
Appendix

MEDSAT: A Public Health Dataset for England Featuring Medical Prescriptions and Satellite Imagery

Contents

A Dataset Licenses	1
B Dataset Storage and Maintenance Plans	2
C Datasheet	2
D Dataset Details	11
D.1 Sociodemographic Features	11
D.2 Environmental Features	11
D.3 Image Features	11
D.3.1 Extracting Image Features per LSOA	11
D.4 Prescription Outcomes	12
D.4.1 Existing Public and Population Health Datasets	12
D.4.2 NHS Medical Prescriptions	14
D.4.3 DrugBank Network	15
E Benchmarks Results	16
E.1 Detailed Health Inequalities	16
E.2 Predicting Prescriptions	17
E.2.1 Spatial Lag Model (SLM)	17
E.2.2 Machine Learning Models	18
E.3 Temporal Analyses	20

A Dataset Licenses

The dataset is released under the CC BY-SA 4.0 license.

B Dataset Storage and Maintenance Plans

The dataset is available and will be maintained on TUMMedia, a data sharing service from Technical University Munich. It can be accessed via the following link: <https://doi.org/10.14459/2023mp1714817>. The code for datasets creation and experiments can be accessed on <https://github.com/sanja7s/MedSat>.

C Datasheet

Motivation

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

Understanding the impact of the environment on human health is crucial for informing policy-making, promoting human well-being, and implementing timely health interventions, particularly in the context of increasing climate change-induced extreme weather events. Earth Observation data has emerged as a valuable resource for addressing critical challenges related to climate change, food security, and poverty [6, 15]. However, current applications that monitor population health using such data have limitations. Health indicators are often derived from surveys [46] and crowdsourcing [24], which may not be representative of the entire population. Additionally, these applications rely on a narrow set of environmental and sociodemographic indicators, hindering a comprehensive understanding of the relevant health factors [5, 17, 13]. Moreover, many of these datasets are not publicly available.

In this study, we aim to address these challenges by providing a publicly available dataset that harnesses the potential of earth observation data to monitor and comprehend the environmental influence on health outcomes. Our dataset combines four complementary data sources to enable comprehensive health modeling across the entire population of England. Specifically, for the years 2019 and 2020, we integrated medical prescription data at the practice level from the NHS, satellite-derived environmental features, Sentinel-2 satellite imagery, and sociodemographic indicators obtained from the latest UK census in 2021. These data sources were combined at the level of Lower Layer Super Output Areas (Lower Layer Super Output Area (LSOA)), which represent small administrative units ranging in size from 1km² to 18km². Our objectives are to:

- Conduct comprehensive health modeling by relating medical prescriptions to environmental, image, and sociodemographic features at a fine-grained spatial level.
- Identify relevant indicators for population health and uncover regional health disparities.
- Understand trends and factors influencing population health over time, including the impact of pandemic years on relevant health factors.

Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

The dataset was created by researchers from:

- **Nokia Bell Labs**, Cambridge, UK.
- **Technical University of Munich**, Munich, Germany.
- **Wasdi platform** (<https://www.wasdi.cloud/>).

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

The creation of the dataset was partly funded by the:

- Nokia Bell Labs,
- German Federal Ministry for Economic Affairs and Climate Action in the framework of the "national center of excellence ML4Earth" (grant number: 50EE2201C),

- Munich Center for Machine Learning,
- AI4EO Beyond Fellowship by The International AI for Earth Observation Future Lab at TUM/DLR,
- ESA Network of Resources Initiative, and
- European Union’s Horizon 2020 research and innovation programme under grant agreement No. 869764, awarded to the GoGreenRoutes project.

Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

For the years covered (2019 and 2020), our dataset contains the following two types of instances:

- **LSOA instance:** Our dataset covers the entire of England by including an instance per every LSOA in England. These instances are represented by point features describing the LSOAs environmental and sociodemographic indicators.
- **Sentinel-2 tile composite instance:** For the benefits of using computer vision to extract rich visual concepts that define environmental health, we provide a set of composite Sentinel-2 satellite image tiles per meteorological season covering the entire of England.

How many instances are there in total (of each type, if appropriate)?

