There is a growing need for three-dimensional (3D) representations of urban models. Three-dimensional (3D) urban models have gained interest because of their applications in many use-cases such as urban planning and virtual reality. However, generating these 3D representations requires LiDAR data, which are not always readily available. Thus, the applicability of automated 3D model generation algorithms is limited to a few locations. In this paper, we propose sat2pc, a deep learning architecture that predicts the point cloud of a building roof from a single 2D satellite image. Our architecture combines Chamfer distance and EMD loss, resulting in better 2D to 3D performance. We extensively evaluate our model and perform ablation studies on a building roof dataset. Our results show that sat2pc was able to outperform existing baselines by at least 18.6%. Further, we show that the predicted point cloud captures more detail and geometric characteristics than other baselines.

1 INTRODUCTION

There is a growing need for three-dimensional (3D) representations of urban models, which play an important role in many useful applications such as urban monitoring, utility services, transportation and virtual reality. Much of the current research to date primarily relies on aerial-based lidar point cloud data to extract accurate and fine-grained 3D representations of urban models. As such, there has been considerable effort towards accelerating the collection of lidar point cloud data, commonly used to develop 3D representations of urban models. Such efforts have been particularly focused on developing and improving data-driven models for reconstructing point clouds using satellite imagery, high-resolution lidar data is also available for download using the 3D Elevation program. Consequently, we can develop data-driven models for reconstructing point clouds using satellite images, and thus, such an approach can benefit from the decades of research on fusing point clouds with imagery to develop urban models.

Unfortunately, point cloud data from lidar sensors are inherently noisy, irregular, and non-uniform. Occlusions from nearby trees and objects may distort the measurements. Thus, reconstructing a 3D point cloud of urban models from images will need to account for noise inherent in aerial-based lidar data.

In this paper, we propose sat2pc that predicts 3D point cloud of building roofs from single 2D satellite images. Our key hypothesis is that advances in deep learning-based techniques have made it feasible to extract and reconstruct 3D aspects of an object from 2D images. Since satellite images are widely and freely available through mapping services such as Google or Bing Maps, the ability to derive 3D point clouds can then automate the construction of urban models in a data-driven and scalable manner. Moreover, satellite images provide rich features and edges that enable the identification of building outlines and roof planes.

We present sat2pc that addresses the problem of extracting geometric details of the roofs. In doing so, we make the following contributions:

**sat2pc Framework:** We present a novel architecture that predicts building point clouds using a single 2D image. Our technique can capture the fine-grained detail and reconstruct a rich representation of the 3D roof. Moreover, our architecture can leverage the strengths...
of Chamfer distance and Earth Mover’s Distance (EMD) loss to achieve a detail-aware and density-aware point cloud. **Building Point Cloud Dataset:** We created a building dataset that consists of 343 satellite images and their corresponding lidar-based point cloud data. The images and lidar data are annotated with building outline and point cloud classification labels. We manually inspected the data and fine-tuned the projections to align the lidar and image data. **Evaluation:** We extensively evaluated our technique and performed ablation studies to show its efficacy in predicting point cloud representations. Our analysis shows that sat2pc achieves 18.6% improvement over the best baseline model. Further, our results indicate that the point cloud is density and detail-aware. We also used the existing planar extraction algorithm to segment planar roof segments from the predicted point cloud. The results indicate that sat2pc can reconstruct the geometric aspect (e.g., planes) in the point cloud.

2 BACKGROUND

2.1 Building Data and Reconstruction

Three-dimensional (3D) building models can be generated from various data sources. For example, aerial images (e.g., satellites) have high-resolution (less than a foot per pixel) data that captures detailed close-up characteristics of buildings and other urban features. They provide building outline and geometrical aspects (e.g., orientation and shape). There are also aerial-based lidar data with accurate depth information of urban objects, ideal for urban modeling. Airborne lidar provides irregular and unordered 3D point measurements and requires preprocessing to create a digital elevation model (DEM). Both data are typically incomplete and each data source has some parts that are in greater detail than others. For instance, aerial images lack depth information but provide texture and rich image details missing in lidar data.

