APPENDIX 1-5: Generation of the ESA Agricultural Use Data Layers (UDLs) from the Cropland Data Layer (CDL)

Use Data Layers (UDLs) spatially represent application sites for agricultural and non-agricultural label uses in EPA’s Endangered Species Biological Evaluations (BEs). They leverage several different landcover and land use datasets acquired from remote sensing[[1]](#footnote-2) technology to create a spatial footprint for a given label use. EPA uses USDA’s Cropland Data Layer[[2]](#footnote-3) (CDL) for the agricultural use sites found in the conterminous United States. Updated annually, this publicly available dataset includes a robust accuracy assessment which is used by EPA to ensure the UDLs used in the BEs are of sufficient accuracy for decision making. This document provides a brief history of how this remotely sensed data is assessed for accuracy, introduces key topics related to assessing remotely sensed data, and outlines the criteria used by EPA when generating the agricultural UDLs and finally outlines the UDLs used in the clothianidin BE.

1. Introduction to Accuracy Assessments

When selecting data sources to use to create its UDLs, EPA prefers to use publicly available national level datasets; however, EPA may use proprietary data if appropriate publicly available data are not available. By using existing datasets, EPA leverages the expertise of other agencies and organizations, rather than becoming a ‘data maker’. Generally, the selected datasets follow national standards for the creation of spatial data and, in the case of remotely sensed data, include accuracy assessments. Accuracy assessments provide a measure of correctness for the data layer. Without this measure of understanding in the spatial layers, decisions based on the dataset may lead to unexpected and possibly unacceptable results (Congalton 2019). The goal of a quantitative accuracy assessment is to identify and measure map errors so that the map can be as useful as possible to the persons making decisions.

Two distinct types of quantitative accuracy assessments exist for spatial data: positional and thematic. Positional accuracy deals with the locational correctness of a map feature by measuring how far a spatial feature on a map is from its true or reference location on the ground (Bolstad 2005). The Federal Geographic Data Committee (FGDC) produced the U.S. National Cartographic Standards for Spatial Accuracy (NCSSA) (FGDC 1998) to create positional accuracy standards for medium- and small-scale maps/data. When possible, EPA leverages datasets adhering to these standards. Thematic accuracy deals with the labels or attributes of the features in the resulting GIS product and will be the focus of the discussion in this document. The thematic labels or attributes are the specific cover classes assigned in the landcover dataset. Each landcover dataset targets specific types of landscape features. In the case of the UDLs, and the underlying CDL, the primary goal of the datasets is to identify cover classes that represent agricultural crops. Other remotely sensed products may target but are not limited to non-agricultural features, non-agricultural plant cover, or water features. Each of the remotely sensed products may use the same satellite imagery, but due to the different goal of each project, the end results can differ. Thematic accuracy assessment provides measures of how different the mapped cover classes are from what occurs on the ground at specific reference locations. This is completed by comparing reference data, known/true classification of samples sites, and classified data for the same sample sites.

1. History of Map Making

Before the invention of aircraft, maps were created from human observations using survey equipment. Today, most map/data makers use remote sensing data rather than collecting data using field observations.To create the spatial data from remotely sensed data, decision tree algorithms use the imagery and information from known sites, referred to as training data, to generate the cover class classifications. These algorithms look for spectral signatures across multiple wavelengths to identify unique cover classes – in the CDL these are crop cover classes. Spectral signatures of various vegetation components include things such as canopy architecture, stem characteristics, leaf orientation, light angle, and shadowing of vegetation (Shah 2019). Even though advances in technology have provided access to remotely sensed information, field observations are still important and provide information at specific sample locations, used as known data for the decision tree, or as a reference site for the accuracy assessment; rather than providing a complete survey of the project area’s map extent.

Map/data making has moved to using remotely sensed data to make maps because it:

* is less expensive and more efficient than creating maps from human observations;
* offers a “bird’s eye” perspective, improving the understanding of spatial relationships and the context of our observations; and
* captures information in electromagnetic wavelengths that humans cannot see, such as the infrared portions of the electromagnetic spectrum, allowing for characterization of the landscape a human could not achieve.

However, no remotely sensed dataset is perfect. It is not possible to reach a complete one-to-one correlation between variation in remotely sensed data and the true variation found on the landscape. This means no resulting dataset will be error free. Several factors influence errors occurring in remotely sensed data, including but not limited to aircraft movement, topography, lens distortions, and other environmental factors (e.g., shadows, clouds, forest cover, snow morphology). These influences can reduce the strength of the relationships between the remotely sensed data and the landscape. However, errors are not limited to remotely sense datasets. The historical method of field observation also included errors due to factors such as observer bias, equipment malfunctions, inaccuracies from sampling errors, or goals of the projects.

