

Local GDP Estimates Around the World*

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Online Appendix

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1 Details of Data Source

1.1 GIS data

- Worldwide country level, province-equivalent level and county-equivalent level maps in Geopackage (“gpkg”) format are downloaded from GADM version 4.1 “geopackage” action in the sentence “You can also download this version as six separate layers (one for each level of subdivision/aggregation), as a geopackage database” from the following website: https://gadm.org/download_world.html. Save the downloaded file with the name “gadm_410–levels.gpkg” in the folder “step1_obtain_gis_data/inputs/CGAZ_ADM1/”.
- Another version of the province-level geometry file is the CGAZ dataset. Download “ADM1” global map in “geojson” format from the website: <https://www.geoboundaries.org/globalDownloads.html> (Runfola et al., 2020). Save the downloaded file with the name “geoBoundariesCGAZ_ADM1.geojson” in the folder “step1_obtain_gis_data/inputs/CGAZ_ADM1/”.
- Worldwide large lakes are excluded from the maps. The data used are “Global Lakes and Wetlands Database: Large Lake Polygons (Level 1)” from the website: <https://www.worldwildlife.org/publications/global-lakes-and-wetlands-database-large-lake-polygons-level-1> (Lehner and Döll, 2004). One with higher computer resources can even exclude permanent open water bodies with a surface area greater and equal to 0.1 km^2 and wetlands using other types of data from the website: <https://www.worldwildlife.org/pages/global-lakes-and-wetlands-database>. Save the downloaded files with filenames starting with “glwd_1.xxx” in the folder “step1_obtain_gis_data/inputs/large_inland_waters_geom_GLWD_level1/”.
- We also need the spatial data from the paper named “DOSE – Global data set of reported sub-national economic output” (Wenz et al., 2023). Use the link: <https://doi.org/10.5281/zenodo.7659599> and download the files from the folder “DOSE replication files/Data/spatial data/”. We also need to download files from https://gadm.org/download_world36.html by clicking the action “shapefiles” in the sentence “You can also download this version as six separate layers (one for each level of subdivision/aggregation), as a geopackage database or as shapefiles). Save the downloaded files in the folder “step1_obtain_gis_data/inputs/DOSE_spatial_data/”.
- China city level geometry shape files are downloaded from the website: <https://github.com/GaryBikini/ChinaAdminDivisonSHP> (GaryBikini, 2024). Download all files in the folder named “3.City”. Save the downloaded files in the folder “step1_obtain_gis_data/inputs/china_city/”.

1.2 GDP data

1.2.1 Regional GDP data

Table 1 lists the sources of regional GDP data by country. Table 2 lists countries in the training sample and their average area of regional units used to construct cell-level GDP data for model training. If a country is included in the training sample, the most granular administrative level data collected are used to construct the cell-level GDP. The following details provide information on where to find the regional GDP datasets referenced in Table 1:

- Obtain data from “DOSE – Global data set of reported sub-national economic output” (Wenz et al., 2023):
 - Click link <https://zenodo.org/records/13773040>, which is their paper’s recommended data download link
 - Download the file “DOSE_V2.11.csv”, and save it to folder “step2_obtain_gdp_data/inputs/gdp_data/regional/DOSE/”
- Obtain data from OECD iLibrary - Regional economy¹ (OECD, 2024b):
 - Click link https://www.oecd-ilibrary.org/urban-rural-and-regional-development/data/oecd-regional-statistics_region-data-en#archive, which refers to OECD iLibrary - OECD Regional Statistics
 - Click the “Archive 2023” under the “Datasets Archives”
 - Click the “csv” bottom beside “Regional economy (Edition 2023)”
 - Save the file with the name “REGION_ECONOM–2023–1–EN–20240216T100059_2.csv” to folder “step2_obtain_gdp_data/inputs/gdp_data/regional/oecd/”
 - Please note that for the following countries: “AUT”, “BEL”, “CAN”, “CHL”, “DNK”, “ESP”, “FIN”, “FRA”, “GBR”, “HUN”, “ITA”, “LVA”, “NLD”, “NOR”, “PRT”, “ROU”, and “SWE”, the OECD provides some unregionalized data. We have removed this unregionalized data and rescaled the regional data to align with national GDP data from the World Bank or IMF.
- Obtain data from “OECD Data Explorer - Regions”² (OECD, 2024a):
 - Use the link <https://data-explorer.oecd.org/>, which refers to OECD Data Explorer main page.
 - Click “Regions” under “Regions, cities and local areas”
 - Choose the dataset “Gross domestic product - Regions”

¹This dataset will also not be updated; therefore, we only retrieve data for the years 2012–2020. Data from 2021 and 2022 should be obtained from “OECD Data Explorer - Regions”.

²The data was downloaded on Sept 22, 2025, and may have been updated since. For replication, the latest files should be downloaded, and the corresponding R scripts must be updated to process the new data correctly.

- Click “Download / Unfiltered data in tabular text (CSV)”, and save the file with the name “OECD.CFE.EDS,DSD_REG_ECO@DF_GDP,2.0+all.csv” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/oecd/”
- Also click “OECD Territorial correspondence table (xlsx)” , and save the file with the name “OECD Territorial correspondence – TL2021.xlsx” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/oecd/”. We need this file to understand the heritage relationships between different id names.
- Obtain Russia’s regional data after 2019³ (*Russian Statistical Yearbook 2022*; *Russian Statistical Yearbook 2023*):
 - Click the website link <https://eng.rosstat.gov.ru/Publications/document/74811>, which refers to Russian Statistical Yearbook
 - Download the “Russian Statistical Yearbook 2023” and “Russian Statistical Yearbook 2022” in “RAR” format. Downloading the “pdf” format is also acceptable because we have to manually collect the data. Save the folders with name “russian_statistical_yearbook_20xx” in the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/RUS/”
 - Match the regions’ names from the yearbooks with OECD’s definitions of id names. Follow the matches in the file “RUS.xlsx” in the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/RUS/”. When updating to new years, add the new data to the file “RUS.xlsx”.
- Obtain Brazil’s regional data in 2021 and 2022 (Geografia e Estatística (IBGE), 2024):⁴
 - Click the website link <https://www.ibge.gov.br/en/statistics/economic/national-accounts/16855-regional-accounts-of-brazil.html>, which refers to the dataset “SCR - System of Regional Accounts” on the Instituto Brasileiro de Geografia e Estatística (IBGE)
 - Download the “xls” file for the “GDP under the point of view of Production (2010-2022)”. Save the file with the name “PIB_Otica_Renda_UF.xls” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/BRA/”.
- Obtain China’s regional data (Statistics of China, 2024):
 - Click the website link <https://data.stats.gov.cn/english/index.htm>, which refers to the main page of National Bureau of Statistics of China.
 - Click “Regional / Annual by Province” and choose the following:

³Russia’s regional GDP data for 2012-2019 are obtained directly from “OECD iLibrary - Regional economy” as described above. Since the OECD no longer updates Russia’s data, regional GDP data for future years must be obtained from alternative sources.

⁴As of the OECD data download date (Sept 22, 2025), Brazil’s regional data had not yet been updated. If, during future updates, OECD publishes Brazil’s province data, this step can be skipped by directly downloading the updated data using the same procedure as for the “OECD Data Explorer.” This step serves as a backup in case Brazil’s data remains unpublished.

- * Year: LATEST20
- * Indicators: Gross
- Download the “xls” format and save it with the name “AnnualbyProvince.xls” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/CHN/”.
- Obtain India’s regional data (India, 2023):
 - Use the website link <https://www.rbi.org.in/Scripts/AnnualPublications.aspx?head=Handbook%20of%20Statistics%20on%20Indian%20States>, which refers to the “Handbook of Statistics of Indian States” on the Reserve Bank of India.
 - Choose the year 2024, download the excel format of “Table 27: Gross State Domestic Product (Current Prices)” and save the file with the name “T28_09122024E699603AE68F445FB6E485839CCB697B.XLSX” in the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/IND/”.
- Obtain Kazakhstan’s regional data (National Statistics Agency for Strategic Planning and Republic of Kazakhstan, 2023):
 - Use the link <https://stat.gov.kz/en/industries/economy/national-accounts/>, which refers to the datasets of “Statistics of national accounts” on the Bureau of National Statistics Agency for Strategic Planning and Reforms of the Republic of Kazakhstan.
 - Find the “Gross regional product”, scroll down, and find the “Gross regional product” under the section of “Dynamic tables”. Download the file and save it with the name “1. Gross regional product.xlsx” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/KAZ/”.
- Obtain USA’s regional data (Economic Analysis U.S. Department of Commerce, 2023):
 - Use the link https://apps.bea.gov/histdatacore/Regional_Accounts_new.html, which refers to the “Regional Economic Accounts - Previously Published Estimates” of the Bureau of Economic Analysis U.S. Department of Commerce.
 - Click “Gross Domestic Product by County and Metro Area / December 7, 2023 / CAGDP2: GDP in Current Dollars by County and MSA”. Download the folder and save it with the name “CAGDP2” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/USA/”.
- Obtain Philippine’s regional data (Authority, 2023):
 - Use the link <https://psa.gov.ph/statistics/grdp/data-series>, which refers to the dataset “GRDP Data Series” on the Philippine Statistics Authority
 - Find the “2000-2024 Gross Regional Domestic Product” in the “Title” section. Download the file “GRDP by Region” and save it with the name “GRDP_Reg_2018PSNA_2000–2023.xlsx” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/PHL/”.

- Obtain Kyrgyzstan’s regional data (Kyrgyz Republic, 2023):
 - Use the link <https://www.stat.kg/en/statistics/nacionalnye-scheta/>, which refers to the dataset “National accounts” on the National Statistical Committee of the Kyrgyz Republic.
 - Download the file “1.01.00.09 Gross regional product (GRP) at current prices” under the section “Dynamic tables”. Save the file with the name “1.01.00.09 Валовой региональный продукт (ВРП) в текущих ценах.xlsx” to the folder “step2_obtain_gdp_data/inputs/gdp_data/regional/KGZ/”.

Table 1: Regional GDP data source by country

ISO	Available Years	Data Level	Source	Date
ALB	2012-2019	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
AUS	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
AUT	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
BEL	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
BGR	2012-2020	Second, Third	OECD iLibrary - Regional economy (2012-2020);	Sept 22nd, 2025
BIH	2012-2019	Second	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
BLR	2012-2019	Second	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
BRA	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); Instituto Brasileiro de Geografia e Estatística - System of Regional Accounts (2021-2022)	Sept 22nd, 2025

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Table 1: Regional GDP data source by country (Continued)

ISO	Available Years	Data Level	Source	Date
CAN	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
CHE	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
CHL	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
CHN	2012-2022	Second	National Bureau of Statistics of China - Regional - Annual by province	Sept 22nd, 2025
COL	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
CZE	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
DEU	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
DNK	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
ECU	2012-2019	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
ESP	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
EST	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025

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Table 1: Regional GDP data source by country (Continued)

ISO	Available Years	Data Level	Source	Date
FIN	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
FRA	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
GBR	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
GRC	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
HRV	2012-2020	Second, Third	OECD iLibrary - Regional economy (2012-2020);	Sept 22nd, 2025
HUN	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
IDN	2012-2020	Second	OECD iLibrary - Regional economy (2012-2020)	Sept 22nd, 2025
IND	2012-2022	Second	Reserve Bank of India - Handbook of Statistics on Indian States (2012-2022)	Sept 22nd, 2025
IRL	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
ISL	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
ISR	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025

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Table 1: Regional GDP data source by country (Continued)

ISO	Available Years	Data Level	Source	Date
ITA	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
JPN	2012-2021	Second	OECD iLibrary - Regional economy (2012-2019); OECD Data Explorer - Regions (2020-2021)	Sept 22nd, 2025
KAZ	2012-2022	Third	National Statistics Agency for Strategic Planning and Republic of Kazakhstan	Sept 22nd, 2025
KEN	2013-2017	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
KGZ	2012-2022	Third	National Statistical Committee of the Kyrgyz Republic	Sept 22nd, 2025
KOR	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
LKA	2013-2019	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
LTU	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
LUX	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
LVA	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
MEX	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020); Instituto Nacional de Estadística y Geografía - National Accounts System (2021-2022)	Sept 22nd, 2025
MOZ	2012-2019	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025

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Table 1: Regional GDP data source by country (Continued)

ISO	Available Years	Data Level	Source	Date
NLD	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
NOR	2012-2021	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021)	Sept 22nd, 2025
NZL	2012-2022	Second	OECD iLibrary - Regional economy (2012-2020) OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
PER	2012-2020	Second	OECD iLibrary - Regional economy (2012-2020)	Sept 22nd, 2025
PHL	2012-2022	Second	Philippine Statistics Authority	Sept 22nd, 2025
POL	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
PRT	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
ROU	2012-2020	Second, Third	OECD iLibrary - Regional economy (2012-2020)	Sept 22nd, 2025
RUS	2012-2022	Second	OECD iLibrary - Regional economy (2012-2019); Federal State Statistics Service - Russian Statistical Yearbook (2020-2022)	Sept 22nd, 2025
SRB	2012-2018	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
SVK	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
SVN	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025

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Table 1: Regional GDP data source by country (Continued)

ISO	Available Years	Data Level	Source	Date
SWE	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
THA	2014-2018	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
TUR	2012-2022	Second, Third	OECD iLibrary - Regional economy (2012-2020); OECD Data Explorer - Regions (2021-2022)	Sept 22nd, 2025
USA	2012-2022	Second, Third	Bureau of Economic Analysis - Regional Economic Accounts	Sept 22nd, 2025
UZB	2012-2019	Second	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025
VNM	2012-2018	Third	DOSE – Global data set of reported sub-national economic output	Sept 22nd, 2025

1.2.2 National GDP data

Table 3 lists the sources of national GDP data by country. The following details provide information on where to find the national GDP datasets referenced in Table 3:

- Obtain data from World Bank (Bank, 2024d; Bank, 2024c; Bank, 2024b; Bank, 2024a):
 - Click link <https://data.worldbank.org/indicator/SP.POP.TOTL> for World Bank Population dataset with file name “API_SP.POP.TOTL_DS2_en_excel_v2_19296.xls”; link <https://data.worldbank.org/indicator/NY.GDP.MKTP.CD> for World Bank GDP in current US\$ with file name “API_NY.GDP.MKTP.CD_DS2_en_excel_v2_19310.xls”; link <https://data.worldbank.org/indicator/NY.GDP.MKTP.PP.CD> for World Bank GDP in current PPP adjusted international\$ with file name “API_NY.GDP.MKTP.PP.CD_DS2_en_excel_v2_19548.xls”; link <https://data.worldbank.org/indicator/NY.GDP.MKTP.PP.KD> for World Bank GDP in constant 2021 PPP adjusted international\$ with file name “API_NY.GDP.MKTP.PP.KD_DS2_en_excel_v2_20528.xls”.
 - Download as “Excel” files and save it in the corresponding folders in “step2_obtain_gdp_data/inputs/gdp_data/national/world_bank_data/xxx”.
- Obtain the “Annual Index Value” data from US Census Bureau (Bureau, 2024):

Table 2: Average area of subnational units used for constructing cell-level GDP data by country

Developed Country	Average Subnational Area (km ²)	Developing Country	Average Subnational Area (km ²)
AUT	2383	ALB	2353
BEL	695	BIH	16988
BGR	3961	BLR	34328
CHE	1548	CHL	48669
CZE	5618	COL	34504
DEU	887	ECU	10695
DNK	3894	IDN	55053
ESP	8548	KEN	12276
EST	8641	KGZ	21134
FIN	16717	LKA	7314
FRA	6305	MOZ	70691
GBR	1356	PER	51699
GRC	2524	PHL	17006
HRV	2667	SRB	3122
HUN	4607	THA	6652
ITA	2756	UZB	29715
JPN	7832	VNM	5240
KOR	5635		
LTU	6459		
LVA	10699		
NLD	877		
NOR	29668		
NZL	21908		
POL	4254		
PRT	3668		
ROU	5642		
SWE	20600		
SVK	6107		
SVN	1692		
TUR	9500		
USA	2514		

- Use the link <https://www.census.gov/en.html>, which refers to main page of United States Census Bureau.
- Click “Topics / Income and Poverty / Income / Guidance for Data Users / Current versus Constant (or Real) Dollars”.
- Download the excel file “Annual Index Value and Annual Percent Change in Price Series: 1947 to 2023” and save it to the folder “step2_obtain_gdp_data/inputs/gdp_data/national/US_census_bureau_data”.

- Obtain data from IMF - WEO (Fund, 2024):⁵
 - Use the link <https://www.imf.org/en/Publications/SPROLLS/world-economic-outlook-databases#sort=%40imfdate%20descending>, which refers to the World Economic Outlook Databases (WEO) in International Monetary Fund (IMF).
 - Choose “World Economic Outlook Database, April 2025”. Click “By Countries / ALL COUNTRIES / Continue”.
 - Choose datasets “Gross domestic product, current prices U.S. DOLLARS”, “Gross domestic product, current prices PURCHASING POWER PARITY; INTERNATIONAL DOLLARS”, “Gross domestic product per capita, constant prices PURCHASING POWER PARITY; 2021 INTERNATIONAL DOLLARS”, and “Population PERSONS”.
 - Click “Continue” and choose “2012” as “Start Year”, “2022” as “End Year”. Click “ISO Alpha-3 Code”.
 - Download the file and save the file with name “WEO_Data.xlsx” in the folder “step2_obtain_gdp_data/inputs/gdp_data/national/IMF_data”.
- Obtain data from UNdata (UNdata, 2024):
 - Use the link <https://data.un.org/Data.aspx?q=gdp&d=SNAAMA&f=grID%3a101%3bcurrID%3aUSD%3bpcFlag%3a1#SNAAMA>, which refers to the dataset “Per capita GDP at current prices - US dollars” in UNdata.
 - Choose “Cuba”, “Democratic People’s Republic of Korea”, “Eritrea”, and years 2012 to 2023.
 - Download the files in csv format, value separated in comma. Save it with the name “UNdata_Export_20250426_211303453.csv” to the folder “step2_obtain_gdp_data/inputs/gdp_data/national/UN_data”.

⁵The primary data source is the IMF, as it converts GDP reported on a fiscal year basis into a calendar year format, aligning with predictors that are primarily satellite-based. When updating to future years, care must be taken in selecting the dataset’s end year, as some entries may be estimates rather than actual values. Additionally, note that data for certain countries may change during updates.

Table 3: National GDP and population data source by country

ISO	Data	Source	Date Retrieved
BMU, CYM, CUW, GRL, KXK, LIE, MCO, SXM, SYR, TCA, PSE	Population	World Bank - Population	Sept 15th, 2025
	GDP in current US dollars	World Bank - GDP (current US\$)	Sept 15th, 2025
	GDP in constant 2021 US dollars	Calculated using World Bank - GDP (current US\$) and Annual Index Value from US Census Bureau	Sept 15th, 2025
	GDP in current international dollars PPP adjusted	World Bank - GDP, PPP (current international \$)	Sept 15th, 2025
	GDP in constant 2021 international dollars PPP adjusted	Calculated using World Bank - GDP, PPP (current international \$) and World Bank - GDP, PPP (constant 2021 international \$)	Sept 15th, 2025
CUB, ERI, PRK	Population	World Bank - Population	Sept 15th, 2025
	GDP in current US dollars	Calculated using UNdata - Per capita GDP at current prices - US dollars and World Bank - Population	Sept 15th, 2025
	GDP in constant 2021 US dollars	Calculated using UNdata - Per capita GDP at current prices - US dollars, World Bank - Population, and Annual Index Value from US Census Bureau	Sept 15th, 2025
	GDP in current international dollars PPP adjusted	NA	Sept 15th, 2025
	GDP in constant 2021 international dollars PPP adjusted	NA	Sept 15th, 2025
Other countries	Population	IMF - WEO - Population	Sept 15th, 2025
	GDP in current US dollars	IMF - WEO - Gross domestic product, current prices, US dollars	Sept 15th, 2025
	GDP in constant 2021 US dollars	Calculated using IMF - WEO - Gross domestic product, current prices, US dollars and Annual Index Value from US Census Bureau	Sept 15th, 2025
	GDP in current international dollars PPP adjusted	IMF - WEO - Gross domestic product, current prices PURCHASING POWER PARITY; INTERNATIONAL DOLLARS	Sept 15th, 2025
	GDP in constant 2021 international dollars PPP adjusted	Calculated using IMF - WEO - Gross domestic product per capita, constant prices PURCHASING POWER PARITY; 2021 INTERNATIONAL DOLLARS and IMF - WEO - Population	Sept 15th, 2025

1.2.3 Calculate Different Measures of GDP

There are four measures of GDP in our study: current USD, constant 2021 USD, current PPP-adjusted international dollars, and constant 2021 PPP-adjusted international dollars. Each type of GDP measure serves a specific purpose and requires different calculations to provide accurate economic comparisons. Below, we will explain what these different GDP measures mean and how to calculate them.

- GDP in Current USD:

- This is the Gross Domestic Product (GDP) measured in current U.S. dollars. It represents the total value of all goods and services produced within a country in a given year, converted to USD using the current exchange rates. This measure is influenced by inflation, exchange rate fluctuations, and changes in the price level. GDP in current USD is useful for understanding the nominal size of an economy and comparing it to others using the same currency (USD).
- GDP in Constant 2021 USD:
 - This is the GDP adjusted for inflation and expressed in constant 2021 U.S. dollars. By using a base year (in this case, 2021), it removes the effects of price level changes over time, allowing for comparison of economic output across different years in real terms. This measure helps to isolate the actual growth in economic activity.
 - In our study, this measure is calculated using:

$$\text{Constant 2021 USD} = \text{Current USD} \times \left(\frac{\text{2021 Price Index}}{\text{Current Year Price Index}} \right) \quad (1)$$
 - The price index is the Chained Consumer Price Index for All Urban Consumers (C-CPI-U) obtained from US Census Bureau.
- GDP in Current PPP-Adjusted International \$:
 - This GDP measure adjusts for purchasing power parity (PPP) and is expressed in current international dollars. Purchasing Power Parity (PPP) is a method of measuring the relative purchasing power of different countries' currencies over the same types of goods and services. International dollars are a hypothetical currency that has the same purchasing power over GDP as the U.S. dollar has in the United States. By using PPP adjustments, this measure accounts for differences in price levels between countries, providing a more accurate comparison of economic output and living standards. Unlike GDP in current USD, which is influenced by exchange rates, the PPP-adjusted measure reflects the value of goods and services in terms of what they can actually buy in each country.
- GDP in Constant 2021 PPP-Adjusted International \$
 - This is the GDP adjusted for both purchasing power parity (PPP) and inflation, expressed in constant 2021 international dollars. By using a base year (2021) and adjusting for PPP, it allows for comparison of economic output across different years and countries, accounting for both inflation and differences in price levels. This measure provides a consistent basis for comparing real economic growth and living standards over time and across countries, isolating real growth from both inflation and price level differences.
 - In our study, this measure is calculated using:

$$\frac{\text{Const 2021 PPP prices}}{\text{PPP prices}} = \frac{\text{Const 2022 PPP prices}}{\text{PPP prices}} \times \left(\frac{\text{2021 GDP in Current PPP Prices}}{\text{2021 GDP in Const 2022 PPP Prices}} \right) \quad (2)$$

1.2.4 China city level GDP data

Please download the following files and place each one into its respective subfolder under “step2_obtain_gdp_data/inputs/regional/CHN/province_yearbook”.