Prior approaches focused mainly on aerial 2D images to model cities at large-scale[6, 21]. These techniques typically segment building outlines using vision-based algorithms to produce polygonized footprints of the building[1]. In addition, building heights can be estimated from multiple or single images to generate the final 3D building model. However, most models often lack detail and assume flat roofs for all buildings. Furthermore, they usually require multi-view images of a building to reconstruct a rich model and are thus not scalable. It is possible to add some details into the model by forming a hypothesis of roof shapes and mapping them to a standard architectural form of the roof[1]. However, this lacks realism and fails to capture the variety that may occur in the real world. As such, most tools and techniques today are designed to use both lidar and high-resolution images to obtain accurate models.

Unfortunately, lidar data is expensive to collect and not available for large parts of the world.

2.2 Inferring 3D Shapes from Single 2D Images

In recent years there have been several efforts to predict the 3D shapes of common objects (e.g., ShapeNet[5]) and urban environments (e.g., cars in Kitti dataset[8]). However, little focus has been on estimating fine-grained details of 3D building models using single 2D images. Recently, [9, 16, 18, 21] take advantage of deep neural network-based approaches such as GAN, CNNs and, encoder decoders to estimate a Digital Surface Map (DSM) or height of buildings using a single aerial image. But they do not focus on estimating the fine-level details of the 3D building. In contrast, our work focus on reconstructing the 3D point cloud representation of a building from 2D satellite images. Note that several techniques fuse lidar point cloud and satellite imagery to create urban models, and thus, can benefit from having a 3D point cloud representation.

2.3 Point Cloud Similarity Metrics

2.3.1 Chamfer Distance: CD is one of the two broadly adopted metrics for calculating the similarity of two point clouds. We define CD as:

$$\mathcal{L}_{CD}(P_1, P_2) = \frac{1}{|P_1|} \sum_{x \in P_1} \min_{y \in P_2} \|x - y\|^2_2 + \frac{1}{|P_2|} \sum_{y \in P_2} \min_{x \in P_1} \|x - y\|^2_2$$

(1)

where, $P_1$ and $P_2$ are two point clouds. Each point finds the closest point in the other point set (and vice-versa) and calculates the average pair-wise point-level distance. CD lacks density awareness but is stricter with capturing details [34]. This causes the model to cluster most points in regions with high point density (e.g., the object’s center).

2.3.2 Earth Mover’s Distance: EMD is another broadly used metric for calculating similarity between two point clouds and is defined as:

$$\mathcal{L}_{EMD}(P_1, P_2) = \min_{\psi: P_1 \rightarrow P_2} \frac{1}{|P_1|} \sum_{x \in P_1} \|x - \psi(x)\|_2$$

(2)

where $\psi$ is a bijection function from $P_1$ to $P_2$ where EMD finds the $\psi$ with the lowest sum of pair-wise distances and returns the average. Since finding a bijection function with the lowest cost is a computationally expensive task, in practice, an approximation version of EMD is often used [7, 20]. Using an approximation approach also relaxes the limitation of using two point clouds with different sizes. As a result, EMD is sensitive to distribution changes but is less strict with detailed structures [7, 34].

3 SAT2PC DESIGN

Our primary goal is to produce a 3D point cloud from a single 2D satellite image. Specifically, given an image of size $m \times n$ and point sample size $N$, we aim to generate a dense point cloud set $P = \{p_i\}_{i=1}^N$ of size $N$ points. Figure 1 depicts our proposed architecture. The sat2pc design has two key components — a Point Cloud Deformation (PCD) network and a refinement network. As illustrated in the figure, the PCD network takes input an image and a randomly generated point cloud of size $N$. It is responsible for producing an intermediate point cloud ($P'$) that captures the structural aspects of the input image. The refinement network takes as input the intermediate point cloud $P'$ and fine-tunes them to generate the final point cloud. Our sat2pc architecture is able to enforce different loss functions, Chamfer and EMD loss, to predict the 3D shape of the roof.
Figure 1: sat2pc architecture consists of two modules. The PCD module takes as input an image and a random point cloud and generates the intermediate point cloud. Next, the refinement module takes the intermediate point cloud and generates the point-wise residuals. These residual values are added to the intermediate point cloud to generate the final output.