The accuracy assessment allows for an understanding of those errors and provides the user the necessary information to decide if the accuracy level meets their decision-making needs. As discussed above, remotely sensed data typically includes two types of accuracy assessment: positional and thematic. The use of remotely sensed data requires an understanding of both.

Positional accuracy is assessed by comparing the coordinates of sample/reference points on a map against the coordinates of the same points derived from a survey or some other independent source. The Federal Geographic Data Committee (FGDC) produced the U.S. National Cartographic Standards for Spatial Accuracy (NCSSA) (FGDC 1998) to create positional accuracy standards for medium- and small-scale maps/data. When possible, EPA leverages datasets adhering to these standards.

Unlike positional accuracy, there is no government or professional society standard for assessing thematic accuracy. This omission is partially due to the inherent complexity of thematic accuracy but primarily because historically, thematic accuracy was generally assumed to be at acceptable levels (Congalton 2019). The following sections explores the history of thematic accuracy and the accuracy goals set by EPA for the UDLs in absence of the government or professional society standard.

1. History of Thematic Accuracy

The history of assessing thematic accuracy of maps derived from remotely sensed data is relatively brief, beginning around 1975 and was divided into four parts or epochs by Congalton in ‘*Assessing the Accuracy of Remotely Sensed Data’* (2019). Initially, no real accuracy assessment was performed on maps; rather, a “it looks good” mentality prevailed. This approach is typical of a new, emerging technology in which everything is changing so quickly that there is no time to assess how well you are doing. Despite the maturing of the technology over the last half century or so, some remote sensing analysts and map users still lean heavily on this mentality.

The second epoch is called the age of non-site-specific assessment. During this period, total acreages for each cover class were compared between reference estimates and measured without regard for location. It did not matter whether you knew where it was; only the how similar the total amounts were when compared. While total acreage is useful, it is equally if not more important to know where a specific landcover exists. Therefore, this second epoch was relatively short-lived and quickly led to the age of site-specific assessments.

In a site-specific assessment, reference locations for cover classes are compared with the classified cover class at the same location, and result in a measure of overall accuracy across all cover classes in the form of a ‘percent correct’. This method far exceeded the non-site-specific assessment but lacked information on individual landcover categories. Site-specific assessment techniques were the dominant method until the late 1980s.

The fourth and current age of accuracy assessment is called the ‘age of the error matrix’. An error matrix compares cover class information for a number of reference sites to the remotely sensed cover class results for the same location, across each cover classes in the data layer. The error matrix is a square array of numbers set out in rows and columns, accounting for each of the cover classes. Generally, the reference data cover classes are represented as the columns and the remotely sense/classified cover classes are represented by the rows. The number in each cell represent the sample sites in the corresponding cover classes from the reference data and the classified data. The major diagonal of this matrix identifies the sites where the reference and classified cover classes match, meaning the classified data correctly identified the cover class. (**Figure 1)**.

Some key terminology when considering these matrices:

* Reference data cover classes: the class label of the accuracy assessment site derived from field or human collected data, assumed to be correct
* Classified data cover classes: the class label of the accuracy assessment site derived from the remotely sensed data.

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**Figure 1. Example Error Matrix and Accuracy Values (Congalton 2019). Numbers within the bolded section of the matrix are the total number of sample sites that were identified for each cover class. In this example there are a total of 434 sample sites. The number in each cell represents the total number of sample sites found with the corresponded reference and classified cover class. For example, the 65 in the top left corner indicates that 65 samples site were identified as “D” for deciduous in both the reference and classified data. However, 65 does not account for all “D” sample sites in either classified or reference data. Moving over once cell to right, there are 4 sample sites identified as “C”, conifer, in the reference data but “D” in the classified data. The classified data misidentified the cover class by including it in the incorrect category – this is an error of commission. Moving down to the cell directly below 65, there 6 sites known to be “D” from the reference data but “C” in the classified data -- here the misidentified cover class results in the exclusion from a category or an error of omission. The diagonal of the error matrix represents the number of sample sites matching in the reference and classified data. The column total provides the number of sample sites found each cover classes based on the reference data, and the row total provided the number of sample sites found in each cover class based on the classified data.**

With each annual release of the CDL, USDA provides error matrices for their thematic classification of cultivated land at both the national and state level.

The next sections provide additional details on the types of reported accuracy metrics provided with the error matrices, how the matrices are collapsed, and accuracy metrics are recalculated to represent the agricultural UDLs. Along with these descriptions is an example of the use of these metrics as outlined in **Figure 1**.

