Discussion of “A Blended Data Approach to Measuring Monthly Housing Starts”

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1. Introduction

For more than 50 years, sample surveys have been the primary foundation for the production of official statistics, not only in the U.S. but in many countries. In this era of big data, secondary data sources are increasingly available. These sources of existing data are not collected directly, but indirectly. Examples include cash register receipts, web-scraped information and, as is the focus for this discussion, remotely sensed data. Supplementing survey data with non-survey data or completely replacing surveys with non-survey data is a major effort throughout the Federal Statistical System.

Federal agencies have used remotely sensed data in an increasing number of ways, including assessing land use and changes in it (Wang et al. 2022), identifying what crops are grown where (Lark et al. 2021, Li et al. 2024), and disaster monitoring (Finco et al. 2012, Li 2023a, 2023b). Integrating remotely sensed data into the production of official statistics has been slower. The authors of this paper have made great strides in a direction that may not only provide solid benefits to the U.S. Census Bureau (Census) but also inspire others to make greater use of these data.

Research in federal statistical agencies focuses on the production of new methodology that improves the official statistics. What is needed to move this research, which is already producing an experimental product, into production? A few technical issues require additional consideration, but the greatest challenge is likely to be the cost of data acquisition and storage. The 50-centimeter (cm), high resolution satellite imagery used in this project is expensive, and it must be collected every month. Storage costs are also substantial. Thus, the key question that will be considered here is "What can be done to reduce data costs while either sustaining or improving accuracy of the estimates?"

In this discussion, a path to a potential answer to this question is considered. In the next section, the types of sensors and resolutions are briefly described. Whether costs can be reduced while maintaining the quality of the estimates by coupling a decrease in spatial resolution with an increase in temporal resolution and the methods needed in such an evolution are then explored in Section 3. Measuring uncertainty of the estimates is discussed in Section 4, and the final section provides additional thoughts and potential directions.

2. Background: Satellites, Resolutions, and Convolutional Neural Networks

Satellites have two basic types of sensors: optical (spectral) sensors and synthetic aperture radar (SAR) sensors. Optical images are much like digital photos taken by cameras (see Figure 1). The sensors capture the solar light reflected from Earth's surface and record it as the intensity of a set of bands of light. More precisely, a dedicated sensor channel or detector array is sensitive to a specific, limited range of wavelengths. A sensor may have multiple, separate channels to record data in different bands, such as red, green, blue, or near-infrared, simultaneously, and each channel is used to record the intensity of the wavelengths within a specific spectral band independently. As with cameras, optical images require daylight and cannot be recorded through clouds, smoke, or anything else obscuring the view of the Earth below.

In contrast, to collect a SAR image, radar signals are generated by on-board electronics and amplified by transmit/receive modules in the antenna, which emits microwave pulses toward Earth and measures the backscattered energy. SAR images can be collected day or night through clouds or smoke. Thus, SAR images are often used to assess the impacts of disasters such as floods, hurricanes, and forest fires. They are noisy, grayscale images (see Figure 1), which lack the clarity this project requires, making optical images the obvious choice.

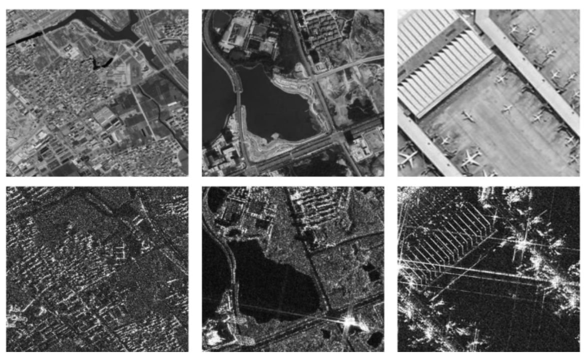

Figure 1 Optical (upper row) compared to SAR satellite images (bottom row). Source: Zhang, et al. 2025.

Three types of resolution are especially relevant to this project: spatial resolution, spectral resolution, and temporal resolution. A brief review of each will provide the foundation for the discussion of a potential approach to reducing costs. Each image is comprised of a matrix of pixels. The spatial resolution is the ground area covered by a single pixel. As an example, an image with a 10-meter (m) resolution is composed of pixels of size 10-m by 10-m, which is an area of 100 m^2. As the size of the pixels decrease, the spatial resolution becomes higher, and the image has finer detail (see Figure 2). In contrast, an image with lower resolution shows larger, less detailed areas, becoming blurry as the spatial resolution decreases. Identifying housing starts requires a high-resolution spatial imagery.