Table 4: City-Level GDP Data Sources for Seven Major Provinces in China

Province	Source	Dataset Name
Guangdong	http://stats.gd.gov.cn/gdtjnj/	Guangdong Province Statistical Yearbook 2024: 2-14 Gross Domestic Product by City
Henan	https://tjj.henan.gov.cn/tjfw/tjcbw/tjnj/	Statistical Yearbook 2024: 2-9 Gross Domestic Product by City (2022)
		Statistical Yearbook 2023: 2-9 Gross Domestic Product by City (2021)
		Statistical Yearbook 2022: 2-9 Gross Domestic Product by City (2020)
		Statistical Yearbook 2021: 2-9 Gross Domestic Product by City (2019)
		Statistical Yearbook 2020: 2-8 Gross Domestic Product by City (2018)
		Statistical Yearbook 2018: 2-9 Gross Domestic Product by City (2017)
		Statistical Yearbook 2017: 3-9 Gross Domestic Product by City (2016)
		Statistical Yearbook 2016: 3-9 Gross Domestic Product by City (2015)
		Statistical Yearbook 2015: 3-9 Gross Domestic Product by City (2014)
		Statistical Yearbook 2014: 3-10 Gross Domestic Product by City (2013)
		Statistical Yearbook 2013: 3-10 Gross Domestic Product by City (2012)
Hubei	https://tjj.hubei.gov.cn/tjsj/sjkscx/tjnj/qstjnj/	Statistical Yearbook 2023: 0115-Gross Domestic Product of Cities and Prefectures (2022).xls
		Statistical Yearbook 2022: 0115-Gross Domestic Product of Cities and Prefectures (2021).xls
		Statistical Yearbook 2021: 0115-Gross Domestic Product of Cities and Prefectures (2020).xls
		Statistical Yearbook 2020: 0115-Gross Domestic Product of Cities and Prefectures (2019).xls
		Statistical Yearbook 2019: 0115-Gross Domestic Product of Cities and Prefectures (2018).xls
		Statistical Yearbook 2018: 0119-Gross Domestic Product of Cities and Prefectures (2017).xls
		Statistical Yearbook 2017: 0119-Gross Domestic Product of Cities and Prefectures (2016).xls
		Statistical Yearbook 2016: 0119-Gross Domestic Product of Cities and Prefectures (2015).xls
		Statistical Yearbook 2015: 0119-Gross Domestic Product of Cities and Prefectures (2014).xls
		Statistical Yearbook 2014: 0119-Gross Domestic Product of Cities and Prefectures (2013).xls
		Statistical Yearbook 2013: 0119-Gross Domestic Product of Cities and Prefectures (2012).xls

Province	Source	Dataset Name
Jiangsu	https://www.jiangsu.gov.cn/col/col184736/index.html	Jiangsu Province Statistical Yearbook 2024: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2023: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2022: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2021: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2020: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2019: 2-12 Gross Domestic Product by Region
		Jiangsu Province Statistical Yearbook 2018: 2-12 Gross Domestic Product by Region
Shandong	http://tjj.shandong.gov.cn/col/col16279/index.html	Shandong Province Statistical Yearbook 2024: 2-6 Gross Domestic Product by Region (2022)
		Shandong Province Statistical Yearbook 2023: 2-6 Gross Domestic Product by Region (2021)
		Shandong Province Statistical Yearbook 2022: 2-6 Gross Domestic Product by Region (2020)
		Shandong Province Statistical Yearbook 2021: 2-6 Gross Domestic Product by Region (2019)
		Shandong Province Statistical Yearbook 2020: 2-6 Gross Domestic Product by Region (2018)
		Shandong Province Statistical Yearbook 2019: 2-9 Gross Domestic Product by Region (2017)
		Shandong Province Statistical Yearbook 2018: 2-9 Gross Domestic Product by Region (2016)
		Shandong Province Statistical Yearbook 2017: 2-9 Gross Domestic Product by Region (2015)
		Shandong Province Statistical Yearbook 2016: 2-8 Gross Domestic Product by Region (2014)
		Shandong Province Statistical Yearbook 2015: 2-8 Gross Domestic Product by Region (2013)
		Shandong Province Statistical Yearbook 2014: 2-9 Gross Domestic Product by Region (2012)
Sichuan	https://oversea.cnki.net/knavi/YearbookDetail?pcode=CYFD&pykm=YSCTN	Sichuan Province Statistical Yearbook 2024: 2-7 Gross Domestic Product by Region
Zhejiang	https://tjj.zj.gov.cn/col/col1525563/index.html	Zhejiang Province Statistical Yearbook 2023: 17-2 Major Indicators of National Economy by City and County (2022)
		Zhejiang Province Statistical Yearbook 2022: 17-2 Major Indicators of National Economy by City and County (2021)
		Zhejiang Province Statistical Yearbook 2021: 17-2 Major Indicators of National Economy by City and County (2020)
		Zhejiang Province Statistical Yearbook 2020: 17-2 Major Indicators of National Economy by City and County (2019)
		Zhejiang Province Statistical Yearbook 2019: 17-2 Major Indicators of National Economy by City and County (2018)
		Zhejiang Province Statistical Yearbook 2018: 17-2 Major Indicators of National Economy by City and County (2017)
		Zhejiang Province Statistical Yearbook 2017: 17-2 Major Indicators of National Economy by City and County (2016)
		Zhejiang Province Statistical Yearbook 2016: 17-2 Major Indicators of National Economy by City and County (2015)
		Zhejiang Province Statistical Yearbook 2015: 17-2 Major Indicators of National Economy by City and County (2014)

Province	Source	Dataset Name
		Zhejiang Province Statistical Yearbook 2014: 17-2 Major Indicators of National Economy by City and County (2013)
		Zhejiang Province Statistical Yearbook 2013: 17-2 Major Indicators of National Economy by City and County (2012)

1.3 Predictors data

- Population data:
 - The population data for our study is sourced from the LandScan Global Metadata, developed by the Oak Ridge National Laboratory (Bright et al., n.d.). The link is <https://landscan.ornl.gov/metadata>.
 - Choose “LandScan Global Metadata” and download for years 2000 to 2022. Save the downloaded files as “landscan-global-20xx.tif” in the folder “step3_obtain_cell_level_GDP_and_predictors_data/inputs/population/”.
- Nighttime Light (NTL) data:
 - The Nighttime Light (NTL) data utilized in our study is the VIIRS VNP46A4 product from NASA’s Black Marble suite (Román et al., 2018). The link is <https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/5000/VNP46A4/>.
 - Data for years 2012 to 2022 are all downloaded and processed. Save the corresponding year files in the folder “step3_obtain_cell_level_GDP_and_predictors_data/inputs/NTL_VNP46A4/20xx/001”.
- Net Primary Productivity (NPP) data
 - The Net Primary Productivity (NPP) data is the MOD17A3HGF Version 6.1 product from the MODIS suite (Running and Zhao, 2021). The link is <https://search.earthdata.nasa.gov/search?q=C2565791034-LPCLOUD>.
 - Data for years 2012 to 2022 are all downloaded and processed. Save the corresponding year files in the folder “step3_obtain_cell_level_GDP_and_predictors_data/inputs/NPP_V061/20xx/”.
- Landcover data:
 - The landcover data that our model uses is the MCD12Q1 version 6.1 product from the MODIS suite (Friedl and Sulla-Menashe, 2022). The link is <https://search.earthdata.nasa.gov/search?q=C2484079608-LPCLOUD>.
 - Data for years 2012 to 2022 are all downloaded and processed. Save the corresponding year files in the folder “step3_obtain_cell_level_GDP_and_predictors_data/inputs/landcover_MCD12Q1V061/20xx/”.
- Carbon dioxide (CO₂) emissions data:

- The carbon dioxide (CO₂) emissions data in our study are sourced from the EDGAR - Emissions Database for Global Atmospheric Research community. Data version “v8.0_GHG 1970-2022 (CO₂, CH₄, N₂O, F-gases)”. The link is https://edgar.jrc.ec.europa.eu/dataset_ghg80.
 - They separate the CO₂ emissions into “IEA-EDGAR CO₂” and “EDGAR_CO₂bio”. For both of them, we aggregate sector-specific emissions to three main categories: manufacturing combustion, heavy industry, and transportation.
 - For manufacturing combustion category, go to the section “Annual sector-specific gridmaps (1970-2022)”, click “IEA-EDGAR CO₂” and “EDGAR_CO₂bio” under the subsection of “Combustion for manufacturing”. Then download the files named “COMPLETE TIMESERIES [2022-1970] ENETCDF (xxx_emi_nc,zip)”.
 - For heavy industry category, it includes the subsection “Power industry”, “Oil refineries & Transformation industry”, “Fuel Exploitation”, “Non-metallic minerals production”, “Iron and steel production”, and “Non-ferrous metals production”. Note for “EDGAR_CO₂bio”, only subsections “Power industry”, “Oil refineries & Transformation industry”, and “Fuel Exploitation” have the data.
 - For transportation category, it includes the subsection “Road transportation”, and “Shipping”.
 - Save the corresponding year files in the folders “step3_obtain_cell_level_GDP_and_predictors_data/inputs/CO₂_bio_specific_sectors/sector name/” and “step3_obtain_cell_level_GDP_and_predictors_data/inputs/CO₂_non_org_specific_sectors/sector name/”.
- Gas flare data:
 - The gas flare data in our study are sourced from the Global Gas Flaring Data dataset in the Global Flaring and Methane Reduction Partnership (GFMR) community (Zhizhin et al., 2021; Elvidge, Zhizhin, Hsu, et al., 2013; Elvidge, Zhizhin, Baugh, et al., 2016). The link is <https://www.worldbank.org/en/programs/gasflaringreduction/global-flaring-data>.
 - Click the “Dataset: 2012 - 2022 Flare Volume Estimates by Individual Flare Location” to download and save the corresponding file in the folder “step3_obtain_cell_level_GDP_and_predictors_data/inputs/gas_flare_data/”. The file should be named “2012-2023-Flare-Volume-Estimates-by-individual-Flare-Location.xlsx”.
- Terrain Ruggedness Index data:
 - We use the Terrain Ruggedness Index produced in Nunn and Puga, 2012, calculated as a 30 arc-second grid across the earth. The link is <https://diegopuga.org/data/rugged/>.
 - The dataset was downloaded on 01/20/2023. Save the corresponding file “step3_obtain_cell_level_GDP_and_predictors_data/inputs/ruggedness/” and name it “tri.txt”.

The figure 1 shows the locations of gas flare spots used in this study.

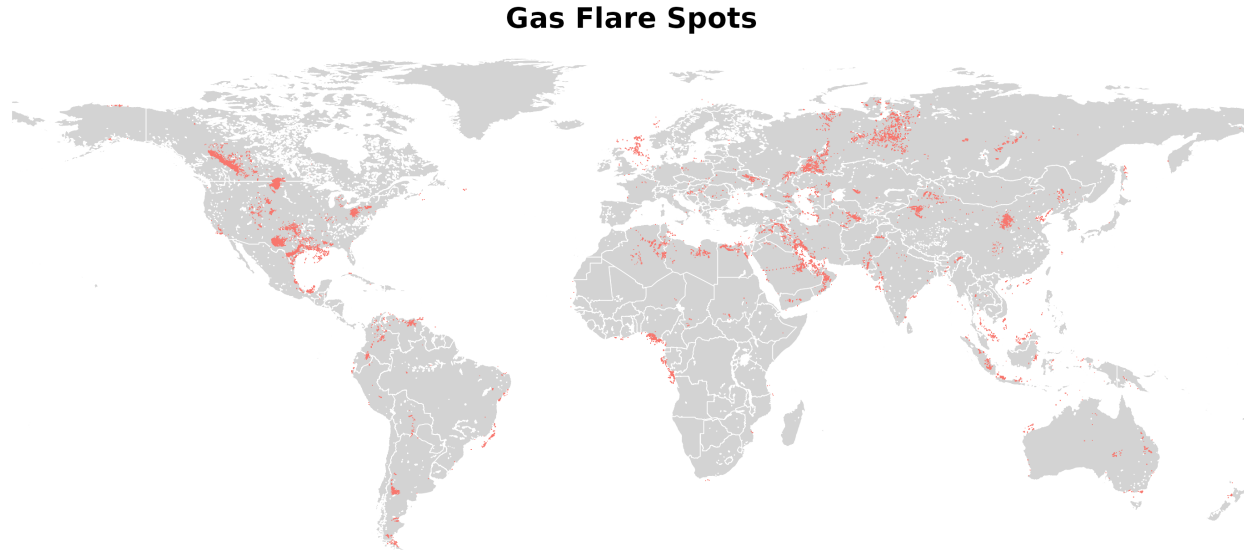


Figure 1: Locations of gas flare spots used in this study

1.4 Data Processing for Predictors

To prepare the geometry units for aggregating predictor data, the world is divided into grids with resolutions of 1° , 0.5° , and 0.25° in the EPSG:4326/WGS84 coordinate system. These grids are intersected with world country maps (as described in Section 1.1) to create country-cell-level geometry units. For specific countries, the geometry is at the state-equivalent level: Australia (8 units), Brazil (27 units), Canada (13 units), China (31 units), India (33 units), Kazakhstan (16 units), Mexico (32 units), Russia (83 units), and USA (51 units). Large inland water areas are then removed from the maps. This creates the final geometry units used for both GDP and predictor data. For NTL data aggregation only, an additional geometry unit is created by dividing the country/state-cell-level geometry into three land use categories: urban, cropland, and others by intersecting it with corresponding land use data.

Before aggregating predictors' data into the geometry unit created above, the following processing steps are needed:

The original NASA VIIRS VNP46A4 Black Marble NTL dataset separates data by satellite angles and into snow-covered and snow-free periods. For this study, we use the snow-free layer covering all satellite angles. The dataset has already been pre-processed to adjust for atmospheric and lunar reflectance conditions and to remove noise sources such as stray light, twilight, clouds, scan edge artifacts, and temporary lights (e.g., lightning, wildfires, fireworks). However, persistent lights from gas flares and fishing boats still remain. To address this, we further process it by excluding the lights within a 0.2deg radius around gas flaring locations with positive gas flaring volumes. Gas flaring locations, provided by the Global Gas Flaring Data from the GFMR community, include annual point locations with estimated flaring volumes. Positive flaring locations for each year are identified and corresponding exclusion zones are applied. The original NTL data are in a sinusoidal coordinate

system and are reprojected to EPSG:4326 using bilinear interpolation. This ensures spatial consistency but can introduce slight changes to original pixel values. The processed data are aggregated to year-country/state-cell-landuse levels.

The NPP dataset is also in a sinusoidal coordinate system and undergoes the same reprojection process as the NTL data.

The original land use data classify land into 11 categories. We select and aggregate them into five categories: urban, water, cropland (combining cropland, forest cropland, and herbaceous cropland), forest (combining open and dense forest), and snow ice. Recall that only large inland waters are removed, so smaller water bodies can still appear in the data.

The original CO_2 emissions data categorizes emissions into multiple sectors. We select and aggregate into six categories: fossil CO_2 manufacturing combustion, biofuel CO_2 manufacturing combustion, fossil CO_2 heavy industry (power industry + oil refineries transformation industry + fuel exploitation + non-metallic minerals production + iron and steel production + non-ferrous metals production), biofuel CO_2 heavy industry (power industry + oil refineries transformation industry + fuel exploitation), fossil CO_2 transportation (road transportation + shipping), biofuel CO_2 transportation (road transportation + shipping). EDGAR generates gridded emissions data by downscaling national emissions to each 0.1deg cell using sector-specific spatial proxies. In our study, we will convert all predictors to share terms rather than level terms, so we only care about EDGAR’s downscaling method. EDGAR allocates industry emissions based on the locations and emissions of energy and manufacturing facilities, while transportation emissions are distributed according to the length and intensity of road networks and shipping routes. This distribution process relies mainly on statistical calculations, not machine learning or economic models. And their input data for each sector are primarily sourced from national government agencies, company reports, and international organizations. Excluding these datasets has minimal impact on GDP level predictions but can reduce the accuracy of growth rate predictions.

The LandScan population dataset, when aggregated to the national level, slightly differs from the IMF WEO and World Bank national population datasets used in this study. To ensure consistency, LandScan data are rescaled to match IMF and World Bank population values.

After preprocessing the predictor data, the values for each cell’s predictors are then extracted and converted into shares, ready for training the random forest model.

2 Training Countries and Reference for GDP Share Prediction

Our model is trained using data from countries that provide GDP information at the county-equivalent level for developed nations and at a slightly broader administrative level for developing ones. These training countries span Northern America, Southern America, Europe, Africa, and Asia. Figure 2 shows the training countries.

Our model predicts cell GDP share which by definition is the proportion of GDP attributed to a specific cell relative to the aggregate GDP of its higher administrative entity. Correspondingly, our predictors are expressed as shares; for instance, the fraction of population, the proportion of nighttime light intensity, and the percentage of urban areas. The

shares are calculated at the national level for most countries, indicating, for example, the share of national nighttime lights that a particular cell occupies. However, to improve the accuracy of our predictions by incorporating more detailed subnational GDP information, we treat province-equivalent units as “parent countries” in nations such as Australia, Brazil, Canada, China, India, Kazakhstan, Mexico, Russia, and the United States, where such province-level GDP data are available. In these cases, both the predictor shares and the predicted cell GDP shares are relative to the provincial level. Figure 2 illustrates the boundaries of “parent countries” in this context.

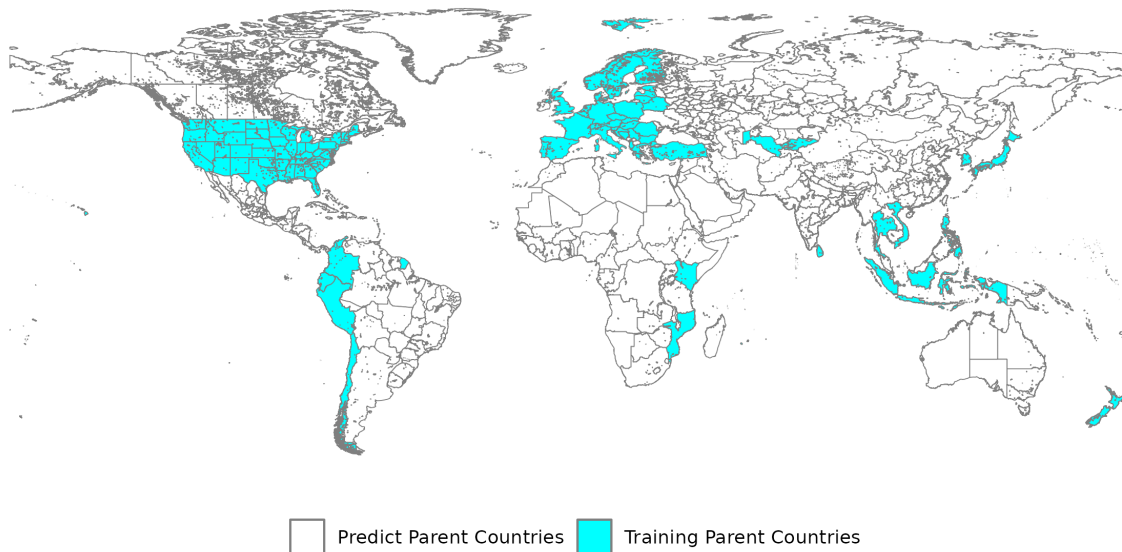


Figure 2: Boundaries of parent countries in the model

3 Method for Constructing Variable Importance Scores

Recall that the random forest models we use for training and prediction adopt cell GDP shares (expressed as a fraction of the parent state or country’s GDP) as the target variable and draw on predictors that are also expressed as shares of the parent state or country. If we were to simply derive the variable importance scores from the prediction process (e.g., using a built-in R function), the scores generated would encompass a *scaling effect*: imagine a cell in Houston that has 1,000 times the population of a cell in West Texas. Since our prediction process concerns the distribution of state or country GDP (which is a known quantity) to cells, we could achieve great strides in prediction by simply distributing 1,000 times more GDP to the cell covering Houston than to the cell in West Texas. Here, population explains most of the margin in cross-cell variation in GDP shares (1,000 times); but, naturally, the variation in per capita GDP across cells within the same state or country is of a much smaller magnitude (e.g., less than 2 or 3 times). This warrants the construction of new variable importance scores that remove this scaling effect, in order to mitigate the bias given to cell population as the predominant predictor.

Our chosen approach considers the variation in $r_i = \log(y_i) - \log(p_i)$, where y_i is the GDP share and p_i is the population share of cell i . Essentially, we are asking the question: how well does each predictor explain the deviation of a cell’s GDP share from what its population share may suggest? This approach does not require re-training or re-estimating the model. We are simply transforming our estimates of cell GDP shares and constructing variable importance scores based on a new form of variation.

We focus on within-country-year variation as we are interested in assessing how well each predictor explains the variation derived from our prediction pipeline which distributes a known country-year GDP to cells within the country-year. However, as shown in Tables 5 to 7, using overall variation does not qualitatively alter our findings.

Let $r_i = \log(y_i) - \log(p_i)$ denote the true log GDP-to-population ratio for cell i , where y_i is the true GDP share and p_i is the population share. Let $\hat{r}_i = \log(\hat{y}_i) - \log(p_i)$ denote the predicted log GDP-to-population ratio, where \hat{y}_i is the model’s predicted GDP share. Meanwhile, let \bar{r}_{ct} denote the mean of r_i for country c in year t , and let $\bar{\hat{r}}_{ct}$ denote the corresponding mean of \hat{r}_i . Define the demeaned values as:

$$\begin{aligned}\tilde{r}_i &= r_i - \bar{r}_{c(i),t(i)}, \\ \tilde{\hat{r}}_i &= \hat{r}_i - \bar{\hat{r}}_{c(i),t(i)},\end{aligned}$$

where $c(i)$ and $t(i)$ denote the country and year to which cell i belongs.

To assess the importance of predictor k , we compare the baseline model performance to performance after replacing predictor X_k with its global mean. Specifically, for each cell i , we replace $X_{k,i}$ with $\bar{X}_k = \frac{1}{N} \sum_j X_{k,j}$, where the sum is over all cells j in the dataset and N is the total number of cells. We then generate new predictions $\hat{y}_i^{(-k)}$ using the model with this replaced predictor, and compute $\hat{r}_i^{(-k)} = \log(\hat{y}_i^{(-k)}) - \log(p_i)$.

We calculate three within-country-year metrics on both the baseline predictions and after each variable replacement. The within R^2 compares prediction errors to within-country-year variance:

$$R_{\text{within}}^2 = 1 - \frac{\sum_i (r_i - \hat{r}_i)^2}{\sum_i (r_i - \bar{r}_{c(i),t(i)})^2}. \quad (3)$$

Meanwhile, the within *Corr* is the Pearson correlation computed on demeaned values:

$$\text{Corr}_{\text{within}} = \text{Corr}(\tilde{r}_i, \tilde{\hat{r}}_i). \quad (4)$$

Furthermore, the within MSE measures the mean squared error of demeaned predictions:

$$\text{MSE}_{\text{within}} = \frac{1}{N} \sum_i (\tilde{r}_i - \tilde{\hat{r}}_i)^2. \quad (5)$$

Variable importance for predictor k is defined as the drop in each metric relative to baseline: $\text{Importance}_k = \text{Baseline metric} - \text{Metric after replacing } X_k$. Larger positive values indicate that within-country-year variation in X_k contributes more to model performance.

The variable importance scores constructed from these three metrics (and their counterparts that capture overall variation) for the baseline model are presented in Tables 5 to 7.

Table 5: Variable Importance: 1deg Resolution

Variable	R^2 drop		$Corr$ drop		MSE increase	
	Within	Overall	Within	Overall	Within	Overall
Lag population (urban)	32.21	27.23	0.2020	0.1865	2.83	4.28
Population (urban)	21.29	18.00	0.1933	0.1811	2.00	2.83
Population (other)	20.23	17.10	0.1815	0.1711	1.98	2.69
Lag population (other)	4.47	3.78	0.1433	0.1422	0.49	0.59
NTL (cropland)	3.55	3.00	0.1365	0.1361	0.39	0.47
Lag NTL (cropland)	2.70	2.28	0.1278	0.1285	0.30	0.36
Population (cropland)	1.30	1.10	0.1038	0.1052	0.14	0.17
Population (total)	0.76	0.59	0.1226	0.1096	7.71	15.68
NTL (urban)	0.37	0.32	0.1021	0.1217	0.02	0.05
Lag NTL (urban)	0.18	0.15	0.0528	0.0648	0.01	0.02
Lag cropland	0.14	0.12	0.0323	0.0356	0.02	0.02
Cropland	0.11	0.10	0.0241	0.0263	0.01	0.02
Lag population (cropland)	0.07	0.06	0.0165	0.0147	0.01	0.01
CO2 bio (manuf. combust.)	0.07	0.06	0.0196	0.0198	0.00	0.01
Lag CO2 non-org (manuf. combust.)	0.05	0.05	0.0202	0.0179	0.00	0.01
CO2 non-org (manuf. combust.)	0.05	0.04	0.0184	0.0166	0.00	0.01
Lag CO2 non-org (heavy industry)	0.05	0.04	0.0099	0.0092	0.00	0.01
Lag CO2 bio (manuf. combust.)	0.03	0.03	0.0055	0.0075	0.00	0.00
NTL (other)	0.02	0.02	0.0096	0.0090	0.00	0.00
Lag CO2 bio (transport)	0.02	0.02	0.0019	0.0032	0.00	0.00

Notes: This table reports importance scores after replacing each variable with its global mean: drop in R^2 (expressed as decimals), drop in $Corr$, and increase in MSE. Variables shown are those ranking in the top 20 based on within-country-year R^2 importance. See Section 3 for the methodology used for constructing these scores.

Table 6: Variable Importance: 0.5deg Resolution

Variable	R^2 drop		$Corr$ drop		MSE increase	
	Within	Overall	Within	Overall	Within	Overall
Population (urban)	41.02	34.74	0.1999	0.1854	3.31	6.21
Lag population (urban)	40.46	34.27	0.1969	0.1828	3.25	6.13
Population (other)	19.61	16.61	0.1805	0.1724	2.02	2.97
Lag CO2 non-org (heavy industry)	16.12	13.65	0.1810	0.1758	1.79	2.44
CO2 non-org (heavy industry)	14.77	12.50	0.1795	0.1747	1.64	2.24
Population (cropland)	8.34	7.06	0.1608	0.1558	0.93	1.26
Lag population (cropland)	7.09	6.00	0.1567	0.1517	0.78	1.07
Lag population (other)	6.96	5.90	0.1559	0.1533	0.81	1.05
NTL (cropland)	6.01	5.09	0.1534	0.1562	0.77	0.91
Lag NTL (urban)	4.30	3.64	0.1433	0.1421	0.50	0.65
NTL (urban)	3.48	2.95	0.1363	0.1351	0.40	0.53
Lag NTL (cropland)	2.92	2.48	0.1292	0.1326	0.38	0.44
Lag CO2 bio (manuf. combust.)	2.08	1.76	0.1253	0.1296	0.25	0.32
NTL (other)	2.02	1.71	0.1177	0.1180	0.24	0.31
CO2 bio (manuf. combust.)	0.98	0.83	0.0995	0.1040	0.09	0.15
Population (total)	0.69	0.48	-0.1073	-0.1090	5.93	13.29
CO2 non-org (manuf. combust.)	0.29	0.24	0.0429	0.0452	0.03	0.04
Lag CO2 nonorg (manuf. combust.)	0.21	0.17	0.0356	0.0389	0.02	0.03
Lag NTL (other)	0.04	0.04	0.0106	0.0101	0.00	0.01
Cropland	0.04	0.04	0.0089	0.0079	0.00	0.01

Notes: This table reports importance scores after replacing each variable with its global mean: drop in R^2 (expressed as decimals), drop in $Corr$, and increase in MSE. Variables shown are those ranking in the top 20 based on within-country-year R^2 importance. See Section 3 for the methodology used for constructing these scores.

Table 7: Variable Importance: 0.25deg Resolution

Variable	R^2 drop		$Corr$ drop		MSE increase	
	Within	Overall	Within	Overall	Within	Overall
Population (urban)	27.13	22.82	0.1682	0.1632	2.20	4.26
Population (other)	18.72	15.75	0.1599	0.1581	1.79	2.94
Lag population (urban)	11.71	9.85	0.1569	0.1568	1.14	1.84
CO2 non-org (heavy industry)	11.66	9.81	0.1589	0.1606	1.22	1.83
Lag CO2 non-org (heavy industry)	10.25	8.62	0.1580	0.1609	1.10	1.61
Population (cropland)	8.17	6.87	0.1489	0.1505	0.86	1.28
Lag population (other)	6.52	5.48	0.1464	0.1500	0.72	1.02
Lag population (cropland)	5.48	4.61	0.1416	0.1450	0.60	0.86
NTL (cropland)	4.79	4.03	0.1429	0.1491	0.57	0.75
NTL (urban)	1.95	1.64	0.1152	0.1196	0.22	0.31
Lag NTL (cropland)	1.81	1.52	0.1115	0.1161	0.22	0.28
Lag NTL (urban)	1.58	1.33	0.1068	0.1113	0.18	0.25
Population (total)	0.97	0.61	-0.1295	-0.1108	5.13	12.95
Lag CO2 bio (manuf. combust.)	0.97	0.82	0.1029	0.1131	0.12	0.15
CO2 bio (manuf. combust.)	0.34	0.28	0.0581	0.0662	0.03	0.05
NTL (other)	0.26	0.22	0.0418	0.0436	0.03	0.04
Lag CO2 nonorg (manuf. combust.)	0.10	0.08	0.0189	0.0199	0.01	0.02
CO2 non-org (manuf. combust.)	0.08	0.07	0.0144	0.0148	0.01	0.01
Lag CO2 bio (transport)	0.01	0.01	0.0033	0.0040	0.00	0.00
Cropland	0.01	0.01	0.0030	0.0035	0.00	0.00

Notes: This table reports importance scores after replacing each variable with its global mean: drop in R^2 (expressed as decimals), drop in $Corr$, and increase in MSE. Variables shown are those ranking in the top 20 based on within-country-year R^2 importance. See Section 3 for the methodology used for constructing these scores.

4 Post-adjustments

This section presents the number of cells affected by the post-adjustment process for each censoring threshold at each resolution.