In each year, there are **33755 LSOA instances** (one per every LSOA in England) and **4 × 35 composite tile instances** (one set of tiles per every meteorological season).

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

Our dataset provides a comprehensive overview of the health landscape in England by incorporating data from *all* LSOAs throughout the country. The prescription outcomes are derived from *all* prescribed items by the NHS, encompassing all patients within the nation during the specified years. Additionally, the census data covers the entire population. In terms of environmental variables, we computed yearly average scores using either all non-cloudy observations or a substantial sample of over 30% of images (e.g., for DynamicWorld) due to computational constraints. This extensive coverage allows for a thorough investigation of health-related factors at a national level. However, it is essential to acknowledge that the representativeness of our dataset diminishes when examining larger geographical regions due to the absence of data from developing countries, and the inherent specificity present even among developed countries.

What data does each instance consist of? “Raw” data (e.g., unprocessed text or images) or features? In either case, please provide a description.

The **LSOA instances** are represented by feature vectors that contain environmental and sociodemographic indicators aggregated over the geographical area covered by an LSOA. In total, there are 43 environmental features describing air quality, greenery, climate, and land-cover distribution. Further, we include 111 sociodemographic variables that represent population counts, age group distribution, gender, ethnicity, religion, marital status, employment status, commuting habits, residence and housing, self-reported health, language skills, deprivation and income (the only non-census variable) levels. On the other hand, the **Sentinel-2 tile composite instances** contain 11 spectral bands that include aerosols, RGB bands, vegetation red edge bands, near-infrared bands and short-wave infrared bands. A detailed overview of the environmental and sociodemographic features and the Sentinel-2

image bands are provided in Figure 1 in the main manuscript and in the "*MedSat Variables.csv*" file in the public dataset directory.

Is there a label or target associated with each instance? If so, please provide a description.

The target variables in our dataset represent medical prescription prevalences on a yearly level. We included the following 7 target variables representing the quantity of:

- **diabetes** and **hypertension** prescriptions associated with *metabolic* conditions,
- **depression** and **anxiety** prescriptions associated with *mental* conditions,
- **asthma** prescriptions associated with *respiratory* conditions,
- **opioids** prescriptions which are predominantly prescribed for pain management, and
- **total** prescriptions as a proxy for general health and well-being.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

In both years, 5,163 LSOA instances (~15% of the available instances) have missing feature values. The missing values for environmental features occur because some of the used satellite products do not provide these features for every LSOA. For example, there are 1,479 (4%) LSOAs for which the variables related to temperature, snow, or radiation derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 product [37] are missing. We observed that this product does not provide these features for LSOAs located near coastal regions. Next, there are 1,507 (4%) LSOAs for which information about the aerosol optical depth and PM2.5 particles is missing from the Copernicus Atmosphere Monitoring Service (CAMS) product [9]. In the future work, we aim to evaluate different satellite products that can provide the missing values for these features. There are 1,956 (6%) LSOAs with missing outcome data. This absence doesn't stem from a lack of prescription data from the NHS. Instead, it arises from a discrepancy between the LSOA shapefiles of the patient data used for outcome calculation from 2018 and the shapefiles from the 2021 census. We opted to utilize the most recent 2021 shapefiles. We await forthcoming releases of NHS patient data that align with these shapefiles, allowing us to incorporate the data for the missing LSOAs. For the sociodemographic indicators, we found that the net annual income is missing for 537 LSOAs as this data was not provided on an LSOA level in the UK census but we derived from the latest 2018 estimates of mean annual household income for Middle layer Super Output Areas (MSOAs) from the Family Resources Survey (and there is a mismatch for a small number of LSOAs and MSOAs due to the latest adjustments to the LSOAs boundaries in 2021).

Notably, we possess Census sociodemographic and image features data for all LSOAs. Depending on the specific analyses intended, the maximum missing value rate could be constrained by the outcomes, standing at 5.7%. For instance, this applies if a user does not require environmental variables from ECMWF or CAMS products.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.

To combine both types of instances, we provide shapefiles describing the LSOAs coordinates that allow extraction of image features for individual LSOAs from the composite Sentinel-2 satellite image. Based on these shapefiles, in our code repository we provide an implementation for the extraction of LSOA-specific image features out of the Sentinel-2 images. Further, the region column in the spatial data files determines the larger geographical area to which the LSOA belongs and can be used to cluster the LSOAs based on their spatial proximity and to perform health analysis over a larger geographical area.

Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.

We recommend the spatial data split described in Section E.2.2 where LSOAs are first clustered into blocks of sizes 28km x 28km. Next, those blocks are randomly assigned to 5 folds, each fold

containing an equal number of blocks. These procedure ensures that LSOAs belonging to a same block do not appear within the training and the test set.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

The environmental and image features utilized in our dataset are derived from high-level satellite products, which undergo preprocessing to mitigate common errors associated with remote sensing acquisition. However, it is important to note that our subsequent processing and spatial aggregation of this data may introduce sources of noise. For instance, we employ a threshold of 0.2 for NDVI values to calculate the fraction of greenery pixels per LSOA. Consequently, different threshold values may yield varying results. Additionally, the prescription values are derived through probabilistic associations between patients and nearby LSOAs, as well as drug names and corresponding conditions. This process, while valuable, is not without imperfections and introduces some level of noise.

In terms of redundancies, our dataset contains many correlated features among the environmental and sociodemographic indicators. A subset of correlated environmental features is presented in Figure 1 where it can be seen that the temperature feature is strongly positively correlated with surface soil temperature, thermal radiation, and atmospheric features while being strongly negatively correlated with snow density. These correlations represent a challenge for many machine learning models and we encourage the researches to investigate approaches for feature selection that can lead to more efficient and accurate health modeling.

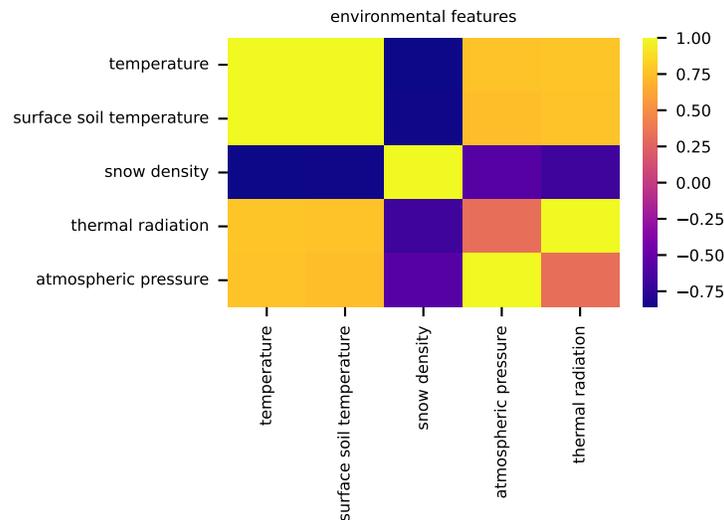


Figure 1: Example of correlated environmental features.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

The dataset is self-contained.

Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals non-public communications)? If so, please provide a description.

Our four complementary dataset components are derived from public data sources. As such, they are not confidential.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.

Our dataset does not contain any data that can be directly perceived as offensive or inappropriate. As mentioned in the limitations section, the only potential concern is the possibility of stigmatization at the level of LSOA. However, it is worth noting that such stigmatization can also be derived from other publicly available data sources.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

Yes.

Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

Our dataset identifies a percentage of subpopulations by age, ethnicity, and gender across LSOAs derived from the UK census. However, these features do not point to any personally identifiable information because the census implements stringent privacy protection measures, including targeted record swapping and cell key perturbation, to ensure data confidentiality without compromising aggregated statistics [1]. The age group and ethnicity distributions are visualized in Figure 2 which shows that the age groups are balanced except for the age groups over 80 years which occur less frequently compared to the age other groups. When it comes to ethnicity and gender, the White ethnicity is dominant in the dataset while the gender distribution is balanced.

