it to suggest that there is very little hope of achieving a perfect calibration between two sensors.

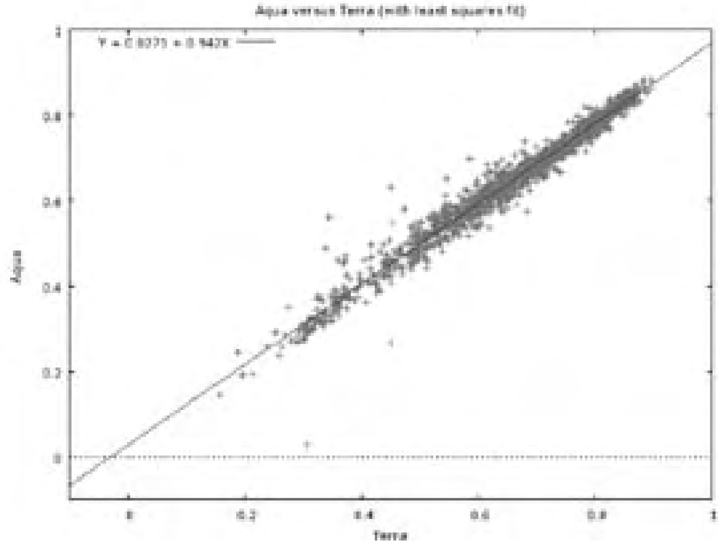

Figure 30. Aqua vs. Terra: Observations 9-18. As we noted, in the growing season with the other sensor regressions, the growing season has better explanation. It appears that this is similar to the same sensor type. This suggests that there is definatley something greater than sensor calibration that is off, but includes other conditions that need to be accounted for. However, this does show that the part of the season has an important impact on the regression calibration.

Piece-wise Regression

The consideration of piece-wise regression is employed to consider further explanation of the data sets, allowing smaller errors and data issues to be considered. This area has not been completely explored, however, some preliminary work has been done to show the possibility that it would have a significant impact on the data set.

For analysis of the 2003 data set, by considering the individual observation numbers, an assumption was made that the data's seasonal values per land type are similar values. If dealing with multi-year data sets, a consideration into offsetting seasonal conditions should be employed. In addition, the second primary focus of moving to a piece-wise regression is to eliminate the need for higher order polynomial functions in the calculation of the data sets.

This work is preliminary as only a single year of data has been used. If this area is to be considered further, a multiyear data set would be needed to give more data points, as well as deal with seasonal offsets.

DISCUSSION

Within each land cover type, there appears to be a connection between the growing part of the season and a higher R^2 for linear regressions. There are most notably two exceptions to this generalization, the urban and the pasture hay land cover types. While it is difficult to conclude any solid observations as to what makes these two land covers different, one speculative answer could relate to the geographically diverse areas that the sample sites were taken from. Both land covers had a wide range of sites taken primarily in the north to south fashion. This would suggest that the relation could involve another factor, namely latitude. However, without more data, there is nothing certain as to what causes this.

Generally, the N17 satellite sensor had a greater amount of scatter when compared with either MODIS sensor than the N16 satellite sensor. Also by looking at the comparison between Aqua and Terra, it is clear that even between the same sensors, there are factors that impede explanation, especially in the non-growing season. The result from this is that it becomes apparent that some type of relationship exists between a growing and a non-growing time of the year. Furthermore, it appears that in certain groupings of land, different factors are influential at different times of the year.

For instance, the deciduous forest when looked at in a two-part regression allows for smaller groups of data that can more easily be reproduced. It has however, become apparent through the examination of the data that the MODIS sensors tend to saturate at a 0.92 NDVI level. Since the MODIS sensors typically find a higher value of NDVI than AVHRR, the MODIS sensor is not able to evaluate high levels of NDVI values. The result is that in areas of extreme growth, such as forests, a ceiling is created for the MODIS NDVI values, causing a two-part regression being mandated to be used. This is primarily the case in the forest areas over the non-forest areas due to the higher rates of growth. In essence, the non-growing season/growing season relationship is far less a matter of time of the season, but rather a saturation problem of the sensor.

There is still strong evidence however, to support the need for a split regression in the examination of the evergreen forest land cover. Such a split in this land cover does allow for better explanation of the growing season. This does not solve the off-growing season problem; however, it would allow some seasonality metrics to be used with some modifications. The correlation of the evergreen forest non-growing season's high rate of scatter may have something to do with the problem of snow and unmasked clouds found in the non-forest land cover types.