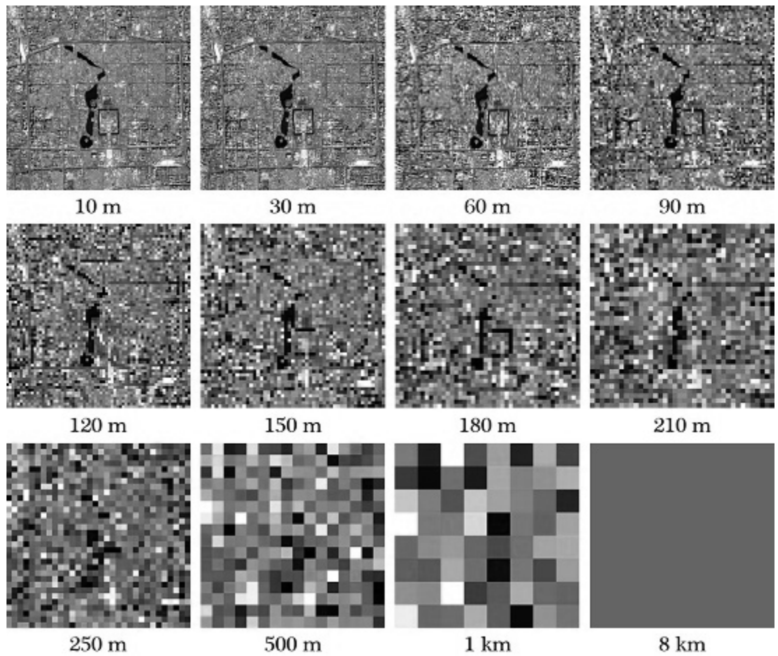

Figure 2. Effect of decreasing spatial resolution on satellite imagery. Source: Tian, et al. 2020.

Spectral resolution measures the width of the spectral bands and the number of different bands a sensor records. A higher (finer) spectral resolution involves more numerous, narrower bandwidths; a lower (coarser) spectral resolution comes from fewer, broader bandwidths. A panchromatic optical sensor has a high spatial resolution, single channel that captures total light intensity across a wide spectrum (visible to near-infrared), providing a sharp, black-and-white image. Multispectral optical sensors have a few, broad bands, and hyperspectral optical sensors have hundreds to thousands of very narrow contiguous bands. When an optical sensor has more than one channel and records a band on each, images can be constructed from a single band or multiple bands.

In Figure 3, a series of images from 4-m imagery illustrate the differences in the ability to discern the outline of the burn scar using either a single band or multiple bands (Pleniou and Koutsias 2025). Channel 4 provides the greatest discrimination of the single-band (red, green, blue (RGB) and near infrared) images. The color composite images, based on multiple channels, improve the separability between the burned areas and other land types; these distinctions are sharper when the images are colored. To use these three bandwidths associated with the three channels, the intensity of each of the three bandwidths must be recorded for each pixel in the image, which can quickly increase the space needed to store the image. Thus, if several bandwidths are available, time is spent to determine how many and which ones are needed to provide the spectral resolution required for the problem being studied.

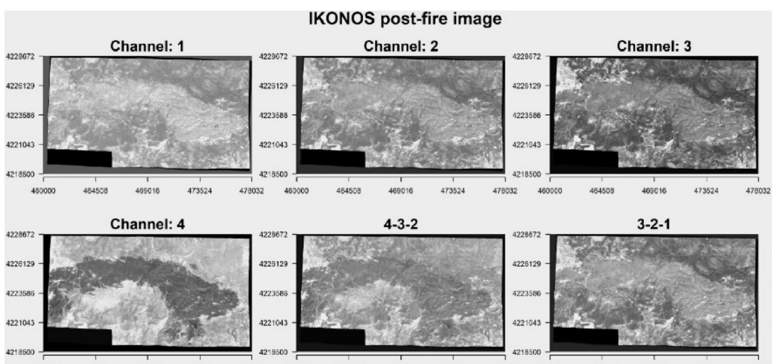

Figure 3. Comparison of single channels and two multiple channel images when identifying burn scar using 4m spatial imagery. The multi-channel images would typically be colored, which would provide additional clarity. Source: Pleniou and Koutsias, 2025.

