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AGRONOMY AND SOILS

Making the Cotton Replant Decision: A Novel and Simplistic Method to Estimate Cotton Plant Population from UAS-calculated NDVI

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ABSTRACT

One proposed use of unmanned aerial systems (UAS) in crop production is to produce quantitative data to support replant decisions by assessing plant stands. Theoretically, analysis of UAS imagery could quickly determine plant populations across large areas. The objective of this research was to investigate the ability of UAS to quantify accurately varying plant populations of cotton (*Gossypium hirsutum* L.). Field studies were conducted in Jackson, Milan, and Grand Junction, Tennessee in three consecutive growing seasons. Treatments included five seeding rates ranging from 8,500 to 118,970 seed ha^{-1}. After emergence, cotton plants were manually counted and images were collected in 2016 and 2017 with a MicaSense RedEdge multispectral sensor and in 2018 with a Sentera Double 4K multispectral sensor. Sensors were mounted to a quad-copter UAS flying at altitudes of 30, 60, 75, and 120 m above ground level. Spectral properties were assessed to generate normalized difference vegetation index (NDVI) thresholds that were used to limit the analysis to only plant material. Images were processed and analyzed to estimate number of plants and compared to actual plant populations within each plot. Images obtained from lower altitudes proved to be more accurate, with greatest correlations to actual ground-truthed plant populations from data collected at an altitude of 30 m. The utilization of the described novel method of estimating cotton plant population from NDVI-calculated UAS imagery might improve upon spatial and temporal efficiency in comparison to current methodology of estimation.

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Numerous management decisions, including determining planting date and plant population, greatly influence cotton growth and development. Environmental conditions also play a major role on growth and development, especially in northern areas of the Cotton Belt such as Tennessee, in which reduced heat accumulation results in shorter growing seasons (Gwathmey and Craig, 2003). In Tennessee, producers have an approximate 20-day window to plant cotton and ensure stands are adequate, with dates ranging from 20 April to 10 May (Craig, 2010). Generally, cotton plants germinate and emerge within 5 to 12 days after planting, leaving limited time to assess if plant populations in fields are acceptable (Wanjura et al., 1969). In the Mississippi Delta, establishing a final plant population between 34,000 and 68,000 plants ha^{-1} is important to achieve optimum yield potential; populations below 34,000 plants ha^{-1} result in reduced yields and delayed maturity (Wrather et al., 2008). Subsequently, the University of Tennessee recommends seeding rates between 74,000 and 148,000 seed ha^{-1} (Main, 2012). Producers must be able to assess their plant stands after emergence quickly to determine if they fall within this acceptable range.

As the adoption and integration of precision agriculture in crop production increases, the interest in remote sensing methods continues to increase (Gwathmey et al., 2010). Remotely sensed data can be an inexpensive source for strategic crop management decision making (Plant et al., 2001). The use of remote sensing in agriculture generally relies on multispectral reflectance data from visible and near-infrared ranges of the electromagnetic spectrum to calculate vegetation indices (VI). Vegetation indices are algebraic manipulations of spectral bands with similar responses to vegetative characteristics of plants (Plant et al., 2001). One of the first VI developed is the leaf area index (LAI), which is based upon the principle that leaves absorb more red than near-infrared light (Jordan, 1969). Jordan used a ratio of 800 to 675 nm to calculate LAI, for which the greater the value, the more leaf area present. LAI quantifies the amount of area of photosynthetic foliage per unit of ground surface area. The most commonly used VI is the normalized difference vegetation index (NDVI), which uses reflectance in the red (R) (~600-700 nm) and near-infrared (NIR) (~700-800 nm) spectral bands to monitor plant biomass and physiological status (Tucker, 1979) and is calculated:

NDVI = (NIR-R)/(NIR+R).

NDVI is highly correlated to the green and red linear relationships of photosynthetically active vegetation, providing the ability to differentiate between photosynthetically active tissue and other matter within the field of view. In-season NDVI data have been shown to correlate to cotton yields; Weigand et al. (1994) found a significant relationship between yield and seasonal accumulated NDVI values. Plant et al. (2000) demonstrated a positive correlation between cotton yield and NDVI-days modeling.

