WORKING PAPER

Localizing the SDG Index with machine learning and satellite imagery

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This working paper builds on research conducted at the SDG Transformation Center, on SDG indicator reporting and how neural networks and remote sensing can be used to downscale the SDG Index to municipality level with worldwide coverage.

Abstract

Progress towards the SDGs has been slow, and significant data gaps hinder the ability to track SDG performance, particularly at the local level. The SDG Transformation Center addresses these gaps by generating new geospatial datasets and refining existing indicators to better capture regional and demographic disparities. Using artificial neural networks and high-resolution satellite imagery, we built on existing methodologies to downscale SDG Index scores from national to subnational levels. This model helps to identify aggregation biases in national SDG indicators, revealing that nearly 43% of the global population may be overlooked when only national averages are considered. Country-specific subnational analyses highlight disparities in SDG progress, especially between urban centers and rural regions. While these findings provide valuable insights, future efforts should focus on refining the model with locally validated SDG data to further improve accuracy and support evidence-based, geographically targeted policies for sustainable development.

Background

The **Sustainable Development Goals** (SDGs) adopted in 2015 by all UN member states and oriented toward 2030 provide an integrated vision to address the triple bottom line of sustainable development: economic, social and environmental development.

Almost ten years after their adoption, the world is not on track to achieving the SDGs (Sachs et al., 2024). Positive and measurable progress was made only on a small fraction of the SDG indicators, mainly related to basic access to services and infrastructure. Moreover, there are persisting data gaps that must be addressed to advance evidence-based policy for the SDGs (Goessmann, 2023).

The SDG Transformation Center is committed to bridging this data gap by producing new datasets for geospatial indicators and localizing existing ones. Throughout the years, working locally with university partners all over the world, the SDSN has documented SDG gaps and progress at the state, province and city level (i.e. Andersen et al., 2020; Cavalli et al., 2020; Cods, 2020; Espey et al., 2018; Fuller et al., 2021; ICS & SDSN, 2021; IDB & SDSN, 2021; Massa et al., 2024; REDS, 2020; Zakzak et al., 2023). Spatially disaggregated data allows us to look at countries not only as a whole, but as the sum of its parts. All communities, including indigenous and historically marginalized populations, must meet SDG goals to ensure that no one gets left behind.

In this working paper, we look at how to ensure no one is left behind by reducing **aggregation bias**[1] in national SDG indicator scores. For instance, a country as a whole can achieve several SDG targets. However, upon analyzing demographic and location-specific information, one might discover certain subgroups experiencing various forms of societal, environmental, and economic inequities. These **disparities** - which can encompass issues such as poverty, hunger, gender disparities, deterioration of land, and detrimental air and water conditions - can affect particular populations,who might get overshadowed when we take a country's aggregated average for SDG indicators.

Disaggregated data is a key component for the development of localized assessments and local implementation strategies of the SDGs. They often take the form of a **Voluntary Local Reviews** (VLRs), a process through which subnational Governments undertake a voluntary review of their progress towards delivering the 2030 Agenda and the SDGs. As of October 2024, there are 223 VLRs compiled by UN DESA (UN DESA, 2024). Yet, in many cases, **no VLR nor local data are available**, making it hard to assess localized SDG performance. Here we explore possibilities for estimating localized scores by looking into new and emerging technologies that mix **artificial neural networks and high resolution satellite imagery**.

Artificial neural networks, satellite imagery, and the MOSAIKS approach

In order to estimate SDG performance at province and municipality level, we replicate the work described by Sherman and colleagues (2023), where a method is proposed for downscaling Human Development Index (HDI) observations at **ADMIN0** (country) and **ADMIN1 levels** (state, region or province) into **ADMIN2 level** (municipality, county or borough) and a regular 0.01º grid estimates.

Their model works by taking a freely available yearly basemap (that is, a mosaic of high resolution satellite imagery representative of the chosen year of reference of 2019) by Planet and processing it through the **MOSAIKS** approach.

[1] Aggregation bias is a common problem in statistical analysis that can lead to misleading results. This bias occurs when data is aggregated at a higher level than the unit of analysis, resulting in a loss of information and potentially biased estimates.