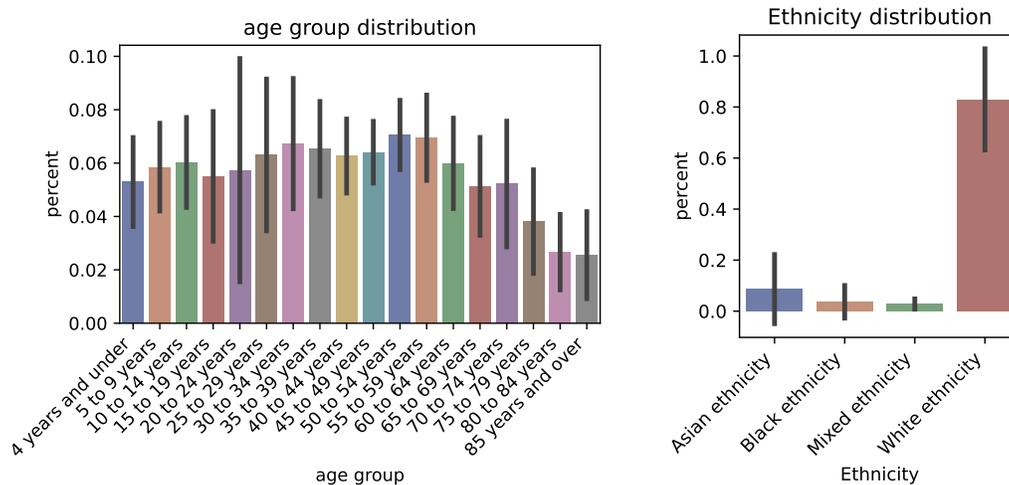


Figure 2: Age group and ethnicity distributions

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how.

No, for the reasons stated above.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

Certainly, we have extracted sensitive information such as ethnicity, religious beliefs, and economic deprivation per LSOA from the census data. However, it is important to note that this information is publicly available through census records.

Collection Process

How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

The environmental variables were already preprocessed by the satellite products, and we didn't perform further validation. They have varying frequencies, from daily to monthly, depending on the specific product. In our dataset, we created the environmental features by averaging the variables derived from these products on a yearly level. The Sentinel-2 tiles were derived by aggregating publicly available, cloud-free Sentinel-2 images per calendar season that were already preprocessed by the Sentinel-2 mission. Further, the sociodemographic variables are obtained as single values from the UK census data, and as such, do not require validation. The target variables include yearly aggregates of prescription quantities issued by the NHS health authorities. While there is limited condition prevalence data available at the LSOA level across England, our tests for London at the ward level showed moderate to high correlations between our prescription prevalence scores and condition prevalence, ranging from 0.76 for diabetes to 0.89 for depression. However, it is important to note that prescription scores and condition prevalence may not correlate perfectly, as they capture different health constructs.

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?

In our data collection process, we developed our own parser for extracting prescription data. Additionally, for gathering environmental variables, we utilized the Google Earth Engine platform [14] for point data collection and the WASDI platform [44] for image data collection. The code for data collection and preprocessing is available on our GitHub repository.

If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

NA

Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?

The data collection process for this study was carried out solely by the co-authors, who were involved in the research as part of their respective roles.

Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.

All the data were collected in 2022.

Were any ethical review processes conducted (e.g., by an institutional review board)?

If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

As publicly available data was used, this was not needed.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

No.

Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?

NA

Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.

NA

Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

NA

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).

NA

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.

NA

Preprocessing/cleaning/labeling

Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.

Yes. The environmental features were averaged on a yearly level, the prescription quantities were normalized according to the number of patients residing in an LSOA, and the Sentinel-2 images were averaged per calendar season.

Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.

No, but the used data sources are available publicly from the NHS and ONS websites, and GEE and WASDI platforms.

Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.

Yes, on the provided github repository.

Uses

Has the dataset been used for any tasks already? If so, please provide a description.

In the main manuscript, we have presented the potential value of our dataset in the context of prescription prediction, analysis of relevant health factors, and examination of health disparities. However, there have been no published works utilizing this dataset to date.

Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.

NA.

What (other) tasks could the dataset be used for?

The geographical division within our dataset presents a challenge in developing machine learning models that can effectively generalize health findings across diverse regions. Additionally, the inclusion of two years of data in our dataset offers the potential for predicting future health outcomes based on historical health data.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

We have meticulously collected and preprocessed the data in accordance with the highest ethical standards to prevent any misuse of our dataset. We strongly urge fellow researchers to conduct responsible analyses and utilize the dataset with integrity.

Are there tasks for which the dataset should not be used? If so, please provide a description.

