## 2018 Statewide Land Use Mapping Accuracy Assessment

After completing the final classification dataset, a comprehensive accuracy assessment was completed. Independent ground truth samples set aside for this purpose ( $25 \%$ of the initial ground truth data, approximately $22 \%$ after QA/QC). A stratified random sampling method was used for accuracy assessment sample selection. The datasets were stratified by land cover type and county boundary. Prior to the accuracy assessment, the validation dataset was cleaned so that each data point corresponded to a single crop at a single point in time in a single field. In the WY 2018 analysis, 12,218 samples were used for accuracy assessment. These sites were not used to train the classification algorithm and therefore represent unbiased reference information.

Accuracy assessment can be divided into three components:

1. Reference data sampling design - how much reference data is collected, when and where
2. Reference data response design - how reference data is collected
3. Analysis - how the reference data is used to determine accuracy and how that accuracy is expressed
In this section, Land IQ's approach to all three of these components is described, and results of the accuracy assessment are provided.

## Sampling Design

In conventional accuracy assessment theory, the minimum number of samples corresponding to a specific accuracy level is calculated; however, this calculation does not take the size of the area being mapped into account. This method of minimum sample size determination is not always applicable to statistics with a spatial component. Therefore, rather than calculating the minimum number of samples needed for the reference data set, then dividing it up proportionately or equally among strata (crop types and cropped areas [e.g., counties]), Land IQ collects reference data by region or county and then partitions it into training and reference data sets for each crop based on an approximate $75 \%-25 \%$ split, respectively.

There are several reasons for this approach, but the main reason is that it is far more efficient to collect both training and validation data simultaneously when the reference data is collected by ground survey. This approach results in both types of data being concentrated where crops are concentrated (e.g., in counties with high acreage of agricultural crops). This approach also results in more data (for both training and testing) being collected for predominant, high acreage crops. The result of this approach repeated over multiple years is that representative reference data is accumulated, in some cases, beyond the minimum number of samples needed for some crops but can be lacking for other, less common crops. For this reason, Land IQ now focuses some of its data collection efforts on crops for which data lacks. These crops are typically lower acreage annual crops.

## Response Design

Reference data can be collected by different means from different sources. Currently, Land IQ collects reference data for model training and validation from cropped areas in California by conducting on-theground "ground truth" survey. For the purposes here, ground truth data and reference data are synonymous.

Because the ground truth surveys are real-time (as opposed to using previously acquired data such as archival imagery) and require presence of staff, logistical considerations must be made. First, on-theground reference data surveys must be made when the crop is growing. This requirement introduces an element of timing, which is especially important for short-season crops. Second, because the area mapped in California is so large, knowledge of where some cropped fields are, especially for minor crops, is approximate and often changes from year to year. In addition, because so many crops are
mapped that vary in acreage, some crops for which there is little existing reference data are prioritized for reference point data collection.

For these reasons, Land IQ uses the basic concepts of sampling design to achieve independent and random samples in addition to considering criteria to prioritize reference point data collection:

- Confidence level - Crops with estimated lower accuracy and confidence levels from the previous year's mapping effort are prioritized for ground truth data collection.
- Peak date -Land IQ uses remote sensing analysis to find dates of peak reflectance in fields to determine the seasonality of crops and help optimize timing of ground truth data collection around peak growing seasons.


## Analysis

Uncertainty in crop classification is related to two issues: accuracy and precision.

## Accuracy

Accuracy is a relative measure of the exactness of an estimate and accounts for systematic errors. Therefore, an accurate estimate does not systematically over- or underestimate the true value. Map accuracy can be quantified by creating an error matrix (also commonly called a confusion matrix), which compares the map classification with a reference classification.

The underlying principle of the accuracy assessment is that it compares the mapped land classification to reliable reference data, collected through sample-based approaches, as described above. The objective of a validation data set, therefore, is to provide a statistically sound estimate of the accuracy of the output map based on an independent reference information source. The accuracy of a map is assessed by measuring the degree of agreement between the output map and the validation data set. An error matrix can be generated that compares the pixels or polygons in the resulting classification map to the known reference points. From this matrix, overall accuracy and accuracy of each class can be determined.

