Predicting cell phone adoption metrics using satellite imagery

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Abstract
Approximately half of the global population does not have access to the internet, even though digital access can reduce poverty by revolutionizing the economic development opportunities available to individuals and businesses. Due to a lack of data, Mobile Network Operators (MNOs), governments and other digital ecosystem actors struggle to effectively determine if telecommunication investments are viable, especially in greenfield areas where demand is unknown. This leads to a lack of investment in network infrastructure, resulting in a phenomenon commonly referred to as the ‘digital divide’. In this paper we present a method that uses publicly available satellite imagery to predict telecoms demand metrics, including cell phone adoption and spending on mobile services, and apply the method to Malawi and Ethiopia. A predictive machine learning approach can capture up to 40% of data variance, compared to existing approaches which only explain up to 20% of the data variance. The method is a starting point for developing more sophisticated predictive models of telecom infrastructure demand using publicly available satellite imagery and image recognition techniques. The evidence produced can help to better inform investment and policy decisions which aim to reduce the digital divide.

Key Words: Cell phone adoption, deep learning, image recognition, satellite imagery.
1. Introduction

How do we predict local cell phone adoption? And, can we also predict if unconnected communities could plausibly pay for roll-out of new digital infrastructure?

Currently, digital ecosystem actors such as governments, regulators and development agencies, as well as many Mobile Network Operators (MNOs), lack this vital insight in unconnected areas. Hence, infrastructure deployment is perceived as riskier in these places, often preventing needed investment, leading to a ‘digital divide’ between those with voice and data access, and those without. Ultimately, having internet access allows users to participate in the digital economy, providing revolutionary economic and societal opportunities. While those without access are left behind.

The United Nation’s Sustainable Development Goals (SDGs) provide a vision for achieving a better future for all which can be sustained over the long term (United Nations, 2019), and SDG9 places a special focus on delivering the necessary infrastructure required to help reduce poverty. Over many decades, Information and Communications Technologies (ICTs) have been seen as a key way to enable digitally-led economic development and help deliver the SDGs, potentially lifting millions out of poverty (Mansell, 2001, 1999; Mansell and Wehn, 1998). Hence, solving the digital divide is critical to this mission. Currently, universal access still remains an ambitious goal even in established frontier economies such as the United States, demonstrating the challenge of achieving viable internet economics in rural and remote areas (Claffy and Clark, 2019). Particularly in the current era of the digital economy, users do not just require a stable 2G voice connection, but also a reliable data connection to enable the current generation of applications and services, which generally rely on 4G (Hidalgo et al., 2020; Tchamyou et al., 2019).

The importance of the analysis reported in this paper is highlighted when we consider the vast quantities of capital invested into digital divide projects globally every year. As just one example, the World Bank’s Digital Development program aims to provide the necessary knowledge and financing to help close the global digital divide, ensuring countries can take full advantage of the adoption of
internet-based technologies for economic development purposes. Over the past four years alone, the World Bank has invested over $3.8 billion (USD) in ICT projects (World Bank, 2019), with over $1.1 billion going to countries on the African continent, as outlined in Table 1.

| Region                     | 2015 ($m) | 2016 ($m) | 2017 ($m) | 2018 ($m) | 2019 ($m) | Total ($m) |
|----------------------------|-----------|-----------|-----------|-----------|-----------|------------|
| Africa                     | 159       | 44        | 274       | 226       | 471       | 1,174      |
| East Asia & Pacific        | 69        | -         | 207       | 80        | 140       | 496        |
| Europe & Central Asia      | 42        | 39        | 8         | 129       | 116       | 334        |
| Latin America & Caribbean | 48        | -         | 122       | 13        | 46        | 229        |
| Middle East & North Africa | -         | 145       | 183       | 62        | 308       | 698        |
| South Asia                 | 38        | 43        | 228       | 232       | 310       | 851        |

| Annual lending             | 356       | 271       | 1,022     | 742       | 1,391     | 3,782      |

With such vast investments targeting the digital divide, there is strong motivation to develop data-driven broadband strategies to inform both investment decisions and policies (Taylor and Schejter, 2013). Existing approaches often focus on collecting survey data via manual on-the-ground activities. While surveys can provide rich context for informing digital divide policies, such as on cell phone adoption, they can be expensive to undertake due to labor-intensive methods. Thus, there is motivation to explore new analytical options for quantifying the digital divide and providing improved evidence to design policies to reduce digital inequalities. Such evidence is essential for governments and international aid agencies (Maitland et al., 2018).

