Abstract

We present a new dataset, Functional Map of the World (fMoW), which aims to inspire the development of machine learning models capable of predicting the functional purpose of buildings and land use from temporal sequences of satellite images and a rich set of metadata features. The metadata provided with each image enables reasoning about location, time, sun angles, physical sizes, and other features when making predictions about objects in the image. Our dataset consists of over 1 million images from over 200 countries. For each image, we provide at least one bounding box annotation containing one of 63 categories, including a “false detection” category. We present an analysis of the dataset along with baseline approaches that reason about metadata and temporal views. Our data, code, and pretrained models have been made publicly available.

1. Introduction

Satellite imagery presents interesting opportunities for the development of object classification methods. Most computer vision (CV) datasets for this task focus on images or videos that capture brief moments [22, 18]. With satellite imagery, temporal views of objects are available over long periods of time. In addition, metadata is also available to enable reasoning beyond visual information. For example, by combining temporal image sequences with timestamps, models may learn to differentiate office buildings from multi-unit residential buildings by observing whether or not their parking lots are full during business hours. Models may also be able to combine certain metadata parameters with observations of shadows to estimate object heights. In addition to these possibilities, robust models must be able to generalize to unseen areas around the world that may include different building materials and unique architectural styles.

Enabling the aforementioned types of reasoning requires a large dataset of annotated and geographically diverse satellite images. In this work, we present our efforts to collect such a dataset, entitled Functional Map of the World (fMoW). fMoW has several notable features, including a variable number of temporal images per scene and an associated metadata file for each image. The task posed for our dataset falls in between object detection and classification. That is, for each temporal sequence of images, at least one bounding box is provided that maps to one of 63 categories, including a “false detection” (FD) category that represents content not characterized by the other 62 categories. These boxes are intended to be used as input to a classification algorithm. Figure 1 shows an example.

Collecting a dataset such as fMoW presents some interesting challenges. For example, one consideration would be to directly use crowdsourced annotations provided by OpenStreetMap (OSM). However, issues doing so include...
inconsistent, incorrect, and missing annotations for a large percentage of buildings and land use across the world. Moreover, OSM may only provide a single label for the current contents of an area, making it difficult to correctly annotate temporal views. Another possibility is to use the crowd to create annotations from scratch. However, annotating instances of a category with no prior information is extremely difficult in a large globally-diverse satellite dataset. This is due in part to the unique perspective that satellite imagery offers when compared with ground-based datasets, such as ImageNet [22]. Humans are seldom exposed to aerial viewpoints in their daily lives and, as such, objects found in satellite images tend to be visually unfamiliar and difficult to identify. Buildings can also be repurposed throughout their lifetime, making visual identification even more difficult. For these reasons, we use a multi-phase process that combines map data and crowdsourcing.

Another problem for fMoW is that full annotation is made very difficult by the increased object density for certain categories. For example, single-unit residential buildings often occur in dense clusters alongside other categories, where accurately discriminating and labeling every building would be very time-consuming. To address this shortcoming, we propose providing bounding boxes as part of algorithm input as opposed to requiring bounding box output, which would be more akin to a typical detection dataset. This avoids full image annotation issues that stem from incomplete map data and visual unfamiliarity. Imagery does not have to be fully annotated, as algorithms are only asked to classify regions with known contents. This allows us to focus collection on areas with more accurate map data and limit annotations to a small number of category instances per image.

Our contributions are summarized as follows: (1) To the best of our knowledge, we provide the largest publicly available satellite dataset containing bounding box annotations, metadata and revisits. This enables joint reasoning about images and metadata, as well as long-term temporal reasoning for areas of interest. (2) We present methods based on CNNs that exploit the novel aspects of our dataset, with performance evaluation and comparisons, which can be applied to similar problems in other application domains. Our code, data, and pretrained models have all been publicly released[11]. In the following sections, we provide an analysis of fMoW and baseline methods for the task.

2. Related Work

While large datasets are nothing new to the vision community, they have typically focused on first-person or ground-level imagery [22][18][6][9][17]. This is likely due in part to the ease with which this imagery can be collected and annotated. Recently, there have been several, mostly successful, attempts to leverage techniques that were founded on first-person imagery and apply them to remote sensing data [13][19][28]. However, these efforts highlight the research gap that has developed due to the lack of a large dataset to appropriately characterize the problems found in remote sensing. fMoW offers an opportunity to close this gap by providing, to the best of our knowledge, the largest quantity of labeled satellite images that has been publicly released to date, while also offering several features that could help unify otherwise disparate areas of research around the multifaceted problem of processing satellite imagery. We now highlight several of these areas where we believe fMoW can make an impact.