No model using precision agricultural tools has been developed to calculate plant populations of cotton at the cotyledon growth stage. With respect to other crops, Shrestha and Steward (2003) created an automated corn plant population measurement by segmenting and singulating corn plants within sequenced video frames from a vehicle-mounted digital video camera. Total number of plant pixels and their median positions were extracted from each pixel row, grouped together, and iterated to count corn plants between the V3 and V4 stages. Shrestha and Steward (2005) improved the method by using image segmentation to detect plant boundaries using chain code methodology and accounted for spatial structure of the crop row; root mean square error (RMSE) between estimates of plant counts and manual counts equaled 3,210 plants ha^{-1}. Thorp et al. (2008) expanded upon this work by using the developed segmentation tool combined with hyperspectral reflectance data to estimate corn plant density in various vegetative and reproductive stages of corn. Various spatial resolutions were used to evaluate reflectance of segmented plants within each raster to estimate the number of plants contained. Principal component analysis was used to assess plant stand density and hyperspectral reflectance at varying spatial resolutions. Huang et al. (2010) successfully predicted soil and crop canopy coverage variability using spatial regression modeling on aerial multispectral images. The use of ordinary least square multiple linear regression, spatial regression, and restricted maximum likelihood geostatistics indicated that aerial images could be used for spatial prediction of soil and crop canopy coverage (Huang et al., 2010). Other practical uses for estimating emergence include field-based crop phenotyping. Sankaran et al. (2015) demonstrated the ability to correlate aerial evaluations of winter wheat emergence and spring stand to ground-based visual ratings with the green normalized difference vegetation index. Jin et al. (2017) estimated wheat density using the Meyer-Neto vegetation index, which is the difference between excess green index and excess red index (Meyer and Neto, 2008).

Today, emerged plant counts, commonly referred to as stand counts, are the most utilized method to determine plant population across a given area (Godfrey et al., 2010; Main, 2012). This method consists of selecting and measuring a linear distance of plant row, counting the number of plants within this selected distance, and repeating in random locations throughout a field to estimate the mean plant population. Distances of row selected typically are based upon the 1/1000th method (Godfrey et al., 2010). When using this method, the assessor determines row m ha^{-1} and divides this number by 1000. The resulting number defines the distance of row in which the assessor should measure, and the assessor counts the number of emerged plants within this area. Next, the assessor multiplies by 1000 to reach an estimate of the total number of emerged plants within a hectare. Although this method requires little time, the approach is reliant upon a highly uniform plant population across the entire field and can be spatially limited. Human bias in selecting areas of the field also influences the estimated plant population, naturally skewing the estimation to favor either replanting or accepting a plant stand. However, the described method does not provide an estimation of plant stand uniformity or detail in a site-specific manner into the areas that possess yield-restricting populations. To determine if a cotton plant stand is acceptable or needs to be replanted, an assessor must be able to evaluate the entire field for both uniformity and plant population.

Theoretically, analysis of UAS imagery could determine plant population and uniformity quickly across large areas. Therefore, the objectives of this research were to: (1) develop and investigate a novel method of processing UAS imagery for the estimation of cotton plant populations and (2) determine optimum altitude of data acquisition for these estimations.