1. Error Matrices, Overall, Producer’s, and User’s Accuracies, Kappa Statistic

Error matrices are effective representations of map accuracy, because the individual accuracies of each map cover class are plainly described on the major diagonal (i.e. classified data that matches the reference data), along with both the errors of inclusion (also referred to as “commission errors”) and the errors of exclusion (also referred to as “omission errors”) when the classified and reference data cover classes do not match. An omission error occurs when a sample site is left out, or omitted, from the correct classes in the classified dataset. This is considered a false positive of the classified data or Type 1 error. A commission error occurs when a sample site is included in an incorrect class in the classified dataset. This is considered a false negative/false match of the classified data or Type 2 error.

In addition to clearly showing errors of omission and commission, the error matrix can be used to compute overall accuracy, producer’s accuracy, and user’s accuracy, which were introduced to the remote sensing community by Story and Congalton (1986). Overall accuracy is simply the sum of the major diagonal divided by the total number of sample units, providing a ‘percent correct’ across all cover classes. In the example error matrix found in **Figure 1,** the overall accuracy is the sum of the values on the major diagonal, where the classified and reference data match, divided by the total number of sample sites or 321/435; resulting in an overall accuracy of 74%. This value is the most commonly reported accuracy assessment statistic. In addition to the overall accuracy, the reporting of producer’s and user’s accuracies allow for additional considerations, specifically of individual cover classes.

Computed to determine individual cover class accuracies, producer’s and user’s accuracies provide important information related to error within the individual cover class from different perspectives. The producer of the map may want to know how well a class matched the reference data, referred to the producer’s accuracy. This value is computed by dividing the value from the major diagonal (the agreement between the reference and classified data) for the class of interest, by the total number of reference data points for the class. Looking at **Figure 1,** the map producer identified 65 sites as deciduous, while the reference data indicate there were a total of 75 deciduous sites. So, 65 of 75 samples were correctly identified, resulting in a producer’s accuracy of 87%, which is quite good. However, this is only half of the story. If you now view the map from the user’s perspective, a user wants to know how many classified data points matched the reference data. In **Figure 1,** you see once again that 65 sites were classified as deciduous on the map that were actually deciduous, but the map shows a total of 115 site classified as deciduous, resulting in a user accuracy of 57%. In evaluating the accuracy of an individual map class, it is important to consider both the producer’s and the user’s accuracies.

The kappa statistic or coefficient is used as another measure of agreement for the resulting remotely sensed data (Cohen, 1960). This measure of agreement is based on the difference between the actual agreement in the error matrix (i.e., the agreement between the remotely sensed classification and the reference data as indicated by the major diagonal) and the chance agreement, which is indicated by the row and column totals (i.e., marginals). The kappa reflects agreement between the classified cover classes and the reference cover classes, and ranges from 0 to 1. If the kappa equals 0 than there is no agreement between the classified and references label. The closer to 1 the kappa, the closer the agreement is, and if it reaches 1 then the classified and reference data match perfectly. Ultimately, a Kappa of 0.85 means there is an 85% or better agreement than chance alone.

$$\hat{Κ}=\frac{observed accuracy-chance agreement}{1-chance agreement}$$

The power of kappa is in its ability to test whether one error matrix is statistically significantly different from another and not in simply reporting this value as another measure of accuracy.

1. Use of Accuracy Values in Understanding Thematic Errors

In the past, an overall accuracy level of 85% was often adopted as representing the cutoff between acceptable and unacceptable data. This standard was first proposed in Anderson et al. (1976) despite the lack of any research being performed to establish this standard. Accuracy depends on many factors, including the amount of effort, level of landscape or classification detail, and variability of the classes. In some instances, an overall accuracy of 85% is more than sufficient; in others it would not be accurate enough; and in others, such an accuracy would be way too expensive to ever achieve (Congalton 2019).

In the example described above and presented in **Figure 1,** the error matrix has an overall map accuracy of 74%. This value tells about how accurate the map is, in general or across all classes, but provides no information within individual classes. For additional information on the deciduous cover class, the producer’s and user’s accuracies can be considered. The producer’s accuracy for this class of 87% is quite good and even higher the overall accuracy of the dataset. However, if we stopped there, one might conclude that although the dataset appears to be average overall (i.e., 74%), it is more than adequate for the deciduous class. Making such a conclusion could be a serious mistake because the user’s accuracy of 57% tells a different story. In other words, although 87% of the deciduous areas have been correctly identified as deciduous, only 57% of the areas called deciduous on the map are actually deciduous based on the reference data. This lower user accuracy tells us that there are errors of commission in the map related to the deciduous classes, meaning there are sample sites that were classified as deciduous that based on the reference belong to a different class. The result of this is more area in the map classified as deciduous than actually occurs on the ground.