There are three measures of accuracy that can be determine from an error matrix:

1. Overall accuracy
2. Producer's accuracy (omission error)
3. User's accuracy (commission error

Typically, accuracy of remotely sensed maps is demonstrated using an error (or confusion) matrix (Table 5). Accuracy measures that can be derived from an error matrix are described below.

## Overall accuracy

Overall accuracy is calculated by dividing the total number of correct pixels by the total number of pixels in the error matrix. In other words, the total number of correctly classified samples are divided by the total number of samples. It measures the accuracy of the whole map but does not refer to any individual classes. It is the probability that a randomly selected location on the map is correctly classified. Overall accuracy is sensitive to sample size and is thus more reliable in classes with larger samples. It is the sum of the major diagonal in an error matrix that runs from the upper left corner to the bottom right corner of the matrix.

## Producer's Accuracy (Omission Error)

Producer's accuracy is also called the omission error and is described by the probability that a reference point is correctly classified. It indicates how well the area represented by the map can be classified. It is shown on the right side of the matrix.

## User's Accuracy (Commission Error)

User's accuracy is the number of correct fields in an individual class divided by the number of pixels that were actually classified in that class. It is called user's accuracy because it is the probability that a field classified on the map actually represents that class on the ground. This measure is also called commission error and is reported at the bottom of the matrix.

## Precision

Precision is related to the random error, which can be quantified by a confidence interval. A confidence interval gives a range that encloses the true value of an unknown fixed quantity with a specified probability. A precise estimate would thus have a small confidence interval.

## Results

Accuracy was assessed based on both the DWR standard legend and Land IQ Legend. As the level of detail of these legends differed somewhat, the accuracy, or ability to correctly determine classifications, differs as well.

## Overall Accuracy

The overall accuracy for WY 2018 crop mapping statewide was $98.3 \%$ at the DWR legend level and $96.5 \%$ at the Land IQ legend level (Table 1).

## Table 1. WY 2018 Overall Accuracy of Statewide Land Use Mapping

| Crop Legend | Overall Accuracy |
| :--- | :--- |
| DWR | 98.3 |
| Land IQ | 96.5 |
|  |  |

The error matrices for crops classed by the DWR legend and the Land IQ legend (Tables 5 and 6 at the end of this report) show overall accuracy as well as omission and commission error, by crop class (in acres).

## Accuracy by Crop Class

Accuracy was calculated for each crop class (number of correct acres divided by total acres in each crop category) for both DWR and Land IQ legends (Tables 2 and 3). Some land cover types (e.g., apples, avocados, bush berries, carrots, cole crops, dates, kiwis) are not included in the accuracy assessment due to insufficient data. In these cases, there were either no or less than five samples available for accuracy assessment. It is notable that some crops are missed; it is challenging to detect every crop instance because satellite data are intermittent and cropping is rotational and, in some cases, short term. For this reason, available data will not always align well with rotational crop timing. However, most missed crops are short season in nature and therefore have a smaller impact on total water use analysis. In total, the new multi crop resolution of mapping data in WY 2018 captures a vast majority of the cropping yearround in the state, allowing data users to characterize crop production and water use more accurately.

Table 2. WY 2018 Statewide Land Use Mapping Accuracy by DWR Crop Legend

| Crop | Correct Acres | Total Acres | Accuracy |
| :--- | :---: | :---: | :---: |
| Young Perennials | 4,128 | 4,128 | $100.0 \%$ |
| Citrus and Subtropical | 16,074 | 16,000 | $99.5 \%$ |
| Rice | 26,210 | 26,210 | $100.0 \%$ |
| Vineyard | 29,479 | 29,320 | $99.5 \%$ |
| Unclassified | 37,380 | 35,873 | $96.0 \%$ |


| Crop | Correct Acres | Total Acres | Accuracy |
| :--- | :---: | :---: | :---: |
| Pasture | 39,141 | 38,115 | $97.4 \%$ |
| Grain and Hay | 39,757 | 37,201 | $93.6 \%$ |
| Field Crops | 58,440 | 57,185 | $97.9 \%$ |
| Truck, Nursery and Berry Crops | 63,011 | 62,335 | $98.9 \%$ |
| Deciduous Fruits and Nuts | 123,175 | 122,914 | $99.8 \%$ |