It has generally been assumed that the most desirable NDVI values are the maximum values. It has also been the assumption that things such as snow, water, ice, smoke, haze, and smog would decrease the values of NDVI. The resulting rationalization of the increased scatter in the evergreen forest results around the concept that during the non-growing season, some areas would still produce a high-level of NDVI due to the nature of the continual greenness. However, if some areas were covered by snow or ice, and not masked out by the sensor, it is possible that the reduction of one sensor may be greater than the other, causing a scatter, which would be relatively unpredictable.

This same concept then would apply to the non-forest land cover types which have a unique problem with the floor saturation level created on by the MODIS sensor. The isolation of the floor effect to the off-season would suggest that the problem could be a result of snow and ice cover. As the floor effect primarily occurred in land cover types that are relatively non-obstructed by snow masking growth, the MODIS sensor lowered the NDVI values greater than the AVHRR sensor.

The majority of the focus within studies has been dealing with artificially low NDVI values and attempting to correct them. However, as alluded to earlier in the discussion, it has been shown in the forest land cover areas in section 3.2 that there are major issues with the comparison of extremely high NDVI levels with the MODIS sensor. This issue was noted by [7], noticing that the initial twelve months of MODIS vegetation data some intensively measured test sites appeared to have a saturation level of 0.90 NDVI. The problem clearly stated observes that, at extremely high values data is information lost, which exists extensively in the deciduous forest land cover but in the other forest types as well as row crops covers, is the result of the problem of the MODIS sensor saturating at 0.92 NDVI.

The problem of saturation raises an interesting and critical question. By adjusting our data to match a sensor that cannot fully describe the differences between two levels of growth due to saturation, should we be creating a calibration that loses data? The NDVI metric was created to work with AVHRR data and has been adapted for a number of sensors. With the MODIS sensor, however, we have an additional problem of having a generally larger NDVI value at all data points. This mixed with the saturation level of 0.92, will result in decreases of accuracy in high NDVI growth areas during the peak time of the year. As the primary use of this data focuses on the higher growth time period, this loss of explanation may not give an accurate representation of the characteristics of a season. Fixing this problem may need to be considered at the fundamental level by attempting to modify either the calculation of NDVI, or finding a way to remove the saturation level from the MODIS sensor. While the MODIS sensor is not viewed to be the next platform for NDVI, the goal being the VIIRS sensor, the MODIS platform will allow for comparison of data that will be necessary in order to allow for continuity between AVHRR's long history of data, and VIIRS continuing coverage of remote sensing issues.

Despite the problem of saturation however, there is still a considerable amount of data that can be gathered by employing some technique of adjustment between legacy data and current data at non-maximum values of NDVI.

CONCLUSION

Through the evaluation of the data we have seen factors that improve the calibration of the AVHRR data to the MODIS data. Most of the factors that have been found deal with MODIS NDVI values being reported as too low. Factors that have significant influence in the regressions include the need to mask clouds and buffering around clouds to deal with cloud interference as well as atmospheric moisture that is surrounding clouds and clouds not detected by the CLAVR algorithm. In addition, although no direct data shows the benefit of using a snow mask, the affects of snow appear to be evident in the non-growing season parts of the year data.

The primary focus of this study has been examining the effect of time periods on the calibration of the sensors. As can be noticed in the data, the middle part of the year, which has been referred to as the growing part of the season has a relatively narrow collection of data running on the regression line. However it should be noted that the edges of the season have characteristics of the season, as well as the off-season. The reason for this is possibly related to a latitude based relation, as the different latitudes will effect the light reflections differently, which cannot be accounted for completely in simply a growing/non-growing season correction. To further prove this would require a closer look at evaluating data based on metric derived values in a more dynamic sense.

The possibility of using a piece-wise regression may prove to be very useful in relating the data. However, without more data, the results may not be able to be applied to a longer calibration based algorithm.

The main benefit of this study has shown that the effect of season based regression is a likely possibility for correctional based algorithms. While more research into the breakdown of the season as well as adding additional factors such as geographic location may improve the results, there is clearly a need to utilize some type of adjustment based on the time period of the season.

ACKNOWLEDGMENTS

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