The algorithms in MOSAIKS automatically classify patterns seen in the images into 4,000 types of features (such as residential buildings, forests, crop fields, coal mines, etc.). The proportion in which these features are seen is computed into ADMIN0, 1 and 2 divisions. By comparing these proportions to actual HDI observations— available at ADMIN0 and 1 levels—, a **neural network model** is trained. This model understands the relationships between HDI scores and the prevalence of different combinations of the over 4,000 types of features extracted from the satellite images. It can then be used to predict values for geographies for which it knows the distribution of spatial features, but not the HDI score—which is the case for all ADMIN2 level boundaries.

Like in most machine learning algorithms, the model's accuracy is assessed by taking the original observations dataset (at ADMIN0 and 1 levels), **dividing it into two subsets** (training and test), and checking how close the results obtained with the training dataset are from the test subset. The correlation coefficient squared (R^2) produced by that regression in the original paper is **0.84**, meaning that the model was successful in **correctly fitting the HDI scores at ADMIN1 level** (Scherman et al. 2023).

Localizing the SDG index

The SDG Index, part of the annual Sustainable Development Report, ranks countries based on their performance across the 17 goals. The Index is a normalized 0 to 100 score that takes the average value from each indicator in each goal. The SDR also features the **Spillover Index**, which assesses how each country's actions can have positive or negative effects on other countries' abilities to achieve the SDGs. Such spillovers are measured along three dimensions: environmental & social impacts embodied into trade, economy & finance, and security. A higher score means that a country causes more positive and fewer negative spillover effects.

In this exercise, we assumed that the **expected variation** in the **SDG and Spillover Indices** should be somewhat similar to that seen in the Human Development Index, as we move to more localized levels. We use **the model trained with the HDI scores** in order to downscale the country scores to ADMIN 1 and 2 levels.

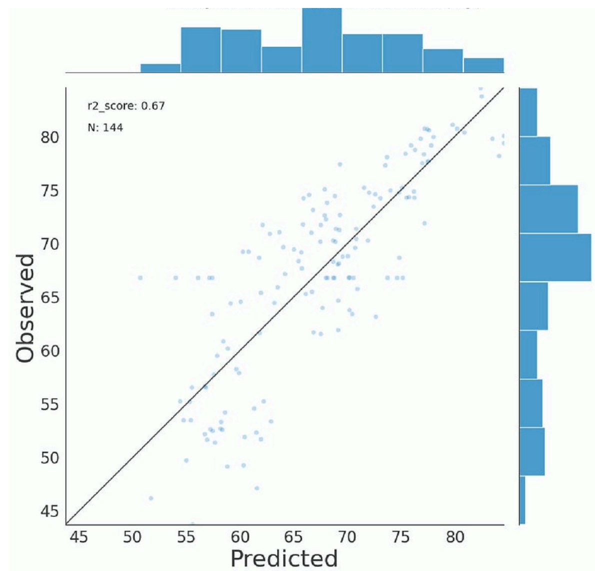

Figure 1 Regression lines comparing training and test subsets for the SDG index at country level.

Data engineering adjustments were necessary in order to adapt the scripts to run these models for the SDG and Spillover indexes. The code is written in python, and uses *sklearn*[2] to handle the neural networks. We assessed the model's accuracy by running the model with a training subset and comparing results with the test subset. The correlations (R^2) for the SDG and Spillover indices are **0.67 and 0.56**. As expected, coefficients are lower than the one from the original study, since the model was trained with HDI scores.

Figure 2 showcases maps with the original 2020 SDG Index scores at ADMIN0 level and the results at ADMIN1 and ADMIN2 scales.

[2] Scikit-learn (sklearn) is a machine learning and data modeling library for Python, featuring classification, regression and clustering algorithms.