Table 8: 1-degree cells affected by post-adjustments: threshold 0 pop per km² land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	21,194	4,112	3,713	2%	399
2013	21,194	3,888	3,466	2%	420
2014	21,194	3,901	3,461	2%	439
2015	21,194	3,928	3,498	2%	429
2016	21,194	3,812	3,366	3%	446
2017	21,194	3,813	3,349	3%	464
2018	21,194	3,924	3,468	3%	456
2019	21,194	4,210	3,726	3%	484
2020	21,194	4,612	4,086	3%	526
2021	21,194	4,420	3,885	3%	534
2022	20,416	3,608	3,071	3%	536

Table 9: 1-degree cells affected by post-adjustments: threshold 0.01 pop per km² land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	21,194	5,283	3,713	9%	415
2013	21,194	5,030	3,466	9%	423
2014	21,194	5,124	3,461	9%	436
2015	21,194	5,119	3,498	9%	432
2016	21,194	5,188	3,366	10%	454
2017	21,194	5,208	3,349	10%	454
2018	21,194	5,253	3,468	10%	436
2019	21,194	5,431	3,726	10%	445
2020	21,194	5,968	4,086	11%	450
2021	21,194	5,848	3,885	11%	461
2022	20,416	5,023	3,071	11%	464

Table 10: 1-degree cells affected by post-adjustments: threshold 0.02 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	21,194	5,692	3,713	11%	419
2013	21,194	5,480	3,466	11%	425
2014	21,194	5,550	3,461	12%	430
2015	21,194	5,548	3,498	12%	426
2016	21,194	5,616	3,366	13%	449
2017	21,194	5,633	3,349	13%	445
2018	21,194	5,706	3,468	13%	431
2019	21,194	5,884	3,726	12%	448
2020	21,194	6,318	4,086	13%	444
2021	21,194	6,244	3,885	14%	451
2022	20,416	5,440	3,071	14%	450

Table 11: 1-degree cells affected by post-adjustments: threshold 0.05 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	21,194	6,383	3,713	15%	420
2013	21,194	6,212	3,466	15%	422
2014	21,194	6,295	3,461	16%	440
2015	21,194	6,327	3,498	16%	443
2016	21,194	6,376	3,366	17%	454
2017	21,194	6,387	3,349	17%	445
2018	21,194	6,411	3,468	17%	428
2019	21,194	6,555	3,726	16%	448
2020	21,194	6,902	4,086	16%	443
2021	21,194	6,877	3,885	17%	458
2022	20,416	6,074	3,071	17%	460

Table 12: 0.5-degree cells affected by post-adjustments: threshold 0 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	73,728	18,327	17,390	2%	919
2013	73,728	17,098	16,071	2%	1,010
2014	73,728	17,211	16,159	2%	1,032
2015	73,728	17,291	16,250	2%	1,020
2016	73,728	17,291	16,204	2%	1,057
2017	73,728	17,370	16,293	2%	1,055
2018	73,728	17,616	16,545	2%	1,043
2019	73,728	18,686	17,601	2%	1,066
2020	73,728	20,570	19,432	2%	1,114
2021	73,728	20,071	18,925	2%	1,129
2022	70,826	16,912	15,750	2%	1,142

Table 13: 0.5-degree cells affected by post-adjustments: threshold 0.01 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	73,728	21,911	17,417	8%	916
2013	73,728	20,655	16,080	8%	972
2014	73,728	20,942	16,165	8%	987
2015	73,728	20,995	16,253	8%	979
2016	73,728	21,221	16,211	9%	1,003
2017	73,728	21,384	16,301	9%	1,000
2018	73,728	21,520	16,569	9%	988
2019	73,728	22,357	17,632	8%	995
2020	73,728	24,452	19,460	9%	962
2021	73,728	24,239	18,952	10%	987
2022	70,826	20,991	15,806	9%	988

Table 14: 0.5-degree cells affected by post-adjustments: threshold 0.02 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	73,728	23,365	17,418	11%	935
2013	73,728	22,165	16,080	11%	958
2014	73,728	22,494	16,165	11%	970
2015	73,728	22,582	16,253	11%	965
2016	73,728	22,820	16,212	11%	984
2017	73,728	22,910	16,301	12%	979
2018	73,728	23,075	16,569	11%	964
2019	73,728	23,888	17,632	11%	971
2020	73,728	25,717	19,460	12%	918
2021	73,728	25,648	18,952	12%	937
2022	70,826	22,503	15,807	12%	945

Table 15: 0.5-degree cells affected by post-adjustments: threshold 0.05 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	73,728	25,744	17,418	15%	960
2013	73,728	24,710	16,080	15%	931
2014	73,728	25,107	16,165	16%	926
2015	73,728	25,156	16,253	15%	942
2016	73,728	25,331	16,212	16%	953
2017	73,728	25,471	16,301	16%	956
2018	73,728	25,649	16,569	16%	946
2019	73,728	26,301	17,632	15%	931
2020	73,728	27,745	19,460	15%	896
2021	73,728	27,830	18,952	16%	909
2022	70,826	24,774	15,807	16%	914

Table 16: 0.25-degree cells affected by post-adjustments: threshold 0 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	271,692	85,793	83,535	1%	2,204
2013	271,692	79,412	76,976	1%	2,365
2014	271,692	80,405	77,957	1%	2,372
2015	271,692	80,784	78,331	1%	2,387
2016	271,692	81,597	79,084	1%	2,435
2017	271,692	82,404	79,855	1%	2,470
2018	271,692	83,015	80,499	1%	2,437
2019	271,692	87,240	84,741	1%	2,436
2020	271,692	94,604	92,134	1%	2,396
2021	271,692	94,284	91,786	1%	2,429
2022	260,590	82,298	79,797	1%	2,439

Table 17: 0.25-degree cells affected by post-adjustments: threshold 0.01 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	271,692	94,485	83,827	6%	2,138
2013	271,692	88,746	77,046	6%	2,213
2014	271,692	89,796	78,006	6%	2,232
2015	271,692	90,074	78,374	6%	2,232
2016	271,692	90,909	79,147	6%	2,284
2017	271,692	91,779	79,920	6%	2,302
2018	271,692	92,196	80,664	6%	2,285
2019	271,692	95,766	84,889	6%	2,284
2020	271,692	103,621	92,268	6%	2,189
2021	271,692	103,731	91,902	7%	2,266
2022	260,590	91,423	80,132	6%	2,280

Table 18: 0.25-degree cells affected by post-adjustments: threshold 0.02 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	271,692	99,391	83,830	8%	2,112
2013	271,692	93,698	77,048	9%	2,144
2014	271,692	94,984	78,008	9%	2,185
2015	271,692	95,406	78,376	9%	2,185
2016	271,692	96,230	79,148	9%	2,208
2017	271,692	97,131	79,920	9%	2,221
2018	271,692	97,528	80,664	9%	2,202
2019	271,692	100,781	84,889	9%	2,180
2020	271,692	108,263	92,269	9%	2,062
2021	271,692	108,850	91,903	9%	2,120
2022	260,590	96,681	80,138	9%	2,146

Table 19: 0.25-degree cells affected by post-adjustments: threshold 0.05 pop per km2 land areas

Year	Total number of cells	Number of cells affected	Affected cells with zero pop	Percentage of inhabited cells affected	Affected cells with positive GDP
2012	271,692	107,285	83,835	12%	2,030
2013	271,692	102,482	77,053	13%	2,014
2014	271,692	104,076	78,010	13%	2,054
2015	271,692	104,417	78,377	13%	2,059
2016	271,692	105,125	79,151	13%	2,066
2017	271,692	106,154	79,921	14%	2,066
2018	271,692	106,446	80,667	13%	2,054
2019	271,692	109,311	84,890	13%	2,010
2020	271,692	115,781	92,272	13%	1,939
2021	271,692	116,742	91,905	14%	1,979
2022	260,590	104,882	80,144	14%	1,994

5 Model Within Training Sample Fit

Recall that in the paper Section 2.1 and 2.2, we present the results of models trained using data from 2012 to 2022 for available countries (excluding China) under the optimal hyper-parameters. Here we present the within-sample fit of the models on the training sample. We report the the R^2 of log GDP levels and annual changes for each country in the training sample. Note that the predicted values are out-of-bag (OOB) estimates. The out-of-bag estimate is calculated using predictions from trees that excluded the cell from their training.

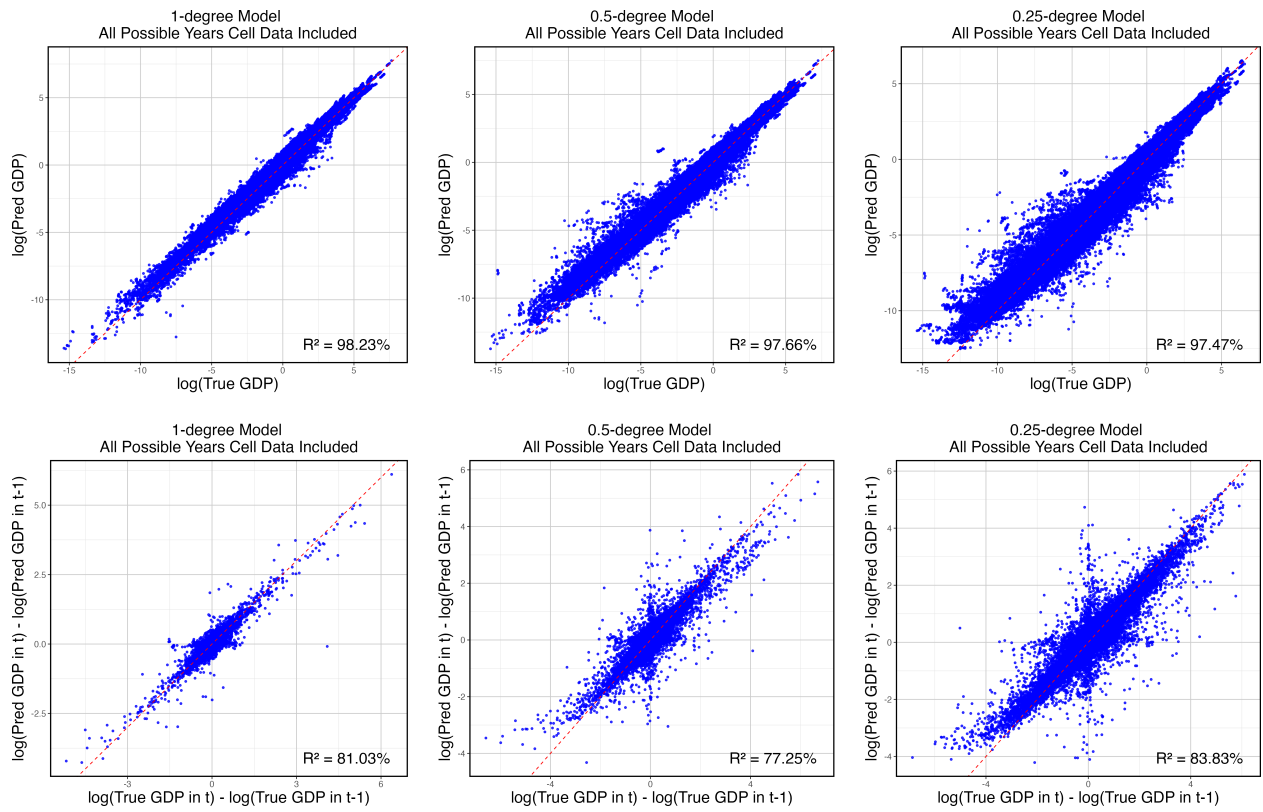


Figure 3: Predicted vs. True GDP Across Different Spatial Resolutions for Training Data

Table 20: R^2 Results for the 1-Degree Model: Comparing Predicted vs. Actual Log Cell GDP

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	99.58%	ALB	96.40%
BEL	98.07%	BGR	98.53%
CHE	97.02%	BIH	92.40%
CZE	99.24%	BLR	98.72%
DEU	98.28%	CHL	98.29%
DNK	99.13%	COL	94.89%
ESP	97.72%	ECU	94.50%
EST	96.16%	HUN	97.78%
FIN	99.30%	IDN	96.33%
FRA	98.63%	KEN	91.09%
GBR	99.31%	KGZ	96.73%
GRC	98.28%	LKA	94.68%
HRV	96.24%	MOZ	95.36%
ITA	97.69%	PER	97.60%
JPN	99.12%	PHL	98.38%
KOR	98.93%	POL	96.79%
LTU	98.94%	ROU	98.46%
LVA	97.24%	SRB	95.39%
NLD	98.54%	THA	85.01%
NOR	99.52%	TUR	92.17%
NZL	98.96%	UZB	98.81%
PRT	99.47%	VNM	93.40%
SVK	98.24%		
SVN	97.84%		
SWE	99.66%		
USA	98.09%		

Table 21: R² Results for the 0.5-Degree Model: Comparing Predicted vs. Actual Log Cell GDP

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	99.30%	ALB	97.08%
BEL	98.70%	BGR	97.60%
CHE	98.71%	BIH	94.75%
CZE	99.43%	BLR	98.09%
DEU	97.22%	CHL	96.93%
DNK	99.37%	COL	94.88%
ESP	98.28%	ECU	90.46%
EST	96.27%	HUN	98.73%
FIN	99.27%	IDN	95.37%
FRA	98.22%	KEN	90.14%
GBR	98.59%	KGZ	96.28%
GRC	98.45%	LKA	98.70%
HRV	98.59%	MOZ	92.41%
ITA	96.19%	PER	97.32%
JPN	98.63%	PHL	97.92%
KOR	99.02%	POL	96.38%
LTU	96.57%	ROU	96.90%
LVA	95.08%	SRB	91.33%
NLD	99.11%	THA	91.27%
NOR	99.21%	TUR	88.39%
NZL	97.81%	UZB	96.69%
PRT	99.08%	VNM	94.62%
SVK	97.95%		
SVN	99.55%		
SWE	99.18%		
USA	97.17%		

Table 22: R^2 Results for the 0.25-Degree Model: Comparing Predicted vs. Actual Log Cell GDP

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	98.51%	ALB	97.56%
BEL	98.43%	BGR	96.13%
CHE	98.56%	BIH	91.76%
CZE	99.37%	BLR	96.74%
DEU	95.57%	CHL	97.55%
DNK	99.33%	COL	94.40%
ESP	98.28%	ECU	90.85%
EST	96.84%	HUN	98.07%
FIN	99.56%	IDN	94.36%
FRA	98.00%	KEN	88.93%
GBR	98.52%	KGZ	94.69%
GRC	97.88%	LKA	98.92%
HRV	98.08%	MOZ	88.65%
ITA	96.11%	PER	97.17%
JPN	98.64%	PHL	96.56%
KOR	98.28%	POL	95.86%
LTU	95.94%	ROU	96.43%
LVA	90.10%	SRB	86.10%
NLD	99.27%	THA	88.32%
NOR	98.86%	TUR	87.18%
NZL	98.34%	UZB	93.86%
PRT	97.62%	VNM	90.66%
SVK	97.91%		
SVN	99.04%		
SWE	99.50%		
USA	97.20%		

Table 23: R^2 Results for the 1-Degree Model: Comparing Predicted vs. Actual Log Differences in Cell GDP ($\log(\text{cell GDP in } t) - \log(\text{cell GDP in } t-1)$)

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	66.58%	ALB	79.95%
BEL	88.33%	BGR	53.74%
CHE	-62.28%	BIH	78.21%
CZE	84.13%	BLR	83.27%
DEU	76.24%	CHL	95.05%
DNK	79.32%	COL	73.36%
ESP	30.13%	ECU	17.16%
EST	84.53%	HUN	72.11%
FIN	92.54%	IDN	66.41%
FRA	87.31%	KEN	55.12%
GBR	81.21%	KGZ	73.53%
GRC	75.37%	LKA	46.14%
HRV	60.37%	MOZ	86.26%
ITA	88.85%	PER	84.17%
JPN	65.10%	PHL	55.20%
KOR	77.20%	POL	82.71%
LTU	84.67%	ROU	68.96%
LVA	6.08%	SRB	71.72%
NLD	24.08%	THA	12.61%
NOR	86.70%	TUR	8.60%
NZL	53.18%	UZB	82.95%
PRT	66.85%	VNM	-19.93%
SVK	90.70%		
SVN	92.29%		
SWE	91.47%		
USA	74.03%		

Table 24: R² Results for the 0.5-Degree Model: Comparing Predicted vs. Actual Log Differences in Cell GDP (log(cell GDP in t) - log(cell GDP in t-1))

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	67.66%	ALB	89.90%
BEL	-522.63%	BGR	60.95%
CHE	31.87%	BIH	89.74%
CZE	84.46%	BLR	87.73%
DEU	69.99%	CHL	84.04%
DNK	93.36%	COL	77.88%
ESP	65.29%	ECU	-22.73%
EST	73.60%	HUN	77.86%
FIN	92.19%	IDN	46.19%
FRA	87.95%	KEN	64.93%
GBR	56.49%	KGZ	68.09%
GRC	71.38%	LKA	71.48%
HRV	76.09%	MOZ	69.39%
ITA	49.77%	PER	86.07%
JPN	69.70%	PHL	62.05%
KOR	67.72%	POL	88.03%
LTU	85.50%	ROU	70.84%
LVA	51.30%	SRB	60.32%
NLD	75.60%	THA	65.80%
NOR	88.01%	TUR	5.05%
NZL	63.26%	UZB	78.90%
PRT	75.24%	VNM	44.88%
SVK	90.02%		
SVN	92.32%		
SWE	91.49%		
USA	74.43%		

Table 25: R² Results for the 0.25-Degree Model: Comparing Predicted vs. Actual Log Differences in Cell GDP (log(cell GDP in t) - log(cell GDP in t-1))

Iso: Developed	R2: Developed	Iso: Developing	R2: Developing
AUT	78.50%	ALB	89.12%
BEL	-24.86%	BGR	70.49%
CHE	18.34%	BIH	89.74%
CZE	88.05%	BLR	87.13%
DEU	80.51%	CHL	90.67%
DNK	92.00%	COL	85.64%
ESP	73.29%	ECU	-216.44%
EST	66.09%	HUN	65.89%
FIN	96.76%	IDN	69.84%
FRA	80.28%	KEN	82.19%
GBR	57.01%	KGZ	67.81%
GRC	88.34%	LKA	72.68%
HRV	88.52%	MOZ	80.20%
ITA	85.81%	PER	87.31%
JPN	72.83%	PHL	63.49%
KOR	67.28%	POL	79.52%
LTU	88.39%	ROU	64.78%
LVA	76.96%	SRB	70.81%
NLD	72.51%	THA	49.65%
NOR	96.03%	TUR	42.81%
NZL	74.71%	UZB	73.58%
PRT	80.71%	VNM	-117.47%
SVK	84.74%		
SVN	91.69%		
SWE	96.32%		
USA	83.72%		

6 Model Performance Under COVID Shock

In the paper, we evaluate the model’s performance under the COVID-19 shock using China’s data, which is excluded from the training sample. Here, we further demonstrate that the model’s strong performance on COVID-affected data is not due to prior exposure to COVID years in the training sample. To verify this, we train the models using data from 2012 to 2019 for all available countries (excluding China) and assess whether the model’s performance remains consistent on out-of-sample data. Note that all years of data for China are treated as out-of-sample and only the years 2020, 2021 and 2022 are considered out-of-sample for the training countries.

The results of the China test, as shown in Figure 4, align closely with the findings presented in the paper. Similarly, the tests conducted on the training countries, presented in Figures 5, 6, and 7, for the years 2020, 2021 and 2022 also demonstrate strong performance. These results highlight the model’s ability to generalize effectively, even in the absence of specific shocks in the training data.

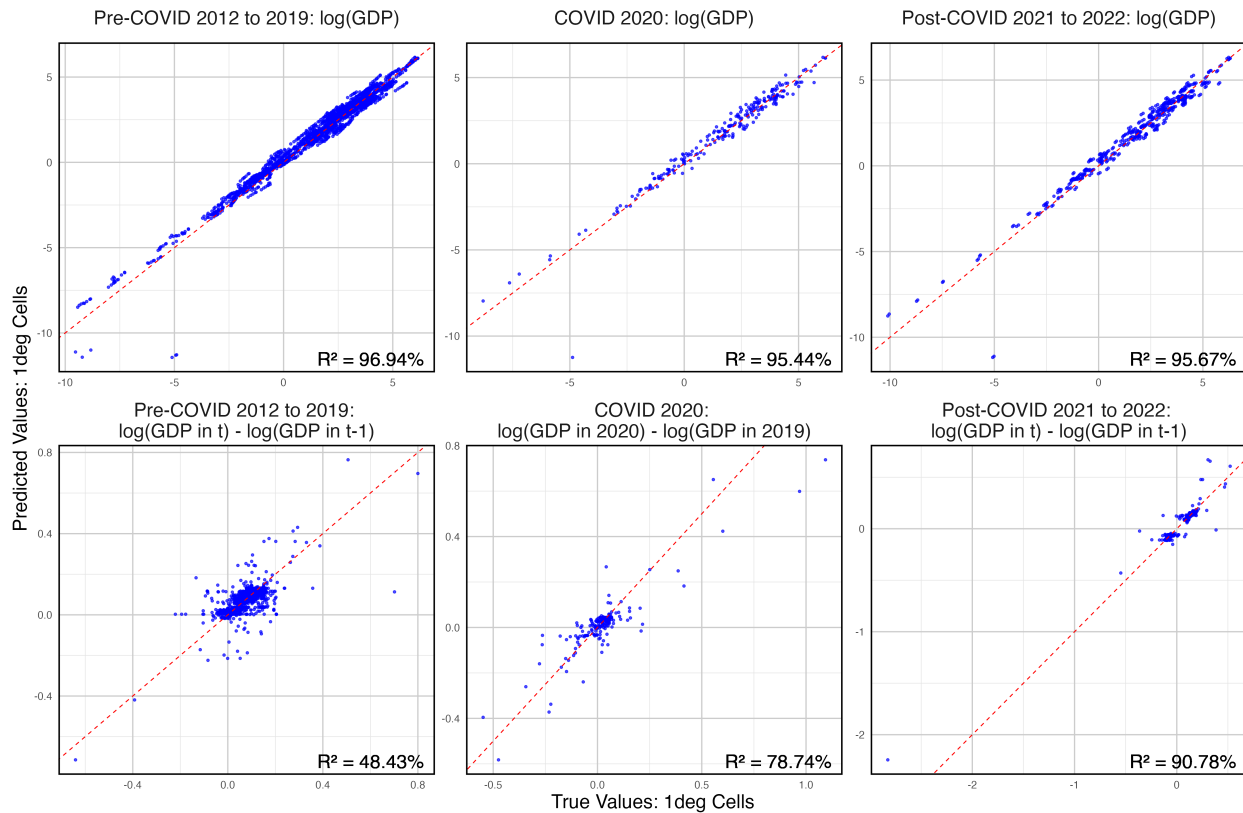


Figure 4: Model Predictions Against Actual Values in Billion Constant 2021 USD for Seven Leading Provinces in China

Note: The red dashed line represents the 45-degree line. Cells with a GDP value of zero are omitted to enable the calculation of logarithmic values.

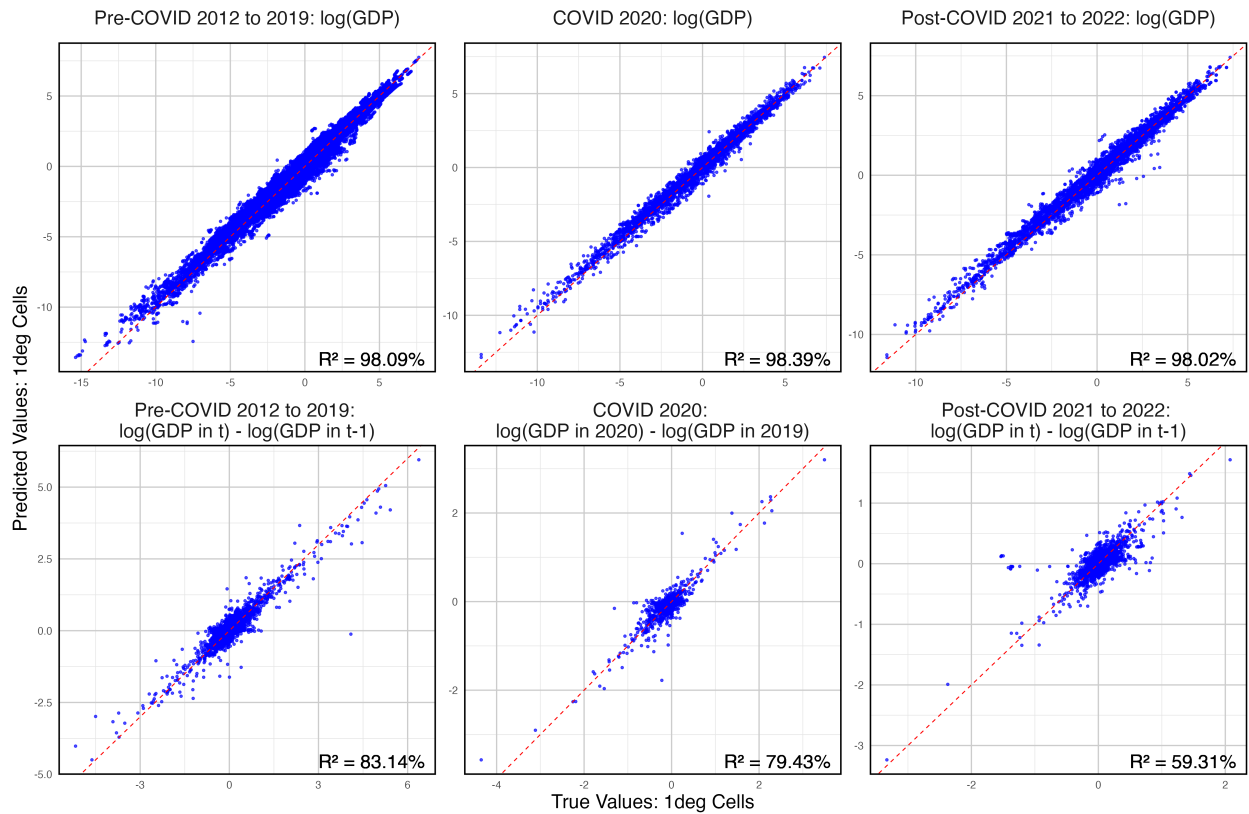


Figure 5: 1deg Model Predictions Against Actual Values in Billion Constant 2021 USD for All Training Countries

Note: The red dashed line represents the 45-degree line. Cells with a GDP value of zero are omitted to enable the calculation of logarithmic values. Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model.