We caution against presenting the results from our dataset in any stigmatizing way, such as highlighting the worst areas based on certain attributes, without a clear purpose or intention to address the underlying issues. It is important to use the data responsibly and consider the potential implications of how the results are presented and interpreted.

Distribution

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.

The dataset will be publicly available.

How will the dataset will be distributed (e.g., tarball on website, API, GitHub) Does the dataset have a digital object identifier (DOI)?

As stated in Section B, the dataset is publicly available on TUMMedia through the following DOI: <https://doi.org/10.14459/2023mp1714817>

When will the dataset be distributed?

The dataset is publicly available.

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

No.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

No.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

No.

Maintenance

Who will be supporting/hosting/maintaining the dataset?

TUMMedia will host and maintain the dataset which ensures the long-term accessibility and citability of our dataset, facilitating its use and reference by the research community.

How can the owner/curator/manager of the dataset be contacted (e.g., email address)?

The email addresses of the authors will be available on the GitHub page.

Is there an erratum? If so, please provide a link or other access point.

No.

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?

As part of our ongoing efforts, we are currently developing a prescription parser that enables the calculation of prescription quantities on a monthly basis and going up to 10 years in the past. Additionally, we are enhancing the drug matching module by leveraging state-of-the-art Large Language Models (LLMs). Once these tasks are completed, we will be able to update the GitHub with the updated parser so that interested researchers can calculate additional target variables and enhance the temporal granularity of those features.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.

No.

Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.

No.

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.

Yes, the code for collecting the four complementary components of the MEDSAT datasets is publicly available on our GitHub repository: <https://github.com/sanja7s/MedSat>.

D Dataset Details

D.1 Sociodemographic Features

All the sociodemographic variables are collected from the UK 2021 Census using https://www.nomisweb.co.uk/sources/census_2021, except for income, which is collected from Family Resources Survey 2018 <https://www.gov.uk/government/collections/family-resources-survey--2>.

D.2 Environmental Features

For this release of the MEDSAT dataset, we used the sources listed in Table 1 to derive our environmental features. We performed spatial reduction and averaging of yearly values at the LSOA level. When reducing image data to our areas of interest, we employed specific spatial resolution scaling values: 1000 m for Sentinel-5, CAMS, and TOMS&OMI, and 10 m for ESA-WorldCover and Sentinel-2. These choices were guided by the original products’ resolutions and the processing limitations within the GEE platform.

Table 1: Sources and Statistics about of Environmental Variables. The links below should all be prepended with <https://developers.google.com/earth-engine/datasets/catalog/>

Type	Satellite/Source	Scale (m)	Resolution (m)	Link to data source
Air Q	Sentinel-5	1000	1113.2	COPERNICUS_S5P_OFFL_L3_NO2
Air Q	TOMS&OMI	1000	111000	TOMS_MERGED
Air Q	CAMS	5000	44528	ECMWF_CAMS_NRT
greenery	Sentinel-2	50	10	COPERNICUS_S2_SR
greenery	ERA5-ECMWF	100	11132	ECMWF_ERA5_LAND_MONTHLY_AGGR
climate	ERA5-ECMWF	100	11132	ECMWF_ERA5_LAND_MONTHLY_AGGR
land cover	DynamicWorld	200	10	GOOGLE_DYNAMICWORLD_V1

D.3 Image Features

To generate composite images, we obtained raw Sentinel-2 satellite data and processed it using the WASDI platform (<https://www.wasdi.net>), which allows access and online processing of both public and commercial datasets. For our analysis, we processed Sentinel-2 images corresponding to the years 2019 and 2020 by calculating the average values for each of the four meteorological seasons in the both years, as defined by the Met Office [32]. Each Sentinel-2 image consists of 13 bands, with four bands at a spatial resolution of 10 m, six bands at 20 m, and three bands at 60 m. We focused on 11 specific bands, as described in main manuscript, which capture environmental factors relevant to health (e.g., B01 captures aerosols, representing air quality). We excluded bands B09 and B10, as the former is primarily used for cirrus cloud detection and the latter is used to map water vapor.