Reasoning Beyond Visual Information Many works have extended CV research to simultaneously reason about other modules of perception, such as joint reasoning about language and vision [2][14][21], audio and vision [10], 2D and 3D information [3], and many others. In this work, we are interested in supporting joint reasoning about temporal sequences of images and associated metadata features. One of these features is UTM zone, which provides location context. In a similar manner, [24] shows improved image classification results by jointly reasoning about GPS coordinates and images, where several features are extracted from the coordinates, including high-level statistics about the population. Although we use coarser location features (UTM zones) than GPS in this work, we do note that using similar features would be an interesting study.

Multi-view Classification Satellite imagery offers a unique and somewhat alien perspective on the world. Most structures are designed for recognition from ground level. For example, buildings often have identifying signs above entrances that are not visible from overhead. As such, it can be difficult, if not impossible, to identify the functional purpose of a building from a single overhead image.

One of the ways in which FMoW attempts to address this issue is by providing multiple temporal views of each object, when available. Along these lines, several works in the area of video processing have been able to build upon advancements in single image classification [15][6][30] to create networks capable of extracting spatio-temporal features. These works may be a good starting point, but it is important to keep in mind the vastly different temporal resolution on which these datasets operate. For example, the YouTube-8M dataset [1], on which many of these video processing algorithms were developed, contains videos with 30 frames per second temporal resolution that each span on the order of minutes. Satellites, on the other hand, typically cannot capture imagery with such dense temporal resolution. Revisit times vary, but it is not uncommon for satellites to require multiple days before they can image the same location; it is possible for months to go by before they can get

[https://github.com/FMoW](https://github.com/FMoW)
an unobstructed view. As such, temporal views in fMoW span multiple years as opposed to minutes. Techniques that attempt to capture features across disjoint periods of time, such as [20], are likely better candidates for the task.

Perhaps the most similar work to ours in terms of temporal classification is PlaNet [26]. They pose the image localization task as a classification problem, where photos are classified as belonging to a particular bucket that bounds a specific area on the globe. They extend their approach to classify the buckets of images in photo albums taken in the same area. A similar approach is used in one of our baseline datasets similar to fMoW is TorontoCity [25]. They provide a large dataset that includes imagery and LiDAR data collected by airplanes, low-altitude unmanned aerial vehicles, and cars in the greater Toronto area. While they present several tasks, the two that are related to land-use classification are zoning classification and area. While they present several tasks, the two that are related to land-use classification are zoning classification and segmentation (e.g., residential, commercial). Aerial images included in TorontoCity were captured during four different years and include several seasons. While this is an impressive dataset, we believe fMoW is more focused on satellite imagery and offers advantages in geographic diversity.

Satellite Datasets One of the earliest annotated satellite datasets similar to fMoW is the UC Merced Land Use Dataset, which offers 21 categories and 100 images per category with roughly 30cm resolution and image sizes of 256x256 [29]. While some categories from this dataset overlap with fMoW, we believe fMoW offers several advantages in that we have three times the number of categories, localized objects within the images, and multiple orders of magnitude more images per category. We also provide metadata, temporal views, and multispectral images.

SpaceNet [5], a recent dataset that has received substantial attention, contains both 30cm and 50cm data of 5 cities. For the most part, the data in SpaceNet currently includes building footprints. However, earlier this year, point of interest (POI) data was also released into SpaceNet. This POI data includes the locations of several categories within the images, and multiple orders of magnitude more images per category. We also provide metadata, temporal views, and multispectral images.