Currently, there has been much development around the use of machine learning techniques to enhance decision making. However, this poses a significant challenge for digital divide researchers because there are very few critical assessments of the effectiveness of these techniques. Indeed, researchers should not accept machine learning conjecture without independent quantitative assessment of these methods, with such assessments conforming to the highest standards of scientific reproducibility. Considering these issues, a single research question is now identified to address in this paper.
How effective are different techniques at predicting cell phone adoption metrics from satellite imagery, such as device penetration and monthly spending on telephone services?

In answering these questions, the key contributions of this paper include:

1. Providing a validated method for predicting cell phone adoption metrics from satellite images.
2. Evaluating independent quantitative data on the effectiveness of machine learning techniques, over existing approaches.
3. Developing a documented open-source codebase for the digital divide community to access, reproduce the results and further develop the method, via the Telecom Analytics for Demand using Deep Learning online repository: https://github.com/edwardoughton/taddle

Having articulated the main contributions, the structure of the paper is now outlined. Section 2 is a literature review focusing on the digital divide literature, and existing metric prediction from satellite imagery. Section 3 details the method employed, before reporting results in Section 4. Limitations with the method are covered in Section 5. Finally, a discussion is undertaken in Section 0 and conclusions are presented in Section 7.

2. Literature review
Two areas of literature are pertinent to the research questions, including issues associated with market failure and the digital divide, and existing analyses which have used satellite imagery to predict metrics of interest.

2.1. Market failure and the digital divide
Mobile network infrastructure is generally delivered via market-based methods. Indeed, evidence suggests that market competition combined with a suitable regulatory environment is positively correlated with telecom performance and better consumer outcomes, encouraging such an approach (Bauer, 2010; Cave, 2006; Wallsten, 2001). Hence, investments are generally made based on rational infrastructure investment decisions by profit maximizing private operators. Thus, there must be a viable return which can feasibly be made, for the necessary infrastructure to be deployed.
The problem therefore is that in areas of demand uncertainty (often exacerbated by a lack of data), the necessary infrastructure required for economic development is not delivered leading to market failure (Oughton et al., 2017; Thoung et al., 2016). Although solving coverage issues alone may not eliminate the digital divide (Reisdorf et al., 2020), infrastructure is a necessary prerequisite to gaining sustainable economic development benefits from digital technologies and the wider positive societal impacts (Chester and Allenby, 2019; Farquharson et al., 2018; Graham and Dutton, 2019; Hall et al., 2016; Oughton and Russell, 2020; Parker et al., 2014; Saxe and MacAskill, 2019). Thus, market failure issues must be addressed. A variety of technology, business model and policy options are available to attempt to do this and usually focus on using wireless technologies as the costs of deployment are lower. An essential prerequisite however is mutual collaboration between private MNOs and governments, as improvements in coverage and capacity are most effective when there is simultaneous growth in both infrastructure and spectrum portfolios to enabling scale economics (Peha, 2017).

From an economic perspective, reducing the digital divide usually involves subsidizing both investments in rural areas and services for low-income people (Rosston and Wallsten, 2019). While the focus of the digital divide debate is very often on supply-side coverage gaps or connection speed differentials, the roll-out of infrastructure to unviable locations must ultimately be accompanied by demand-side programs to increase device ownership and digital literacy, as these are key determinants of adoption (Hauge and Prieger, 2010). Too often, digital divide issues are heavily compounded by existing socio-economic disparities, meaning lower income groups can be most affected (Riddlesden and Singleton, 2014). This can too often have a greater disproportionate effect on minority ethnic groups (Gant et al., 2010; Turner-Lee and Miller, 2011).