A more careful look at the error matrix reveals significant confusion in discriminating deciduous from barren and shrub. Therefore, although the producer of this map can claim that 87% of the time an area that was deciduous on the ground was identified as such on the map, a user of this map will find that only 57% of the time that the map says an area is deciduous will it actually be deciduous on the ground, and may often be barren/scrub.

The intended use of the data/map can drive the need to address some of the error. For example, the lower user accuracy in the example above often resulted from the confusion between discriminating deciduous from barren/shrub. Collapsing these two classes together into a deciduous/barren/shrub class increase the user's accuracy to 83% but lowers the producer’s accuracy to 85% (**Figure 2)**.The higher user’s accuracy means when the map identifies this grouped cover class it matches what is found on the ground more often than the two individual classes. Under certain situations it may be worth the slightly lower producer accuracy and sacrificing one of the cover classes, meaning the map will no longer distinguish between deciduous and shrub/barren.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | D/SB | C | AG | Row total |
| D/SB | 183 (65+4 +114) | 11 | 25 | 219 |
| C | 14 (6+8) | 81 | 5 | 100 |
| AG | 19 (0+19) | 11 | 85 | 115 |
| Column total | 216 | 103 | 115 | 434 |

Producer’s accuracy = $\frac{183}{216}=85\%$ User’s accuracy = $\frac{183}{219}=83\%$

**Figure 2. Example collapsing cover class to address error of commission, building off the error matrix in Figure 1 here the deciduous and barren/shrub are combined and accuracy metric recalculated.**

For the purposes of the UDL, EPA’s targets at least 85% in both the producer’s and user’s accuracy and at least 90% for an overall accuracy when combining individual crops from the CDL into the UDL cover classes.

1. EPA’s Accuracy Value Goals for Use Data Layers Used in BEs

The native CDL landcover dataset includes over 100 cultivated cover classes in its thematic classification. The error matrices released with the CDL data provide overall, producer and user measures of accuracy at both the state and national level as well as the associated Kappas. In recent years, the overall accuracy of the CDL dataset has been in the low to mid-80% with Kappa just over 0.80. The producer’s and user’s accuracy for the individual cultivated classes range from less than 5% to 98%, and less than 15%-97%, respectively (Boryan 2011). When considering the individual cultivated classes of the CDL, the user’s accuracy is slightly better than producer’s accuracy, resulting in a lower commission error, or false negative/Type 2 error. However, when considering these BEs, reducing the false positive/Type 1 error is equally or more important. Improving all accuracy metrics as well as leveling out the producer and user accuracies is an overall goal when grouping crops into the UDLs cover classes.

To improve the overall, user and producer accuracies for the UDLs, the 100+ thematic cultivated classes found in CDL are reclassified into 13 crop groupings. Consolidating CDL into aggregated categories is a documented way to significantly improve the accuracy of assessments by eliminating misclassification errors within the combined classes (Johnson 2013a, Johnson 2013b, Wright 2013 and Lark 2017). Each of the 100+ thematic cultivated classes from the original CDL, are found in at least one state but not every state will include all 100+ classes. For this reason, while the focus is on the accuracy at the national level, there are instances when the state accuracy for a UDL would be higher than observed at the national level.

When deciding how to group crops from the CDL, EPA refers to the grouping used by the U.S. Geological Survey (Baker and Capel, 2011) and the Generic Endangered Species Task Force (Amos et al 2010). This information considers environmental factors that influence the location of crops and the error matrices provided by USDA with the original CDL data. By considering these agronomic factors in addition to the error matrices it is possible to improve the accuracy for these UDLs while retaining agronomic similarities. There is an infinite number of ways to group the crop cover classes found in the CDL, and each structured grouping can be reviewed in terms of recalculated accuracy compared to the native dataset.

When collapsing the available error matrices provided with the CDL into the 13 UDL groups, the sample site values for each of the CDL crops found in a UDL are summed across both rows and columns in the error matrix. Currently the 13 UDL groups bring the overall accuracy to 90%, increased from 80% for the CDL, with a Kappa of 0.88 (**Table 1)**. As described above, it is important to consider the producer’s and user’s accuracy of the individual thematic classes in addition to the overall accuracy.