3.1 Point Cloud Deformation Module

Our input satellite image consists of planar roof segments that make up the overall structure of the building. In this stage, our objective is to extract the geometric features from the satellite image to produce the point cloud. As such, for our initial feature extraction and 3D point cloud generation, we use the GraphX-Conv architecture proposed in [22]. The proposed GraphX considers the spatial correlation between points and encodes point-specific and global features of the image onto a random point cloud, which helps reconstruct the final point cloud. Below, we describe the key aspects of GraphX and refer the readers to the original paper [22].

GraphX-Conv consists of three main steps. First, it has an image encoder to obtain a multi-scale representation of the input image. GraphX uses a similar VGG architecture as described in [22]. The next step is feature blending, where the point-specific and global shape information are concatenated with an initial randomly generated point cloud. Point-specific shape information is extracted by projecting the initial random points onto the extracted feature maps from the image encoder. And, global shape information is extracted using Adaptive Instance Normalization (AdaIN) [10], a style transfer method which aligns the mean and variance of a sample to a target style. The AdaIN helps to transfer the style of extracted features from the image encoder to the initial point cloud and encode the global shape information. The final step is a deformation that uses a ResGraphX module that generates a point cloud representation of the input image by using the features vector created in the previous step. ResGraphX is a deformation module inspired by X-Convolution [17] and graph-convolution [12] which has a lower computational cost than X-Convolution and is more flexible than graph-convolution.

The size of the initial random point cloud dictates the final size of the reconstructed point cloud. Since the deformation module deforms the input point cloud, the predicted point cloud retains the same number of points. Although there is no limitation on the number of points of the input cloud, we observed that a large point cloud size could significantly slow down the training process.

3.2 Refinement Module

The predicted point cloud from PCD forms an intermediate point cloud in our network and lacks fine-grain structural characteristics of the roof. Although it captures the overall structure, a lack of density-awareness leads to irregular and non-uniform point clouds. Since we are interested in retaining the overall shape of the roof, the characteristics of the individual planar roof segments must be retained in the final output. That is, point cloud points should be distributed uniformly on the same plane for a plane extraction algorithm to detect them as a part of the same plane. If retained, off-the-shelf planar extraction can be used to identify and extract these planar segments to evaluate the geometry of the 3D point cloud. To add these fine-grain structural details, we use a similar residual network as suggested by [20]. The residual network takes the point cloud predicted by the PCD module and predicts the point-wise residual. This network consists of seven 1D convolutional layers that generates a three-channel residual for each point (one for each dimension of the point). The final point cloud results from adding these residuals to the PCD’s output. We use a similar residual network to [20]. However, in our case, the residual network only receives an N×3 point cloud and predicts an N×3 residual vector, where N is the size of the input point cloud.

3.3 Loss Function

As described in section 2.3, Chamfer distance and EMD are the two most popular metrics for measuring similarity between two point clouds. However, each one of these metrics has its strength and shortcomings. For example, Chamfer distance is more detail-oriented but lacks density awareness, whereas EMD is sensitive to density while ignoring local details [34]. These issues lead us to use both metrics but at different stages of our architecture. This approach helps us to get the best of two worlds and have a detailed point cloud, using Chamfer distance, while utilizing the limited number of available points by having a density-aware metric like EMD.

Since PCD has direct access to the input image, it can extract geometric features from the satellite image and incorporate more details in the predicted point cloud. As such, we find that having
Chamfer distance to calculate the loss for PCD’s output results in obtaining better shape information. It ensures the predicted point cloud is detailed and captures the overall shape information. However, as we show in section 5, Chamfer loss clusters point towards a specific part of the predicted point cloud, reducing the overall quality of the 3D shape. The point cloud shape distribution is also irregular and non-uniform, making it difficult for the plane extraction algorithm to extract planar roof segments. On the other hand, the refinement network produces residual values for each point in the point cloud. We use this network to refine the density and ensure uniformity in the predicted point cloud. Thus, we use EMD loss that is density-aware and achieves point distribution similar to the ground truth. We combine the Chamfer and EMD loss, an use \( \alpha \) parameter to control the ratio of the different losses. Our final loss is defined as follows.

\[
\mathcal{L}(X_{\text{inter}}, X_{\text{final}}, Y) = \mathcal{L}_{\text{CD}}(X_{\text{inter}}, Y) + \alpha \mathcal{L}_{\text{EMD}}(Y, X_{\text{final}})
\]

where \( X_{\text{inter}} \) is the intermediate prediction from PCD module, \( X_{\text{final}} \) is the final prediction from the refinement module, \( Y \) is the ground truth point cloud. And, \( \mathcal{L}_{\text{CD}} \) and \( \mathcal{L}_{\text{EMD}} \) are Chamfer and EMD loss, respectively. Our combined loss function makes the predicted point cloud have both the details and density-awareness of Chamfer and EMD loss, respectively.