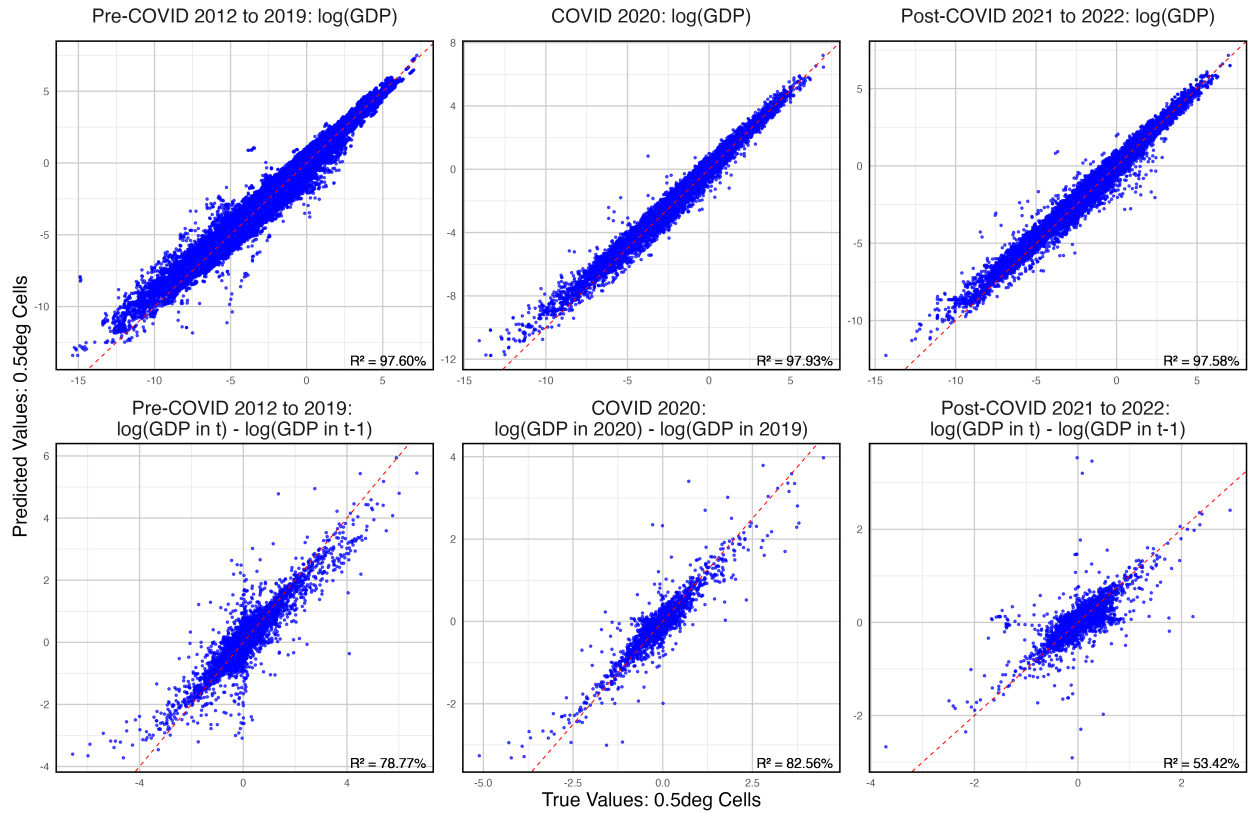


Figure 6: 0.5deg Model Predictions Against Actual Values in Billion Constant 2021 USD for All Training Countries

Note: The red dashed line represents the 45-degree line. Cells with a GDP value of zero are omitted to enable the calculation of logarithmic values. Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model.

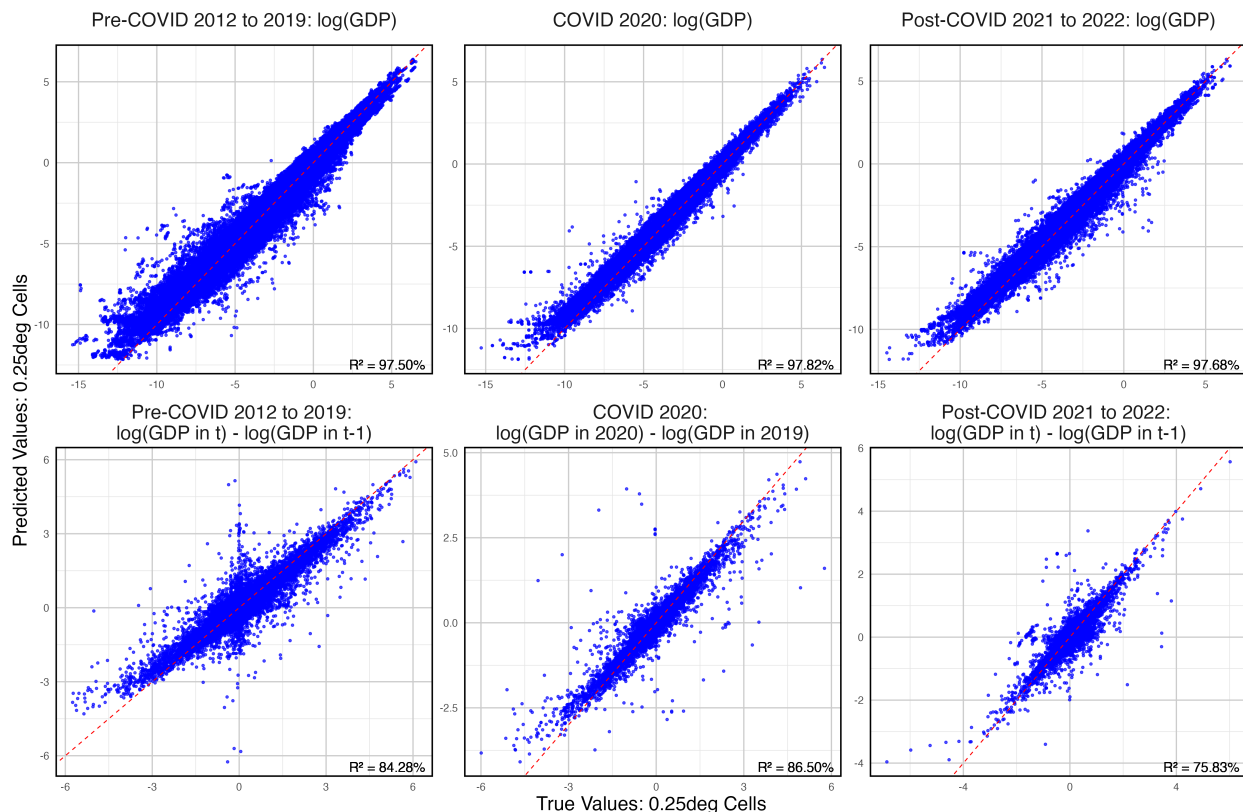


Figure 7: 0.25deg Model Predictions Against Actual Values in Billion Constant 2021 USD for All Training Countries

Note: The red dashed line represents the 45-degree line. Cells with a GDP value of zero are omitted to enable the calculation of logarithmic values. Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model.

7 Robustness of Model Specification

7.1 Compare Benchmark Models with Models Tuned Based on Mean Square Error

In this section, we compare the results of two models: the model trained using data from 2012 to 2022 for all available countries (excluding China) with hyperparameters chosen to maximize the R^2 of annual log changes in GDP, and a model trained on the same data but with hyperparameters chosen to minimize the mean squared error (MSE) of GDP share. This comparison is essential because traditional hyperparameter tuning in machine learning is often based on minimizing MSE for the predicted variable - in our case, GDP share.

Table 26 shows the cross-validation performance of the model tuned to minimize MSE. Compare this table with the corresponding table in the paper, we show that while GDP level predictions are largely similar between the two models, tuning for maximizing annual log change R^2 improves the accuracy of year-over-year GDP changes, especially for 1deg model.

We then use the two models to predict all global cells and compare their predictions. Figure 8 demonstrates that the level predictions are highly consistent, while the annual changes exhibit slight differences especially at the 1deg and 0.25deg resolutions.

We also performed the same tests on the MSE-tuned model for comparison with the benchmark model, as shown in Figures 9, 10, and 11. The results indicate that the benchmark model outperforms the MSE-tuned model in capturing annual changes in GDP.

Table 26: Cross-Validated Performance Metrics Across Spatial Resolutions (MSE Objective)

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: Mean Square Error (MSE)</i>						
MSE (Developed)	0.00046	0.00018	0.00001			
MSE (Developing)	0.00040	0.00009	0.00001			
MSE (All)	0.00033	0.00011	0.00001			
Weighted MSE	0.00042	0.00011	0.00001			
<i>Panel B: R^2 of Log GDP Level</i>						
R^2 (Developed)	97.81%	97.40%	97.87%			
R^2 (Developing)	95.61%	95.75%	93.83%			
R^2 (All)	97.66%	97.12%	96.96%			
Weighted R^2	96.22%	96.21%	94.96%			
<i>Panel C: R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	66.71%	73.69%	82.97%			
R^2 (Developing)	76.27%	76.21%	64.58%			
R^2 (All)	71.38%	72.91%	77.05%			
Weighted R^2	73.60%	75.51%	69.72%			
<i>Panel D: Variable Importance Scores</i>						
	R^2	$Corr$	R^2	$Corr$	R^2	$Corr$
Lag population (urban)	17.32	0.0547	0.17	0.0457	4.19	0.2157
Population (urban)	12.54	0.0480	0.32	0.0955	15.89	0.2595
Lag CO2 non-org (heavy industry)	0.00	0.0000	15.88	0.1795	10.74	0.2548
Population (other)	14.82	0.0407	0.02	0.0038	11.36	0.2533
CO2 non-org (heavy industry)	0.00	0.0000	14.19	0.1783	12.03	0.2573
NTL (cropland)	0.00	0.0000	6.71	0.1562	4.75	0.2241
Population (cropland)	0.00	0.0000	0.02	0.0056	2.52	0.1896
Lag NTL (cropland)	0.00	0.0000	2.07	0.1169	0.79	0.1222
Lag population (other)	0.00	0.0000	0.06	0.0115	1.58	0.1669
Population	0.25	-0.1838	0.75	-0.0769	1.21	0.0641
Lag population (cropland)	0.00	0.0000	0.31	0.0548	0.91	0.1310
Lag CO2 bio (manuf. combust.)	0.00	0.0000	0.08	0.0193	0.62	0.1257
CO2 bio (manuf. combust.)	0.00	0.0002	0.15	0.0345	0.57	0.1202
CO2 bio (heavy industry)	0.00	0.0000	0.02	0.0041	0.14	0.0362
Lag CO2 bio (transport)	0.00	0.0000	0.00	0.0003	0.13	0.0368
Lag CO2 bio (heavy industry)	0.00	0.0000	0.03	0.0049	0.10	0.0275
CO2 bio (transport)	0.00	0.0000	0.00	0.0007	0.10	0.0300
Forest	0.00	0.0000	-0.00	0.0130	0.08	0.1074
NTL (urban)	0.06	0.0121	0.07	0.0155	0.07	0.0188
NTL other (snow-free period)	0.00	0.0008	0.07	0.0176	0.04	0.0122

Notes: Panels A, B, and C report cross-validated MSE and R^2 metrics. Panel D reports variable importance scores: drop in within-country R^2 and $Corr$ when each variable is replaced with its global mean. Variables shown are the top 20 by their maximum R^2 importance score across the three degree levels.

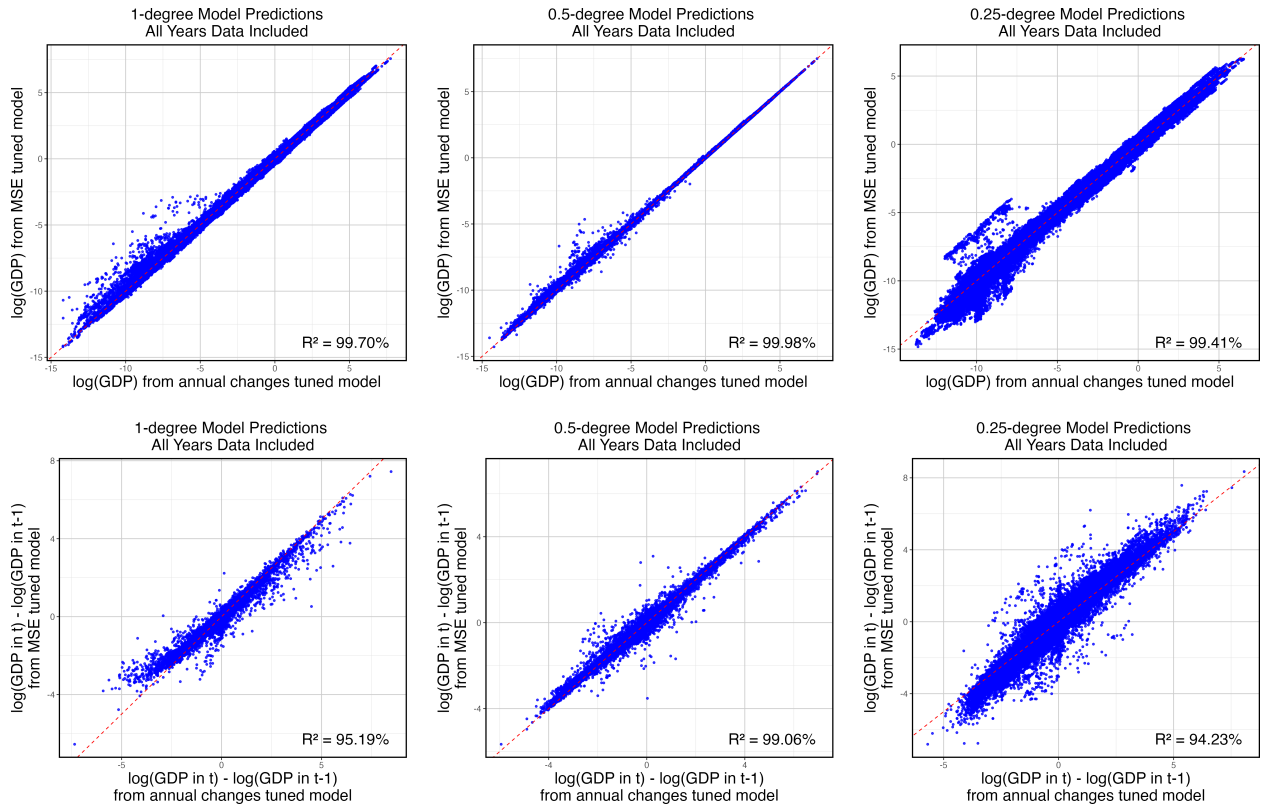


Figure 8: Comparison of Model Predictions: MSE-Tuned vs. Annual Change-Tuned Models

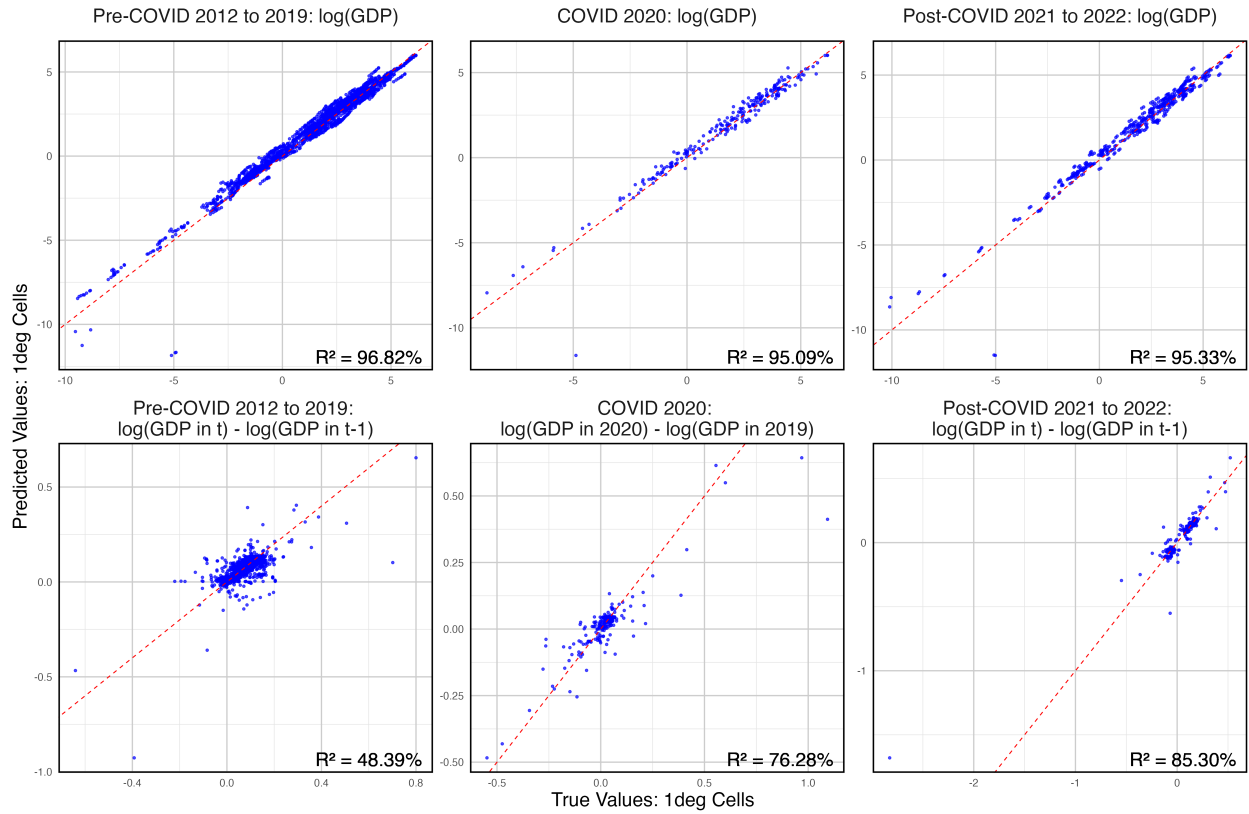


Figure 9: Model Predictions Against Actual GDP Values for China's Seven Leading Provinces, Using the Model Trained on years 2012 to 2022 Data and Tuned for Minimizing MSE

Note: This plot is comparable with the same plot in the paper. The only difference is the way hyperparameters are tuned.

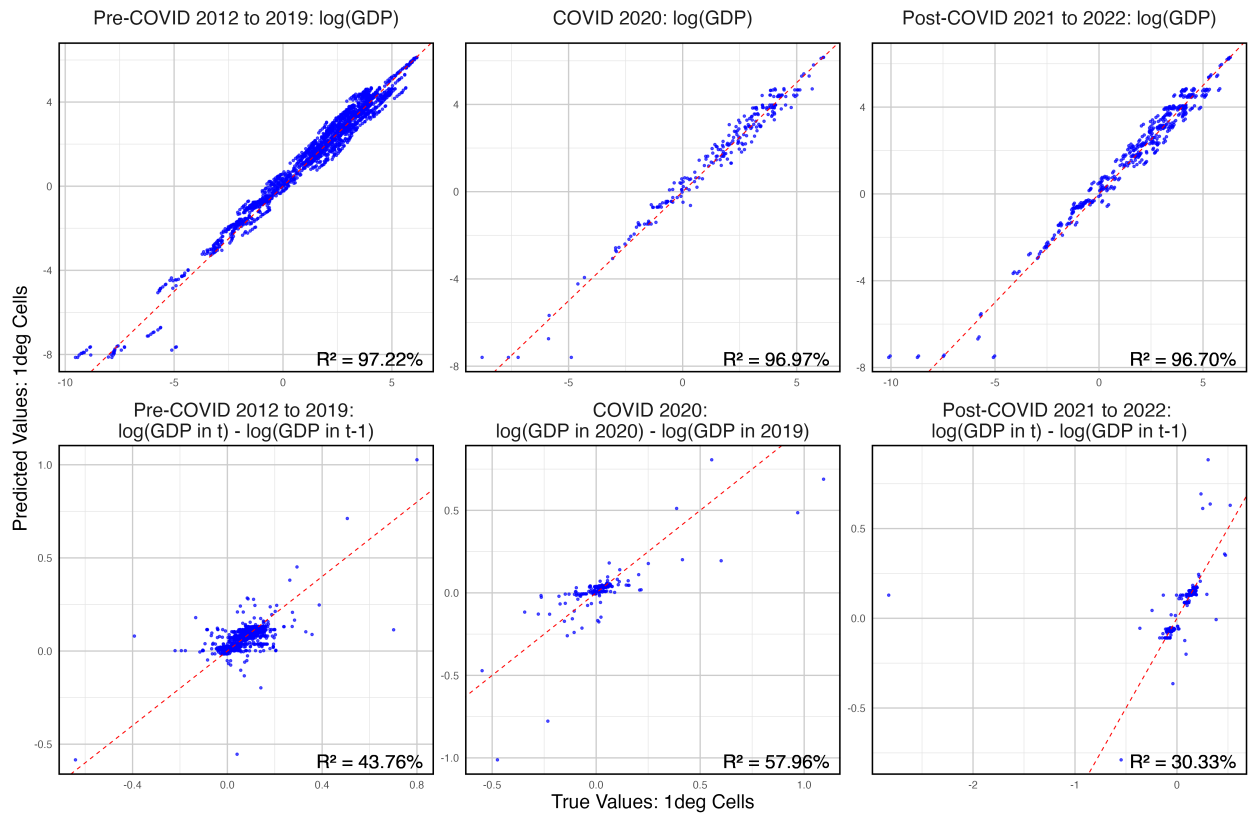


Figure 10: Model Predictions Against Actual GDP Values for China's Seven Leading Provinces, Using the Model Trained on years 2012 to 2019 Data and Tuned for Minimizing MSE

Note: This plot is comparable with Figure 4. The only difference is the way hyperparameters are tuned.

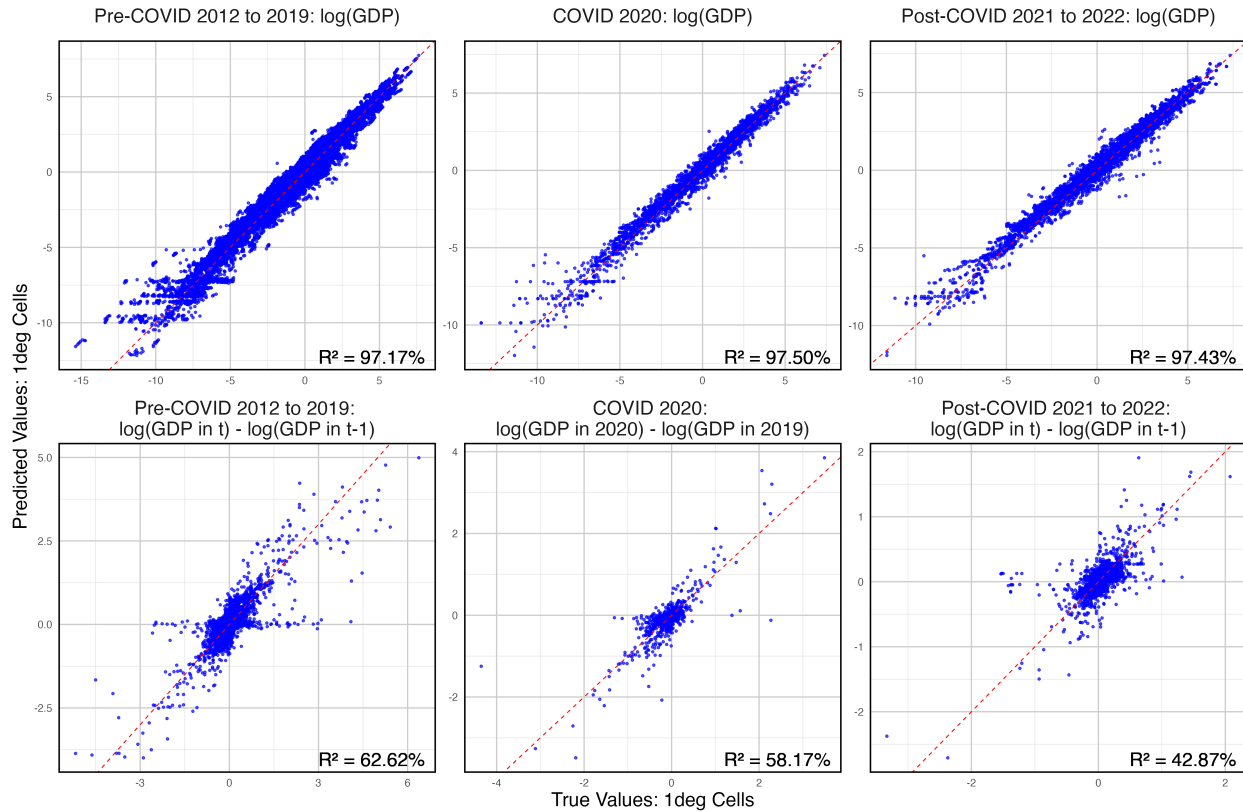


Figure 11: Model Predictions Against Actual GDP Values for All Training Countries, Using a Model Trained on years 2012 to 2019 Data and Tuned for Minimizing MSE

Note: Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model. This plot is comparable with Figure 5. The only difference is the way hyperparameters are tuned.

7.2 Compare Benchmark Models with Models Trained Without Weights

The models used in the paper are trained with weights to address the imbalance between cells from developed and developing countries in the training sample. The weights are the rescaling factors of cell shares from developed and developing countries in the training sample, adjusted to match their real-world proportions. Cells can only be assigned one of the two weights: one assigned to cells from developed countries and the other to cells from developing countries, depending on their classification. These weights influence the probability of each cell being selected in the bootstrap sample used to build each decision tree. By assigning higher probabilities to underrepresented groups, the model ensures that both developed and developing regions are adequately represented during training.

Here we compare the predictions from models trained with and without weights. Table 27 and Figure 12 illustrate that the differences between the two approaches are minimal and the weights have a limited impact on the overall predictive performance of the methodology.

We also performed the same tests on the model trained without weights for comparison

with the benchmark model (trained with weights), as shown in Figures 13, 14, and 15. The results continue to show the limited impact of weights on predictions.

Table 27: Cross-Validated Performance Metrics Across Spatial Resolutions

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: R^2 of Log GDP Level</i>						
R^2 (Developed)	98.32%	97.45%	97.65%			
R^2 (Developing)	95.95%	95.84%	94.63%			
R^2 (All)	97.95%	97.16%	97.06%			
Weighted R^2	96.61%	96.29%	95.47%			
<i>Panel B: R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	73.43%	74.50%	84.07%			
R^2 (Developing)	79.35%	76.58%	80.62%			
R^2 (All)	76.19%	73.52%	81.84%			
Weighted R^2	77.69%	76.00%	81.58%			
<i>Panel C: Variable Importance Scores</i>						
	R^2	$Corr$	R^2	$Corr$	R^2	$Corr$
Population (urban)	21.76	0.1924	40.94	0.1999	24.66	0.1743
Lag population (urban)	31.78	0.2002	40.48	0.1968	11.29	0.1629
Population (other)	20.43	0.1804	19.50	0.1803	16.75	0.1660
Lag CO2 non-org (heavy industry)	0.05	0.0100	16.13	0.1809	10.29	0.1644
CO2 non-org (heavy industry)	0.01	0.0026	14.79	0.1795	12.11	0.1662
Population (cropland)	1.27	0.1020	8.19	0.1602	7.35	0.1529
Lag population (cropland)	0.07	0.0164	7.16	0.1570	3.03	0.1316
Lag population (other)	4.76	0.1441	6.83	0.1553	5.08	0.1471
NTL (cropland)	3.42	0.1343	6.02	0.1533	4.86	0.1487
Lag NTL (urban)	0.18	0.0525	4.39	0.1439	0.01	0.0023
NTL (urban)	0.37	0.1002	3.41	0.1355	0.02	0.0054
lag NTL (cropland)	2.59	0.1256	2.90	0.1289	1.47	0.1080
Lag CO2 bio (manuf. combust.)	0.03	0.0056	2.04	0.1244	0.59	0.0879
NTL other (snow-free period)	0.02	0.0099	1.97	0.1167	0.15	0.0294
Population	0.75	0.1118	0.69	-0.1069	1.00	-0.1081
CO2 bio (manuf. combust.)	0.06	0.0196	0.96	0.0988	0.18	0.0355
CO2 non-org (manuf. combust.)	0.05	0.0174	0.32	0.0458	0.05	0.0096
Lag CO2 non-org (manuf. combust.)	0.06	0.0207	0.20	0.0354	0.05	0.0090
Lag cropland	0.14	0.0324	0.04	0.0076	0.04	0.0088
Cropland	0.09	0.0194	0.04	0.0090	0.01	0.0030

Notes: Panels A and B report cross-validated R^2 metrics. Panel C reports variable importance scores: drop in within-country R^2 and $Corr$ when each variable is replaced with its global mean. Variables shown are the top 20 by their maximum R^2 importance score across the three degree levels.