Estimating demand metrics particularly in greenfield areas is a serious challenge for both MNOs (Suryanegara, 2018), telecom regulators and analysts (Oughton et al., 2019a, 2019b; Oughton and Frias, 2016), leading to simplified modeling assumptions which do not necessarily reflect reality.
Building new infrastructure is a balancing act (Greenstein, 2010), between delivering to areas of guaranteed demand (motivated by profit maximizing behavior), and incrementally rolling out new infrastructure to areas where coverage is needed but take-up of new services is uncertain (motivated by equitable access policies). Although revenue metrics are frequently developed, they are rarely translated into spatial estimates of how and where infrastructure investment should next be directed, which for unviable areas may require government action (Sevastianov and Vasilyev, 2018; Vincenzi et al., 2019). Similarly, in forecasts of user adoption for cellular technologies such as 4G (Jha and Saha, 2020), MNOs are left with very little spatial understanding of how many potential users of new services there might be in each local area, despite this being important.

In conclusion, it would be beneficial to have new evidence on local adoption of cell phone metrics to help inform both private and governmental actions to reduce the digital divide.

2.2. Metric prediction from satellite imagery

While cell phone adoption has been studied for many countries, including across Africa (Wesolowski et al., 2012), researchers usually focus on analyzing survey data, with few attempt to develop predictions at the national scale. This is surprising given that internet-enabled technologies are increasingly being used to address a range of issues relating to health, climate change, economic development and disaster resilience. Therefore, it is essential to know who is connected, and where.

Currently there is considerable research which uses cell phone call records or location data, obtained from MNOs, to metrics of interest, such as population density (Deville et al., 2014), urban growth (Bagan and Yamagata, 2015), cellular network anomalies (Sultan et al., 2018) and socio-economic characteristics (Fernando et al., 2018; Koebe, 2020; Schmid et al., 2017). However, the limitations of this approach relate to there being (i) no call data in areas with no coverage, and (ii) privacy issues associated with this type of data, affecting data sharing.

It is increasingly common for statistical frameworks to be developed which take advantage of satellite data to augment official statistics. Many papers have focused on using nightlight luminosity data to
assess questions relating to economics (Henderson et al., 2012, 2011), human development (Bruederle and Hodler, 2018), urban extent (Zhou et al., 2015), conservation (Mazor et al., 2013), atmospheric composition (Proville et al., 2017) and measuring the post-disaster impacts of natural hazards (Elliott et al., 2015; Gillespie et al., 2014). While the analysis of mobile phone data is well established (Steenbruggen et al., 2015), new developments are taking advantage of a combination of machine learning with call records and satellite imagery, to address a similar set of questions relating to poverty estimation (Ayush et al., 2020; Jean et al., 2016; Perez et al., 2017; Steele et al., 2017), ecosystem monitoring (Cord et al., 2017), estimating land cover types (Goldblatt et al., 2018) and creating data layers relevant to the Sustainable Development Goals (Boyd et al., 2018; Pokhriyal and Jacques, 2017). However, such approaches have rarely been used to assess the digital divide. Importantly, a key advantage of remote sensing using satellite data is that (i) there is access to an abundant, routinely collected body of data, (ii) has very wide geographic coverage of such data allowing scalability across countries, and (iii) has very high spatial resolution (Donaldson and Storeygard, 2016).

An increasingly used technique is transfer learning, where pretrained models are reapplied to new tasks to help tackle data limitations, such as with survey data (Jean et al., 2016). The goal of transfer learning is to reuse low-level learned aspects of the feature domain, from abundant data such as luminosity images or mobile phone records. High-level specific features can then be learnt for problems with the limited data available, preventing the need to fit a model from scratch. Several types of transfer learning have been surveyed in the literature (Pan and Yang, 2010), but inductive transfer learning is a commonly applied approach, where the domain of two machine learning problems are the same, but the task is different.

3. Method

The method contains five steps. First, it introduces the available data. Then, it details all data preprocessing steps. Afterwards, it explains the concept of transfer learning and how this approach is
used to turn an image into a feature vector. Then, it explains how the feature vector is used to predict the metrics of interest. Lastly, it explains how to generalize onto new regions.