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More broadly, fMoW was created using a three-phase workflow consisting of location selection, image selection, and bounding box creation. The location selection phase was used to identify potential locations that map to our categories while also ensuring geographic diversity. Potential locations were drawn from several Volunteered Geographic Information (VGI) datasets, which were conflated and curated to remove duplicates. To ensure diversity, we removed neighboring locations within a specified distance (typically 500m) and set location frequency caps for categories that have severely skewed geographic distributions. These two factors helped reduce spatial density while also encouraging

**Dataset Collection**

Prior to the dataset collection process for fMoW, a set of categories had to be identified. Based on our target of 1 million images, collection resources, plan to collect temporal views, and discussions with researchers in the CV community, we set a goal of including between 50 and 100 categories. We searched sources such as the OSM Map Feature [4] list and NATO Geospatial Feature Concept Dictionary [4] for categories that highlight some of the challenges discussed in Section 2. For example, “construction site” and “impoverished settlement” are categories from our dataset that may require temporal reasoning to identify, which presents a unique challenge due to temporal satellite image sequences typically being scattered across large time periods. We also focused on grouping categories according to their functional purpose, which should encourage the development of approaches that reason about contextual information, both visually and in the associated metadata.

Beyond research-based rationales for picking certain categories, we had some practical ones as well. Before categories could be annotated within images, we needed to find locations where we have high confidence of their existence. This is where maps play a crucial role. “Flooded road”, “debris or rubble”, and “construction site” were the most difficult categories to collect because open source data does not generally contain temporal information. However, with more careful search procedures, reuse of data from humanitarian response campaigns, and calculated extension of keywords to identify categories even when not directly labeled, we were able to collect temporal stacks of imagery that contained valid examples.

All imagery used in fMoW was collected from the DigitalGlobe constellation images were gathered in pairs, consisting of 4-band or 8-band multispectral imagery in the visible to near-infrared region, as well as a pan-sharpened RGB image that represents a fusion of the high-resolution panchromatic image and the RGB bands from the lower-resolution multispectral image. 4-band imagery was obtained from either the QuickBird-2 or GeoEye-1 satellite systems, whereas 8-band imagery was obtained from WorldView-2 or WorldView-3.

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the selection of locations from disparate geographic areas. The remaining locations were then processed using DigitalGlobe’s GeoHIVE crowdsourcing platform. Members of the GeoHIVE crowd were asked to validate the presence of categories in satellite images, as shown in Figure 2.

Figure 2: Sample image of what a GeoHIVE user might see while validating potential fMoW dataset features. Instructions can be seen in the top-left corner that inform users to press the ‘1’, ‘2’, or ‘3’ keys to validate existence, non-existence, or cloud obscuration of a particular object.

The image selection phase comprised of a three-step process, which included searching the DigitalGlobe satellite imagery archive, creating image chips, and filtering out cloudy images. Approximately 30% of the candidate images were removed for being too cloudy. DigitalGlobe’s IPE Data Architecture Highly-available Object-store (IDAHO) service was used to process imagery into pan-sharpened RGB and multispectral image chips in a scalable fashion. These chips were then passed through a CNN architecture to classify and remove any undesirable cloud-covered images.

Finally, images that passed through the previous two phases were sent to a curated and trusted crowd for bounding box annotation. This process involved a separate interface from the first phase, one that asked crowd users to draw bounding boxes around the category of interest in each image and provided some category-specific guidance for doing so. The resulting bounding boxes were then graded by second trusted crowd to assess quality. In total, 642 unique GeoHIVE users required a combined total of approximately 2,800 hours to annotate category instances for fMoW.

4. Dataset Analysis

Here we provide some statistics and analysis of fMoW. Two versions of the dataset are publicly available:

- **fMoW-full** The full version of the dataset includes pan-sharpened RGB images and 4/8-band multispectral images (MSI), which are both stored in TIFF format. Pan-sharpened images are created by “sharpening” lower-resolution MSI using higher-resolution panchromatic imagery. All pan-sharpened images in fMoW-full have corresponding MSI, where the metadata files for these images are nearly identical.
- **fMoW-rgb** An alternative JPEG compressed version of the dataset, which is provided since fMoW-full is very large. For each pan-sharpened RGB image we simply perform a conversion to JPEG. For MSI images, we extract the RGB channels and save them as JPEGs.

For all experiments presented in this paper, we use fMoW-rgb. We also exclude RGB-extracted versions of the MSI in fMoW-rgb as they are effectively downsampled versions of the pan-sharpened RGB images.

4.1. fMoW Splits

We have made the following splits to the dataset:

- **seq** This is the sequestered portion of the dataset that is not currently publicly available. It will be released after it is used for final testing in the public challenge centered around the dataset.
- **train** Contains 65.2% and 72.13% of the total bounding boxes with and without seq included, respectively.
- **val** Contains 11.4% and 12.6% of the total bounding boxes with and without seq included, respectively. This set was made representative of test, so that validation can be performed.
- **test** Contains 13.8% and 15.3% of the total bounding boxes with and without seq included, respectively.
The total number of bounding box instances for each category can be seen in Figure 5.