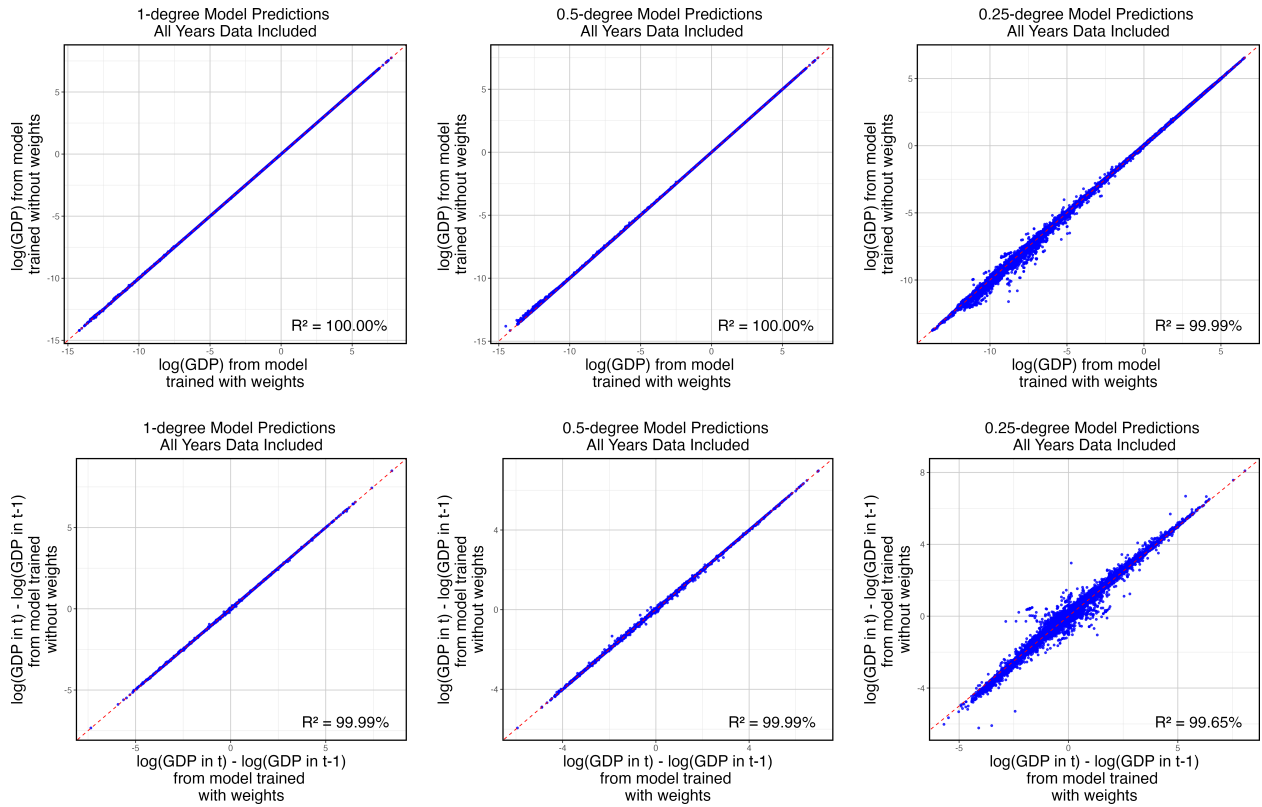


Figure 12: Comparison of Model Predictions: Models Trained With and Without Weights

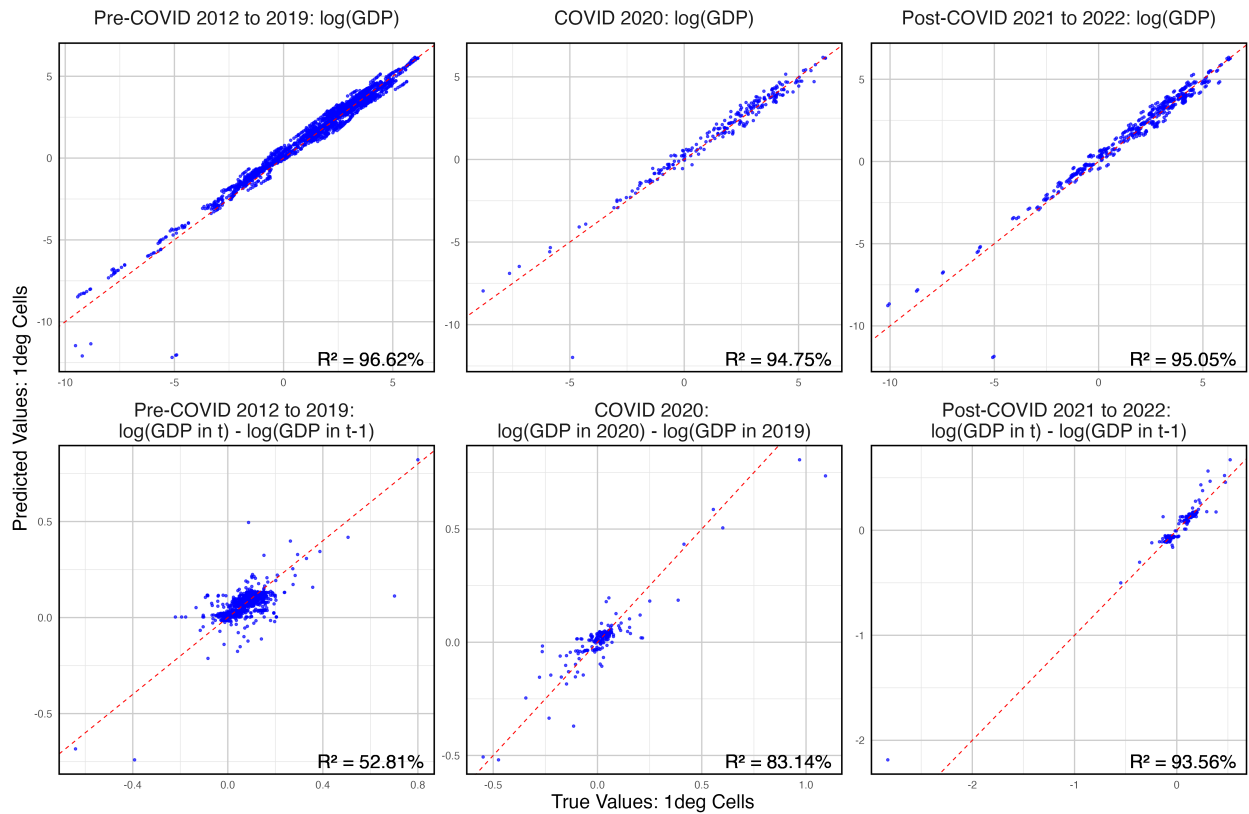


Figure 13: Model Predictions Against Actual GDP Values for China’s Seven Leading Provinces, Using the Model Trained on years 2012 to 2022 Data and Without Weights

Note: This plot is comparable to the corresponding plot in the paper, with the only difference being whether the models were trained with or without weights.

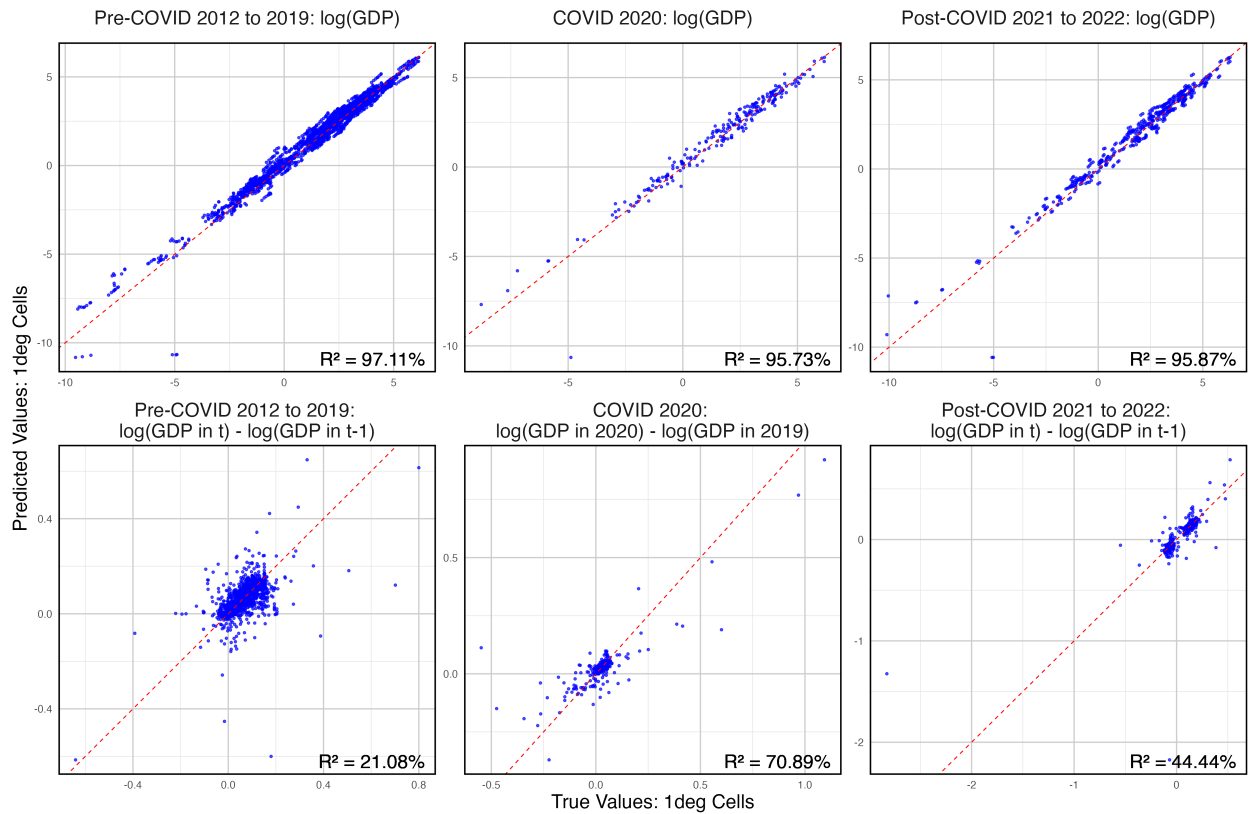


Figure 14: Model Predictions Against Actual GDP Values for China’s Seven Leading Provinces, Using the Model Trained on years 2012 to 2019 Data and Without Weights

Note: This plot is comparable with Figure 4. The only difference lies in whether the models were trained with or without weights.

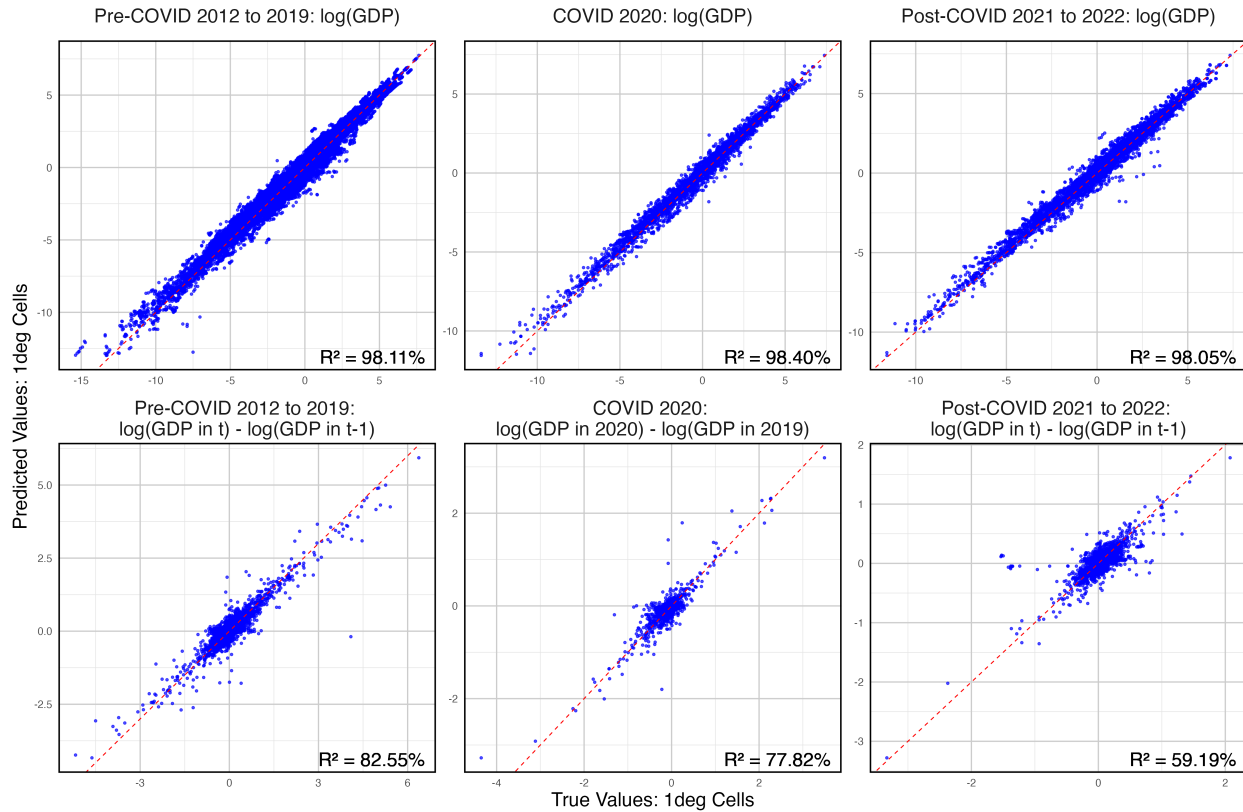


Figure 15: Model Predictions Against Actual GDP Values for All Training Countries, Using the Model Trained on years 2012 to 2019 Data and Without Weights

Note: Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model. This plot is comparable with Figure 5. The only difference lies in whether the models were trained with or without weights.

7.3 Compare Benchmark Models with Models Trained Without Developing Countries Data

This section presents the results of models trained without data from developing countries. Note that weights are also excluded when developing country data is not included. Table 28 summarizes the cross-validated performance across all three resolutions. No large differences are observed. The models were then used to predict data for cells in developing countries, and the results were compared with the truth. Tables 29, 30, and 31 demonstrate that the models perform well in predicting developing country data, even without having been trained on it. When applied to predict all world cells, Figure 16 reveals that level predictions are highly consistent, while slight differences are observed in annual changes.

We also performed the same tests on the model trained without developing countries for comparison with the benchmark model (trained with developing countries), as shown in Figures 17, 18, 19 and 20. The results show that the models continue to behave well even when developing countries are excluded.

Table 28: In-Sample Performance Metrics Across Spatial Resolutions

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: R^2 of Log GDP Level</i>						
R^2 (All)	98.79%	98.95%	98.89%			
<i>Panel B: R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (All)	80.07%	86.31%	90.07%			
<i>Panel C: Variable Importance Scores</i>						
	R^2	Corr	R^2	Corr	R^2	Corr
Lag population (urban)	17.90	0.7095	66.74	0.4207	10.16	0.1983
Lag CO2 non-org (transport)	45.80	0.7750	10.14	0.3529	15.01	0.1996
Population (other)	44.79	0.7662	42.30	0.3965	36.18	0.2072
Population (urban)	13.49	0.6647	40.79	0.4103	7.34	0.1951
Lag population (other)	27.91	0.7179	12.82	0.3597	8.76	0.1921
CO2 non-org (transport)	27.83	0.7221	7.93	0.3433	14.39	0.1992
Population (cropland)	19.17	0.6730	16.06	0.3678	14.15	0.1985
Lag NTL (urban)	16.92	0.6713	0.01	0.0043	0.00	0.0014
Lag population (cropland)	10.94	0.6021	16.43	0.3687	5.10	0.1840
NTL from Urban	14.35	0.6562	0.01	0.0050	0.01	0.0040
CO2 bio (transport)	13.31	0.6346	0.01	0.0107	0.00	0.0008
Lag CO2 bio (transport)	11.70	0.6184	0.03	0.0238	0.00	0.0011
Lag NTL (cropland)	7.75	0.5626	0.01	0.0051	0.00	0.0006
Lag CO2 nonorg (manuf. combust.)	6.25	0.5511	1.67	0.2629	0.19	0.0699
NTL (cropland)	4.54	0.4867	0.00	0.0039	0.87	0.1342
CO2 non-org (manuf. combust.)	4.45	0.5035	1.39	0.2504	0.41	0.1040
Lag cropland	2.51	0.3985	0.02	0.0148	0.00	0.0011
Cropland	2.10	0.3703	0.02	0.0156	0.00	0.0009
Population	1.68	0.6198	0.90	0.1203	0.99	-0.0703
Lag CO2 bio (manuf. combust.)	1.18	0.2830	0.01	0.0108	0.00	0.0001

Notes: Panels A and B report in-sample R^2 metrics. Panel C reports variable importance scores: drop in within-country R^2 and Corr when each variable is replaced with its global mean. Variables shown are the top 20 by their maximum R^2 importance score across the three degree levels.

Table 29: 1-degree Model Performance Metrics for Developing Group

ISO	R ² for log(GDP)	GDP Loss	R ² for log(GDP in t) - log(GDP in t-1)
ALB	98.29%	8.70%	95.78%
BIH	97.50%	10.66%	80.66%
BLR	99.11%	6.12%	95.51%
CHL	95.46%	10.36%	92.58%
COL	95.27%	10.35%	96.10%
ECU	93.73%	6.22%	87.66%
IDN	95.59%	11.50%	91.00%
KEN	88.63%	13.07%	89.48%
KGZ	95.82%	24.20%	94.87%
LKA	90.75%	22.79%	80.18%
MOZ	95.58%	14.32%	92.27%
PER	98.03%	13.11%	97.45%
PHL	98.38%	6.59%	94.77%
SRB	95.43%	10.40%	93.64%
THA	86.72%	23.64%	92.73%
UZB	98.37%	9.56%	98.13%
VNM	91.52%	14.76%	90.44%

Table 30: 0.5-degree Model Performance Metrics for Developing Group

ISO	R ² for log(GDP)	GDP Loss	R ² for log(GDP in t) - log(GDP in t-1)
ALB	94.08%	23.19%	97.19%
BIH	95.27%	8.80%	89.03%
BLR	98.44%	10.00%	95.44%
CHL	96.89%	11.76%	94.87%
COL	95.30%	13.01%	97.56%
ECU	87.19%	12.27%	81.67%
IDN	95.06%	11.16%	91.39%
KEN	88.58%	20.77%	89.95%
KGZ	95.87%	29.92%	97.32%
LKA	98.45%	9.18%	94.34%
MOZ	92.71%	20.08%	89.79%
PER	97.85%	13.55%	97.13%
PHL	98.01%	9.87%	97.58%
SRB	78.77%	12.12%	76.64%
THA	89.67%	27.12%	93.71%
UZB	98.06%	8.91%	97.51%
VNM	92.82%	15.21%	93.54%

Table 31: 0.25-degree Model Performance Metrics for Developing Group

ISO	R ² for log(GDP)	GDP Loss	R ² for log(GDP in t) - log(GDP in t-1)
ALB	93.64%	20.36%	96.43%
BIH	92.30%	6.61%	90.84%
BLR	96.51%	14.67%	95.44%
CHL	96.40%	14.97%	96.59%
COL	94.44%	16.95%	97.67%
ECU	89.18%	16.50%	86.27%
IDN	94.84%	19.59%	93.42%
KEN	89.29%	17.23%	92.55%
KGZ	95.08%	32.36%	97.96%
LKA	98.38%	9.93%	97.21%
MOZ	89.10%	27.36%	90.28%
PER	97.19%	13.64%	97.64%
PHL	97.04%	15.07%	98.97%
SRB	81.14%	17.14%	80.88%
THA	86.32%	29.02%	91.18%
UZB	97.18%	16.57%	97.31%
VNM	91.23%	18.24%	92.59%

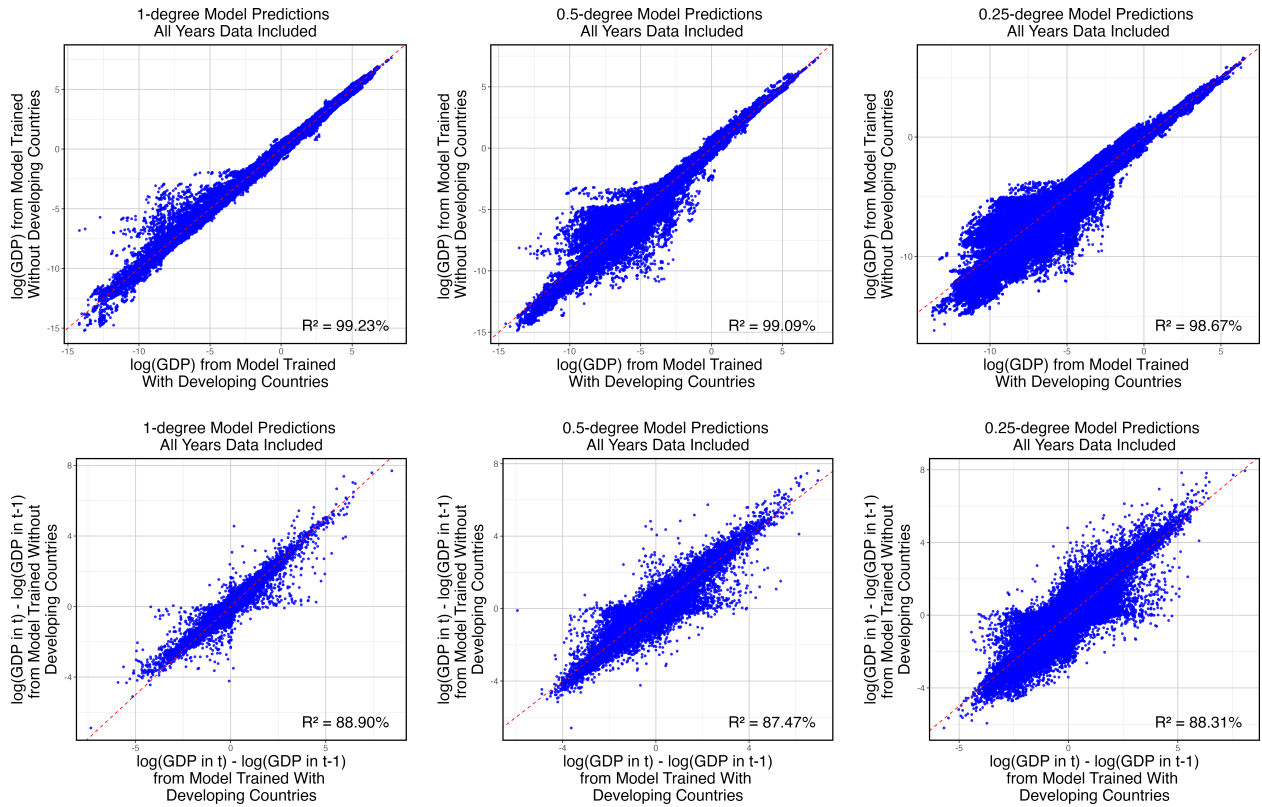


Figure 16: Comparison of Model Predictions: Models Trained With and Without Developing Countries Data

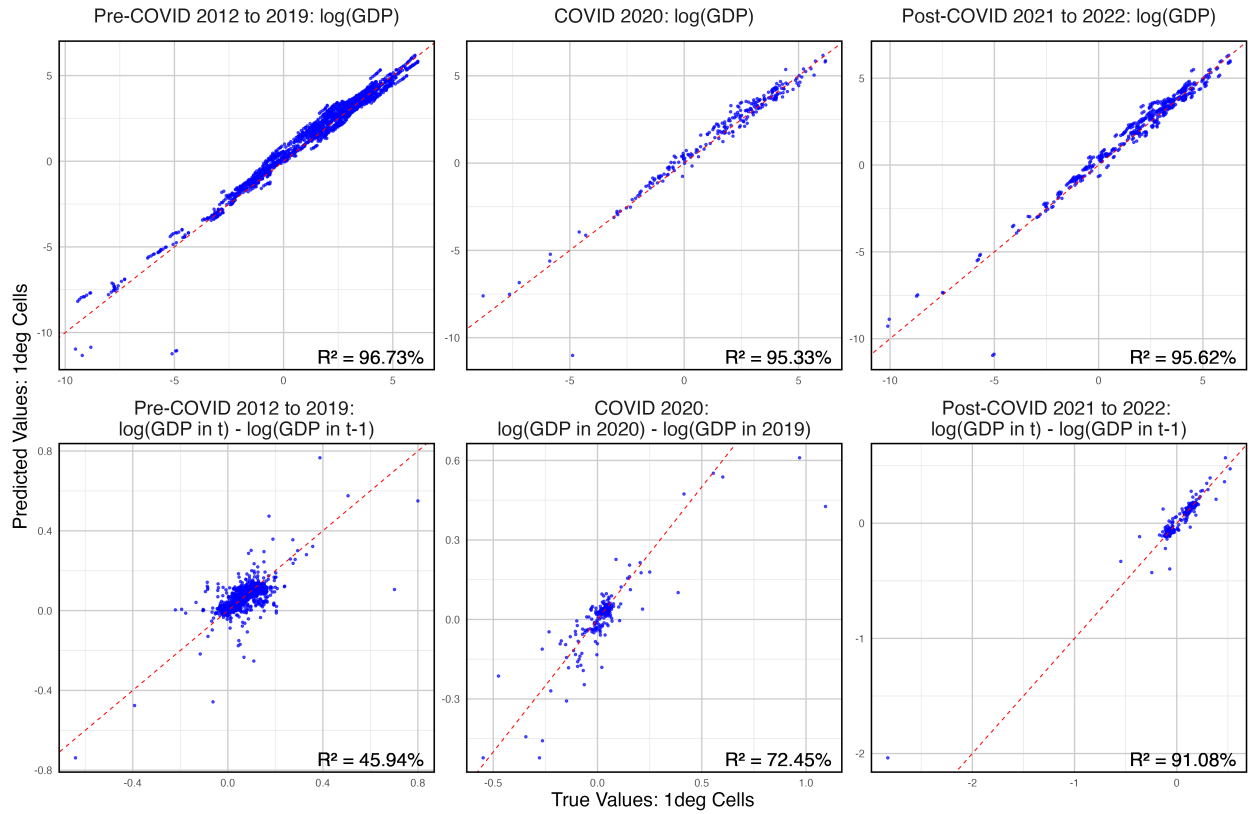


Figure 17: Model Predictions Against Actual GDP Values for China’s Seven Leading Provinces, Using a Model Trained on years 2012 to 2022 Data and Without developing countries data

Note: This plot is comparable to the corresponding plot in the paper, with the only difference being whether the models were trained with or without developing countries data.