Table 3. WY 2018 Statewide Land Use Mapping Accuracy by Land IQ Crop Legend

| Crop | Correct Acres | Total Acres | Accuracy |
| :---: | :---: | :---: | :---: |
| Alfalfa and Alfalfa Mixtures | 26,843 | 27,851 | 96\% |
| Almonds | 74,409 | 74,441 | 100\% |
| Apples | 235 | 265 | 89\% |
| Avocados | 1,694 | 1,761 | 96\% |
| Beans (Dry) | 2,492 | 2,617 | 95\% |
| Bush Berries | 591 | 622 | 95\% |
| Carrots | 2,880 | 3,010 | 96\% |
| Cherries | 1,416 | 1,416 | 100\% |
| Citrus | 10,813 | 10,939 | 99\% |
| Cole Crops | 9,848 | 12,430 | 79\% |
| Corn, Sorghum and Sudan | 34,073 | 35,208 | 97\% |
| Cotton | 12,399 | 12,575 | 99\% |
| Dates | 333 | 333 | 100\% |
| Flowers, Nursery \& Christmas Tree Farms | 615 | 766 | 80\% |
| Grapes | 29,320 | 29,491 | 99\% |
| Kiwis | 183 | 183 | 100\% |
| Lettuce/Leafy Greens | 9,891 | 11,615 | 85\% |
| Melons, Squash and Cucumbers | 3,745 | 4,052 | 92\% |
| Miscellaneous Deciduous | 227 | 392 | 58\% |
| Miscellaneous Field Crops | 2,487 | 2,581 | 96\% |
| Miscellaneous Grain and Hay | 37,201 | 40,316 | 92\% |
| Miscellaneous Grasses | 2,885 | 4,296 | 67\% |
| Miscellaneous Subtropical Fruits | 16 | 33 | 48\% |
| Miscellaneous Truck Crops | 4,756 | 6,713 | 71\% |
| Mixed Pasture | 6,969 | 7,179 | 97\% |
| Olives | 2,885 | 2,886 | 100\% |
| Onions and Garlic | 5,549 | 5,846 | 95\% |
| Peaches/Nectarines | 2,523 | 2,572 | 98\% |
| Pears | 571 | 606 | 94\% |
| Peppers | 1,208 | 1,469 | 82\% |
| Pistachios | 16,243 | 16,243 | 100\% |
| Plums, Prunes and Apricots | 3,717 | 3,731 | 100\% |
| Pomegranates | 857 | 861 | 100\% |
| Potatoes or Sweet Potatoes | 2,624 | 2,716 | 97\% |


| Crop | Correct Acres | Total Acres | Accuracy |
| :--- | :---: | :---: | :---: |
| Rice | 26,210 | 26,210 | $100 \%$ |
| Safflower | 1,827 | 1,998 | $91 \%$ |
| Strawberries | 2,339 | 2,565 | $91 \%$ |
| Sunflowers | 3,622 | 3,635 | $100 \%$ |
| Tomatoes | 12,313 | 12,478 | $99 \%$ |
| Unclassified Fallow | 35,873 | 37,380 | $96 \%$ |
| Walnuts | 22,552 | 22,648 | $100 \%$ |
| Young Perennials | 4,128 | 4,128 | $100 \%$ |
|  |  |  |  |

## Precision by Crop

Two-tailed confidence intervals (95\%) were calculated using the method in Olofsson et al. (2014) for the commission error of each crop class and are shown in Table 4 in order of highest to lowest precision. As noted above, precision is related to the random error, which can be quantified by a confidence interval. A confidence interval gives a range that encompasses the true value of an unknown fixed quantity with a specified probability. A precise estimate would thus have a small confidence interval. For example, pears were mapped at $94 \%$ accuracy with a confidence interval of plus or minus $1 \%$. This means that $95 \%$ of the time, we are confident that the pear classification was between 93 and $95 \%$ correct.