MATERIALS AND METHODS

Field Site Establishment and Management. Field studies were conducted in 2016-2018 at Ames Plantation in Grand Junction, TN; the West Tennessee Research and Education Center (WTREC) in Jackson, TN; and the Milan Research and Education Center (MREC) in Milan, TN. Treatments consisted of five seeding rates: 10.5 seed m^{-1} (118,970 seed ha^{-1}), 6.75 seed m^{-1} (76,480 seed ha^{-1}), 3 seed m^{-1} (33,990 seed ha^{-1}), 1.5 seed m^{-1} (17,000 seed ha^{-1}), and 0.75 seed m^{-1} (8,500 seed ha^{-1}). Each trial was managed without tillage (no-till) and used a randomized complete block design containing four replications. Plot size consisted of four rows 9 m in length. Row spacing for all trials equaled 97 cm. DeltaPine 1522 B2XF (Monsanto Co., St. Louis, MO), was planted on the dates listed in Table 1. Seed for each treatment was counted into individual seed packets for each row and planted with an ALMACO Cone Planter (ALMACO, Nevada, IA). All in-season management practices followed the University of Tennessee Extension Service recommendations for cotton production (Main, 2012) and management decisions were based upon growth and development of the 118,970 seeds ha^{-1} plots.

UAS and Ground-Truthing. After complete emergence, the number of plants within each row of each plot were manually counted. Plants were counted approximately 20 d after planting. During 2016 and 2017, aerial imagery was collected by a custom-built quad-copter equipped with a MicaSense RedEdge (MicaSense, Seattle, WA) multispectral sensor. In 2018, aerial imagery was collected by a DJI Inspire 2 (SZ DJI Technology Co., Ltd., Shezen, Guangdong) equipped with a Sentera Double 4K (Sentera, Minneapolis, MN) multispectral sensor (Table 2). The change in sensor was the result of available equipment. The acquired spatial resolution from each sensor, reported as ground sampling distance, was the result of factory settings at each sampling altitude and subsequently varied by sensor (Table 2). Image resolution was not modified after acquiring the image. In 2016 and 2017, autonomous flight patterns were generated using Mission Planner (ArduPilot, Indianapolis, IN); in 2018, Sentara's proprietary flight program, Field Agent, was used to generate grids. Flights were arranged in a serpentine "lawn-mower" pattern perpendicular to the planted rows at altitudes of 30, 60, 75, and 120 m above ground level with 80% image overlap and sidelap to generate the highest quality image possible. Images were subjected to Pix4Dmapper (Pix4D Inc., San Francisco, CA) and orthomosaics were generated, resulting in a 16-bit geotiff file (.tif) with a single image of the plot area of interest and embedded metadata.

Table 1. Planting dates for each trial location during the 2016-2018 growing seasons

Year	Location		
	Grand Junction, TN	Jackson, TN	Milan, TN
2016	10 May	-	-
2017	18 May	16 May	17 May
2018	4 May	3 May	15 May

Table 2. Unmanned Aerial System (UAS) multispectral sensor specifications

Sensor	Ground Sampling Distance (cm/pixel)				Sensor Width (mm)	Focal Length (mm)	Image Width (pixels)	Image Height (pixels)
	Flight Altitude (m)							
	30	60	75	120				
RedEdge	2.1	4.2	5.2	8.3	4.8	5.4	1280	960
Double 4K	0.9	1.72	2.2	3.4	6.2	5.4	4000	3000

	Spectral Resolution			
	Red Band (nm)		Near-Infrared Band (nm)	
	Center Wavelength	Bandwidth	Center Wavelength	Bandwidth
RedEdge	668	10	840	40
Double 4K	650	70	840	20

Plant Population Estimation Thresholding and Processing. Plant population estimations were generated within ArcMap 10.6 (ESRI, Redland, CA). A Python script was constructed within PythonWin (Python Software Foundation, Beaverton, CA) to streamline the analysis process (Fig. 1.). The ArcPy command prompt was executed for utilization of ArcGIS tools. Values within the resulting rasters were reclassified as cotton plants, soil, or field residue using the Reclassify tool in the Spatial Analyst toolbox. Threshold values for respective sensors were established by manually determining value ranges for cotton plants, soil, and field residue (Table 3). All pixels classified as soil or field residue were excluded. The remaining raster, consisting of cotton plant tissue, was subjected to the Raster-to-Polygon tool within the Conversion toolbox producing an area measurement for each individual polygon in the attribute table, reflected as cotton plants. Using the Add Geometry Attributes function, a new field containing each area measurement was added to the vector layer attribute table. Next, the Update Cursor feature was used to threshold plant areas to minimize the number of plants represented by multiple pixels within the prior raster. The Search Cursor function was then used to identify areas for each polygon within the attribute table. To distinguish multiple plants within a row that bordered or overlapped their neighbor, a loop was coded where each of the four smallest areas were divided by themselves such that they would equal one. All areas larger than the fourth smallest polygon area were divided by the value of the fourth smallest polygon area and products were recorded within the attribute table. Polygons with resulting values greater than one were considered overlapping or bordering cotton cotyledons. Polygons were constructed for each individual plot area and data were spatially joined from the concluding layer feature class to each plot; plants were counted by calculating the sum of the values of respective polygons within each plot. The specific Python script executed is included in the Appendix.