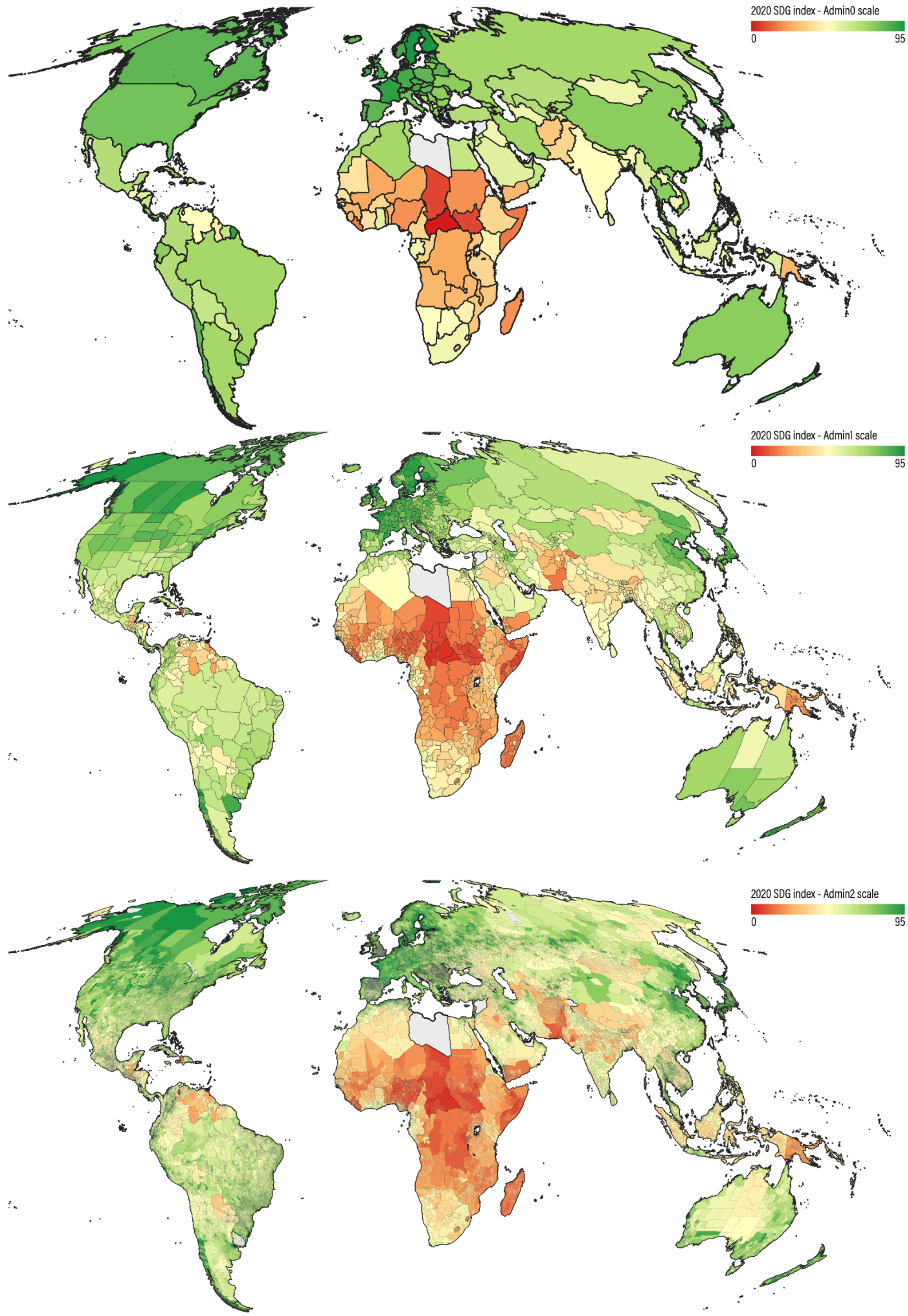

Figure 2 Three world maps showcasing the 2020 observed SDG Index, and the predicted downscaled scores at ADMIN1 and 2 levels.

Key insights

Although results are revealing, they should only be used in an indicative way. While we cannot be certain that the scores at subnational levels are correct, they give us a good sense of how many people we might be ***leaving behind*** when reporting and making decisions looking solely at national-level maps.

The results indicate that **43% of the global population**, which represents **41% of all municipalities**, had been assigned to a different SDG Index quartile than the one predicted, due to aggregation bias resulting from lower resolution estimates (see Figure 3).

Countries presenting higher predicted scores at municipality level than those observed at country level include Argentina—where several '*partidos*' have shown score differences as large as 26 points—, Russia, the United States and the United Kingdom.