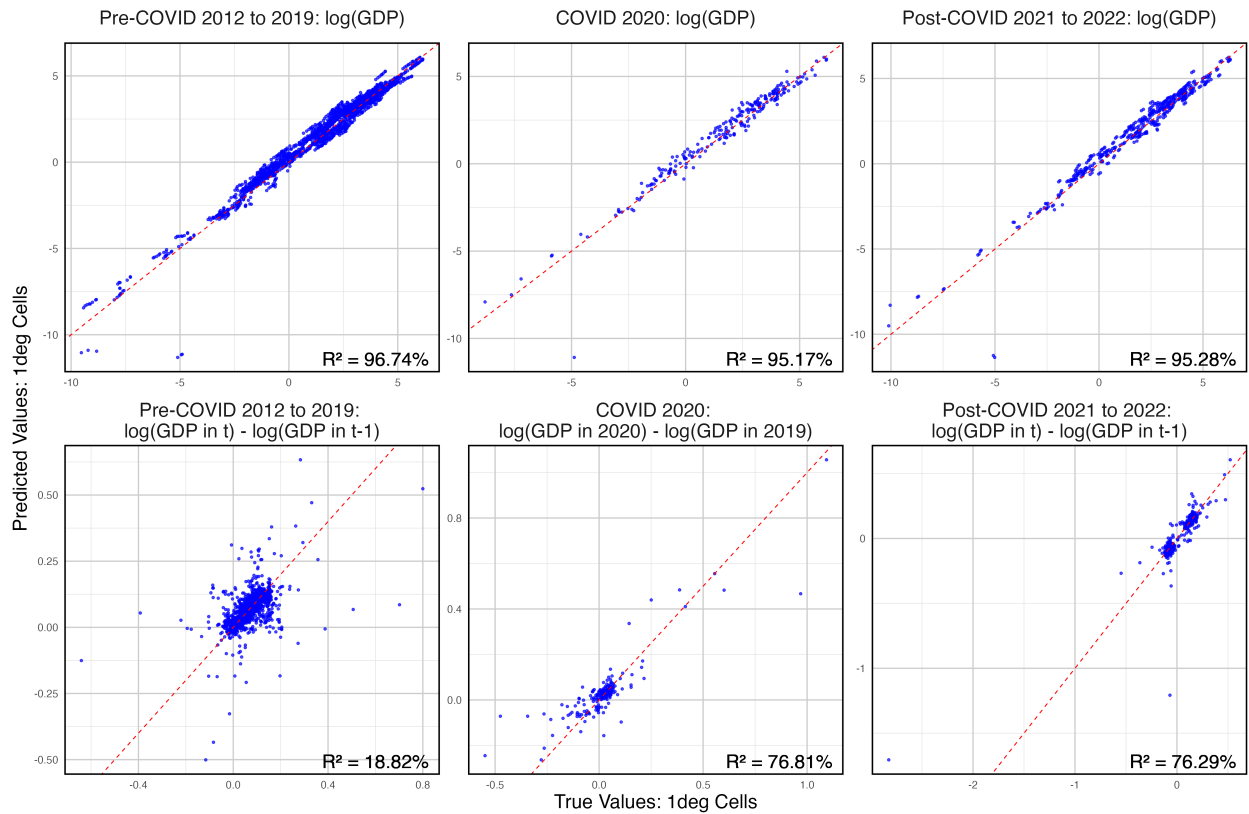


Figure 18: Model Predictions Against Actual GDP Values for China’s Seven Leading Provinces, Using a Model Trained on years 2012 to 2019 Data and Without developing countries data

Note: This plot is comparable with Figure 4. The only difference lies in whether the models were trained with or without developing countries data.

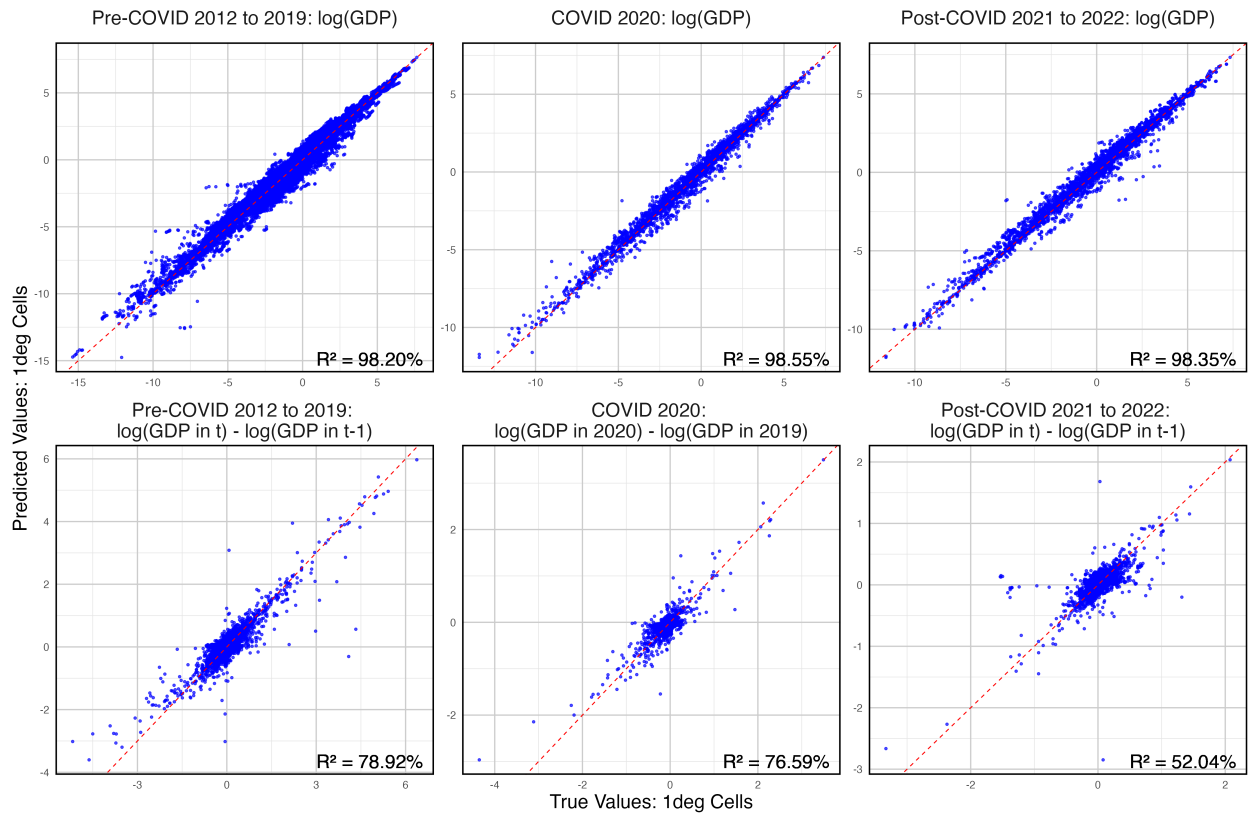


Figure 19: Model Predictions Against Actual GDP Values for All Training Countries, Using a Model Trained on years 2012 to 2019 Data and Without developing countries data

Note: Data for 2012 to 2019 are within training sample, so use out-of-bag predictions. Data for years 2020 to 2022 are predictions from the model. This plot is comparable with Figure 5. The only difference lies in whether the models were trained with or without developing countries data.

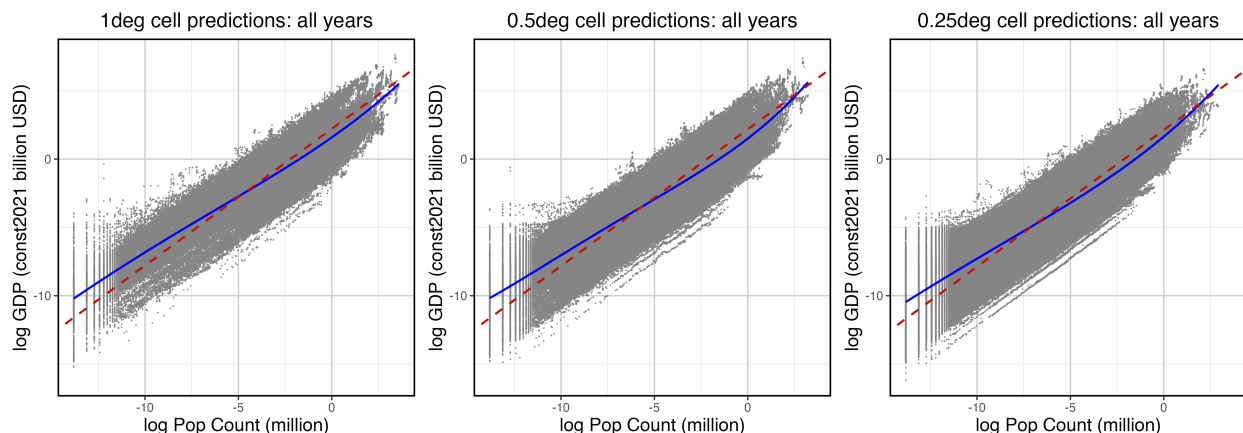


Figure 20: Cell Population Against Cell GDP, Using Models Trained Without developing countries data

Note: For the 1-degree resolution, the blue solid line is $y = 1.59 + 0.96x + 0.03x^2 + 0.002x^3 + 0 * x^4$ and the red dashed line is $y = x + 2.21$. For the 0.5-degree resolution, the blue solid line is $y = 1.5 + 1.05x + 0.05x^2 + 0.005x^3 + 0.0001x^4$ and the red dashed line is $y = x + 2.18$. For the 0.25-degree resolution, the blue solid line is $y = 1.64 + 1.14x + 0.05x^2 + 0.003x^3 + 0 * x^4$ and the red dashed line is $y = x + 2.13$.

7.4 Performance Dropping Individual Predictors

In this section, we assess the sensitivity of model performance to the exclusion of four distinct families of predictors from our baseline set of 36 predictors. The four families excluded are: (i) total population share (1 predictor), (ii) all one-year lag variables (15 predictors), (iii) all CO₂ emission variables and their lags (12 predictors), and (iv) national GDP per capita (1 predictor). Each specification is re-tuned via grid search over the same hyperparameter space as the baseline model and evaluated using the same five-fold cross-validation method. Tables 32–35 report cross-validated out-of-sample R^2 metrics (Panels A–D) and variable importance scores (Panel E) for each specification.

Table 32: Cross-Validated Performance: Dropping Total Population

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: Overall R^2 of log GDP Level</i>						
R^2 (Developed)	95.25%	94.88%	94.40%			
R^2 (Developing)	92.83%	93.70%	92.86%			
R^2 (All)	95.85%	95.17%	94.79%			
Weighted R^2	93.51%	94.03%	93.29%			
<i>Panel B: Overall R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	49.95%	59.45%	71.97%			
R^2 (Developing)	62.41%	61.44%	63.98%			
R^2 (All)	60.14%	61.62%	71.31%			
Weighted R^2	58.93%	60.88%	66.20%			
<i>Panel C: Within R^2 of log GDP Level</i>						
R^2 (Developed)	94.01%	93.23%	91.83%			
R^2 (Developing)	91.72%	92.00%	90.85%			
R^2 (All)	94.44%	93.16%	92.04%			
Weighted R^2	92.36%	92.34%	91.12%			
<i>Panel D: Within R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	40.93%	54.07%	68.43%			
R^2 (Developing)	39.61%	52.81%	57.98%			
R^2 (All)	52.96%	56.11%	67.43%			
Weighted R^2	39.98%	53.16%	60.89%			
<i>Panel E: Variable Importance Scores</i>						
	R^2	$Corr$	R^2	$Corr$	R^2	$Corr$
Lag population (urban)	83.65	0.0684	62.76	0.0795	43.07	0.0422
Population (other)	81.85	0.0672	55.78	0.0772	48.59	0.0413
Population (urban)	71.37	0.0680	74.58	0.0808	60.10	0.0444
Lag population (cropland)	57.39	0.0657	44.82	0.0768	30.59	0.0407
Population (cropland)	41.67	0.0644	34.76	0.0756	38.04	0.0409
Lag population (other)	21.43	0.0601	19.13	0.0725	25.26	0.0397
Lag NTL (urban)	0.24	0.0172	18.58	0.0737	7.55	0.0363
NTL (urban)	0.29	0.0167	17.39	0.0733	6.37	0.0359
Lag CO2 non-org (heavy industry)	0.06	0.0016	16.82	0.0726	9.76	0.0382
CO2 non-org (heavy industry)	0.03	0.0007	14.17	0.0714	11.27	0.0388
Lag NTL (cropland)	9.30	0.0525	5.15	0.0606	7.15	0.0369
NTL (cropland)	6.44	0.0477	5.74	0.0619	7.69	0.0371
Lag CO2 bio (manuf. combust.)	0.23	0.0132	3.28	0.0589	5.48	0.0381
NTL other (snow-free period)	0.26	0.0164	4.03	0.0584	1.45	0.0256
CO2 bio (manuf. combust.)	0.62	0.0339	3.44	0.0639	2.13	0.0338

Notes: This specification drops total population share (1 of 36 baseline predictors). The remaining model uses 35 predictors. Panels A–D report cross-validated R^2 metrics. Panel E reports variable importance scores: drop in within-country-year R^2 (expressed as decimals) and $Corr$ when each variable is replaced with its global mean. Variables shown are the top 15 by their maximum R^2 importance score across all degree levels.

Table 33: Cross-Validated Performance: Dropping All Lag Variables

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: Overall R^2 of $\log GDP$ Level</i>						
R^2 (Developed)	98.30%	97.17%	97.53%			
R^2 (Developing)	95.94%	95.73%	94.44%			
R^2 (All)	97.94%	96.95%	96.92%			
Weighted R^2	96.60%	96.13%	95.30%			
<i>Panel B: Overall R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	71.85%	70.83%	84.11%			
R^2 (Developing)	77.44%	75.23%	81.31%			
R^2 (All)	74.71%	70.91%	82.10%			
Weighted R^2	75.88%	74.00%	82.09%			
<i>Panel C: Within R^2 of $\log GDP$ Level</i>						
R^2 (Developed)	97.87%	96.24%	96.35%			
R^2 (Developing)	95.30%	94.58%	92.97%			
R^2 (All)	97.27%	95.69%	95.29%			
Weighted R^2	96.02%	95.05%	93.91%			
<i>Panel D: Within R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	66.77%	66.91%	82.05%			
R^2 (Developing)	68.32%	70.87%	78.52%			
R^2 (All)	70.16%	66.71%	79.68%			
Weighted R^2	67.89%	69.76%	79.50%			
<i>Panel E: Variable Importance Scores</i>						
	R^2	$Corr$	R^2	$Corr$	R^2	$Corr$
Population (urban)	26.44	0.0657	46.78	0.0488	22.15	0.0333
Population (other)	15.58	0.0611	18.87	0.0453	16.90	0.0323
NTL (urban)	0.60	0.0542	18.38	0.0457	3.54	0.0293
CO2 non-org (heavy industry)	0.05	0.0069	17.40	0.0460	12.34	0.0330
Population (cropland)	0.47	0.0300	10.18	0.0432	5.92	0.0306
NTL (cropland)	0.00	-0.0015	6.43	0.0415	5.14	0.0309
NTL other (snow-free period)	0.04	0.0084	4.02	0.0391	1.00	0.0224
CO2 bio (manuf. combust.)	0.09	0.0137	3.34	0.0404	0.83	0.0236
CO2 non-org (manuf. combust.)	0.10	0.0191	1.66	0.0320	0.36	0.0140
Urban	0.00	0.0004	1.32	0.0286	0.00	0.0000
CO2 non-org (transport)	0.03	0.0037	0.35	0.0141	0.01	0.0004
Cropland	0.16	0.0172	0.15	0.0079	0.02	0.0018
CO2 bio (heavy industry)	0.03	0.0012	0.04	0.0022	0.01	0.0005
CO2 bio (transport)	0.04	0.0033	0.03	0.0013	0.00	0.0003
Mean ruggedness	0.00	0.0013	0.00	0.0019	0.00	0.0006

Notes: This specification drops all 15 one-year lag predictors from the baseline model: lagged NTL (urban, cropland, other), lagged urban and cropland land cover shares, lagged population (urban, cropland, other), lagged NPP, and lagged CO₂ emissions (bio and non-organic: manufacturing, heavy industry, transport). The remaining model uses 21 predictors. Panels A–D report cross-validated R^2 metrics. Panel E reports variable importance scores: drop in within-country-year R^2 (expressed as decimals) and $Corr$ when each variable is replaced with its global mean. Variables shown are the top 15 by their maximum R^2 importance score across all degree levels.

Table 34: Cross-Validated Performance: Dropping All CO₂ Variables

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: Overall R² of log GDP Level</i>						
R ² (Developed)	98.32%	97.56%	97.40%			
R ² (Developing)	95.79%	95.82%	94.09%			
R ² (All)	97.92%	97.21%	96.75%			
Weighted R ²	96.49%	96.31%	95.01%			
<i>Panel B: Overall R² of log(GDP_t) – log(GDP_{t-1})</i>						
R ² (Developed)	73.31%	75.55%	84.07%			
R ² (Developing)	78.91%	75.43%	80.17%			
R ² (All)	75.77%	73.37%	81.84%			
Weighted R ²	77.34%	75.46%	81.26%			
<i>Panel C: Within R² of log GDP Level</i>						
R ² (Developed)	97.89%	96.75%	96.17%			
R ² (Developing)	95.12%	94.78%	92.53%			
R ² (All)	97.25%	96.08%	95.06%			
Weighted R ²	95.90%	95.33%	93.54%			
<i>Panel D: Within R² of log(GDP_t) – log(GDP_{t-1})</i>						
R ² (Developed)	68.52%	72.20%	82.02%			
R ² (Developing)	70.79%	71.31%	77.23%			
R ² (All)	71.35%	69.60%	79.40%			
Weighted R ²	70.16%	71.56%	78.56%			
<i>Panel E: Variable Importance Scores</i>						
	<u>R²</u>	<u>Corr</u>	<u>R²</u>	<u>Corr</u>	<u>R²</u>	<u>Corr</u>
Lag population (urban)	37.31	0.0627	38.69	0.0454	13.69	0.0212
Population (urban)	25.48	0.0617	37.09	0.0458	28.67	0.0219
Population (other)	24.03	0.0599	18.80	0.0434	20.32	0.0209
Population (cropland)	4.11	0.0511	8.56	0.0411	10.08	0.0205
Lag population (other)	8.23	0.0553	6.36	0.0400	6.52	0.0204
Lag NTL (urban)	0.20	0.0249	6.45	0.0404	1.66	0.0167
NTL (cropland)	5.06	0.0524	6.26	0.0403	4.74	0.0206
Lag population (cropland)	4.38	0.0514	5.75	0.0395	5.15	0.0198
NTL (urban)	0.41	0.0415	4.49	0.0388	0.01	0.0007
Lag NTL (cropland)	0.00	0.0001	3.14	0.0365	2.03	0.0177
NTL other (snow-free period)	0.05	0.0097	0.09	0.0080	0.48	0.0112
Lag cropland	0.22	0.0206	0.03	0.0026	0.05	0.0022
Cropland	0.18	0.0173	0.02	0.0014	0.01	0.0007
Lag NTL (other)	0.04	0.0081	0.07	0.0066	0.00	0.0007
Water	0.00	0.0003	0.04	0.0034	0.00	0.0000

Notes: This specification drops all 12 CO₂ emission predictors: bio and non-organic CO₂ shares for manufacturing combustion, heavy industry, and transport, and their lags (12 of 36 baseline predictors). The remaining model uses 24 predictors. Panels A–D report cross-validated R² metrics. Panel E reports variable importance scores: drop in within-country-year R² (expressed as decimals) and Corr when each variable is replaced with its global mean. Variables shown are the top 15 by their maximum R² importance score across all degree levels.

Table 35: Cross-Validated Performance: Dropping National GDP per Capita

	1-degree Model	0.5-degree Model	0.25-degree Model			
<i>Panel A: Overall R^2 of log GDP Level</i>						
R^2 (Developed)	98.27%	97.38%	97.56%			
R^2 (Developing)	95.91%	95.81%	94.74%			
R^2 (All)	97.93%	97.11%	97.07%			
Weighted R^2	96.57%	96.25%	95.53%			
<i>Panel B: Overall R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	73.45%	74.25%	83.05%			
R^2 (Developing)	79.53%	76.01%	80.42%			
R^2 (All)	76.10%	73.03%	81.03%			
Weighted R^2	77.83%	75.52%	81.15%			
<i>Panel C: Within R^2 of log GDP Level</i>						
R^2 (Developed)	97.83%	96.53%	96.41%			
R^2 (Developing)	95.26%	94.72%	93.38%			
R^2 (All)	97.25%	95.93%	95.52%			
Weighted R^2	95.98%	95.22%	94.22%			
<i>Panel D: Within R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	68.72%	70.78%	80.88%			
R^2 (Developing)	71.79%	71.94%	77.63%			
R^2 (All)	71.80%	69.18%	78.53%			
Weighted R^2	70.93%	71.61%	78.53%			
<i>Panel E: Variable Importance Scores</i>						
	R^2	<i>Corr</i>	R^2	<i>Corr</i>	R^2	<i>Corr</i>
Lag population (urban)	36.22	0.0702	45.05	0.0615	13.14	0.0571
Population (urban)	24.97	0.0690	40.54	0.0617	25.76	0.0588
Population (other)	21.96	0.0669	20.73	0.0588	18.23	0.0574
Lag CO2 non-org (heavy industry)	0.09	0.0099	16.06	0.0589	10.31	0.0570
CO2 non-org (heavy industry)	0.02	0.0023	14.80	0.0587	11.87	0.0573
Population (cropland)	5.55	0.0597	10.57	0.0563	8.02	0.0551
Lag population (other)	7.13	0.0613	8.76	0.0558	6.28	0.0546
Lag NTL (urban)	0.18	0.0246	8.28	0.0555	1.82	0.0461
Lag population (cropland)	2.49	0.0529	7.44	0.0546	3.94	0.0518
NTL (cropland)	2.88	0.0542	5.78	0.0534	4.90	0.0539
NTL (urban)	0.37	0.0436	5.68	0.0533	1.62	0.0452
Lag NTL (cropland)	2.90	0.0543	3.49	0.0494	1.73	0.0455
Lag urban	2.86	0.0544	0.00	0.0005	0.00	0.0002
NTL other (snow-free period)	0.02	0.0042	2.36	0.0463	0.13	0.0121
Lag CO2 bio (manuf. combust.)	0.04	0.0034	2.25	0.0476	2.18	0.0527

Notes: This specification drops national GDP per capita (1 of 36 baseline predictors), the only predictor that varies at the country level rather than the cell level. The remaining model uses 35 predictors.

Panels A–D report cross-validated R^2 metrics. Panel E reports variable importance scores: drop in within-country-year R^2 (expressed as decimals) and *Corr* when each variable is replaced with its global mean. Variables shown are the top 15 by their maximum R^2 importance score across all degree levels.

8 Robustness of Out-of-Sample Evaluation

Our main specification evaluates out-of-sample performance via 5-fold cross-validation, with cells grouped by ISO code so that all cells in a country belong to either the training or the test fold. To assess the robustness of these methodological choices, this section presents within-country cross-validated R-squared metrics alongside R-squared metrics from two alternative evaluation approaches: (i) a finer-grained spatial holdout *within* countries, and (ii) removing the GDP *rescaling* step that normalizes predicted shares to sum to one within each country-year.

8.1 Within-Country Cross-Validation Performance

The overall R^2 reported in Table 1 of the main text pools all cells across countries. A natural concern is that the high R^2 may partly reflect cross-country variation in GDP levels. Table 36 reports the within-country R^2 , computed by first demeaning log GDP and its prediction by their respective country-year means and then calculating R^2 on the residuals. This metric isolates the model’s capacity to predict the spatial distribution of economic activity within each country, net of country-level differences.

The within-country R^2 for log GDP levels exceeds 93% across all resolutions and country groups, only modestly below the overall R^2 . For annual changes, the within-country R^2 ranges from 69% to 82%, again tracking the overall metrics closely. These results confirm that the model captures within-country spatial distribution of GDP and GDP changes in log.

Table 36: Within-Country Cross-Validated R^2

	1-degree Model	0.5-degree Model	0.25-degree Model
<i>Panel A: Within-Country R^2 of Log GDP Level</i>			
R^2 (Developed)	97.89%	96.62%	96.48%
R^2 (Developing)	95.29%	94.78%	93.23%
R^2 (All)	97.29%	96.00%	95.49%
Weighted R^2	96.02%	95.29%	94.14%
<i>Panel B: Within-Country R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>			
R^2 (Developed)	68.83%	71.02%	81.99%
R^2 (Developing)	71.71%	72.62%	78.30%
R^2 (All)	71.93%	69.73%	79.47%
Weighted R^2	70.91%	72.18%	79.33%

Notes: Within-country R^2 computed by demeaning log GDP and predicted log GDP by their country-year means before calculating R^2 . Cross-validated using the same 5-fold country-level holdout as Table 1 in the main text.

8.2 Spatial Block Cross-Validation

In our main cross-validation design, each country is assigned to either the training or testing fold, so that all cells within a country appear in the same fold. Because the model never

observes any cells in any year from a held-out country during training, so mechanical spatial linkage or temporal linkage problem does not appear. Therefore, the evaluation is robust to spatial and temporal spillover *by construction*.

However, to what extent *would* spatial autocorrelation inflate performance metrics if we did not hold out entire countries? To answer this, we implement a spatial block cross-validation exercise for the 1-degree model that varies the size of the spatial units held out within each country. We focus on the 1-degree model because this exercise requires re-training the model for each cluster size and fold combination, making it computationally intensive. We first partition grid cells into contiguous clusters of size S via k -means clustering on cell centroids. We then randomly assign clusters into 5 folds, with each fold holding out approximately 20% of the clusters. After that, we re-train the model on the training folds, predict all cells, rescale within each (country, year) pair, and report metrics evaluated based only on the held-out cells.