### 3.1. Available data

To obtain measurements of the metrics of interest, data are taken from the World Bank’s Living Standards Measurement Survey (LSMS), a multi-topic household survey undertaken in partnership with various national statistical offices. The LSMS collects up-to-date information for measuring poverty, livelihood, and living conditions. Data are downloaded for the Malawian Fourth Integrated Household Survey 2016-2017 (World Bank, 2016a) and Ethiopian Socioeconomic Survey 2015-2016 (World Bank, 2016b), reported by metric in Table 2. Penetration is defined by the percentage of households with at least one cellphone, and consumption of phone services is based on the monthly spending on telephone services per capita (which is broadly similar to the Average Revenue Per User).

| Country | Variable description | Data file | Column |
|---------|----------------------|-----------|--------|
| Malawi  | Household has a phone | hh_mod_f  | hh_f34 |
|         | Spend on phone services | hh_mod_f  | hh_f35 |
| Ethiopia| Household has a phone | sect9_hh_w3 | hh_s9q22 |
|         | Spend on phone services | sect9_hh_w3 | hh_s9q23 |

The data are collected at what is called the “cluster” level – a small geographic region with a distinct latitude and longitude. Surveys are conducted in each cluster, and for the sake of anonymity LSMS cluster coordinates are offset by a small random amount. In Malawi, there are 780 clusters and 12,447 households surveyed, whereas in Ethiopia, there are 530 clusters and 4,954 household surveyed. To obtain images, the Planet web Application Programming Interface is used allowing image queries within the specified time range (2014-2016), with the most recent available image being selected. Hence, the data and images are temporally consistent. The challenge therefore is to be able to predict the desired metrics of interest from satellite images. Section 3 explains how this is done.
3.2. Data preprocessing
There are two cases to consider: 1) training a model to work in a single country (“single country”), and 2) generalizing the model to work on multiple countries (“cross country”). Cross-country generalization is limited in this study as only data from Malawi and Ethiopia is used. However, this analysis is conducted as a baseline to enable future cross-country improvements. Using the LSMS data, 10km x 10km bounding box is generated around the geometric centroid of each surveyed cluster. For each bounding box 20 download locations are uniformly samples. For Malawi, 780 clusters with 20 images per cluster leads to 15,600 images, and in Ethiopia, 530 clusters with 20 images per cluster leads to 10,600 images. Each metric has four numeric ranges (“bins”) identified using a quantile cut, based on equally distributed segments. Binning is chosen because it reflects the training process of the pre-trained model (as described in the following section) and helps to reduce the influence of numerical outliers. Each cluster and its images are assigned to the corresponding bin. The CNN is trained to classify an image’s bin. Lastly, the clusters that should be held out from the training process are identified in order to properly validate the model. In the single-country case, 30% of the clusters are randomly held out for validation. In the cross-country case, an entire country is held out. The limitations of this approach are discussed later in the paper.

3.3. Transfer learning
A parameter transfer method is utilized, where the parameters learned by a pretrained model are applied to a current task. In this application, the University of Oxford Visual Geometry Group (VGG) pretrained model is applied, which is widely used because the architecture is both highly effective and open-source (Simonyan and Zisserman, 2015). The CNN is trained on the ImageNet dataset where the model learned how to classify 1000 objects. ImageNet contains millions of images which makes this mapping a difficult challenge. By pretraining on ImageNet, VGG is a very good tool for parameter transfer learning, as specifically (i) the domains are the same (images), (ii) the tasks are different (general classification vs nightlight luminosity), and (iii) the VGG has learned useful general relations in the input domain.
To train the model, a pretrained VGG network is downloaded via PyTorch. Specific layers are reinitialized to function on a four-output classification task. An image preprocessor is added during training that randomly chooses a subsection of the image to crop and pass to the CNN, preventing the CNN from being handed the same image repeatedly, reducing overfitting. A learning rate of $3 \times 10^{-6}$ is used with a batch size of 8, along with a custom loss function and the Adam optimizer. The custom loss function is designed to mitigate the issue of assigning a real-valued variable into bins. For a significant number of cases, clusters will be “close” to the bin boundary, but that information will be lost because of the binning process. Cross entropy loss aims to maximize the probability of the correct class, yet for continuous variables the concept of correct class is artificial. The custom loss function defines anything in the top 10% of a bin to be “close” to the higher bin, and anything in the bottom 10% of a bin to be “close” to the lower bin. For images that are not “close” to another bin, a regular cross-entropy loss is applied. For images that are “close” to another bin, the loss function is the following in equation (1):

$$L(o, l) = \alpha \times CEL(o, l) + (1 - \alpha) \times CEL(o, N(l))$$  \hspace{1cm} (1)$$