4.2. fMoW Statistics

Variable length sequences of images are provided for each scene in the dataset. Figure 4 shows what percentage of the sequences in the dataset belong to each sequence length. 21.2% of the sequences contain only 1 view. Most (95%) of the sequences contain 10 or less images.

A major focus of the collection effort was global diversity. In the metadata, we provide UTM zones, which typically refer to 6° longitude bands (1-60). We also concatenate letters that represent latitude bands (total of 20) to the UTM zones in the metadata. Figure 5 illustrates the frequency of sequences within the UTM zones on earth, where the filled rectangles each represent a different UTM zone. Green colors represent areas with higher numbers of sequences, while blue regions have lower counts. As seen, fMoW covers much of the globe. The images captured for fMoW also have a wide range of dates, which allows algorithms to analyze areas on earth over long periods of time in some cases. Figure 6 shows a distribution for years and local times (converted from UTC) in which the images were captured. The average time difference between the earliest and most recent images in each sequence is approximately 3.8 years.

5. Baselines and Methods

Here we present 5 different approaches to our task, which vary by their use of metadata and temporal reasoning. All experiments were performed using fMoW-rgb. Two of the methods presented involve fusing metadata into a CNN architecture. The following provides a summary of the metadata features that are used, as well as any preprocessing operations that are applied:

- **UTM Zone** One of 60 UTM zones and one of 20 latitude bands are combined for this feature. We convert these values to 2 coordinate values, each between 0 and 1. This is done by taking the indices of the values within the list of possible values and then normalizing.
- **Timestamp** The year, month, day, hour, minute, second, and day of the week are extracted from the timestamp and added as separate features. The timestamp provided in the metadata files is in Coordinated Universal Time (UTC).
Figure 5: This shows the geographic diversity of fMoW. Data was collected from over 400 unique UTM zones (including latitude bands). This helps illustrate the number of images captured in each UTM zone, where more green colors show UTM zones with a higher number of instances, and more blue colors show UTM zones with lower counts.

Figure 6: Distribution over (a) years the images were captured, and (b) time of day the images were captured (UTC converted to local time for this figure).

- **GSD**  Ground sample distance, measured in meters, is provided for both the panchromatic and multispectral bands in the image strip. The panchromatic images used to generate the pan-sharpened RGB images have higher resolution than the MSI, and therefore have smaller GSD values. These GSD values, which are used directly without any preprocessing.

- **Angles**  These identify the angle at which the sensor is imaging the ground, as well as the angular location of the sun with respect to the ground and image. These features can be added without preprocessing. The following angles are provided:
  - **Off-nadir Angle**  Angle in degrees (0-90°) between the point on the ground directly below the sensor and the center of the image swath.
  - **Target Azimuth**  Angle in degrees (0-360°) of clockwise rotation off north to the image swath’s major axis.
  - **Sun Azimuth**  Angle in degrees (0-360°) of clockwise rotation off north to the sun.
  - **Sun Elevation**  Angle in degrees (0-90°) of elevation, measured from the horizontal, to the sun.

- **Image+box sizes**  The pixel dimensions of the bounding boxes and image size, as well as the fraction of the image width and height that the boxes occupy are added as features.

After preprocessing the metadata features, we perform mean subtraction and normalization using values calculated for train + val. A full list of metadata features and their descriptions can be found in the appendix.

It is worth noting here that the imagery in fMoW is not registered, and while many sequences have strong spatial correspondence, individual pixel coordinates in different images do not necessarily represent the same positions on the ground. As such, we are prevented from easily using methods that exploit registered sequences.

The CNN used as the base model in our various baseline methods is DenseNet-161 [12], with 48 feature maps (k=48). During initial testing, we found this model to outperform other models such as VGG-16 [23] and ResNet-50 [11]. We initialize our base CNN models using the pre-trained ImageNet weights, which we found to improve performance during initial tests. Training is performed using a crop size of 224x224, the Adam optimizer [16], and an initial learning rate of 1e-4. Due to class imbalance in our dataset, we attempted to weight the loss using class frequencies, but did not observe any improvement.