Statistical Design and Analyses. To determine the accuracy of this method with increasing altitude, estimated plant populations for each respective altitude were subjected to dummy regression (indicator variable) statistical analysis in SAS v 9.4 (SAS Institute, Cary, NC). Dummy regression is particularly beneficial when both analysis of variance (ANOVA) and regression terms are of interest. Upon evaluating the full model in which all parameters are unequal, nonsignificant terms were identified and removed. Significance levels were set at an alpha-level equal to 0.05. Slopes were compared for trueness, with values closest to one representing greater accuracy. To evaluate accuracy of the described method to current scouting methods, all actual plant populations for each trial location were summated to be considered a simulated field. One row from the first replication of each treatment at each location was selected and plant populations ha^{-1} were calculated using the 1/1000th method described previously. Current stand count estimations and simulated field populations were subjected to simple linear regression in JMP 14 (SAS Institute, Cary, NC). Coefficient of determination and slope values between the two methods were compared for accuracy differences.

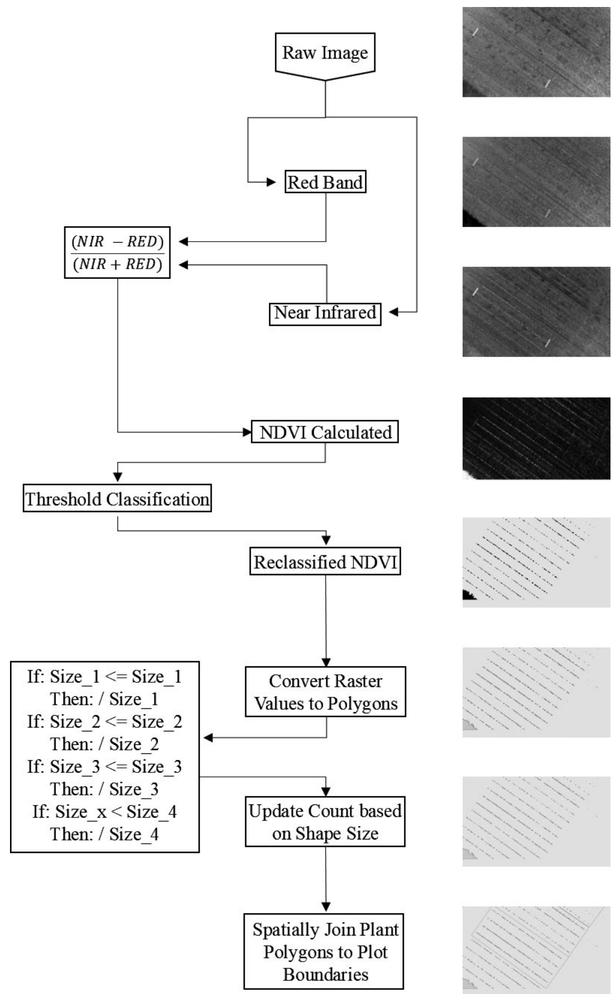

Figure 1. Flowchart illustrating stages of cotton plant population estimations for unmanned aerial systems imagery. Steps include: 1. calculating the normalized difference vegetation index; 2. thresholding image to select for cotton cotyledons; 3. convert raster data to vector data, resulting in polygons for individual or groups of plants; 4. update count based on size of plants to account for overlapping cotyledons; and 5. summate number of estimated plants within boundary of interest.