$o$ is a vector representing the real-valued predictions for each bin and $l$ is the integer label for the correct bin. $CEL$ refers to the cross-entropy loss. $N(l)$ returns the integer label of the nearby bin (the bin the cluster is “close” to). A weighting factor ($\alpha$) is assigns a degree of priority to the true class and a degree of priority to the nearby class. This custom loss function prevents the model from being punished too harshly if it predicts the nearby class in cases where there is some ambiguity about which bin the cluster belongs to. The first 5 epochs are used to train only the new layers (all other layers are “frozen” to use PyTorch terminology). Another 25 epochs are spent training the entire model.

### 3.4. Prediction

The vector output of a layer near the end of the CNN is used as a feature vector representation of the image, with each layer being reported in Table 3. After the CNN finishes training, layer 33 is extracted, with an output vector of length 4096. Layer 36 is reinitialized for the four-output class rather than the previous 1000-output class.
| Layer | Description     | Layer | Description       | Layer | Description |
|-------|----------------|-------|-------------------|-------|-------------|
| 0     | Conv2d         | 12    | BatchNorm2d      | 24    | ReLU        |
| 1     | BatchNorm2d    | 13    | ReLU             | 25    | Conv2d      |
| 2     | ReLU           | 14    | MaxPool2d        | 26    | BatchNorm2d |
| 3     | MaxPool2d      | 15    | Conv2d          | 27    | ReLU        |
| 4     | Conv2d         | 16    | BatchNorm2d      | 28    | MaxPool2d   |
| 5     | BatchNorm2d    | 17    | eLU              | 29    | AdaptiveAvgPool2d |
| 6     | ReLU           | 18    | Conv2d          | 30    | Linear      |
| 7     | MaxPool2d      | 19    | BatchNorm2d     | 31    | ReLU        |
| 8     | Conv2d         | 20    | ReLU            | 32    | Dropout     |
| 9     | BatchNorm2d    | 21    | MaxPool2d       | 33    | Linear      |
| 10    | ReLU           | 22    | Conv2d         | 34    | ReLU        |
| 11    | Conv2d         | 23    | BatchNorm2d     | 35    | Dropout     |
|       |                |       |                  | 36    | Linear      |

Image feature vectors are averaged per cluster to find an aggregate cluster feature vector. Using only the clusters reserved for training, both random cross validation and spatial cross validation are performed to fit five models, each trained on four-fifths (4 “folds”) of the training data and validated on the other fifth (the “fold” held out). Each time a fold is held out, a hyperparameter search is performed internally on the four training folds. The only hyperparameter in Ridge Regression is the regularization coefficient. A list of potential regularization coefficients is enumerated, and for each coefficient an “inner” cross-validation is undertaken on the four folds. The coefficient with the best average $R^2$ is chosen. It is important to remember that this hyperparameter search does not pick the coefficient that works best on the original 5th fold held out, but rather the one that works best in the “inner” cross-validation. This tests generalization onto the 5th fold correctly.