To merge metadata features into the model, the softmax layer of DenseNet is removed and replaced with a concatenation layer to merge DenseNet features with preprocessed metadata features, followed by two 4096-d fully-connected layers with 50% dropout layers, and a softmax layer with 63 outputs (62 main categories + FD). An illustration of this base model is shown in Figure 7.

![Figure 7: An illustration of our base model used to fuse metadata features into the CNN. This model is used as a baseline and also as a feature extractor (without softmax) for providing features to an LSTM. Dropout layers are added after the 4096-d FC layers.](image-url)
We test the following approaches with fMoW:

- **LSTM-M** An LSTM architecture trained using temporal sequences of metadata features. We believe training solely on metadata helps understand how important images are in making predictions, while also providing some measure of bias present in fMoW.

- **CNN-I** A standard CNN approach using only images, where DenseNet is fine-tuned after ImageNet. Softmax outputs are summed over each temporal view, after which an argmax is used to make the final prediction. The CNN is trained on all images across all temporal sequences of train + val.

- **CNN-IM** A similar approach to CNN-I, but with metadata features concatenated to the features of DenseNet before the fully connected layers.

- **LSTM-I** An LSTM architecture trained using features extracted from CNN-I.

- **LSTM-IM** An LSTM architecture trained using features extracted from CNN-IM.

All of these methods are trained on train + val. Since tight bounding boxes are typically provided for category instances in the dataset, we add a context buffer around each tight bounding boxes are typically provided for category in-

result is much harder to visually show why the methods succeed

All of these methods are trained on train + val. Since tight bounding boxes are typically provided for category instances in the dataset, we add a context buffer around each tight bounding box before extracting the region of interest from the image. We found that it was useful to provide more context for categories with smaller sizes (e.g., single-unit residential) and less context for categories that generally cover larger areas (e.g., airports).

Per-category F1 scores for test are shown in Table 1. From the results, it can be observed that, in general, the LSTM architectures show similar performance to our approaches that sum the probabilities over each view. Some possible contributors to this are the large quantity of single-view images provided in the dataset, and that temporal changes may not be particularly important for several of the categories. CNN-I and CNN-IM are also, to some extent, already reasoning about temporal information while making predictions by summing the softmax outputs over each temporal view. Qualitative results that show success and failure cases for LSTM-I are shown in Figure 8. Qualitative results are not shown for the approaches that use metadata, as it is much harder to visually show why the methods succeed in most cases.

It could be argued that the results for approaches using metadata are only making improvements because of bias exploitation. To show that metadata helps beyond inherent bias, we removed all instances from the test set where the metadata-only baseline (LSTM-M) is able to correctly predict the category. The results of this removal, which can be found in Table 2, show that metadata can still be useful for improving performance.

To further confirm the importance of temporal reasoning, we compare the methods presented above with two additional methods, CNN-I-1 and CNN-IM-1, which make

![Table 1: F1 scores for different approaches on test. Color formatting was applied to each column independently. The average values shown at the bottom of the table are calculated without FD scores.](image-url)

predictions for each individual view. We then have all other methods repeat their prediction over the full sequence. This is done to show that, on average, seeing an area multiple times outperforms single-view predictions. We note that these tests are clearly not fair for some categories, such as
Figure 8: Qualitative examples from test of the image-only approaches. The images presented here show the extracted and resized images that are passed to the CNN approaches. The top two rows show success cases for LSTM-I, where CNN-I was not able to correctly predict the category. The bottom two rows show failure cases for LSTM-I, where CNN-I was able to correctly predict the category. We also note that sequences with $\geq 9$ views were chosen. The second row was trimmed to keep the figure consistent. However, we note that variable temporal views are provided for throughout the dataset.

"construction site", where some views may not even contain the category. However, we perform these tests for completeness to confirm our expectations. Results are shown in Table 2. Per-category results can be found in the appendix.