The cluster size S controls the degree of spatial separation between training and evaluation data. At one extreme ($S = 1$), each cell forms its own cluster and is individually held out. This is the case most susceptible to spillovers across cells, as the model can freely exploit information from nearby training cells, which potentially results in overly optimistic performance metrics. As S increases, held-out blocks grow larger and more spatially separated from the training data, progressively limiting the model's ability to interpolate from neighboring cells. When S reaches the total number of cells in a country, that country collapses to a single cluster and the exercise converges to our baseline country-level holdout.

Table 37 reports the results for cluster sizes $S \in \{1, 2, 5, 10, 25, 50\}$ alongside the baseline. All models use the same tuned hyperparameters as the main specification. The overall R^2 of log GDP levels (Panel A) is remarkably stable across all cluster sizes, ranging from 97.93% to 98.05%, compared with 97.95% for the baseline. The within-country R^2 (Panel C) is similarly stable. For annual changes (Panels B and D), performance shows modest variation across cluster sizes but no systematic decline. Notably, even the $S = 1$ specification, where individual cells are held out and neighboring cells remain in training, produces R^2 values that match or exceed the baseline. This confirms that the model's predictive power does not rely on interpolating from spatially contiguous training cells, even if we relax the country-level holdout design.

Table 38 provides the number of 1-degree grid cells per training country for reference.

Table 37: Spatial Block Cross-Validation: Out-of-Sample R^2

	$S = 1$	$S = 2$	$S = 5$	$S = 10$	$S = 25$	$S = 50$	Baseline
<i>Panel A: Overall R^2 of Log GDP Level</i>							
R^2 (Developed)	98.44%	98.43%	98.45%	98.40%	98.39%	98.26%	98.32%
R^2 (Developing)	96.89%	96.88%	96.86%	96.85%	96.62%	96.53%	95.94%
R^2 (All)	98.05%	98.04%	98.05%	98.03%	98.02%	97.93%	97.95%
Weighted R^2	97.32%	97.32%	97.30%	97.28%	97.12%	97.01%	96.60%
<i>Panel B: Overall R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>							
R^2 (Developed)	76.06%	75.11%	76.59%	73.61%	74.76%	74.53%	73.55%
R^2 (Developing)	83.90%	83.15%	80.14%	81.82%	76.33%	77.66%	79.37%
R^2 (All)	80.47%	80.47%	79.15%	78.58%	76.79%	78.60%	76.20%
Weighted R^2	81.71%	80.91%	79.15%	79.53%	75.89%	76.79%	77.74%
<i>Panel C: Within-Country R^2 of Log GDP Level</i>							
R^2 (Developed)	97.78%	97.72%	97.74%	97.79%	97.79%	97.81%	97.89%
R^2 (Developing)	95.82%	95.77%	95.71%	95.62%	95.21%	95.24%	95.29%
R^2 (All)	97.11%	97.04%	97.04%	97.10%	97.03%	97.03%	97.29%
Weighted R^2	96.37%	96.32%	96.28%	96.22%	95.93%	95.96%	96.02%
<i>Panel D: Within-Country R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>							
R^2 (Developed)	68.58%	66.25%	69.14%	64.75%	68.72%	68.84%	68.83%
R^2 (Developing)	80.19%	79.06%	74.39%	75.23%	69.08%	72.34%	71.71%
R^2 (All)	75.32%	74.70%	72.68%	71.34%	70.95%	72.96%	71.93%
Weighted R^2	76.95%	75.48%	72.92%	72.30%	68.98%	71.36%	70.91%

Notes: This table reports out-of-sample R^2 under spatial block cross-validation with varying cluster sizes ($S =$ cells per cluster). Within each training country, grid cells are partitioned into contiguous spatial clusters via k -means on cell centroids.

Clusters are randomly assigned to 5 folds; each fold holds out $\sim 20\%$ of clusters. The model predicts all cells and rescales within (country, year) globally, then metrics are evaluated only on held-out cells. As S increases toward the number of cells in a country, that country collapses to a single cluster and the exercise converges to the baseline. “Baseline” reports the standard random country-level group V -fold CV ($V=5$) from the main specification. All models use the same tuned hyperparameters as the main specification.

Table 38: Number of 1-Degree Grid Cells per Training Country (Total: 4,056 cells across 48 countries)

ISO	Cells	ISO	Cells
USA	973	ROU	47
IDN	384	BLR	44
NOR	195	ECU	42
CHL	161	KGZ	37
PER	148	PRT	29
COL	133	BGR	25
FRA	117	AUT	24
TUR	117	DNK	23
SWE	115	HRV	23
JPN	113	HUN	22
MOZ	103	CZE	21
FIN	100	LVA	21
ESP	96	EST	20
PHL	90	KOR	20
UZB	82	LTU	19
ITA	76	SRB	17
GBR	75	BIH	15
THA	74	SVK	15
DEU	69	CHE	14
KEN	69	NLD	14
NZL	65	LKA	12
VNM	60	BEL	11
POL	58	ALB	9
GRC	52	SVN	7

Notes: Each row shows a training country (ISO-3 code) and its number of unique 1-degree grid cells. US states are aggregated to country level. Sorted by descending cell count.

8.3 Performance Without GDP Rescaling

In the main specification, the random forest predicts GDP shares for each cell, which are then rescaled to sum to one within each country-year before being multiplied by the country’s total GDP to obtain cell-level GDP estimates. A natural concern is that this rescaling step may introduce correlated errors across cells within a country: if one cell’s GDP share is overestimated, the shares of other cells must be mechanically pushed down for the country total to remain correct. Here we show that our out-of-sample performance at all three resolutions is robust to skipping the rescaling step entirely.

Table 39 reports the results. Across all panels and resolutions, the “without rescaling” columns are virtually identical to the baseline, and in some cases marginally higher. This confirms that the rescaling step has minimal impact on our model’s out-of-sample performance.

Table 39: Out-of-Sample R^2 with and without Rescaling

	1-degree Model		0.5-degree Model		0.25-degree Model	
	With Rscl.	W/o Rscl.	With Rscl.	W/o Rscl.	With Rscl.	W/o Rscl.
<i>Panel A: Overall R^2 of Log GDP Level</i>						
R^2 (Developed)	98.32%	98.54%	97.45%	97.79%	97.62%	97.73%
R^2 (Developing)	95.94%	96.61%	95.84%	95.84%	94.63%	94.77%
R^2 (All)	97.95%	98.09%	97.16%	97.31%	97.04%	97.14%
Weighted R^2	96.60%	97.15%	96.29%	96.38%	95.46%	95.59%
<i>Panel B: Overall R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	73.55%	73.94%	74.47%	74.53%	84.05%	84.08%
R^2 (Developing)	79.37%	79.52%	76.60%	76.95%	81.03%	81.08%
R^2 (All)	76.20%	76.44%	73.51%	73.64%	81.88%	81.92%
Weighted R^2	77.74%	77.96%	76.00%	76.27%	81.87%	81.91%
<i>Panel C: Within-Country R^2 of Log GDP Level</i>						
R^2 (Developed)	97.89%	98.17%	96.62%	97.07%	96.48%	96.66%
R^2 (Developing)	95.29%	95.98%	94.78%	94.78%	93.23%	93.42%
R^2 (All)	97.29%	97.47%	96.00%	96.22%	95.49%	95.65%
Weighted R^2	96.02%	96.59%	95.29%	95.42%	94.14%	94.32%
<i>Panel D: Within-Country R^2 of $\log(GDP_t) - \log(GDP_{t-1})$</i>						
R^2 (Developed)	68.83%	69.29%	71.02%	71.08%	82.00%	82.04%
R^2 (Developing)	71.71%	71.98%	72.62%	73.04%	78.30%	78.35%
R^2 (All)	71.93%	72.21%	69.73%	69.88%	79.47%	79.52%
Weighted R^2	70.91%	71.23%	72.18%	72.50%	79.33%	79.38%

Notes: “With Rscl.” denotes the baseline model where predicted GDP shares are rescaled to sum to one within each country-year before computing cell-level GDP. “W/o Rscl.” uses raw (unrescaled) predicted shares. All metrics are out-of-sample.

9 Prediction Accuracy in Challenging Geographic Settings

The preceding sections demonstrate that our model achieves strong out-of-sample performance in aggregate. This section examines whether prediction errors are systematically related to specific geographic or economic features. Throughout, the log prediction errors are derived from the 5-fold cross-validation procedure described in the main text, so that each cell’s prediction error reflects a genuinely out-of-sample forecast. We focus on three diagnostics: (i) whether the country-level allocation mechanism induces artificial discontinuities at national borders, (ii) whether the model underperforms in areas with high cropland coverage, and (iii) whether emissions-based predictors mechanically inflate predicted output along major transport corridors.

9.1 Border Discontinuity

Our random forest model generates raw predictions for cell GDP *shares* (i.e., the cell’s share of national GDP), before multiplying predicted GDP shares by national GDP to arrive at our cell GDP estimates. Because both the predicted GDP shares and the predictor values in the random forest model are defined relative to national aggregates, the national boundary is a discrete unit of analysis: two neighboring cells on opposite sides of a border belong to different national pools and are therefore predicted independently of each other. To the extent that national GDP levels differ across borders, this allocation mechanism can induce sharp discontinuities in predicted cell-level GDP at border crossings. If such discontinuities are large, they would reflect a mechanical artifact of the country-level allocation rather than a genuine feature of the spatial distribution of economic activity.

To assess this, we classify each grid cell as either a border cell — defined as any cell adjacent to a cell belonging to a different country (or a different U.S. state, since states are treated as national units in our training process) — or an interior cell. We then compare out-of-sample prediction errors between the two groups, where prediction errors are computed as the average difference between predicted and true GDP across cells in all five test folds of the cross-validation. Only cells in the training sample are used (see Table 2) as true GDP is unavailable for the remaining cells. Conceptually, if the allocation mechanism introduces systematic distortions at borders, we would expect prediction errors to be larger for border cells than for interior cells.

Table 40 reports the overall R^2 of log GDP levels separately for border and interior cells. Across all three resolutions, border cells achieve R^2 values that are comparable to or slightly higher than those of interior cells (e.g., 0.9812 versus 0.9753 at the 1-degree level). Table 41 regresses the absolute log prediction error on a border indicator, controlling for population share, log cell area, and country fixed effects; the control for log cell area is particularly important because border cells are systematically smaller than interior cells, an artifact of segmenting cells along country borders during the training process. The border coefficient is small, negative, and statistically insignificant at all three resolutions, providing no evidence that our allocation mechanism introduces systematic distortions at borders.

Table 40: Prediction Accuracy: Border vs. Interior Cells

	1-degree Model		0.5-degree Model		0.25-degree Model	
	N	R^2	N	R^2	N	R^2
Border cells	19,210	98.12%	43,113	97.59%	88,945	97.66%
Interior cells	19,971	97.53%	84,299	97.11%	350,370	96.98%
All cells	39,181	97.88%	127,412	97.30%	439,315	97.13%

Notes: Overall R^2 on log GDP levels. Border cells are adjacent to a cell in a different country or US state. Pooled 2012–2022, in-sample countries.

Table 41: Regression of Absolute Log Prediction Error on Border Status

	(1) 1-degree	(2) 0.5-degree	(3) 0.25-degree
Border	-0.0125 (0.0116)	-0.0104 (0.0070)	-0.0048 (0.0036)
Pop. share	-0.2421*** (0.0596)	-0.3865*** (0.0878)	-0.2446* (0.1383)
log(cell area)	-0.0361*** (0.0033)	-0.0478*** (0.0032)	-0.0685*** (0.0027)
ISO FE	Yes	Yes	Yes
N	39,181	127,412	439,315
Clusters (cells)	3,606	12,179	43,451
Adj. R^2	0.2215	0.1884	0.2057

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dep. var.: $|\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})|$. Border = 1 if the cell is adjacent to a cell in a different country or US state. Cell area is defined as the polygon area (km²) of the country-clipped sub-cell. ISO FE at finest available level (US state for USA, country for others). Cluster-robust SEs (clustered at the cell level, HC1) in parentheses. Pooled 2012–2022.

9.2 Cropland Proportion: Levels

Changes in agricultural output are often driven by factors, such as the adoption of new crop varieties, shifts in irrigation, or changes in farming practices, that may not be fully captured by the remote sensing indices in our predictor set. While Net Primary Productivity measures photosynthetic activity and land cover shares indicate the extent of cropland, neither directly observes crop type, yield, or the value of agricultural production. If the model systematically underperforms in areas with high cropland coverage, this would suggest a limitation in the predictor set’s ability to capture the spatial distribution of agricultural GDP.

To test this, we compute the cropland proportion for each cell: the fraction of the cell’s land area devoted to agriculture, where cropland area includes cropland, forest cropland, and herbaceous cropland, and land area excludes water. Cells in the top 5% and 10% of cropland proportion within each country are flagged as highly agricultural. We then regress the out-of-sample log prediction error on cropland proportion, controlling for population share and country fixed effects. The construction of prediction errors and the sample coverage follow Section 9.1.

Table 42 reports the overall R^2 of log GDP levels for cells grouped by cropland proportion. Across all resolutions, the top 10% most cropland-intensive cells achieve R^2 values comparable to those of the remaining cells (e.g., 0.9732 versus 0.9727 for the 1-degree model). Table 43 regresses the signed log prediction error on cropland proportion, controlling for population share and country fixed effects. The coefficient is small, inconsistent in sign across resolutions, and statistically insignificant at all three resolutions.

To assess the quantitative importance of these over- and underpredictions, we use the regression coefficients for the following back-of-the-envelope calculation. Among cells in

the top 5% within country, 1-degree cells have an average cropland proportion of 0.619, corresponding to a mean overprediction of 1.44%; 0.5-degree cells have an average cropland proportion of 0.747, corresponding to a mean underprediction of 0.75%; and 0.25-degree cells have an average cropland proportion of 0.851, corresponding to a mean underprediction of 0.35%. These magnitudes suggest that the bias in our model relating to agriculture is relatively muted.

Table 42: Prediction Accuracy by Cropland Proportion

	1-degree Model		0.5-degree Model		0.25-degree Model	
	N	R^2	N	R^2	N	R^2
Top 5%	1,413	97.68%	3,903	96.76%	10,262	95.67%
Top 10%	2,793	97.32%	7,775	96.66%	21,401	95.52%
Bottom 90%	24,619	97.27%	69,700	96.80%	202,480	96.50%
All cells	39,181	97.88%	127,412	97.30%	439,315	97.13%

Notes: Overall R^2 on log GDP levels. Cropland proportion = cropland area / land area (within-cell). Cropland area includes cropland, forest cropland, and herbaceous cropland. Top 5%/10% defined by within-ISO percentile rank. Pooled 2012–2022, in-sample countries.

Table 43: Regression of (Signed) Log Prediction Error on Cropland Proportion

	(1) 1-degree	(2) 0.5-degree	(3) 0.25-degree
Cropland proportion	0.0231 (0.0308)	−0.0101 (0.0155)	−0.0042 (0.0079)
Pop. share	−0.5659*** (0.1153)	−0.8151*** (0.1560)	−1.3265*** (0.2568)
ISO FE	Yes	Yes	Yes
N	27,412	77,475	223,881
Clusters (cells)	2,598	7,766	23,247
Adj. R^2	0.1961	0.1759	0.1787

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dep. var.: $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$. Cropland proportion = cropland area / land area (within-cell, excluding water); cells with zero cropland proportion are excluded. Pop. share = cell share of country population. ISO FE at finest available level (US state for USA, country for others). Cluster-robust SEs (clustered at the cell level, HC1) in parentheses. Pooled 2012–2022, in-sample countries.

9.3 Cropland Proportion: Annual Changes

The exercise in Section 9.2 evaluates prediction accuracy in cropland-intensive cells using log levels of GDP. As a complement, we repeat the exercise targeting year-over-year log changes, which directly tests whether the model can track the growth of GDP in highly agricultural

cells. If agricultural dynamics—shifts in irrigation, the adoption of new crop varieties, or changes in farming practices—are not captured by our remote sensing predictors, growth-rate predictions in cropland-intensive cells could be systematically biased even if level predictions match well.

We follow the construction in Section 9.2, but replace the dependent variable with the growth-rate prediction error: $\Delta \log(\widehat{\text{GDP}}) - \Delta \log(\text{GDP}^{\text{true}})$, where Δ denotes a year-over-year log difference. Cells are assigned to cropland-intensity groups based on the same within-ISO percentile rank used in Section 9.2. The pooled sample covers 2013–2022 (2012 drops out due to the lag), and a valid observation requires positive true and predicted GDP in both t and $t - 1$.

Table 44 reports the overall R^2 of log changes in GDP for cells grouped by cropland proportion. Levels of R^2 are mechanically lower than in the levels exercise because year-over-year changes are inherently noisier, but the top 10% most cropland-intensive cells achieve R^2 values broadly comparable to the bottom 90%, with no evidence that the model systematically tracks growth worse in cropland-heavy cells. Table 45 regresses the growth-rate prediction error on cropland proportion, controlling for population share and country fixed effects. The cropland-proportion coefficient is small in magnitude across all three resolutions, with a sign that is inconsistent across resolutions and statistical significance only at 0.25-degree, mirroring the level results: the model’s bias with respect to agricultural intensity remains muted when we move from levels to changes.

Table 44: Prediction Accuracy on Log Changes by Cropland Proportion

	1-degree Model		0.5-degree Model		0.25-degree Model	
	N	R^2	N	R^2	N	R^2
Top 5%	1,272	63.57%	3,521	55.53%	9,253	68.53%
Top 10%	2,497	56.06%	7,011	52.82%	19,293	68.84%
Bottom 90%	22,213	62.29%	62,861	63.05%	182,745	74.72%
All cells	35,234	79.78%	114,520	76.59%	393,598	82.84%

Notes: Overall R^2 computed on year-over-year log differences of cell-level GDP. Cropland proportion = cropland area / land area (within-cell). Cropland area includes cropland, forest cropland, and herbaceous cropland. Top 5%/10% defined by within-ISO percentile rank. Pooled 2013–2022 (2012 drops out due to lag). Valid observations require positive true and predicted GDP in both t and $t - 1$. In-sample countries.

Table 45: Regression of Growth-Rate Prediction Error on Cropland Proportion

	(1) 1-degree Model	(2) 0.5-degree Model	(3) 0.25-degree Model
Cropland proportion	−0.0016 (0.0020)	0.0014 (0.0010)	0.0013** (0.0005)
Pop. share	−0.0339*** (0.0052)	−0.0658*** (0.0099)	−0.0641*** (0.0124)
ISO FE	Yes	Yes	Yes
N	24,710	69,872	202,038
Clusters (cells)	2,595	7,739	23,153
Adj. R^2	0.0045	0.0057	0.0046

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dep. var.: $\Delta \log(\widehat{\text{GDP}}) - \Delta \log(\text{GDP}^{\text{true}})$, i.e., the growth-rate prediction error, where Δ denotes a year-over-year log difference. Cropland proportion = cropland area / land area (within-cell, excluding water). Cells with zero cropland proportion are excluded. Pop. share = cell share of country population. ISO FE at finest available level (US state for USA, country for others). Cluster-robust SEs (clustered at the cell level, HC1) in parentheses.

Pooled 2013–2022, in-sample countries.

9.4 Transport Corridors

Among our predictors, CO₂ transportation emissions are spatially allocated by the EDGAR database according to the density and intensity of road networks and shipping routes. A concern is that this allocation method could cause the model to mechanically assign higher predicted GDP to cells along major transport corridors, even when economic output is not actually concentrated there. For example, a highway passing through a sparsely populated area would generate high transportation emissions in that cell, potentially inflating its predicted GDP share.

To assess this, we define corridor intensity as the ratio of a cell’s transportation CO₂ emissions share to its population share within the same country: cells with a ratio well above one have transport emissions that are disproportionately large relative to their population. As in the cropland exercise, we regress the out-of-sample log prediction error on corridor intensity, controlling for population share and country fixed effects.

Table 46 reports the overall R^2 of log GDP levels for cells grouped by corridor intensity. The top 5% most transport-intensive cells show somewhat lower R^2 values than the bottom 90%, particularly at finer resolutions (e.g., 0.9351 versus 0.9704 at 0.25-degree). Table 47 regresses the signed log prediction error on corridor intensity, controlling for population share and country fixed effects. The coefficient is positive and statistically significant across all resolutions, indicating that the model overpredicts GDP in cells with high transport emissions relative to their population.

To assess the quantitative importance of these overpredictions, we use the regression coefficients for the following back-of-the-envelope calculation. Among cells in the top 5% within country, the mean corridor intensity is 181 at the 1-degree level, 394 at 0.5-degree, and 610 at 0.25-degree, corresponding to mean overpredictions of 1.95%, 4.54%, and 5.32%, respectively. For cells in the 90th–95th percentile within country, mean corridor intensity

falls sharply to 20.6, 56.4, and 126.6, and the implied overpredictions shrink to just 0.22%, 0.64%, and 1.08%. This large drop between the top 5% and the 90–95% bin reflects the pronounced right-skew of the corridor intensity measure: a small number of cells dominated by shipping lanes, airports, and major highways account for the bulk of transport emissions relative to population, so the top 5% is driven by genuine outliers whose implied biases do not extend to cells just below them.

Table 46: Prediction Accuracy by Transport Corridor Intensity

	1-degree Model		0.5-degree Model		0.25-degree Model	
	N	R^2	N	R^2	N	R^2
Top 5%	1,948	97.08%	6,067	93.58%	20,096	93.51%
Top 10%	3,851	97.24%	12,091	94.46%	40,153	94.59%
Bottom 90%	34,277	97.62%	108,450	97.22%	361,041	97.04%
All cells	39,181	97.88%	127,412	97.30%	439,315	97.13%

Notes: Overall R^2 on log GDP levels. Corridor intensity = transport CO₂ share / population share. Top 5%/10% defined by within-ISO percentile rank. Pooled 2012–2022.

Table 47: Regression of (Signed) Log Prediction Error on Corridor Intensity

	(1) 1-degree	(2) 0.5-degree	(3) 0.25-degree
Corridor intensity	0.000107*** (0.000013)	0.000113*** (0.000024)	0.000085*** (0.000011)
Pop. share	−0.6471*** (0.1081)	−1.0537*** (0.1369)	−1.7476*** (0.2287)
ISO FE	Yes	Yes	Yes
N	38,128	120,541	401,194
Clusters (cells)	3,500	11,453	39,173
Adj. R^2	0.1890	0.1682	0.1501

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dep. var.: $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$. Corridor intensity = transport CO₂ share / population share. ISO FE at finest available level (US state for USA, country for others). Cluster-robust SEs (clustered at the cell level, HC1) in parentheses. Pooled 2012–2022.

10 Uncertainty of GDP Estimates

A natural question for any gridded economic dataset is how precise the estimates are at the cell level. Our random forest model consists of approximately 1,500 individual decision trees, each of which produces its own prediction for every cell. We exploit this ensemble structure to quantify prediction uncertainty: rather than extracting a single point estimate, we propagate each tree’s predictions through the full post-processing pipeline — censoring low-population cells, rescaling shares within each country-year, and multiplying by national GDP — and compute the distribution of cell-level GDP estimates across trees. The dispersion of this distribution provides a natural measure of model uncertainty for each cell, without requiring additional assumptions beyond the random forest itself.

We summarize this uncertainty by reporting the standard deviation of log GDP across trees for each cell, which captures proportional uncertainty and can be compared across cells of different sizes.

10.1 Tree-Level Variation and Standard Deviation

For each cell, we compute the standard deviation of log GDP across all trees in the trained random forest. Unlike the previous section, which relied on out-of-sample cross-validation predictions generated during training, the uncertainty measure here is computed from the fully trained model. For each cell, we take each tree’s prediction, pass it through the post-processing pipeline described above, and compute the standard deviation of the resulting log GDP values across trees. This measure captures proportional uncertainty — a standard deviation of 0.10 in log GDP corresponds to approximately 10% uncertainty in levels — and because it is computed in log space, it is invariant to the currency unit.

Table 48 reports the average SD of log GDP across cells, broken down by developed versus developing countries and by in-sample versus out-of-sample countries, for all three resolutions. The average SD ranges from 0.157 (in-sample countries, 0.25-degree) to 0.232 (out-of-sample countries, 1-degree), corresponding to roughly 16–23% proportional uncertainty in GDP levels. Uncertainty is modestly higher for out-of-sample countries and for the coarser 1-degree resolution, as expected. Developed and developing countries show similar levels of uncertainty. Figures 21 and 22 map the cell-level SD of log GDP for 2019 at the 1-degree and 0.5-degree resolutions; the corresponding 0.25-degree map is presented in Figure 5 of the main text.

Figure 23 overlays kernel density estimates of the cross-cell distribution of this measure for all three resolutions in 2019, using a Gaussian kernel with bandwidth selected by Silverman’s rule of thumb and a horizontal axis truncated at 0.8. All three resolutions exhibit a right-skewed distribution, reflecting the concentration of high-uncertainty cells in sparsely populated areas. The 1-degree model shows a visibly wider spread (median 0.198) than the 0.5-degree model (median 0.152) and the 0.25-degree model (median 0.148), consistent with its coarser spatial resolution and smaller cell count.

Table 48: Average SD of $\log(\text{GDP})$ Across Random Forest Trees

	1-degree Model	0.5-degree Model	0.25-degree Model
Developed	0.225	0.176	0.169
Developing	0.227	0.187	0.190
In-sample	0.211	0.158	0.157
Out-of-sample	0.232	0.192	0.194
All	0.227	0.184	0.186

Notes: Each entry reports the average across cells of the standard deviation of $\log(\text{GDP})$ across random forest trees, computed directly from all tree-level predictions. “In-sample” countries are those used for model training (see Table 2); “Out-of-sample” countries are all others. All statistics are pooled across years (2012–2022).

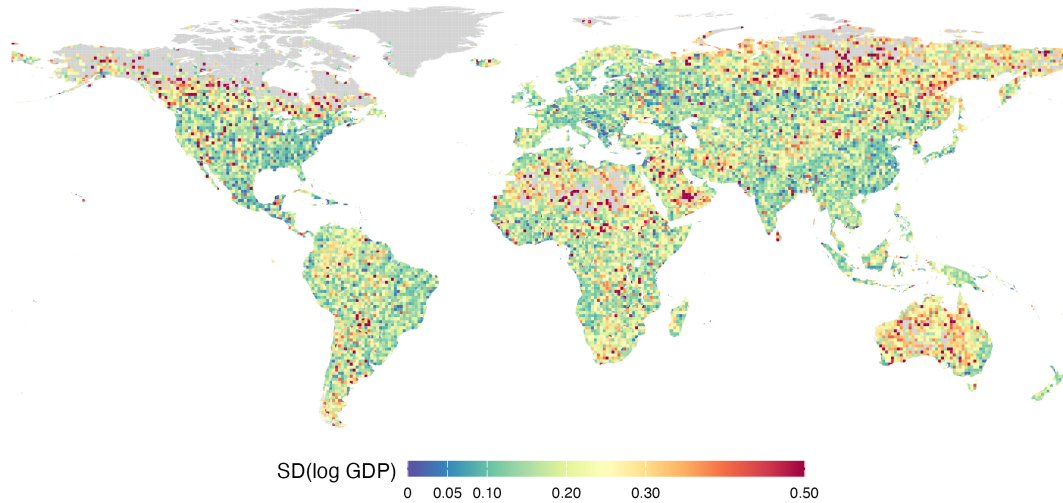


Figure 21: Standard Deviation of $\log(\text{GDP})$ Across Trees (2019, 1-degree)

Note: Cell-level SD of $\log(\text{GDP})$ across all trees in the random forest ensemble. Higher values indicate greater prediction uncertainty. Values above 0.5 are top-coded for visualization.