When considering the user’s and producer’s accuracy, EPA targets at least 85% for each UDL, while retaining at least a 90% overall accuracy. Following the thematic grouping into the 13 UDLs and the recalculation of the user and producer accuracies, by year of the CDL, to help address errors of commission, additional steps to lower the omission errors, are implemented. These include the temporal aggregation of multiple CDL years into the UDL, and expanding the crop area found in the UDL layer to meet or exceed the area for the same suite of crops as reported in the Census of Agriculture. The goal of each of these steps is to improve the accuracy of the UDLs by minimizing the rate of omission error. However, these steps are not directly related to the existing error matrices provided with the CDL, and therefore new accuracy values are not calculated following the temporal aggregation, and area expansion. By reducing the omission errors, these steps result in a more protective landcover classification for each UDL.

If an individual crop class in the CDL has both the producer and user accuracies that are over 85%, the corresponding UDLs is that same as the CDL crop cover class, for example cotton from the CDL is found in the cotton UDL. These UDLs include corn, cotton, grapes/other vineyards, rice, soybeans and wheat. Five of these UDLs have user and producer accuracies in the low to mid 90%, with Kappas ranging from ~0.89 to 0.97. The user’s and producer’s accuracy for the remaining cotton UDL falling above 85% with Kappas of ~ 0.85. Due to the geographically limited occurrence of cotton, this crop is only grown in the south, lower national accuracy is expected compared to other crops with a broader geographic range. This is due to the fact that cotton growing states may classify cotton well, however, there is a lower accuracy in identifying cotton in states where cotton doesn’t grow and this brings down the national accuracy.

When an individual crop cover class in the CDL is below 85%, grouping multiple crops together and ultimately reducing the number of total thematic crop groups, improves the accuracy of the resulting UDL. When deciding which crops to group, error of omission and commission of the remotely sensed data are considered, in addition to environmental and agronomic practices. EPA targets an accuracy of at least 85%; however, it is not always possible to reach the target without compromising the environmental/agronomic practices. For this reason, some of the UDLs that contain multiple crop classes have slightly lower than 85% accuracy.

The UDLs containing a number of crops include alfalfa/other agricultural grasses, citrus, other crops, other grains, other orchards, other row crops, and vegetables and ground fruit. Two of these UDLs, other crops and other grains, did not meet an 85% accuracy for user’s and producer’s accuracy. Two additional UDLs, other row crops and vegetables and ground fruit, did not reach 85% for just the producer’s accuracy. See **Table 1** for a complete list of accuracy values across all 13 UDLs. Of the 13 UDLs 9 were used to map the agricultural label uses for clothianidin. A list of the pertinent UDLs can be found in **Figure 3.** As mentioned above, the focus of the discussion is on the national accuracies. But due to the variety and regional nature of some crops found in the UDLs, state based accuracy assessments often reach 85% even though the national level assessment for the same UDL does not.

Additional challenges when identifying some crops include higher frequency of change in agricultural practices (*e.g*., crop rotation), and/or lower total area on the landscape for minor crops. These two challenges are related to errors of omission, rather than errors of commission addressed by grouping crops into the UDL categories a common practice implemented to increase accuracy of remotely sensed data (Johnson 2013a, Johnson 2013b, Wright 2013 and Lark 2017). Two additional steps address some of the uncertainty related to these errors of omission, specifically, the known downward estimates of acres for remotely senses data and changes in crop patterns over time. These steps are implemented on all UDLs, but have the most impact in addressing uncertainty around error of omission for the UDLs containing multiple crops with lower accuracy values. First, a temporal aggregation of multiple years of the CDL into the UDLs is performed to account for changing agricultural practices, for example crop rotation, from year to year. Second, the total area of the temporally aggregated UDL is compared to the reported area found in the Census of Agriculture, accounting for some of the error/difficulty in identifying minor crops. If the area of the UDL is less than the reported area in the Census of Agriculture, the UDL is grown out to meet or exceed the Census of Agriculture. Referred to as region growing, expanding the UDL area to meet or exceed the area reported in the Census of Agriculture is a conservative measure take to minimize the error of omission. However, the Census of Agriculture generated once every 5 years, represents a single year in time. The CDL generated every year may capture agricultural practices, such as rotations, not captured in the Census Agriculture. For this reason, there is uncertainty around the crop area found in the Census of Agriculture being representative across all years of the CDL.

At the end of the whole process, the resulting UDLs provide a more protective landcover estimate for the purposes of the Endangered Species Biological Evaluations, making them the best available spatial agricultural data to use in the ESA BEs.