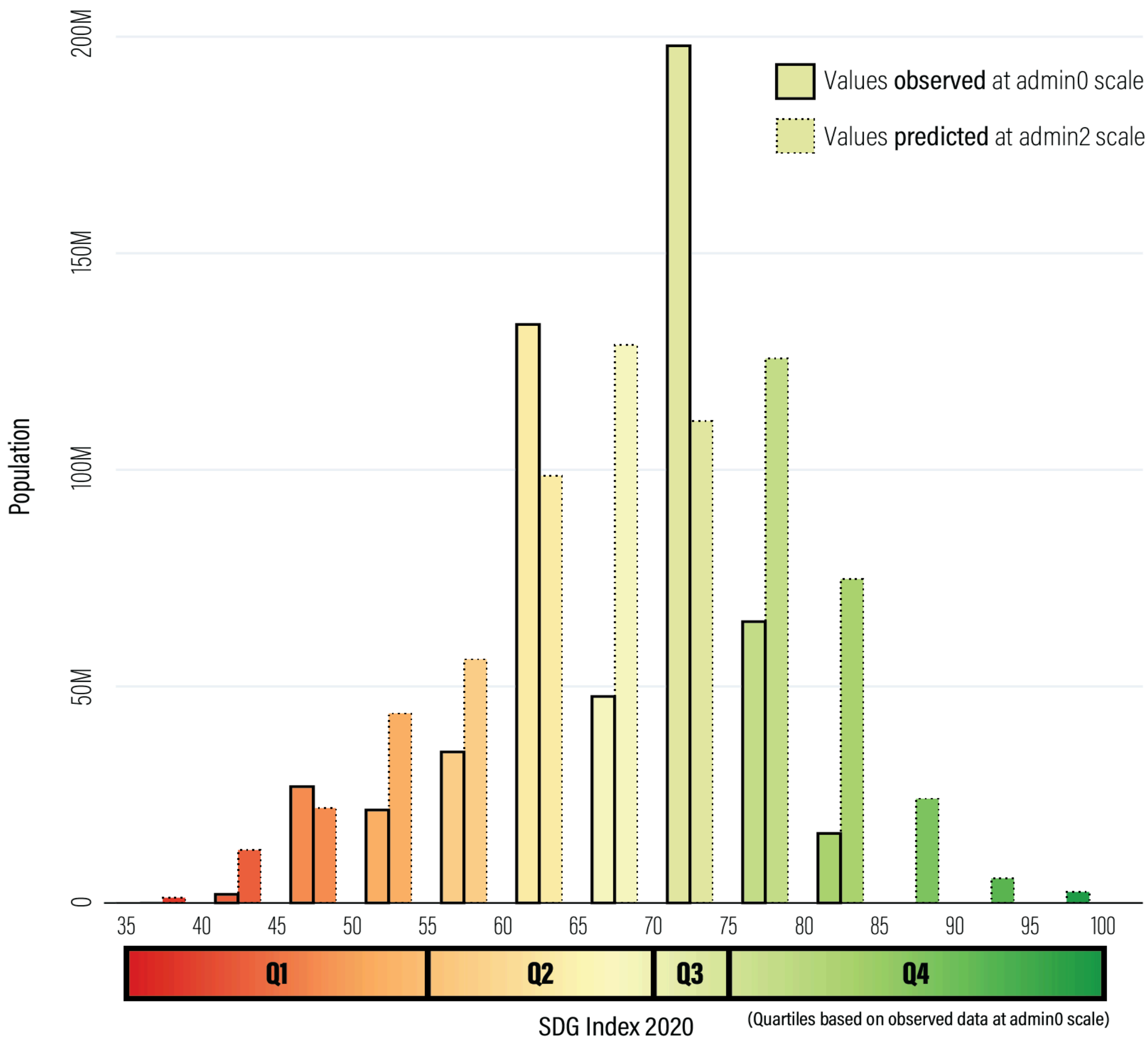

Figure 3 Changes in population distribution in each quartile according to the observed and predicted datasets.