Table 3. Normalized Difference Vegetation Index (NDVI) plant thresholding parameters

Sensor	NDVI		
	Cotton	Residue	Soil
	Value Range		
RedEdge	0.24 - 0.76	0.06 - 0.2	-0.05 - 0.1
Double 4K	0.23 - 0.91	-0.64 - 0.35	-0.34 - 0.13
	Mean Value		
RedEdge	0.55	0.11	0.08
Double 4K	0.46	-0.26	-0.04

RESULTS AND DISCUSSION

Cotton Plant Identification. The described method to identify emerged cotton plants using calculated NDVI proved to be accurate at low altitudes (slope at 30 m equaled 0.903; Table 4, Fig. 2). Results are consistent with previous work conducted in corn (*Zea mays* L.), sunflower (*Helianthus annus* L.), sugarcane (*Saccharum officinarum* L.), and wheat (*Triticum aestivum* L.) (de Souza et al., 2017; Torres-Sanchez et al., 2015). For analysis of images acquired from the RedEdge sensor, the manual thresholding procedure resulted in NDVI values ranging from 0.24 to 1.0 were considered as plants and values less than 0.24 were excluded from further analyses (Table 3.). For the Double 4K sensor, the manual thresholding procedure resulted in NDVI values ranging from 0.23 to 1.0 were considered as plants and values less than 0.23 were excluded from further analyses. The described method of thresholding bordering or neighboring plants based upon pixel size was noted to have the least scatter at lower plant populations. Accuracy at lower populations is of greater importance in that these plant density ranges most commonly will provoke the decision of replanting or accepting the emerged stand. It should be noted that planter type might have influenced the accuracy of the measurement at greater populations. When the number of seed per row increases above the number of cells in the cone, seed spacing from research cone planters closely resembles that of a hill-drop plate. In contrast, seed spacing more closely resembles a singulated plate when seed number declines to or below the number of cells per cone. It is hypothesized that soil texture, soil color, light intensity, and any other factors that impact plant reflectance (herbicide injury, insect feeding, etc.) could influence values from field to field or site to site within a field. Calibration methods, or the use of training data, have been demonstrated to improve accuracy and detection of plant density and in-row skip lengths (de Souza et al., 2017; Perez-Ortiz et al., 2016). The development of a calibration procedure could have the potential to improve accuracy using the described method when analyzing imagery in different environments.

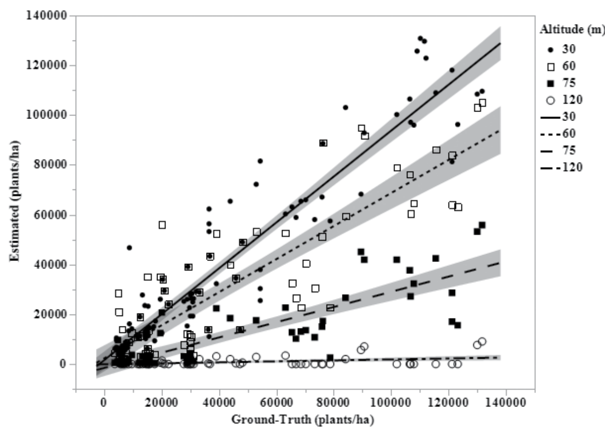

Figure 2. Dummy regression analysis of estimated versus actual plants by altitude (m).

Table 4. Dummy regression analysis of estimated vs. actual plant population by altitude (m)

Altitude (m)	Slope	Pr > F[z]
30	0.903	< .0001
60	0.645	< .0001
75	0.286	< .0001
120	0.000	< .0001
Intercept	Pr > F = 0.5457	
R^2	0.8771	
CV	48.506	
RMSE	10874.92	
Mean	22419.78	

[z] Significance based upon an alpha-level equal to 0.05.