### Table 2: Results on test instances where the metadata-only baseline (LSTM-M) is not able to correctly predict the category. These are the average F1 scores not including FD. These results show that metadata is important beyond exploiting bias in the dataset.

| LSTM-M | CNN-I | LSTM-I | CNN-IM | LSTM-IM |
|--------|-------|--------|--------|---------|
| 0      | 0.685 | 0.693  | 0.695  | 0.702   |

Table 3: Average F1 scores, not including FD, for individual images from test. CNN-I-1 and CNN-IM-1 make predictions for each individual view. All other methods repeat their prediction over the full sequence.

| CNN-I-1 | CNN-I | LSTM-I | CNN-IM-1 | CNN-IM | LSTM-IM |
|---------|-------|--------|----------|--------|---------|
| 0.618   | 0.678 | 0.684  | 0.666    | 0.722  | 0.735   |

6. Conclusion and Discussion

We present fMoW, a dataset that consists of over 1 million image and metadata pairs, of which many are temporal views of the same scene. This enables reasoning beyond visual information, as models are able to leverage temporal information and reason about the rich set of metadata features (e.g., timestamp, UTM zone) provided for each image. By posing a task in between detection and classification, we avoid the inherent challenges associated with collecting a large, geographically diverse, detection dataset, while still allowing for models to be trained that are transferable to real-world detection systems. Different methods were presented for this task that demonstrate the importance of reasoning about metadata and temporal information. All code, data, and pretrained models have been made publicly available. We hope that by releasing the dataset and code, other researchers in the CV community will find new and interesting ways to further utilize the metadata and temporal changes to a scene. We also hope to see fMoW being used to train models that are able to assist in humanitarian efforts, such as applications involving disaster relief.
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Appendix Overview

In this document, we provide:
- Appendix I Descriptions of the metadata features and distributions for country codes and UTM zones.
- Appendix II Additional collection details.
- Appendix III Additional results.
- Appendix IV Examples from our dataset.

Appendix I. Metadata Features and Statistics

1. **ISO Country Code** ISO Alpha-3 country code (String). There are a total of 247 possible country codes, 207 of which are present in fMoW.
2. **UTM Zone** Universal Transverse Mercator. There are 60 UTM zones, which are 6° in width. We provide a number for the UTM zone (1-60), along with a letter representing the latitude band. There are a total of 20 latitude bands, which range from “C” to “X” (“I” and “O” are not included).
3. **Timestamp** UTC timestamp. Datetime format (Python): “%Y-%m-%dT%H:%M:%S” (String).
4. **Cloud Cover** Fraction of the image strip, not image chip, that is completely obscured by clouds on a scale of 0-100 (Integer).
5. **Scan Direction** The direction the sensor is pointed when collecting an image strip. Either “Forward”, when the image is collected ahead of the orbital path or “Reverse” when the image is taken behind the orbital path (String).
6. **Pan Resolution** Ground sample distance of panchromatic band (pan-GSD) in the image strip, measured in meters (Double). start, end, min, and max values are also included. start and end represent the pan-GSD for the first and last scan lines, respectively. min and max represent the minimum and maximum pan-GSD for all scan lines, respectively.
7. **Multi Resolution** Ground sample distance of multispectral bands (multi-GSD) in the image strip, measured in meters (Double). start, end, min, and max values are also included. start and end represent the multi-GSD for the first and last scan lines, respectively. min and max represent the minimum and maximum multi-GSD for all scan lines, respectively.
8. **Target Azimuth** Azimuth angle of the sensor with respect to the center of the image strip, measured in degrees (Double). start, end, min, and max values are also included. start and end represent the target azimuth for the first and last scan lines, respectively. min and max represent the minimum and maximum target azimuth for all scan lines, respectively.
9. **Sun Azimuth** Azimuth angle of the sun measured from north, clockwise in degrees, to the center of the image strip, measured in degrees (Double). min and max values are also included. min and max represent the minimum and maximum sun azimuth for all scan lines, respectively.
10. **Sun Elevation** Elevation angle of the sun measured from the horizontal, measured in degrees (Double). min and max values are also included. min and max represent the minimum and maximum sun elevation for all scan lines, respectively.
11. **Off-Nadir Angle** The off-nadir angle of the satellite with respect to the center of the image strip, measured in degrees (Double). start, end, min, and max values are also included. start and end represent the off-nadir angle for the first and last scan lines, respectively. min and max represent the minimum and maximum off-nadir angle for all scan lines, respectively.

Country Codes Here we show the counts for each unique country code in fMoW. Counts are incremented once for each sequence instead of once per metadata file.