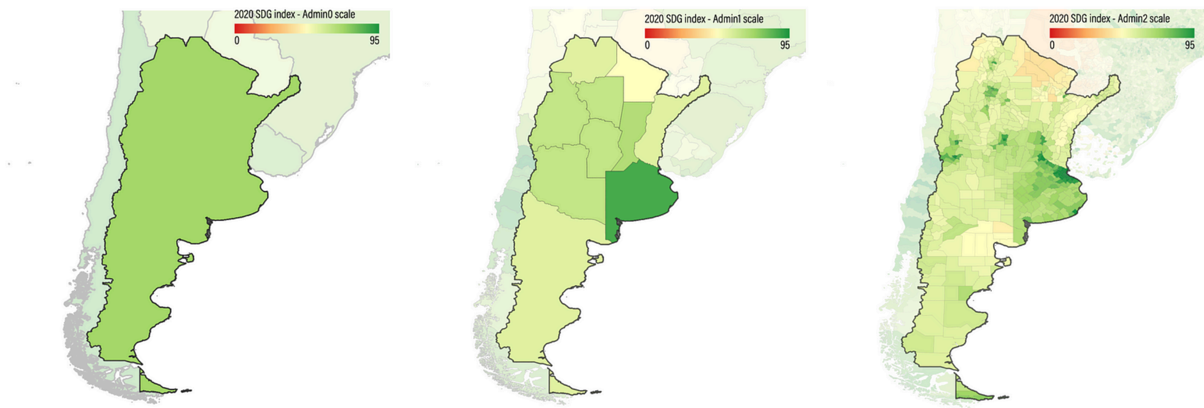

Figure 4 Downscaling of the SDG Index in Argentina. As the resolution gets higher, the more one can see higher scores around the capital Buenos Aires.

To an extent, the aggregation bias can *still* be perceived in the provincial level (ADMIN 1) estimates, where the divide between wealthier city centers and poorer suburbs of capital cities can't be seen like they are in the municipal level maps.

Another identified pattern for several countries shows that the SDG Index tends to be higher in coastal areas and in regions along rivers and other water sources, while deserts and inland areas display significantly lower scores.

Limitations and future developments

While the main goal in performing this operation is to reduce aggregation bias, there's a potential ecological fallacy effect to these results. An **ecological fallacy** occurs when inferences about the nature of individuals are deduced from inferences about the group to which those individuals belong. In the MOSAIKS method, the processed satellite imagery is used to deviate the subdivisions' scores positively or negatively based on the initial national score. This is done in order to honor hierarchy, so that sub-national results are not too far-off from the country's score.

A particular limitation to this implementation is that a model trained with HDI scores was used in order to estimate SDG Index score variation. A possible future development would be training the classifier with SDG Index scores from the SDG Transformation Center's subnational reports, such as the USA, Paraguay, Uruguay, Brazil and Benin.

Local and regional governments are the tier of governance closest to local communities, able to better **understand their needs and priorities**, and to **better address policymaking**. Our results can be used to conduct simulation exercises to explore how geographically targeted policies based on national vs municipal SDG data might achieve different outcomes to better deliver essential public services and act as catalysts for transformative change.

Results and methods presented here may also inform and learn from research on policy bottlenecks at the regional and city level, another of the SDG Transformation Center's fields of expertise. Examples of works with great alignment with this theme are: a survey conducted in 2024 by the SDSN, OECD and Committee of the Regions with regional and local leaders, which aimed to understand how the SDGs were used as a policy and monitoring framework and understand the main barriers for implementation (OECD, 2024); and the SDSN Global Commission for Urban SDG Finance, set up in June 2023, which provides actionable recommendations for how cities can obtain more and better financing for projects that contribute to achieving the SDGs (SDSN, 2024).

Finally, other datasets can be leveraged as a source of granular data used to train the model, beyond simple raw satellite imagery. Recent studies conducted at the SDSN have looked at providing spatially explicit distribution of land use change, deforestation drivers and the linkage of these phenomena with global supply chains (Iablonovski et al., 2024). If this is used as a proxy, better fit models can be trained to understand the spatial distribution of the Spillover Index.

Strengthening the integration of low resolution and geospatially explicit information into SDG financing and public policy pathways will remain an important research area for the SDG Transformation Center in the coming years.

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