**Figure 3** provide a summary of the UDLs used to map the agricultural label uses for clothianidin with a complete crosswalk of the original CDL crops to the UDL class provided in **Table 2.** For the clothianidin BE these UDL specifically represent the foliar and soil uses. Seed treatment and other non-spray uses are considered separately, see **APPENDIX 1-6 and APPENDIX 4-5.**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Alfalfa | Citrus | Corn | Cotton | Grapes | Other Crops | Other Grains | Other Orchards | Other Row Crops | Rice | Soybeans | Vegetables and ground fruit | Wheat | **User's Accuracy** | **Commission** | **Kappa** |
| Alfalfa | 2157632 | 325 | 49580 | 6026 | 440 | 38838 | 45476 | 4745 | 4226 | 131 | 27170 | 13039 | 29148 | 89% | 11% | 0.87 |
| Citrus | 147 | 244865 | 37 | 25 | 12 | 185 | 112 | 103 | 1 | 0 | 0 | 164 | 3 | 99% | 1% | 1.00 |
| Corn | 39172 | 26 | 4222089 | 6598 | 241 | 18927 | 32759 | 1636 | 6212 | 1454 | 124498 | 20895 | 13154 | 94% | 6% | 0.92 |
| Cotton | 5368 | 12 | 9800 | 974234 | 51 | 9753 | 17664 | 1405 | 43844 | 509 | 36809 | 5983 | 15474 | 87% | 13% | 0.86 |
| Grapes | 426 | 30 | 546 | 35 | 93320 | 1372 | 47 | 3206 | 607 | 0 | 56 | 288 | 92 | 93% | 7% | 0.93 |
| Other Crops | 26196 | 385 | 12842 | 7554 | 581 | 729904 | 37343 | 6695 | 4335 | 2888 | 11038 | 9363 | 32155 | 82% | 18% | 0.82 |
| Other Grains | 16615 | 23 | 14503 | 7531 | 20 | 18118 | 597678 | 312 | 3603 | 210 | 8702 | 7707 | 34988 | 84% | 16% | 0.83 |
| Other Orchards | 2870 | 234 | 1305 | 1717 | 1862 | 3680 | 521 | 353321 | 950 | 26 | 524 | 1424 | 412 | 96% | 4% | 0.96 |
| Other Row Crops | 2528 | 0 | 3208 | 13781 | 208 | 2860 | 4999 | 466 | 315797 | 165 | 3933 | 2981 | 782 | 90% | 10% | 0.89 |
| Rice | 150 | 0 | 1061 | 154 | 1 | 3158 | 340 | 5 | 36 | 275819 | 2509 | 190 | 106 | 97% | 3% | 0.97 |
| Soybeans | 28675 | 0 | 139339 | 54449 | 101 | 29702 | 25116 | 427 | 10953 | 15386 | 4754850 | 16137 | 27339 | 93% | 7% | 0.90 |
| Vegetables and ground fruit | 5221 | 83 | 6822 | 1587 | 289 | 6397 | 7439 | 1209 | 3009 | 106 | 3263 | 361780 | 5496 | 90% | 10% | 0.90 |
| Wheat | 22383 | 0 | 11027 | 18183 | 99 | 44103 | 81911 | 525 | 1618 | 10 | 22050 | 13228 | 1833412 | 89% | 11% | 0.88 |
| **Producer's Accuracy** | 85% | 99% | 93% | 89% | 95% | 78% | 68% | 93% | 79% | 93% | 94% | 79% | 90% |  |
| **Omission** | 15% | 1% | 7% | 11% | 5% | 22% | 32% | 7% | 21% | 7% | 6% | 21% | 10% |
| **Kappa** | 0.82 | 0.99 | 0.91 | 0.88 | 0.95 | 0.77 | 0.67 | 0.93 | 0.79 | 0.93 | 0.91 | 0.79 | 0.89 |
|  | **Overall Accuracy** | 90% |  |
| **Overall Kappa** | 0.88 |

**Table 1. Collapsed national error matrix from the 2018 CDL, example of the 13 national UDLs with associated measures of accuracy.**

**Figure 3.** **Summary of Use Data Layer Classes for clothianidin** **(foliar and soil applications)**

*These classes are not mutually exclusive to one another and are further reclassified into 13 national agricultural UDL classes. 9 UDLs are used to map clothianidin labelled agricultural uses. The complete crosswalk for all 13 UDL classes can be found in* ***Table 2.***

**Cotton:** 20, 25, 26, 42

**Rice**: 30

**Soybeans**: 40, 42, 45, 48, 14

**Vegetables & Ground Fruit**: 60, 61, 68, 26, 56

**Other Orchards**: 70

**Vineyards:** 71

**Citrus:** 72

**Other Row Crops:** 90

**Other Crops:** 100

| Summary of Use Data Layers (UDL) Classes |
| --- |
| **Reclass Value** | **UDL General Classes** |
| 14 | Corn/soybeans |
| 20 | Cotton |
| 25 | Cotton/wheat |
| 26 | Cotton/vegetables |
| 30 | Rice |
| 40 | Soybeans |
| 42 | Soybeans/cotton |
| 45 | Soybeans/wheat |
| 48 | Soybeans/grains |
| 56 | Wheat/vegetables |
| 58 | Wheat/grains |
| 60 | Vegetables and ground fruit |
| 61 | (ground fruit) |
| 68 | Vegetables/grains |
| 70 | Other Orchards |
| 71 | Vineyards |
| 72 | Citrus |
| 90 | Other row crops |
| 100 | Other crops |