The five models create an ensemble by applying spatial cross-validation and implementing an equal voting scheme that averages the predictions of the five models. Given the limited number of samples, this captures input variability better. The spatially validated models are then used because the $R^2$ of those models on the training set tends to be far closer to the generalized $R^2$ on the validation set. Finally, the model ensemble is tested on the validation clusters. For the single-country case, the validation clusters are the 30% of clusters held out. For the cross-country case, the validation clusters are all clusters belonging to the country held out.
Prediction intervals are computed using a probabilistic formulation of linear regression, as shown in equation (2):

$$\arg \max (\sigma, \alpha) \prod P(y_i|x_i) = \frac{1}{(2\pi \sigma^2)^{N/2}} e^{-\frac{\alpha}{2\sigma^2}}$$

(2)

Where $$\alpha = ||Y - X\omega||^2$$, $$Y$$ is a N x 1 matrix of observed values, and $$X$$ is a N x 4096 matrix of features. $$y_i$$ refers to the $$i$$th row of $$Y$$, as does $$x_i$$ with $$X$$. $$\omega$$ is the vector of linear weights. Note that this is equivalent to minimizing the classic linear regression objective. Once $$\omega$$ is solved, $$\alpha$$ becomes a constant, which enables $$\sigma$$ to be solved as in equation (3):

$$\sigma = \sqrt{\frac{\alpha}{N}}$$

(3)

These equations do not strictly apply to the method for two reasons: 1) the method includes L2 regularization (hence ridge regression) in its objective, and 2) the method creates an ensemble of regression models. For the sake of simplicity, the average of all ridge regression $$\omega$$’s will be substituted into $$\alpha$$. These two simplifications are not too drastic because regularization maintains a very similar objective and an ensemble of linear models is equivalent to a single linear model that contains averages of all model weights. With these simplifications $$\alpha$$ can be determined (and then $$\sigma$$). Also, $$R^2$$ can be used to refer to multiple metrics. In this analysis the Nash-Sutcliffe (NS) model efficiency coefficient is chosen because it conveniently contains a built-in comparison to a baseline model that predicts the mean for all values. If this number is negative, the model is worse than always predicting the mean. However, several related papers, including Jean et al. (2016), use the square of the Pearson R correlation coefficient ($$P^2$$) as the $$R^2$$. The advantage of the Nash-Sutcliffe metric over Pearson $$R^2$$ is because it considers errors directly and includes a comparison to a baseline model (the mean). However, both are reported for the sake of completeness.

In order to compare the results to a baseline, non-CNN models are constructed based on (i) population density, and (ii) nighttime luminosity. Specifically, Ridge Regression is applied using the same cross validation techniques with a model ensemble and held-out clusters. Nightlight luminosity data are
collected using annual composites from 2015 via the Visible Infrared Imaging Radiometer Suite (VIIRS) dataset. Population data obtained from the World Population (WorldPop) 1 km² raster data layer (Stevens et al., 2015; Tatem, 2017).

3.5. Application step
Each country boundary is extracted from the Global Administrative Database of Areas (GADM) (GADM, 2019) and split into 10km x 10km grid squares. In total, 20 images are downloaded per grid and passed through the CNN to obtain their feature vector representation. Vectors are averaged across each grid to get a feature vector per grid. This is passed through the ensembled ridge regression model to obtain predictions for each metric per grid tile. Grid squares with very low populations are dropped to avoid these affecting the results. Finally, predictions are mapped. Figure 1 summarizes the method process, from model creation, to prediction validation, to application.

*Figure 1 Method overview*
4. Results
The validated CNN accuracies are reported in Table 4. As there are four equally represented bins, accuracies above 25% are an improvement over random guessing. Both metrics perform better than the 25% baseline in the single country case. However, in the cross-country case the accuracies only slightly exceed random guessing.

| Type         | Name | Binned device penetration | Binned monthly cost |
|--------------|------|---------------------------|---------------------|
| Single-country | Malawi | 44%                       | 41%                 |
|              | Ethiopia | 38%                       | 38%                 |
| Cross-country | Malawi | 29%                       | 31%                 |
|              | Ethiopia | 30%                       | 29%                 |

Validation of the ensembled ridge regression models are shown in Table 5 for both single country and cross-country results. The results indicate that single-country CNN models outperform generalized cross-country usage, and that for both countries and metrics, single-country CNN models far outperform the baseline models.