As Table 4 shows, twelve crops were mapped with $100 \%$ accuracy and $0 \%$ confidence interval ( $100 \%$ confidence or precision): almonds, citrus, cotton, kiwi fruit, olives, pistachios, pomegranates, rice, young perennials, plums, prunes and apricots, sunflowers and walnuts. An additional seven crops were mapped at accuracies ranging from 97 to $99 \%$ with $100 \%$ confidence). Table 9 also shows that the number of ground truth points directly influences the level of precision. As the number of ground truth points increases, precision (confidence) generally also increases and the confidence interval becomes smaller. Some crops are mapped with high accuracy with few ground truth points (such as kiwi fruit) because they are very distinct and relatively easy to distinguish from other crops. Other crops have a lower accuracy but relatively high precision (miscellaneous truck crops) because the number of ground truth points was relatively high. Some crops, such as apples, were mapped with high accuracy but lower precision (e.g. apples, dates) because of very few ground truth points.

Table 4. WY 2018 Statewide Land Use Mapping Accuracy and Precision by Crop

| Crop Class | User's Accuracy (Number of correctly classified acres/total acres) | Number of Groundtruth (Reference Sample Acres) | 95\% Two-tailed Confidence Interval |
| :---: | :---: | :---: | :---: |
| Almonds | 100\% | 74,441 | 0\% |
| Cherries | 100\% | 10,940 | 0\% |
| Dates | 100\% | 12,575 | 0\% |
| Kiwis | 100\% | 183 | 0\% |
| Olives | 100\% | 2,886 | 0\% |
| Pistachios | 100\% | 16,243 | 0\% |
| Rice | 100\% | 862 | 0\% |
| Young Perennials | 100\% | 26,210 | 0\% |
| Plums, Prunes and Apricots | 100\% | 22,648 | 0\% |
| Sunflowers | 100\% | 29,491 | 0\% |
| Walnuts | 100\% | 40,315 | 0\% |
| Pomegranates | 100\% | 2,572 | 0\% |
| Grapes | 99\% | 3,635 | 0\% |
| Citrus | 99\% | 3,010 | 0\% |
| Tomatoes | 99\% | 35,209 | 0\% |
| Cotton | 99\% | 3,730 | 0\% |
| Peaches/Nectarines | 98\% | 12,478 | 0\% |
| Mixed Pasture | 97\% | 27,851 | 0\% |
| Corn, Sorghum and Sudan | 97\% | 37,381 | 0\% |
| Potatoes or Sweet Potatoes | 97\% | 1,416 | 1\% |
| Alfalfa and Alfalfa Mixtures | 96\% | 393 | 1\% |
| Miscellaneous Field Crops | 96\% | 1,760 | 1\% |
| Avocados | 96\% | 2,565 | 1\% |
| Unclassified Fallow | 96\% | 4,052 | 1\% |
| Carrots | 96\% | 606 | 1\% |
| Beans (Dry) | 95\% | 2,580 | 1\% |
| Bush Berries | 95\% | 5,847 | 1\% |
| Onions and Garlic | 95\% | 2,716 | 1\% |
| Pears | 94\% | 4,128 | 1\% |
| Melons, Squash and Cucumbers | 92\% | 1,998 | 1\% |
| Miscellaneous Grain and Hay | 92\% | 2,617 | 1\% |
| Safflower | 91\% | 12,429 | 1\% |
| Strawberries | 91\% | 7,179 | 1\% |
| Apples | 89\% | 11,615 | 1\% |
| Lettuce/Leafy Greens | 85\% | 4,297 | 1\% |
| Peppers | 82\% | 6,713 | 1\% |
| Flowers, Nursery and Christmas Tree Farms | 80\% | 265 | 2\% |
| Cole Crops | 79\% | 766 | 2\% |
| Miscellaneous Truck Crops | 71\% | 622 | 2\% |
| Miscellaneous Grasses | 67\% | 1,469 | 2\% |
| Miscellaneous Deciduous | 58\% | 333 | 3\% |
| Miscellaneous Subtropical Fruits | 48\% | 32 | 11\% |

## Table 5. Statewide Land Use Mapping Error Matrix by DWR Crop Legend (acres)



Table 6. Statewide Land Use Mapping Error Matrix by Land IQ Crop Legend (acres)