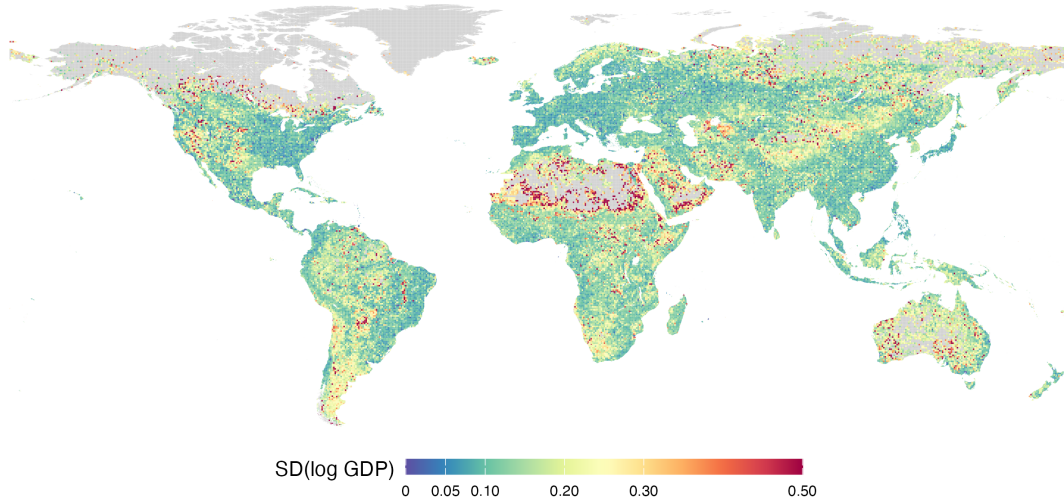


Figure 22: Standard Deviation of $\log(\text{GDP})$ Across Trees (2019, 0.5-degree)

Note: Cell-level SD of $\log(\text{GDP})$ across all trees in the random forest ensemble. Higher values indicate greater prediction uncertainty. Values above 0.5 are top-coded for visualization.

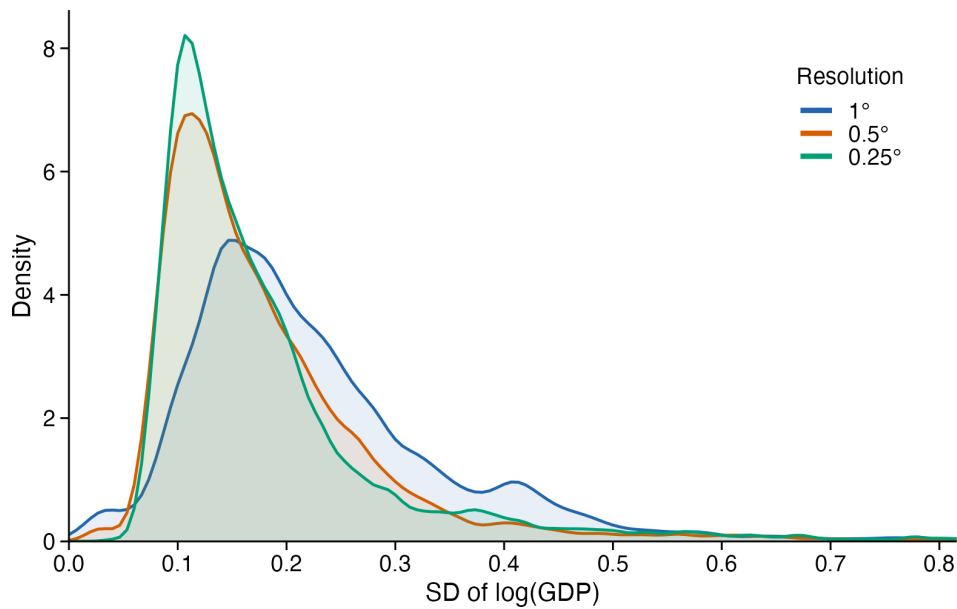


Figure 23: Distribution of SD of $\log(\text{GDP})$ Across Cells (2019, All Resolutions)

Note: Kernel density estimates of the cell-level SD of $\log(\text{GDP})$ across random forest trees in 2019, overlaid for the three resolutions (17,463 cells at 1-degree, 56,075 at 0.5-degree, 186,732 at 0.25-degree). All cells with positive predicted GDP are included. Estimation uses a Gaussian kernel with bandwidth selected by Silverman's rule of thumb.

11 Out-of-Sample Log Prediction Errors

The tree-level uncertainty measures in the preceding section capture model uncertainty — the disagreement among trees — but do not directly measure prediction accuracy, since accuracy requires comparison to observed data. Here we present the out-of-sample log prediction error, $\log(\widehat{\text{GDP}}) - \log(\text{GDP})$, assessed via cross-validation during the training process; unlike the tree-level SD, this measure is available only for countries in the training sample (see Table 2). Figures 24–26 map the geographic pattern of over- and under-prediction for 2019 at all three resolutions, highlighting regions where the model performs well and regions where systematic biases may remain.

Figure 27 overlays kernel density estimates of the cross-cell distribution of these errors for all three resolutions in 2019, using a Gaussian kernel with bandwidth selected by Silverman’s rule of thumb and a horizontal axis truncated at ± 3 . The shape of the distribution is remarkably similar across resolutions: all three are centered near zero, approximately symmetric, and exhibit heavy tails driven by a small number of cells where prediction is difficult. Prediction accuracy varies systematically with the scale of economic activity: the model is less accurate in cells with low true GDP, where predictor signals are weakest and the GDP share being predicted is a small fraction of the national total. Because our model predicts GDP shares that are then multiplied by national GDP, a small absolute error in a tiny predicted share translates into a large proportional error in GDP levels. This pattern is consistent with the uncertainty maps discussed above, where the highest standard deviations coincide with the most sparsely populated cells.

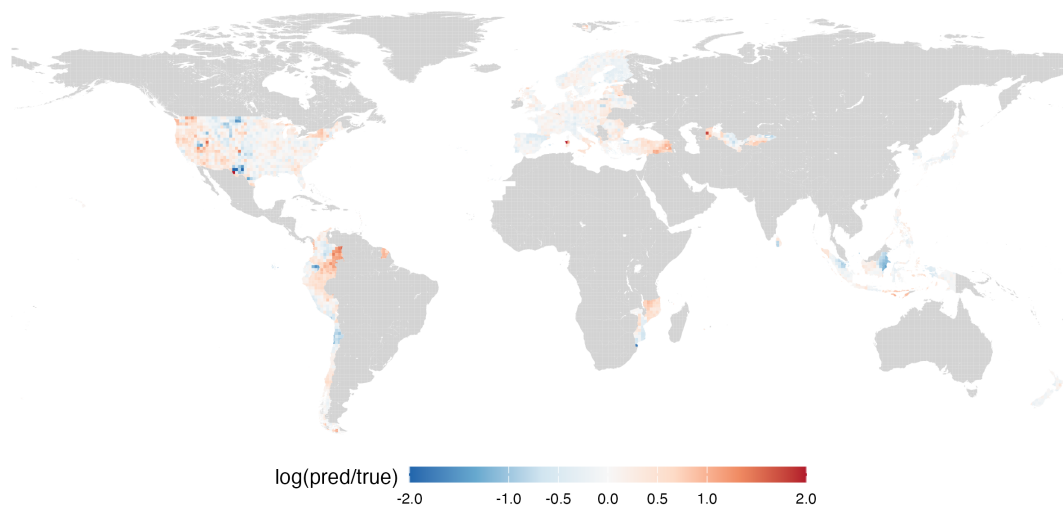


Figure 24: Out-of-Sample Log Prediction Error (2019, 1-degree)

Note: Map shows $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$ using cross-validation predictions generated during the training process. Red indicates overprediction; blue indicates underprediction. The color scale is clipped at ± 2 ; cells with larger log errors are shown at the bounds. Out-of-sample countries are shown in gray.

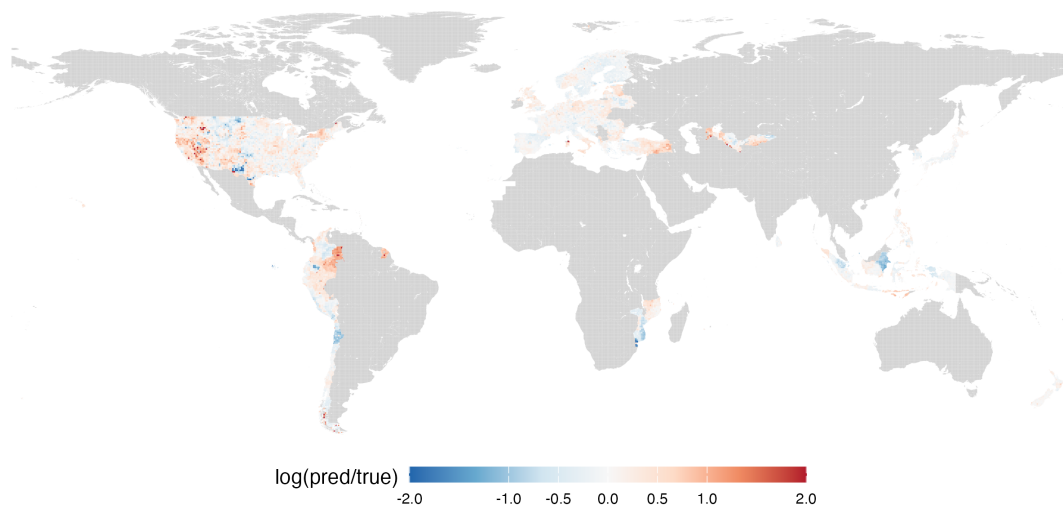


Figure 25: Out-of-Sample Log Prediction Error (2019, 0.5-degree)

Note: Map shows $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$ using cross-validation predictions generated during the training process. Red indicates overprediction; blue indicates underprediction. The color scale is clipped at ± 2 ; cells with larger log errors are shown at the bounds. Out-of-sample countries are shown in gray.

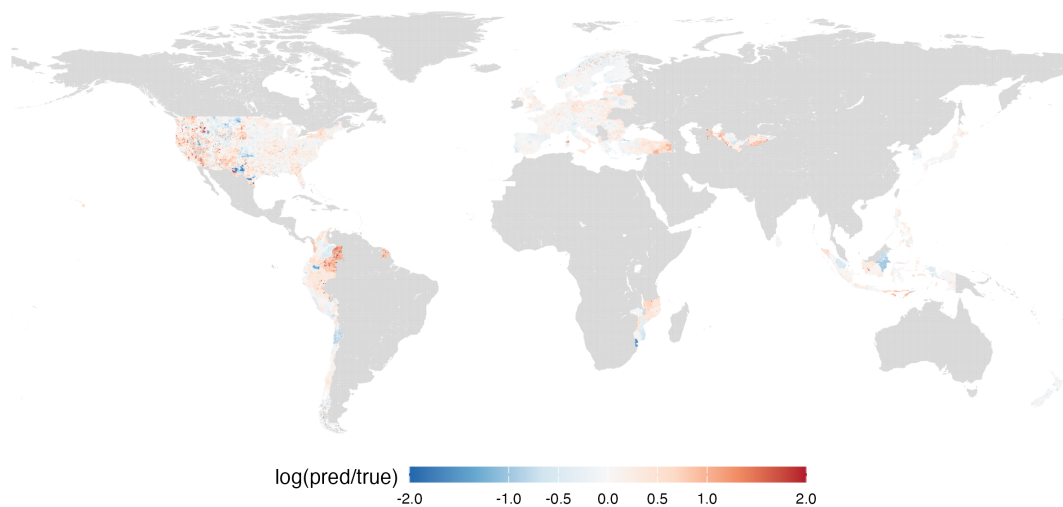


Figure 26: Out-of-Sample Log Prediction Error (2019, 0.25-degree)

Note: Map shows $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$ using cross-validation predictions generated during the training process. Red indicates overprediction; blue indicates underprediction. The color scale is clipped at ± 2 ; cells with larger log errors are shown at the bounds. Out-of-sample countries are shown in gray.

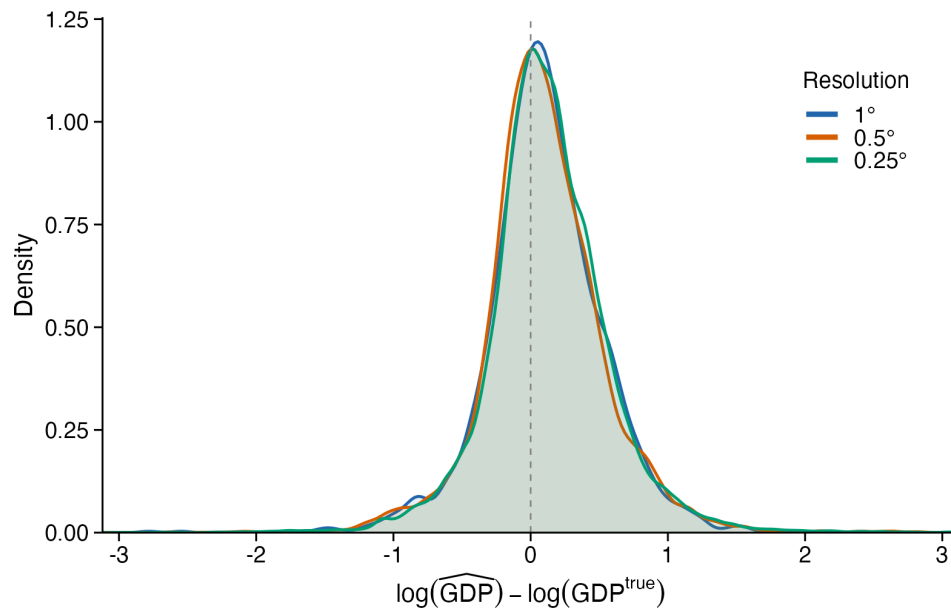


Figure 27: Distribution of Out-of-Sample Log Prediction Error Across Cells (2019, All Resolutions)

Note: Kernel density estimates of $\log(\widehat{\text{GDP}}) - \log(\text{GDP}^{\text{true}})$ using cross-validation predictions generated during the training process, overlaid for the three resolutions (3,671 cells at 1-degree, 11,892 at 0.5-degree, 40,947 at 0.25-degree). Dashed line marks zero. Only in-sample countries are included. Estimation uses a Gaussian kernel with bandwidth selected by Silverman's rule of thumb.

12 Consistency of Predictions Across Resolutions and Dataset Versions

12.1 Consistency Across Resolutions

In this section, we demonstrate that the predictions from models at different spatial resolutions are consistent. Figure 28 compares the predictions generated by our benchmark models in the paper: trained using data from all available countries (excluding China) from 2012 to 2022 with optimized hyperparameters for each resolution. To evaluate consistency, we aggregate the predictions from finer resolutions to match the coarser resolution and compare the results. Figure 28 shows that the predictions remain relatively consistent and confirms the robustness of our models across different spatial scales.

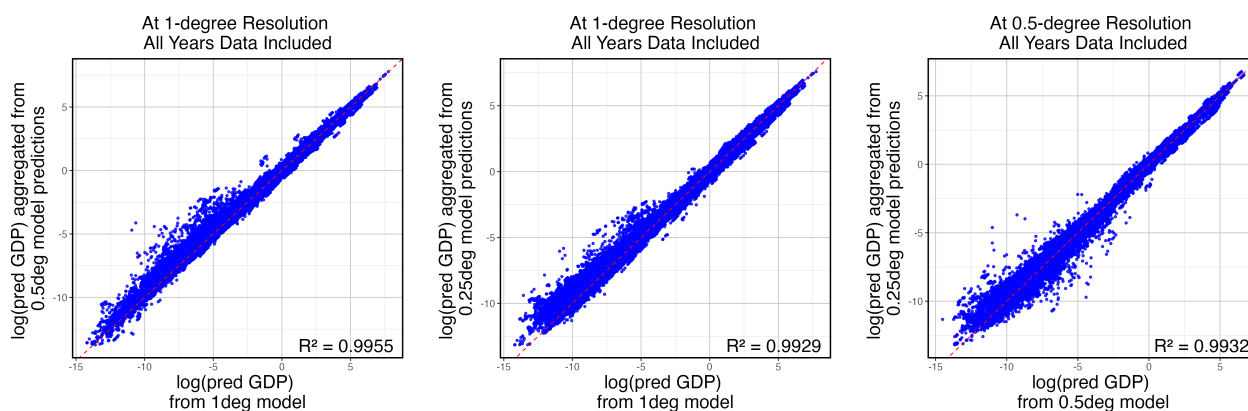


Figure 28: Comparison of Model Predictions Across Resolutions: Aggregated vs. Direct Predictions

12.2 Consistency Across Dataset Versions

Our datasets are updated annually, and this process involves incorporating new training samples. As a result, predictions may change, not only for the new years but also for the previously published years. This highlights the importance of testing whether our models produce consistent predictions across different dataset versions. To conduct this test, we trained two versions of the model: 1) uses data from all available countries (excluding China) for the years 2012 to 2019 2) uses data from the same countries but extends the coverage to include years 2012 to 2022. We compared the predictions for both the newly updated years (2020, 2021 and 2022) and selected previous years (2018 and 2019). Figures 29 and 30 illustrate that, despite minor discrepancies, the models produce highly similar results across versions for both new and old years.

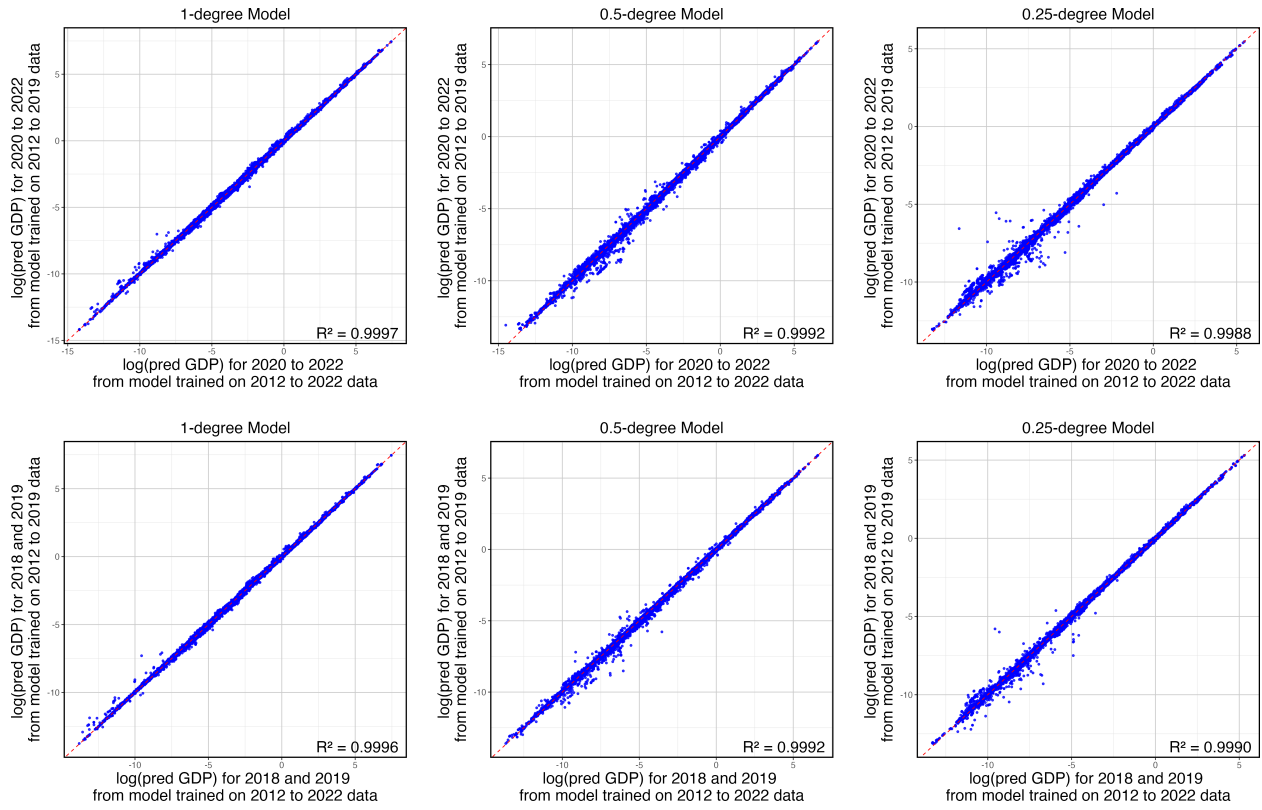


Figure 29: Comparison of Predicted Cell GDP Levels Across Model Versions

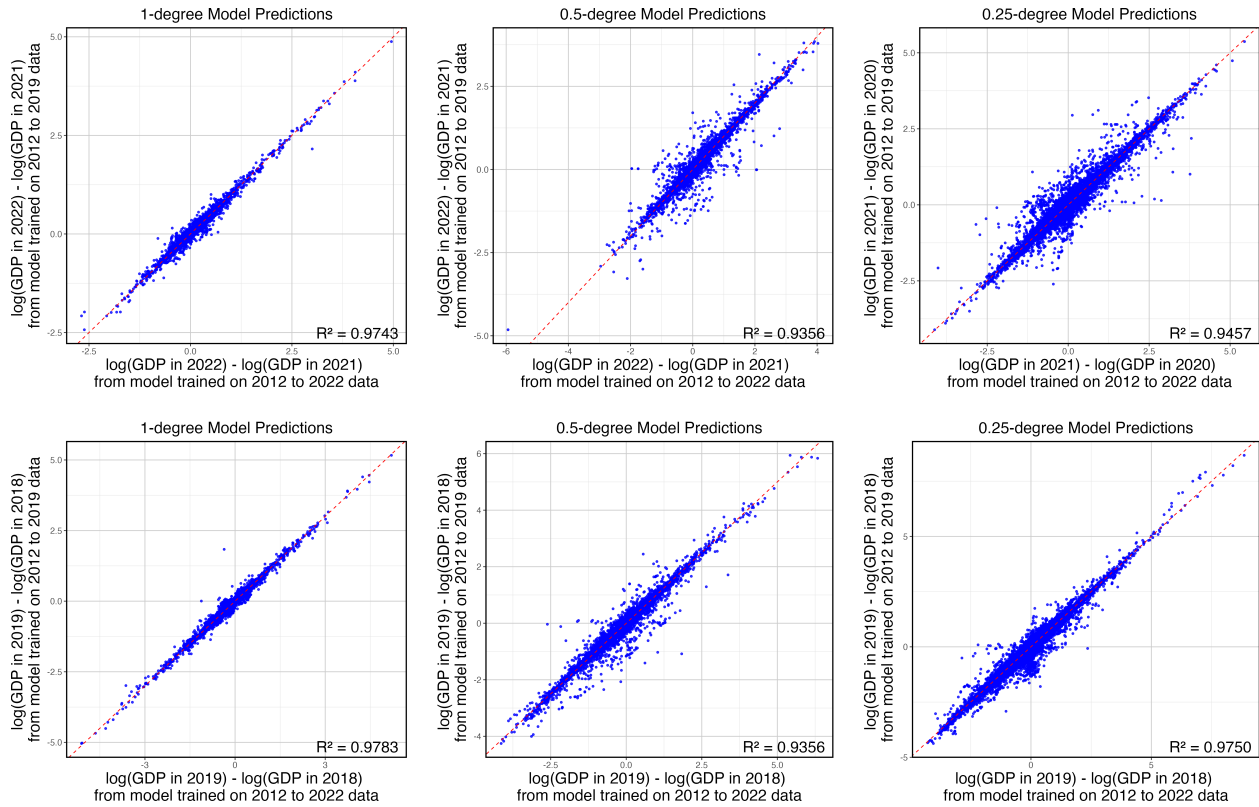


Figure 30: Comparison of Predicted Cell GDP Annual Changes Across Model Versions

12.3 Consistency When Dropping 2012

A separate robustness concern attaches to the very start of our sample window. 2012 is the first year of Black Marble nighttime lights coverage, so no true prior-year lag is available, and the main specification uses the 2012 nighttime lights data as its own lagged value. We therefore re-estimate the model excluding 2012 to verify that this concession does not materially distort predictions. The full model is trained on data from 2012 to 2022, the drop-2012 model on data from 2013 to 2022, and both predict on the same global predictor data through the same post-adjustment pipeline (rescaling within country to the national GDP), so any difference is attributable solely to the training-year set. Because retraining at finer resolutions is computationally expensive, we restrict this exercise to the 1-degree model. Figure 31 shows that log GDP predictions from the two models are essentially indistinguishable: points lie tightly along the 45-degree line across all global cells.

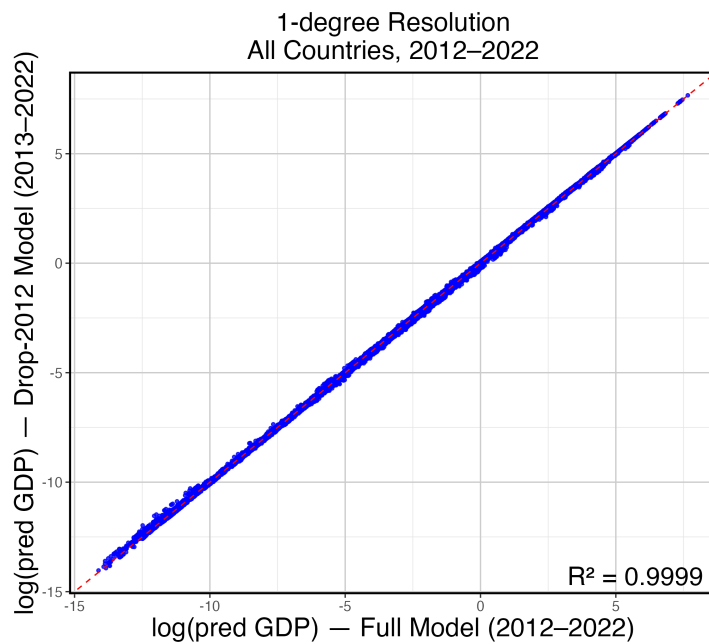


Figure 31: Comparison of 1-degree Log GDP Predictions: Full Model vs. Drop-2012 Model

Note: Each point is a cell-year (global, in-sample and out-of-sample countries pooled), with $\log(\widehat{\text{GDP}})$ from the full model (trained on 2012–2022) on the horizontal axis and $\log(\widehat{\text{GDP}})$ from the drop-2012 model (trained on 2013–2022) on the vertical axis. The red dashed line is the 45-degree line.

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