Table 5 Model $R^2$ country validation

| Model         | Type | Name | Cross-validation technique | Device penetration | Monthly cost |
|---------------|------|------|----------------------------|--------------------|--------------|
| Population density | Single country | Malawi | Random | 0.176 | 0.182 | 0.2 | 0.201 |
|                |      |      | Spatial | 0.178 | 0.182 | 0.2 | 0.201 |
|                |      |      | Random | 0.047 | 0.069 | 0.071 | 0.086 |
|                |      |      | Spatial | 0.009 | 0.069 | 0.051 | 0.086 |
| Nightlight luminosity | Single country | Malawi | Random | 0.20 | 0.211 | 0.181 | 0.183 |
|                |      |      | Spatial | 0.198 | 0.211 | 0.182 | 0.183 |
|                |      |      | Random | 0.07 | 0.083 | 0.128 | 0.152 |
|                |      |      | Spatial | 0.069 | 0.083 | 0.145 | 0.152 |
| CNN            | Single country | Malawi | Random | 0.413 | 0.414 | 0.247 | 0.251 |
|                |      |      | Spatial | 0.412 | 0.413 | 0.244 | 0.245 |
|                |      |      | Random | 0.225 | 0.233 | 0.268 | 0.278 |
|                |      |      | Spatial | 0.227 | 0.234 | 0.258 | 0.273 |
| CNN            | Cross-country | Malawi | Random | 0.100 | 0.165 | 0.082 | 0.090 |
|                |      |      | Spatial | 0.098 | 0.169 | 0.100 | 0.124 |
|                |      |      | Random | 0.061 | 0.144 | 0.138 | 0.168 |
|                |      |      | Spatial | 0.099 | 0.151 | 0.137 | 0.162 |
The observed versus the predicted values are illustrated in Figure 2 with the associated prediction intervals. Malawi generally performed better in predicting cell phone adoption, whereas Ethiopia performed better in estimating the cost of phone services.

Figure 2 Observed versus predicted values by metric

Finally, prediction maps can be created from the results, as shown for Malawi in
Figure 3 at 10 km x 10 km spatial resolution. Evaluation of the spatial results are consistent with expectations. For example, the model estimates higher phone density in the capital Lilongwe in the mid-west area of Malawi, as well as in other populated areas such as Blantyre in the south east and Mzuzu in the north.
5. Limitations
There are two main limitations with the method, including (i) justifying results and (ii) the validation technique.

It is quite challenging to explain how a CNN arrives at a predicted result due to the vast quantity of parameters, and the size and structure of the network. Broadly speaking, lack of model interpretability has become an important inhibitor of widespread adaptation of deep learning methods. Activation maps have emerged as one way to interpret a CNN. The idea is simple – project areas on the image that are “activated” by the CNN onto the original image. This way, it is possible to visually inspect which parts of the image the CNN focuses on. By using activation maps we can evaluate the behavior and limitations of the CNN. One approach to create activation maps is guided backpropagation. This method passes an image through the CNN and performs backpropagation on the known target class.
At the first layer, we store the gradient with respect to each pixel in the image and remove those less than 0. Then, we plot a grayscale map of those gradients. They are the same shape as the original image, and the intensity corresponds to a stronger (positive) gradient. The reason we use a gradient approach is because backpropagation finds partial derivatives; a larger partial derivative can be thought of as a larger contribution.
Figure 4 activation maps are presented for three images, with the original satellite image on the left-hand side, and the activation map on the right hand side. In the top and middle images, we can see that the road network is able to be identified by the CNN. However, large bodies of water can produce strange results, an example being the top left of the top image, where a lake leads to activation of the CNN. Furthermore, in the bottom figure, where the image provider has accidentally inserted a nighttime image, the CNN is also activating. These activations occur in meaningless parts of the image and are much more prevalent than those in either of the two “good” images. As these observations are qualitative and require individual analysis, it is challenging to make a statement about the whole dataset of >20,000 images. Consequently, it is difficult to make a claim about the robustness and generalizability of the CNN itself beyond traditional model validation. However, this means that during application, there could be unpredictable, unexpected, and unexplainable behavior.
As for model validation, the two biggest constraints are the limited sample size and the long training time. In theory, 5-fold cross validation would be a good way to test generalization. However, two countries, two metrics, and five folds would mean training a CNN 20 times. Furthermore, instead of randomized cross-validation there is also spatial cross-validation which would make each fold contain
clusters that are geographically close. Consequently, each iteration of cross-validation would be testing generalization not only onto unseen clusters, but unseen geographic areas. This prevents the model from training on one cluster and validating on another nearby cluster (which likely has very similar metrics). The advantage of spatial cross-validation is that it more closely reflects the use case of applying the model to new regions. However, this would raise the number of CNN runs to 40. To maintain a reasonable number of training runs, a simple random 30% is held out for validation of single country models. The downside of this approach is that we do not get the numerical stability that comes with random cross-validation (averaging five results is much better than doing just one), and generalization onto new areas is not tested as thoroughly as could be with spatial cross-validation. Lastly, because the method only involves two countries further research needs to assess (i) how well the approach works when scaled to many countries, and (ii) what kind of training procedure and data quantity will be sufficient for cross-country generalization.