4 EVALUATION METHODOLOGY

In this section, we describe our dataset, metrics, and experimental setup to evaluate our proposed approach.

4.1 Dataset Collection and Description

While there are existing datasets that provide point cloud[4, 13] and satellite images, these datasets have many limitations. For example, DFC dataset’s satellite images does not have high enough resolution. Similarly, most high-resolution data are not large-scale or have enough building variety. These datasets consist of mostly high rises that have flat roofs. Thus, we created a high-resolution building dataset of satellite images and lidar information from existing mapping APIs to evaluate our approach. Table 1 highlights the key differences between our dataset and available datasets.

| Dataset                  | Ours | DALES [30] | DFC [13] | SpaceNet 2 [3] | Vaihingen [4] |
|--------------------------|------|------------|----------|----------------|---------------|
| Lidar Building Outline   | Yes  | Yes        | Yes      | No             | Yes           |
| Satellite Image          | Yes  | No         | Yes      | Yes            | Yes           |
| Pre-Processed Building Data | Yes  | No         | No       | No             | No            |

Table 1: Comparison of our dataset with existing datasets.

Our data collection process is as follows. We collected the lidar data [26, 28] from OpenTopography website[23], which contains high-resolution data for various cities in the US. Next, we downloaded the building outline using the location information in lidar data. We used the OpenStreetMap API that provides the building outline of all homes within a region. Next, we used this outline to extract the corresponding point cloud from the lidar data. In addition, we used the MapBox API to download the corresponding satellite image for each building using the location coordinates.

While collecting and mapping the lidar and satellite images from existing APIs seems straightforward, we faced many challenges in creating the dataset. We learned from experience that the lidar data sometimes did not match the satellite images. There were instances when the 3D building roof structures had a different shape than their 2D counterpart, indicating either the lidar or satellite data was outdated. As such, we meticulously removed these instances from our dataset. Similarly, we also removed images where the buildings were entirely occluded by nearby trees. In addition, we found instances where the lidar point clouds were noisy — points had either very high or low values and indicated an error during data collection. To fix this issue involved manually plotting and inspecting each building from multiple angles, which proved to be time-consuming. In some cases, when the projections were transformed from lidar coordinates (in latitude and longitude) to image coordinates (in x-y coordinates), the building outline did not align well. As a result, we often had to fine-tune the values by adjusting the offset to get accurate mappings between pixel coordinates of images and points in the point cloud.

Our sat2pc roof dataset consists of 343 samples from Dunedin, Florida. The dataset covers different roof types such as flat, gable, hip, and combination of them. Each sample consists of a 224x224 satellite image, a point cloud representing the building, and the building and roof planes outlines. The code for extracting and fine-tuning lidar data and the dataset will be made available to enable future research in this area.

4.2 Metrics

We note that standard metrics such as Chamfer distance and EMD are not ideal for capturing the geometric characteristics of the roof. While they measure the general structure and density discrepancy, they do not reveal whether the planar structures of the building roof were reconstructed in the predicted model. For instance, any outlier points may not significantly impact the Chamfer loss but may change the roof’s building outline and planar structures. Thus, we use the metrics proposed in [2] that are commonly used to capture the characteristics of a 3D building roof. These metrics are as follows.

Completeness calculates the proportion of ground truth’s roof planes that are present in the prediction and defined as:

\[
C_m = \frac{TP}{TP + FN}
\]

where TP is the number of planes that are present in both ground truth and prediction point clouds. A plane from prediction is true positive when it’s matched with a plane from the ground truth. Plane \( P_i \) from prediction is a match for plane \( G_j \) from ground truth if, their IoU is the largest, and their intersection is larger than or equal to 40% of the area of \( G_j \). And, FN is the number of planes that are present in ground truth but missing in the predicted point cloud.