Temporal resolution is the frequency with which the satellite sensor captures images at the same location. If the satellite revisits the same location every 10 days, it has a 10-day temporal resolution. Because optical sensors cannot record data at night or in the presence of clouds or smoke, a higher temporal resolution (shorter time between revisits) provides an opportunity to capture more clear images.

Convolution Neural Networks (CNNs) are a tool that is often employed for analyzing visual imagery. Applications include image classification (Chen et al. 2021), object detection in autonomous vehicles (Turay and Vladimirova 2022), crop disease detection (Ngugi et al. 2024), and medical image analysis, such as detecting cancer, tumors and other disease (Chen et al. 2025). The decision to use a CNN in combination with the Activation-U Architecture is certainly a reasonable one. The CNN model is applied to each month's data; the temporal nature of the data is not considered.

3. Moving from Research to Production

The data (satellite images for this project come from the Airbus Pléiades-1A satellite, which was launched in 2011. The available images are 50-cm panchromatic or 2-m multispectral. Four bands (RGB and near infrared) are available. The three RGB bands were used in this project. The temporal resolution is 26 days, which allows one pass during the project's monthly data collection window.

In the research phase, the highest spatial and spectral resolutions available and affordable are generally used because, if the study objectives cannot be met with the best possible data, then the overall approach needs to be reconsidered. Once the proof of concept has been established consideration of whether lower resolution imagery could be used is a natural progression, especially as an agency considers scaling from the study area to the national level. In Figure 4, images with spatial resolutions from 5 m to 30 cm illustrate the effect of increasing spatial resolution in a targeted study area. The higher resolution data facilitates identification of housing starts. The primary reason to consider lower resolution imagery is a reduction in costs, which will be substantial using the current 50-cm spatial resolution. If the spatial resolution could be decreased and the ability to identify housing starts maintained, both the costs of data acquisition and storage would be decreased. A reduction in the number of spectral bands would lead to a reduction in storage costs, though the savings would be less than that associated with reducing spatial resolution.

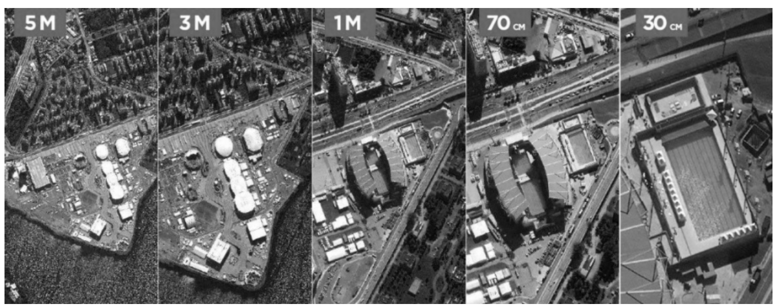

Figure 4. Increasingly high spatial resolution. Source: Geospatial Agency Innoter

Options are available for reducing the costs by purchasing lower resolution satellite imagery. Ideally, the imagery could be obtained without cost so this is explored first. Under a joint NASA and USGS initiative, the first Landsat satellite was launched in 1972. Landsat 8 and 9 are now providing 30-meter spatial imagery, which is freely available. The Landsat sensors have 11 spectral bands (visible, near infrared, and short-wave infrared), and the images have a 30-meter spatial resolution. Each Landsat has a temporal resolution of 16 days and, when combined, provide an 8-day temporal resolution. Although these are useful for many purposes, the 30-m resolution is too low for accurate identification of housing starts.

As part of the Copernicus program, the European Space Agency has funded the Sentinel satellites since 2014. Sentinel-1 offers SAR imagery with a spatial resolution as high as 5 m. However, as noted earlier, these noisy, grayscale, synthetic images do not provide the clarity required to identify housing starts. Sentinel-2 provides optical imagery with 13 spectral bands (visible, near infrared, and short-wave infrared). Only four bands (RGB and near infrared) have a 10-m spatial resolution; of the other bands, six have 20 m resolution and three have 60 m resolution. The Sentinel-2 spatial resolution is as high as 10 m, and the temporal resolution is 5 days. It is not evident that 10-m satellite imagery is fit-for-use for this project. If other information could be used with the 10-m resolution data, then it might be possible, and this potential should be explored.