6. Discussion
This section returns the focus to the research question stated in the introduction:

*How effective are different techniques at predicting cell phone adoption metrics from satellite imagery, such as device penetration and monthly spending on telephone services?*

This paper demonstrated a machine learning approach for predicting spatially granular estimates for cell phone adoption with significant improvement over baseline modeling techniques. For example, population density is a common baseline model for predicting cell phone adoption metrics yet only captures 18% of the variance in the data in Malawi (Ethiopia being much worse). The use of nightlight luminosity was only marginally better at capturing just 20% of the variance in the best case. By contrast, the CNN method described in this paper captured 41% of the variance, twice as much as either baseline.

There are several key use cases for the high-resolution, accurate predictions generated by the method in the paper, primarily relating to national assessments. Firstly, international development institutions
can quantitatively identify underserved areas and more effectively design interventions for the billions of dollars they invest annually into digital development projects each year in support of the SDGs. Secondly, national and local governments, including telecommunication regulators, can access data which support policy decision making on the digital divide. A standard decision-making tool used in telecoms is the Long Run Incremental Cost (LRIC) model, which is usually spreadsheet-based and focused on modeling a ‘hypothetical operator’ with average characteristics (e.g. assets, spectrum portfolio, market share etc.). Many assumptions are often used in this approach, particularly relating to the number of cell phones in rural areas and the level of existing demand. Rather than using hypothetical data and assumptions, the method produced here can help to reduce this uncertainty, helping make more effective decisions.

Finally, Mobile Network Operators can gain an understanding of two key demand metrics (device penetration and cost per month, which can be also be thought of as average revenue per user) in green field areas where demand is unknown. One key advantage of this method is that it only utilizes satellite images which are globally available. Therefore, the method can be used in data limited locations where we have no cellphone records or electricity usage data. By solely using images, the method learns to associate levels of local development, with the availability of devices and the available consumer purchasing power to spend on phone services. Consequently, in an underserved area with little existing coverage, the method extrapolates its acquired understanding of the relationship between development and telecoms demand onto the new area. Thus, in an application context it does more than just predict existing device ownership and spending, but rather the general capability of residents to own devices and pay for service based on visual evidence alone using a widely available data source.

7. Conclusion
This paper assessed the effectiveness of different modeling methods at estimating essential cell phone metrics, such as phone adoption and the cost of service. A main finding is that baseline models
performed relatively poorly, predicting only a maximum of ~20% of the data variance, whereas the image recognition approach developed here was twice as effective, predicting up to 40% of the data variance. This is a significant improvement and demonstrates that this approach could be very useful at providing informative predictions that help quantify risk, increase investment, and ultimately reduce the digital divide.

The key contributions of the paper were threefold. Firstly, an accurate and validated method was provided that predicts telecoms demand metrics from satellite images. Secondly, there was a quantitative comparison of this method to existing methods. Finally, the codebase used for the analysis has been made open-source for other researchers and analysts to utilize, reproduce the results, and further develop the method via the online repository: Telecom Analytics for Demand using Deep Learning. Future research needs to be done to expand the assessment method to include other indicators necessary for achieving the SDGs and explore the application of the method to additional countries, including in high-income nations such as the USA.

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