**Table 2. Cross-walk between CDL class and UDL agricultural classes.**

| **CDL Value** | **CDL Class Name** | **Reclass Category for UDLs** | **Double Crop (Y)** | **Reclass Code** |
| --- | --- | --- | --- | --- |
| 1 | Corn | Corn |   | 10 |
| 2 | Cotton | Cotton |   | 20 |
| 3 | Rice | Rice |   | 30 |
| 4 | Sorghum | Other grains |   | 80 |
| 5 | Soybeans | Soybeans |   | 40 |
| 6 | Sunflower | Other row crops |   | 90 |
| 10 | Peanuts | Other row crops |   | 90 |
| 11 | Tobacco | Other row crops |   | 90 |
| 12 | Sweet Corn | Vegetables and ground fruit |   | 60 |
| 13 | Popcorn Corn | Vegetables and ground fruit |   | 60 |
| 14 | Mint | Vegetables and ground fruit |   | 60 |
| 21 | Barley | Other grains |   | 80 |
| 22 | Durum Wheat | Wheat |   | 50 |
| 23 | Spring Wheat | Wheat |   | 50 |
| 24 | Winter Wheat | Wheat |   | 50 |
| 25 | Other Small Grains | Other grains |   | 80 |
| 26 | Double Crop Winter Wheat/Soybeans | Soybeans/Wheat | Y | 45 |
| 27 | Rye | Other grains |   | 80 |
| 28 | Oats | Other grains |   | 80 |
| 29 | Millet | Other grains |   | 80 |
| 30 | Speltz | Other grains |   | 80 |
| 31 | Canola | Other grains |   | 80 |
| 32 | Flaxseed | Other grains |   | 80 |
| 33 | Safflower | Other grains |   | 80 |
| 34 | Rape Seed | Other grains |   | 80 |
| 35 | Mustard | Vegetables and ground fruit |   | 60 |
| 36 | Alfalfa | Alfalfa/agricultural grasses |   | 110 |
| 38 | Camelina | Other grains |   | 80 |
| 39 | Buckwheat | Other grains |   | 80 |
| 41 | Sugarbeets | Other row crops |   | 90 |
| 42 | Dry Beans | Vegetables and ground fruit |   | 60 |
| 43 | Potatoes | Vegetables and ground fruit |   | 60 |
| 44 | Other Crops | Other crops |   | 100 |
| 45 | Sugarcane | Other grains |   | 80 |
| 46 | Sweet Potatoes | Vegetables and ground fruit |   | 60 |
| 47 | Misc Vegs & Fruits | Vegetables and ground fruit |   | 60 |
| 48 | Watermelons | Vegetables and ground fruit |   | 60 |
| 49 | Onions | Vegetables and ground fruit |   | 60 |
| 50 | Cucumbers | Vegetables and ground fruit |   | 60 |
| 51 | Chick Peas | Vegetables and ground fruit |   | 60 |
| 52 | Lentils | Vegetables and ground fruit |   | 60 |
| 53 | Peas | Vegetables and ground fruit |   | 60 |
| 54 | Tomatoes | Vegetables and ground fruit |   | 60 |
| 55 | Caneberries | Vegetables and ground fruit |   | 61 |
| 56 | Hops | Other row crops |   | 90 |
| 57 | Herbs | Vegetables and ground fruit |   | 60 |
| 58 | Clover/Wildflowers | Other crops |   | 100 |
| 59 | Sod/Grass Seed | Other crops |   | 100 |
| 60 | Switchgrass | Alfalfa/agricultural grasses |   | 110 |
| 61 | Fallow/Idle Cropland | Other crops |   | 100 |
| 66 | Cherries | Other orchards |   | 70 |
| 67 | Peaches | Other orchards |   | 70 |
| 68 | Apples | Other orchards |   | 70 |
| 69 | Vineyards | Vineyards |   | 71 |
| 70 | Christmas Trees | Other trees |   | 75 |
| 71 | Other Tree Crops | Other orchards |   | 70 |
| 72 | Citrus | Citrus |   | 72 |
| 74 | Pecans | Other orchards |   | 70 |
| 75 | Almonds | Other orchards |   | 70 |
| 76 | Walnuts | Other orchards |   | 70 |
| 77 | Pears | Other orchards |   | 70 |
| 92 | Aquaculture | Other crops |   | 100 |
| 141 | Deciduous Forest | Forest |   | 140 |
| 142 | Evergreen Forest | Forest |   | 140 |
| 143 | Mixed Forest | Forest |   | 140 |