To generate composite images for each season, we collected and parsed all images within the corresponding three-month period (on average ~ 1000 images per season). This amounted to parsing around 2TB per season and around 8TB per year (see Table 2). For image processing, we conducted several steps to ensure data consistency and quality. Firstly, we resampled the selected bands from their original resolutions of 60 m and 20 m to a uniform resolution of 10 m. This resampling allowed for a consistent analysis across all bands. Next, we applied the cloud mask provided with each Sentinel-2 image to each of the 11 bands. This cloud mask effectively identified and excluded pixels affected by cloud cover, ensuring the accuracy and reliability of the data. Then, we computed a pixel-per-pixel average over time, considering only values observed in cloud-free conditions. This averaging process ensured that the final composite images represented the typical environmental characteristics for each season. Visualizations of a subset of composite bands for the summer of 2020 for LSOAs with the highest and lowest total prescriptions per capita are shown in Figure 3.

D.3.1 Extracting Image Features per LSOA

To extract per-LSOA features from Sentinel-2 composite images, we segmented each image into LSOA-specific imagelets with the procedure depicted in Figure 4. For every imagelet, we computed five descriptive statistics: *min*, *max*, *mean*, *std*, and *median*. Our examination of these statistics

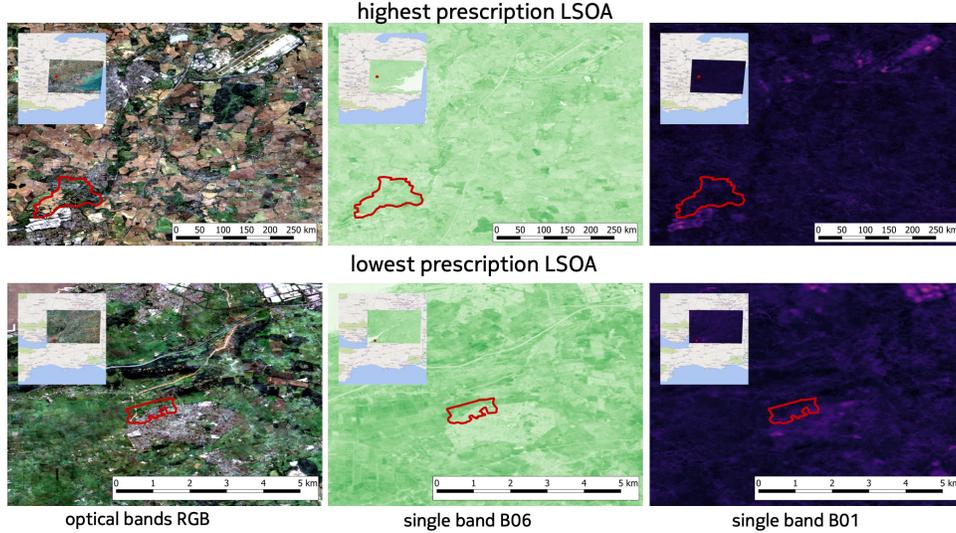


Figure 3: Visualization of the selected MEDSAT Sentinel-2 composite bands for the LSOAs with highest/lowest total prescriptions quantity per capita.

revealed inter-correlations, leading to three distinct classes of correlated bands for each image (e.g., cross-correlation of mean values between summer and winter composite images for 2020 can be seen in Figure 5). Further assessment of the statistics' distributions showed skewness in some (like *min*) and both skewness and extreme outliers in others (specifically *max*). Moreover, certain statistics, such as *mean* and *median*, exhibited inherent correlations.

D.4 Prescription Outcomes

D.4.1 Existing Public and Population Health Datasets

Fine-grained spatial and temporal indices for prevalence of medical conditions are rarely available. Public health agencies typically collect data infrequently through representative surveys (e.g., National health and nutrition examination survey (NHANES) [11], Health Survey for England (HSE) [29], or Behavioral Risk Factor Surveillance System (BRFSS) [33]) or on population samples with cohort studies (e.g., Framingham Heart Study [26], The Swiss National Cohort (SNC) [38], or The UK Biobank [39]). Surveys come with well-known biases, such as sampling [7], non-response [36], recall [19], or question wording [40] bias. While cohort studies aim at limiting these biases by complementing participant questionnaire responses with their health records, or even genetic