Correctness measures the proportion of prediction’s roof planes that are present in the ground truth and is defined as:
We first compare our approach to prior work on 2D to 3D point cloud prediction. We consider two baseline techniques — namely PointSet technique and GraphX-Conv [22]. Both techniques use a single image to predict the point cloud. To the best of our knowledge, there is no study on predicting building point cloud. Thus, these models were trained for our use case using the code released by the authors. In GraphX-Conv [22], the authors use only Chamfer loss to train their model. We modified the code to include EMD loss to train the GraphX models.

Table 2 shows the quantitative comparison of our approach with the baseline techniques. Our results show sat2pc, which combines both the Chamfer and EMD loss, outperforms in terms of quality and completeness metrics by a large margin. Recall that these metrics are calculated by extracting the roof planes from the point cloud and comparing them to the ground truth planar segments. This demonstrates the effectiveness of our sat2pc in reconstructing the geometric shapes in comparison to other baselines and shows that combining Chamfer and EMD loss helps in obtaining rich shape information.

Although the PointSet technique has a higher correctness metric, the overall structure reconstructed is less accurate. In our analysis, we observed that the roof planar extraction technique could extract only a small number of planes from the PointSet output. Although these extracted planes had a high overlap with ground truth, indicating a higher correctness value, the technique could not extract many roof planar segments due to poor shape quality. In order to achieve good shape quality, we need correctness, completeness, and quality value to be high. Our sat2pc model achieves high values in these metrics, indicating that the planar extraction technique was able to identify and segment roof planes from the output successfully.

We note that both GraphX-conv and sat2pc achieve similar IoU. This comes as no surprise as these models are capable of learning global semantics, and the augmentation of lidar points helps in achieving accurate outlines of the roof planes. Similarly, we observe that Chamfer and EMD loss are similar in most cases for GraphX-Conv and sat2pc. However, as indicated above, the output of GraphX-Conv performs lower compared to sat2pc with respect to shape information, indicating that Chamfer loss alone may not be sufficient in capturing the details.

Key takeaway: Using Chamfer or EMD loss alone doesn’t capture the characteristics of the building. In contrast, using a combination of Chamfer and EMD losses, sat2pc is able to obtain rich 3D shape information of roofs from 2D satellite images. sat2pc achieved 18.6% improvement in quality metrics over the best baseline model.

5.2 Qualitative Results

Figure 2 shows the qualitative results. As depicted in the figure, our approach helps produce better 3D point clouds of buildings. In particular, we observe that PointSet technique is unable to yield rich shape information when compared to GraphX and sat2pc. Although GraphX-Conv predicts the overall shape, we observe that it misses details that are otherwise observed in sat2pc shape output. For example, in sample A, the shape generated by GraphX-Conv fails to capture the gap between two adjoining roofs and identifies it as a single roof plane. In contrast, sat2pc output predicts the gap and preserves the overall structure. This problem is also depicted in sample C, where GraphX-Conv fails to capture the gap.

We further investigate the density of predicted points. To do so, we use the ground truth points and calculate the number of points...
Figure 2: Qualitative results of sat2pc, GraphX-Conv, and PointSet. The color of each point in the point clouds indicates its height relative to the points in that point cloud.

Table 2: Baseline comparisons of sat2pc with existing approaches.

| Model          | Loss Function | EMD With Pad | Chamfer With Pad | EMD With Pad Removed | Chamfer With Pad Removed | Outline IoU | Completeness | Correctness | Quality |
|----------------|---------------|--------------|------------------|----------------------|--------------------------|-------------|--------------|-------------|---------|
| GraphX [22]    | Chamfer       | 2.54         | 0.08             | 1.08                 | 0.09                     | 0.84        | 0.55         | 0.65        | 0.43    |
| GraphX [22]    | EMD           | 0.29         | 0.10             | 0.25                 | 0.13                     | 0.81        | 0.47         | 0.28        | 0.21    |
| PointSet [?]   | Chamfer       | 2.43         | 0.09             | 0.87                 | 0.11                     | 0.81        | 0.32         | 0.72        | 0.30    |
| sat2pc (Ours)  | Chamfer + EMD | 0.26         | 0.08             | 0.22                 | 0.1                      | 0.84        | 0.67         | 0.67        | 0.51    |