Altitude Analysis. Primary differences in accuracy of determining existing plant stands were the result of change in spatial resolution and image quality, impacted by the increase in flight altitude. Linear regression lines separately fit flight altitudes of 30, 60, 90, and 120 m using dummy regression modeling (Fig. 2.). Due to individual thresholding of each sensor and consistency of flight protocols (overlap, pattern) differences in results due to the use of different sensors were negligible. The model explained 88% of the variation in plant populations across flight altitudes (Table 4). Treatment intercepts did not differ ($p = 0.5457$), although slope differences were highly significant (p < .0001) (Table 4.). Images obtained from an altitude of 30 m resulted in the greatest accuracy (linear slope of 0.903) in predicting cotton stands using the described methodology. As flight altitude increased and spatial resolution decreased, slope also decreased, with slope equaling 0 from data collected at an altitude of 120 m. The linear regression slope and coefficient of determination for plant estimations collected from 30-m altitude was nearly identical to previous work by Shrestha et al. (2003) in which a digital camera was mounted to a ground traveling vehicle at a height of 0.6 m. Decreased slope can be interpreted as an increased number of false negatives (uncounted plants) as spatial resolution dissolved from increases in flight altitude. This is consistent with work conducted on wheat plant density by Jin et al. (2017). It is suspected the increase in ground sampling size as altitude increased (Table 2) relative to the static size of each emerged plant prevented the sensor from reading reflectance values above the defined thresholds at greater altitudes. Although an acceptable level of error based on the relationship between plant population and yield must be determined, it is likely a balance between error and temporal efficiency will be reached when data are collected between 30- and 60-m altitudes using factory sensor settings.

NDVI Versus 1/1000th Method. When interpreting the simple linear regression of simulated 1/1000th method of plant population estimation to the total number of plants within the trial area, data were highly correlated with a coefficient of determination equal to 0.971 (Table 5.) Trueness was also high with a slope equaling 0.9606. This strong correlation would be expected as uniform treatment populations were established in areas of limited variability. Although the coefficient of determination was greater for the 1/1000th method than the UAS approach, the benefit was marginal. One issue with population assessment from an aerial image is overlapping cotyledons; the approach described here occasionally fails to differentiate plants that are growing closely together. This error will be acceptable in cotton for several reasons. First, actual plant population often has less influence on yield than the uniformity of the stand. As a compensatory plant, the yield potential of one, two, or three plants in a cluster will closely match the yield potential of a single plant. Research by McCarty et al. (2017) indicated skips larger than 61 cm resulted in reduced yields, but adjacent plants were able to compensate across smaller skips. Therefore, the most important component of making the replant decision in cotton is the identification and quantification of skips (Craig, 2010). Although the method described here could incorrectly classify overlapping cotyledons from multiple seedlings as a single plant and thereby underestimate plant population, this method could be applied within an alternative approach that focuses on the within-row distance between plants. Although the detection of skip length was beyond the scope of the current objectives, our results suggest a similar thresholding method with a different approach could determine skip length and ultimately drive the replant decision.

Table 5. Correlation of 1/1000th method to summated plant population of trial locations

Statistic	Value
Slope	0.9606
Intercept	2821
R^2	0.971
RMSE	3477
Pr > F	0.0003[z]
1/1000th Mean	40573
Total Plant Mean	42358

[z] Significance based upon an alpha-level equal to 0.05.

Sensor Comparison. Although it was beyond the scope of this study to compare the two sensors used, differences were noted. Sentera Double 4K imagers have much higher spatial resolution than the Micasense RedEdge, however, lower spectral resolution often prevented the Double 4K from successfully separating living plant material from soil/residue using NDVI due to the constraints on returned values. The influence of the red wavelength highly influences the determination of NDVI values, and the wide bandwidth limited the imagers' ability to distinguish minor differences in the reflectance of cotton plants and field residue in the red color spectrum. Alternatively, the lower spatial resolution of the Micasense RedEdge caused limitations using the described thresholding method at higher altitudes. As new sensor technology is released, a sensor with narrow bandwidths and high spatial resolution could improve temporal efficiency by allowing for increased flight altitudes without spatial resolution limitations. Currently, it appears the Sentera Double 4K might have greater potential to assess cotton plant population from higher altitudes with factory sensor settings if using RGB-based imagery. A subsequent study would need to be conducted to compare and determine differences in accuracy between the two sensors.