[“USA”, 18750], [“FRA”, 7470], [“ITA”, 6985], [“RUS”, 6913], [“CHN”, 6597], [“DEU”, 4686], [“GBR”, 4496], [“BRA”, 3820], [“CAN”, 3128], [“TUR”, 2837], [“JPN”, 2542], [“IDN”, 2448], [“ESP”, 2402], [“AUS”, 2105], [“DZA”, 1849], [“IND”, 1804], [“UKR”, 1735], [“CZE”, 1713], [“POL”, 1386], [“MEX”, 1274], [“ARG”, 1248], [“DZA”, 1224], [“BEL”, 1190], [“PHL”, 1179], [“IRQ”, 1129], [“EGY”, 1041], [“ZAF”, 924], [“CHL”, 888], [“LTU”, 871], [“LBY”, 863], [“KOR”, 809], [“CHE”, 788], [“LVA”, 772], [“PRT”, 722], [“YEM”, 9]
UTM Zones

Here we show the counts for each unique UTM zone in fMoW. Counts are incremented once for each sequence instead of once per metadata file.

(31U, 5802), (32T, 4524), (33T, 4403), (30U, 4186), (32U, 3864), (33U, 3315), (31T, 3150), (18T, 2672), (17T, 2339), (34U, 2049), (37S, 1718), (30T, 1686), (37U, 1672), (23K, 1627), (18S, 1481), (11S, 1388), (16T, 1283), (54S, 1244), (38S, 1229), (31S, 1227), (35U, 1137), (35V, 1116), (52S, 1115), (165, 1110), (51P, 1086), (51R, 1069), (36S, 1046), (35T, 1038), (36R, 1037), (49M, 1026), (48M, 1021), (10T, 1010), (53S, 1001), (10S, 955), (14R, 935), (19T, 928), (30S, 912), (17S, 875), (17R, 874), (43P, 854), (50S, 796), (36U, 767), (50R, 751), (33S, 751), (32S, 746), (14S, 730), (34T, 728), (12S, 716), (37M, 705), (135, 676), (37T, 667), (36T, 653), (155, 629), (55H, 618), (34S, 604), (29S, 600), (38P, 598), (15T, 586), (22J, 585), (18Q, 549), (15R, 539), (35S, 511), (10U, 497), (21H, 492), (36V, 491), (19F, 482), (48R, 476), (49S, 459), (48S, 446), (49Q, 444), (29T, 438), (16P, 429), (56H, 425), (14Q, 422), (40R, 420), (39R, 413), (39U, 406), (18N, 385), (35I, 383), (37V, 380), (50T, 379), (56I, 355), (34V, 351), (43V, 347), (29U, 346), (38U, 345), (17M, 328), (38T, 323), (19P, 323), (51S, 317), (54H, 311), (49R, 295), (34H, 293), (22K, 293), (48N, 276), (20H, 273), (50Q, 268), (28P, 262), (18L, 260), (24M, 258), (24L, 256), (21J, 255), (41V, 254), (13T, 254), (47N, 253), (40U, 253), (45R, 251), (43Q, 245), (51Q, 243), (51T, 240), (39S, 239), (19K, 238), (19Q, 237), (59G, 236), (43R, 234), (12T, 230), (49T, 227), (41U, 223), (32V, 219), (30V, 212), (13Q, 212), (40V, 210), (16R, 210), (20T, 210), (38R, 204), (36F, 203), (46T, 200), (45T, 197), (44U, 196), (15Q, 190), (50L, 190), (32P, 184), (60H, 182), (47P, 182), (20P, 181), (24K, 178), (17Q, 178), (35K, 169), (20J, 168), (11U, 165), (18H, 164), (52T, 163), (11T, 161), (36N, 158), (39V, 157), (20K, 157), (39Q, 155), (12U, 149), (38V, 147), (18P, 147), (23L, 147), (18G, 146), (31N, 146), (19F, 142), (33P, 141), (40Q, 136), (13R, 136), (47T, 132), (47R, 126), (48U, 124), (32R, 123), (15P, 121), (39P, 117), (48P, 117), (33R, 116), (45U, 113), (43S, 111), (44N, 109), (54T, 109), (32N, 109), (36W, 108), (17P, 108), (36P, 105), (31R, 104), (56K, 101), (20Q, 101), (39T, 97), (16Q, 96), (29R, 95), (25L, 92), (45Q, 91), (46Q, 91), (48T, 90), (44Q, 89), (42V, 87), (29N, 87), (43U, 86), (4Q, 86), (47Q, 85), (48Q, 84), (30N, 83), (19G, 82), (25M, 81), (42Q, 80), (44P, 80), (20L, 77), (501, 77), (53U, 76), (38N, 75), (27W, 75), (44R, 75), (33V, 74), (34R, 72), (49L, 70), (36M, 69), (40S, 69), (12R, 68), (37P, 68), (52R, 65), (14T, 64), (50U, 62), (35H, 62), (50H, 61), (28R, 60), (54U, 59), (46V, 58), (44T, 56), (21K, 56), (55G, 56), (22L, 56), (35P, 55), (31P, 54), (29P, 54), (35R, 52), (50R, 51), (19U, 50), (53T, 49), (46U, 49), (50N, 48), (47S, 48), (42R, 48), (37Q, 47), (19L, 47), (14U, 47), (28Q, 46), (37N, 45), (19F, 45), (42U, 44), (36K, 42), (37R, 40), (37W, 40), (108, 40),...
Appendix II. Dataset Collection