5.3 Effect of Loss Function

We analyze the impact of different Chamfer and EMD loss combinations within the sat2pc architecture. Table 3 shows the overall performance for different combinations, with \( \alpha \) set to 1. We observe that the overall quality drops when we use the same loss function in sat2pc. This is because Chamfer and EMD loss captures different shape characteristics: global structure versus local density. We also observe that the order of loss function in the architecture can significantly impact the final output. In particular, using the Chamfer loss function on the point cloud deformation module and EMD on the refinement module offers the best performance. Since the point cloud deformation module has access to the input image, we conjecture that having Chamfer loss helps capture the overall details from that image. On the other hand, density and small refinements based on the point’s location can be effective without loss and the global structure of chamfer loss results in a rich point cloud representation.

Key takeaway: sat2pc provides a uniform point cloud and has a much better appearance in comparison to other baseline techniques. The ability to combine the density-awareness of EMD loss and the global structure of chamfer loss results in a rich point cloud representation.
Table 3: Analyzing the impact of changing the order of loss functions in different modules in our architecture.

| Deformation Loss | Refinement Loss | EMD With Pad | Chamfer With Pad | EMD Removed Pad | Chamfer Removed Pad | Outline IoU | Completeness | Correctness | Quality |
|------------------|----------------|--------------|------------------|-----------------|---------------------|------------|--------------|-------------|---------|
| Chamfer          | EMD            | 0.26         | 0.08             | 0.22            | 0.1                 | 0.84       | 0.67         | 0.67        | 0.51    |
| Chamfer          | Chamfer        | 3.13         | 0.1              | 1.18            | 0.15                | 0.8        | 0.44         | 0.73        | 0.39    |
| EMD              | EMD            | 0.26         | 0.08             | 0.22            | 0.12                | 0.84       | 0.65         | 0.62        | 0.47    |
| EMD              | Chamfer        | 0.25         | 0.08             | 0.22            | 0.11                | 0.84       | 0.64         | 0.61        | 0.45    |

Key takeaway: The combination of different losses helps in improving the overall performance of the model. Using Chamfer with access to image details and EMD at the refinement stage can boost the model’s performance.

5.4 Effect of Alpha

Table 4 shows the different \( \alpha \) values on the overall performance of sat2pc. Note that the \( \alpha \) parameter controls the overall importance of each loss function in the architecture. We observe that the overall quality of output increases as we increase from 0.2 to 1. When \( \alpha = 1 \), both Chamfer and EMD loss have equal weightage, and we observe better output quality. However, when the \( \alpha \) value is greater than 1, the model’s performance reduces in terms of quality, correctness, and completeness metrics.

Key takeaway: When \( \alpha = 1 \), the trained sat2pc models perform best in terms of completeness, correctness, and quality metrics — likely due to better-predicted shape.

5.5 Effect of Refinement Module

Next, we analyze the output of the Point Cloud Deformation (PCD) module and refinement module in sat2pc. Recall that PCD module in sat2pc produces an intermediate point cloud, which is further processed by the refinement module. To do so, we ran the planar extraction algorithm on the output of the point cloud deformation (PCD) module and refinement module and calculated the completeness, correctness, and quality. Table 5 shows the performance of the point cloud output. We observe that the final output from the refinement module further refines and improves the 3D shape. This is demonstrated by the higher completeness, correctness, and quality values.

Key takeaway: The refinement module in sat2pc helps improve the overall shape of the final point cloud.