In moving from 50-cm to 10-m spatial resolution, each side of a 10-m pixel would have twenty 50-cm pixels, leading to 400 50-cm pixels within each 10-m pixel. This reduction times the number of 10-m pixels in an image, which is billions for the continental U.S., would also lead to substantial savings in storage costs. Sentinel-2's 10-m resolution bands are the same (RGB and near infrared) as those from Airbus Pléiades-1A so it is assumed here the same three (RGB) would be used.

The need to detect change in remotely sensed images between two time periods arises in numerous applications, including identifying changes in land use and land cover (LULC) (Shi et al. 2022, urban expansion (Wang and Wu 2025), and natural disaster damage assessment (Brunner et al. 2010). Supervised change detection methods is a rapid area of research, which has led to the emergence of a large number of methods. Currently, the state-of-the art methods are deep learning methods that can be broadly categorized into two groups: CNN-based methods and Transformer-based methods (Chen et al. 2024, Lei et al. 2026). For this housing project, CNNs are likely to be preferred because they are better able to capture fine spatial structures and have inherent robustness to speckle noise. In a Siamese network, two identical CNNs, which share the same weights, extract features from two images taken at different time points and compare them to identify changed areas. With the Siamese network and a CNN, the Siamese weight-sharing encoders, which extract features, and a U-Net-based decoder structure, which provides localization, are a good architecture (Tang et al. 2024), though work in this area is rapidly evolving (Lei et al. 2026). The authors will likely want to review their choices of CNN model, network, and architecture periodically as they advance their work.

4. Measuring Uncertainty

The estimation process being adopted incorporates all available data in a statistically principled manner. The authors have identified key areas for further investigation, including imputation for missing data. As they noted, in deriving measures of uncertainty, the satellite data and values imputed for missing data are assumed to have no error, which is a reasonable assumption in the initial stages of research. However, these errors can be substantial. As an example, NASS creates the annual Cropland Data Layer, which is an annual map of where more than 110 crops are grown across the continental U.S. Substantial ground truth data are available for model development and assessment (Boryan et al. 2011). The accuracy can be above 95% for major crops, such as corn in a state within the Cornbelt, but is less for minor crops; the overall accuracy has historically been at least 75%. Propagating these errors through a specific application is challenging.

As the methods are matured for this application, additional sources of uncertainty can be incorporated into the estimation process over time. To illustrate, when the USDA National Agricultural Statistics Service first began using models as the foundation of estimates for the Census of Agriculture, the first measures of uncertainty reported for the 2012 Census only included model error. In 2017, the uncertainties due to estimation of the model parameters and to calibration were added. In 2022, the error due to model selection was also included in the reported measures of uncertainty. A similar approach could be adopted here.

5. Further Discussion

The advent of Generative (Gen) AI has had an impact on numerous areas, including remote sensing. Generative Adversarial Networks (GANs) have been used to increase the spatial resolution, such as upscaling 10-m resolution images to near 1-m resolution images (Li et al. 2024). If the 10-m remotely sensed images from the Sentinel-2 satellite do not have a sufficiently high resolution even when incorporating a temporal component, it may be worth exploring whether a GAN can be used to develop 1-m resolution images derived from the 10-m publicly available ones that would support the identification of housing starts. If so, Census could derive substantial savings from using the free 10-m imagery, though the storage costs would not be lowered.

GANs and denoising diffusion models have been developed for cloud removal in satellite imagery (Edirisinghe et al. 2026). Diffusion methods have been found to provide superior spatial and structural fidelity due to iterative noise reduction. Integrating SAR imagery or other auxiliary data can enhance cloud removal accuracy. This is another area of active research that may be useful to this project.

In summary, this is a very nice application with the potential to save large amounts of time and hence money. The primary challenge in moving this project from research to production is likely to be the costs of data acquisition and storage as the work must be scaled to the national level. Considering the best combination of temporal and spatial resolutions may serve as an approach for reducing the costs by moving toward lower spatial resolution while increasing the temporal resolution in the models. This is an exciting area of research with many new developments on the horizon and a wonderful use case that illustrates the potential value of remotely sensed data in the production of federal statistics.

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