CONCLUSIONS

Cotton producers need quicker, site-specific methods to determine plant populations. The described methods of estimating plant population from multispectral images acquired from UAS have the potential to provide growers with population estimates along with detailing in what specific areas of a field stand is inadequate. Estimations from low altitudes were highly correlated to the number of actual plants. Estimating plant populations with aerial imagery will significantly reduce the amount of time required to assess a field and will provide more spatially dense, site-specific information. Although some error will likely be introduced with a UAS system, this error is countered by a complete assessment of all areas of the field and is contrasted by the limited spatial density of measurements collected by a field scout. The major limitation of image acquisition falls upon the utility of the UAS, such that battery life and field of view determine the amount of time required to cover the scope of the field. Other potential issues with the currently described methods include the threshold or reclassification portions of the models and the time required to complete the described method. Further development of the described method to include training data might not only improve overall accuracy, temporal efficiency might also be positively influenced as images from higher flight altitudes with current sensor technology become more functional.

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Appendix

Python Code

```
import arcpy, string

from arcpy import env
from arcpy.sa import*

size_1 = 0.000361
size_2 = 0.000722
size_3 = 0.001038
size_4 = 0.001369

arcpy.CheckOutExtension("spatial")

#Input Image File Location
arcpy.env.workspace = r'E:\Test'
arcpy.env.overwriteOutput = True

#Input Image File
input = r'E:\Test'

#Name File Result
result = "NDVI_Done.tif"

#Input Band Name
NIR = input + "\pop\Pop_Band4"
Red = input + "\pop\Pop_Band3"

#Name Band Result
NIR_out = "Results\NIR.tif"
Red_out = "Results\Red.tif"

arcpy.CopyRaster_management(NIR,NIR_out)
arcpy.CopyRaster_management(Red, Red_out)

Num = arcpy.sa.Float(Raster(NIR_out) - Raster(Red_out))
Denom = arcpy.sa.Float(Raster(NIR_out) + Raster(Red_out))
NDVI_Done = arcpy.sa.Divide(Num, Denom)

NDVI_Done.save(result)

#Reclassify NDVI
outReclass = Reclassify(NDVI_Done, "Value",
             RemapValue([[-1,0.24,"NODATA"],[0.24,1,1]]))
outReclass.save("E:\Test\Results\Plnt_Rcls")

#Raster to Polygon
arcpy.RasterToPolygon_conversion(outReclass, "Rast2Poly",
"NO_SIMPLIFY", "VALUE")

Rast2Poly = r'E:\Test\Rast2Poly.shp'
#Area in Attribute Table
arcpy.AddGeometryAttributes_management(Rast2Poly,
"AREA", "", "SQUARE_METERS","")

if arcpy.Exists(Rast2Poly):
 outputDir = r"E:\Test\Results"
 output = outputDir + "\PolyUpd"
 arcpy.CopyFeatures_management(Rast2Poly, output)
 cursor = arcpy.UpdateCursor("PolyUpd")
 Count = "Poly_Area"
 for row in cursor:
  if row > 0 and row <=size_1:
   row.setValue(Count, row.getValue(Count) / size_1)
  elif row > size_1 and row <=size_2:
   row.setValue(Count, row.getValue(Count) / size_2)
  elif row > size_2 and row <=size_3:
   row.setValue(Count, row.getValue(Count) / size_3)
  elif row > size_3 and row <=size_4:
   row.setValue(Count, row.getValue(Count) / size_4)
  elif row > size_4:
   row.setValue(Count, row.getValue(Count) / size_4)
  cursor.updateRow(row)

summed_total = 0
with arcpy.da.SearchCursor(output, Count) as cursor:
 for row in cursor:
  summed_total = summed_total + row[0]
```