5.6 Effect of Point Cloud Resolution

Finally, we vary the initial random cloud size to analyze the impact of point cloud size on the overall shape quality. Table 6 shows the results for varying point cloud size. We observe that increasing the number of points from 3000 to 4000 improves the overall results, although the improvement is marginal. We also visually inspected the point cloud, and the predicted point surface was smooth and uniform. However, further increasing the point cloud size reduces the overall performance. In particular, we see a reduction in quality and correctness metric — presumably due to the resolution of ground truth lidar data, which has a maximum of 3000 points. In terms of training time, increasing the number of points in the point cloud also increases training time. In particular, increasing the number of points from 3000 to 4000 almost doubles the training time.
We believe that we can leverage these approaches to predict trees will also require the prediction of trees and other structures (e.g., Adversarial Networks (GAN) can help recover partially occluded structure has seen renewed interest in constructing models from ever, the recent success of deep learning techniques in 3D recon-
struction relied primarily on stereo or multi-view images [11, 33]. How-
2D to 3D Object Reconstruction Prior work on 3D reconstruction relied primarily on stereo or multi-view images [11, 33]. However, the recent success of deep learning techniques in 3D reconstruction has seen renewed interest in constructing models from single images. Although an ill-posed problem, many techniques have attempted to predict the 3D shape from a single image using prior knowledge and learning the geometries available in the image. 3D shape of an object can be represented in various forms, namely — voxel [19], mesh [33], and point cloud [7, 22]. While there have been several works on predicting these different 3D representations, our work primarily focuses on point cloud representation because of the accessibility of point cloud building data. In addition, point cloud representations are also computationally more efficient compared to voxel-based representations [25]. Fan et al. [7] introduced an architecture that directly generates point cloud representations using single images. Subsequently, there have been follow-up work in this direction [22]. Unlike prior work, we use a combination of loss functions to show significant improvement in improving the quality of the point cloud. Further, we evaluate our work on real-world lidar sensor data of buildings prone to be noisy.

There has also been considerable work on network architectures that complete or upsamples 3D shape [31]. These upsampling techniques generate a dense and uniform point cloud from sparse point cloud data. Similarly, work on 3D shape completion completes missing parts of point cloud due to occlusions [20, 31]. As in [31], these techniques may also use upsampling and refinement to ensure that the final 3D shape does not deviate from the overall structure. We use the residual network in our work to help the model learn the density.

3D Building reconstruction.

There have been several decades of research in developing large-scale urban models. Generating 3D building shapes from images is a classical remote sensing problem, as satellite images provide a cost-effective means of collecting large-scale building data. For example, several techniques use multi-view images to extract the shape or use 3D primitives to estimate the shape of the building [1, 16, 21]. With the availability of point cloud lidar, studies have focused on combining lidar and image features to create accurate 3D urban models [14]. Recently, deep learning-based approaches have been proposed to estimate the height of a building from single 2D images [18]. Separately, there has been work on segmenting images to estimate the 3D shape of the roof. In [1], the authors propose a multi-scale convolutional–deconvolutional network (MSCDN) that predicts the Digital Surface Model (DSM) of the buildings from a single aerial RGB image. In contrast, our work focuses on predicting a point cloud from 2D images. To the best of our knowledge, this is the first work that aims to predict point cloud from a single satellite image.

| $\alpha$  | EMD W/Pad | Chamfer W/Pad | EMD No Pad | Chamfer No Pad | Outline IoU | Completeness | Correctness | Quality |
|---------|----------|--------------|-----------|---------------|-------------|--------------|-------------|--------|
| 0.2     | 0.37     | 0.17         | 0.23      | 0.09          | 0.83        | 0.6          | 0.64        | 0.44   |
| 0.3     | 0.34     | 0.15         | 0.23      | 0.1           | 0.83        | 0.6          | 0.64        | 0.45   |
| 0.5     | 0.29     | 0.1          | 0.22      | 0.1           | 0.84        | 0.6          | 0.64        | 0.45   |
| 0.8     | 0.25     | 0.09         | 0.22      | 0.1           | 0.84        | 0.6          | 0.67        | 0.48   |
| 1       | 0.26     | 0.08         | 0.22      | 0.1           | 0.84        | 0.67         | 0.67        | 0.51   |
| 1.5     | 0.25     | 0.07         | 0.22      | 0.1           | 0.84        | 0.66         | 0.66        | 0.49   |
| 2       | 0.23     | 0.07         | 0.23      | 0.1           | 0.84        | 0.63         | 0.62        | 0.47   |

Table 4: Impact of varying alpha value on performance.

| Point Cloud Output | Completeness | Correctness | Quality |
|--------------------|--------------|-------------|---------|
| Point Cloud Deformation | 0.65 | 0.64 | 0.49 |
| PCD + Refinement  | 0.67 | 0.67 | 0.51 |

Table 5: Impact of refinement module on performance.