| 152 | Shrubland | Shrubland |   | 160 |
| 204 | Pistachios | Other orchards |   | 70 |
| 205 | Triticale | Other grains |   | 80 |
| 206 | Carrots | Vegetables and ground fruit |   | 60 |
| 207 | Asparagus | Vegetables and ground fruit |   | 60 |
| 208 | Garlic | Vegetables and ground fruit |   | 60 |
| 209 | Cantaloupes | Vegetables and ground fruit |   | 60 |
| 210 | Prunes | Other orchards |   | 70 |
| 211 | Olives | Other orchards |   | 70 |
| 212 | Oranges | Citrus |   | 72 |
| 213 | Honeydew Melons | Vegetables and ground fruit |   | 60 |
| 214 | Broccoli | Vegetables and ground fruit |   | 60 |
| 216 | Peppers | Vegetables and ground fruit |   | 60 |
| 217 | Pomegranates | Other orchards |   | 70 |
| 218 | Nectarines | Other orchards |   | 70 |
| 219 | Greens | Vegetables and ground fruit |   | 60 |
| 220 | Plums | Other orchards |   | 70 |
| 221 | Strawberries | Vegetables and ground fruit |   | 61 |
| 222 | Squash | Vegetables and ground fruit |   | 60 |
| 223 | Apricots | Other orchards |   | 70 |
| 224 | Vetch | Alfalfa/agricultural grasses |   | 110 |
| 225 | Double Crop Winter Wheat/Corn | Corn/Wheat | Y | 15 |
| 226 | Double Crop Oats/Corn | Corn/Grains | Y | 18 |
| 227 | Lettuce | Vegetables and ground fruit |   | 60 |
| 229 | Pumpkins | Vegetables and ground fruit |   | 60 |
| 230 | Double Crop Lettuce/Durum Wheat | Wheat/Vegetables | Y | 56 |
| 231 | Double Crop Lettuce/Cantaloupe | Vegetables and ground fruit |   | 60 |
| 232 | Double Crop Lettuce/Cotton | Cotton/Vegetables | Y | 26 |
| 233 | Double Crop Lettuce/Barley | Vegetables/Grains | Y | 68 |
| 234 | Double Crop Durum Wheat/Sorghum | Wheat/Grains | Y | 58 |
| 235 | Double Crop Barley/Sorghum | Other grains |   | 80 |
| 236 | Double Crop Winter Wheat/Sorghum | Wheat/Grains | Y | 58 |
| 237 | Double Crop Barley/Corn | Corn/Grains | Y | 18 |
| 238 | Double Crop Winter Wheat/Cotton | Cotton/Wheat | Y | 25 |
| 239 | Double Crop Soybeans/Cotton | Soybeans/Cotton | Y | 42 |
| 240 | Double Crop Soybeans/Oats | Soybeans/Grains | Y | 48 |
| 241 | Double Crop Corn/Soybeans | Corn/Soybeans | Y | 14 |
| 242 | Blueberries | Vegetables and ground fruit |   | 61 |
| 243 | Cabbage | Vegetables and ground fruit |   | 60 |
| 244 | Cauliflower | Vegetables and ground fruit |   | 60 |
| 245 | Celery | Vegetables and ground fruit |   | 60 |
| 246 | Radishes | Vegetables and ground fruit |   | 60 |
| 247 | Turnips | Vegetables and ground fruit |   | 60 |
| 248 | Eggplants | Vegetables and ground fruit |   | 60 |
| 249 | Gourds | Vegetables and ground fruit |   | 60 |
| 250 | Cranberries | Vegetables and ground fruit |   | 61 |
| 254 | Double Crop Barley/Soybeans | Soybeans/Grains | Y | 48 |
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1. Remote sensing is defined as the collection and interpretation of information about an object from a

distant vantage point. Remote sensing systems involve the measurement of electromagnetic energy

reflected or emitted from an object and include instruments on balloons, aircraft, satellites, and

unmanned aerial systems (UAS) (Congalton 2019). [↑](#footnote-ref-2)
2. Available at USDA’s National Agricultural Statistic Survey website: https://www.nass.usda.gov/Research\_and\_Science/Cropland/SARS1a.php [↑](#footnote-ref-3)