The location selection phase was used to identify potential locations that map to our categories while also ensuring geographic diversity. Potential locations were drawn from several Volunteered Geographic Information (VGI) datasets, which were conflated and curated to remove duplicates and ensure geographic diversity. The remaining locations were then processed using DigitalGlobe’s GeoHIVE crowdsourcing platform. Members of the GeoHIVE crowd were asked to validate the presence of categories in satellite images, as shown in Figure 9. The interface uses center-point location information to draw a circle around a possible object of interest. The interface then asks users to rapidly verify the existence of a particular label, as extracted from the VGI datasets, using the ‘1’, ‘2’, and ‘3’ keys to represent existence, non-existence, and cloud cover.

For validation of object localization, a different interface is used that asks users to draw a bounding box around the object of interest after being given an initial seed point. The visualization for this is shown in Figure 10 and the seed point can be seen as a green dot located on the object of interest. Users are additionally provided some instructions regarding how large of a box to draw, which may vary by object class. This interface is more complex than the location selection interface, which is why it is performed after object existence can be confirmed and non-cloudy high-quality imagery is obtained. A smaller and more experienced group of users is also used for this task to help ensure the quality of the annotations.

Appendix III. Additional Results

Introduced in the main paper, CNN-I-1 and CNN-IM-1 make predictions for each individual view. All other methods repeat their prediction over the full sequence. Again, we note that these tests are clearly not fair to some categories, such as “construction site”, where some views may not even contain the category. However, we show results for these tests for completeness. Only the average values, which do not include “false detection” results, are shown in the main paper. We show per-category results in Table 4.

Appendix IV. Dataset Examples

Figure 11 shows one example for each category in our dataset. For viewing purposes, regions within the full image chip were extracted using the scaled bounding box coordinates for the categories. For the baseline approaches
Draw a rectangle around the Bus Station located in the center of this image.

Using your mouse, click and drag a rectangle around the “Bus Station” with your mouse.

Please do the following:

- Drag a box around the “Bus Station” closer to the road green circle.
- Select one of the boxes in the categories shown below, and then box again, this the empty of the Bus Station.
- Draw a box around the name on the green circle, and then box again, this is the name of the Bus Station.
- Draw the box around the name of the Bus Station.
- For the box around the name on the green circle, then box around the name of the Bus Station.
- For the empty of the Bus Station.
- For the empty of the Bus Station.

(a) ground transportation station

Figure 10: Sample images of the interface used to more precisely localize objects within an image. In each example, a green dot is placed near the center of the pertinent object. Users are able to draw a bounding box by clicking and dragging. Instructions at the top of each example inform the user how to use the interface and also provide any category-specific instructions that may be relevant. Comments regarding issues such as clouds or object misclassification can be entered near the bottom of the page before submitting an annotation.

(b) helipad

Table 4: F1 scores for different approaches on an individual image basis. Color formatting was applied to each column independently. The average values shown at the bottom of the table are calculated without the false detection scores. CNN-I-1 and CNN-IM-1 make predictions for each individual view. All other methods repeat their prediction over the full sequence.

to keep in mind that the images for each category in the full dataset vary in quality, have different weather conditions (e.g., snow cover), contain drastically different context (e.g., desert vs. urban), have different levels of difficulty for recognition, and other variations.
Figure 11: One example per category in fMoW.
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