Key Takeaway: Increasing the number of points to 4000 improves the overall results.

However, a further increase reduces the overall quality of the output.

6 DISCUSSION

Our current approach predicts point cloud at an individual building level. However, it is possible to easily scale our approach to create 3D urban models using satellite images at scale cost-effectively. Recall that our approach requires a building outline. This can easily be obtained using online mapping APIs (e.g., OpenStreet Maps). Moreover, we can use existing vision-based models to extract building roofs with high accuracy. We can then use our model to predict the building roof point clouds using the segmented 2D roof and use the location coordinates to project these point clouds. There are also other design considerations for scaling our proposed approach. First, our approach did not consider occluded roofs from trees or nearby structures. While our work can predict point cloud of roof images with shadows from nearby trees present in our dataset, partially occluded images will require hallucination of the roof size and shape. We believe that architectures such as Generative Adversarial Networks (GAN) can help recover partially occluded roofs and remain part of future work. To generate an urban model will also require the prediction of trees and other structures (e.g., utility poles). We observed that, in some cases, the final point cloud also detected the presence of trees, marked by the higher z-values of points along the edges. There has been recent work on detecting and predicting tree crowns and their height using images [32]. We believe that we can leverage these approaches to predict trees and vegetation. Separately, urban models will require predicting the height of the building. And, there has been recent work on predicting building height using single 2D images [9, 18, 24].

7 RELATED WORK

3D Building reconstruction.

There have been several decades of research in developing large-scale urban models. Generating 3D building shapes from images is a classical remote sensing problem, as satellite images provide a cost-effective means of collecting large-scale building data. For example, several techniques use multi-view images to extract the shape or use 3D primitives to estimate the shape of the building [1, 16, 21]. With the availability of point cloud lidar, studies have focused on combining lidar and image features to create accurate 3D urban models [14]. Recently, deep learning-based approaches have been proposed to estimate the height of a building from single 2D images [18]. Separately, there has been work on segmenting images to estimate the 3D shape of the roof. In [1], the authors propose a multi-scale convolutional–deconvolutional network (MSCDN) that predicts the Digital Surface Model (DSM) of the buildings from a single aerial RGB image. In contrast, our work focuses on predicting a point cloud from 2D images. To the best of our knowledge, this is the first work that aims to predict point cloud from a single satellite image.
We also showed that planar extraction algorithms could extract planar segments from the predicted point cloud. Furthermore, sat2pc outperforms existing baseline techniques in terms of the overall shape quality of 3D models. We also showed that planar extraction algorithms could extract planar segments from the predicted point cloud.

8 CONCLUSION

In this paper, we present sat2pc, an architecture for predicting building 3D point cloud from a single satellite image. In addition, we provide a new building-oriented dataset that includes high-resolution satellite images and LiDAR information along with building outlines. We extensively evaluated our approach and performed ablation studies to show the efficacy of our proposed approach. Our results showed that sat2pc can reconstruct the 3D point cloud from 2D images. Furthermore, sat2pc outperforms existing baseline techniques in terms of the overall shape quality of 3D models. We also showed that planar extraction algorithms could extract planar segments from the predicted point cloud.

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| Number of Points | Time Per Epoch(s) | EMD With Pad | Chamfer With Pad | EMD Removed Pad | Chamfer Removed Pad | Outline IoU | Completeness | Correctness | Quality |
|------------------|-------------------|-------------|-----------------|-----------------|---------------------|------------|-------------|-------------|---------|
| 3000             | 31.5              | 0.26        | 0.08            | 0.22            | 0.84                | 0.67       | 0.67        | 0.51        |         |
| 4000             | 37.8              | 0.17        | 0.06            | 0.17            | 0.85                | 0.68       | 0.7          | 0.32        |         |
| 6000             | 41.7              | 0.29        | 0.08            | 0.21            | 0.85                | 0.66       | 0.6          | 0.45        |         |
| 8000             | 62.2              | 0.21        | 0.08            | 0.22            | 0.85                | 0.69       | 0.61        | 0.47        |         |

Table 6: Performance of sat2pc in predicting point cloud output with different point cloud size.