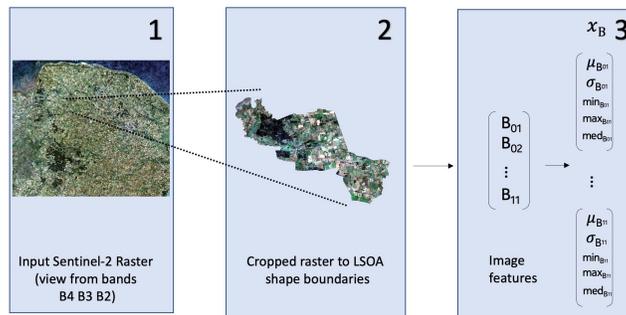


Figure 4: **Extracting Image Features:** For each seasonal Sentinel-2 composite image, we extracted a set of five metrics per LSOA from each band $B_i \in \{B_{01}, \dots, B_{11}\}$: *mean*, *stdev*, *min*, *max*, and *median*. While we show only 3 representative bands for visualization purposes, features were extracted from all 11 bands, resulting in a total of 55 features per seasonal image.

Table 2: The size of the data processed on WASDI platform while producing the environmental image features for each month.

date from	date to	GB
2018-12-01	2018-12-31	671.4277637
2019-01-01	2019-01-31	671.1432031
2019-02-01	2019-02-31	652.6567187
2019-03-01	2019-03-31	648.4059570
2019-04-01	2019-04-31	632.4159082
2019-05-01	2019-05-31	617.2984863
2019-06-01	2019-06-31	641.2775684
2019-07-01	2019-07-31	650.5995117
2019-08-01	2019-08-31	661.7470703
2019-09-01	2019-09-31	631.0063281
2019-10-01	2019-10-31	631.5184570
2019-11-01	2019-11-31	666.4724512
2019-12-01	2019-12-31	688.0771484
2020-01-01	2020-01-31	657.6159668
2020-02-01	2020-02-31	648.8922559
2020-03-01	2020-03-31	614.7591406
2020-04-01	2020-04-31	654.5712695
2020-05-01	2020-05-31	676.6889844
2020-06-01	2020-06-31	640.9450684
2020-07-01	2020-07-31	648.6113184
2020-08-01	2020-08-31	647.2279785
2020-09-01	2020-09-31	654.1471207
2020-10-01	2020-10-31	648.9410100
2020-11-01	2020-11-31	655.3504297
2020-12-01	2020-12-31	622.1216504
2021-01-01	2021-01-31	672.5485547

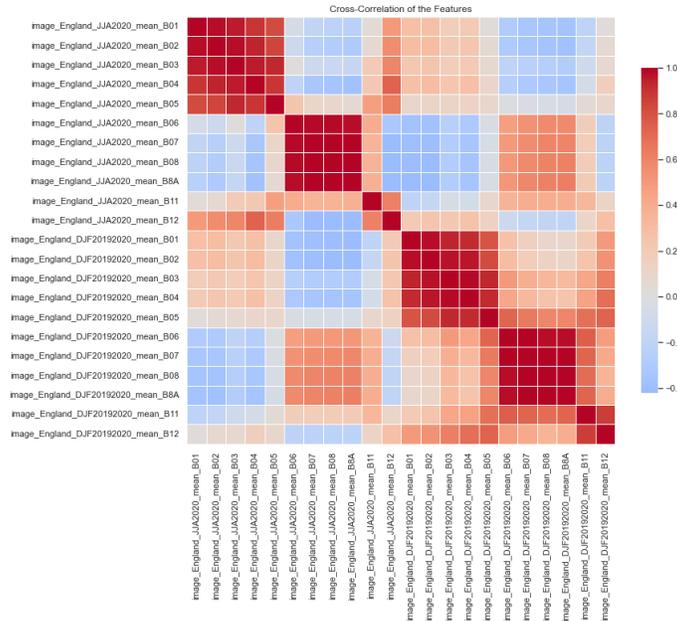


Figure 5: **Cross-correlation matrix for mean band values extracted from summer (JJA) and winter (DJF) Sentinel-2 composites for 2020.** We see that bands $B01 - B05$, and $B06 - B8A$, as well as $B11 - B12$ form clusters of highly correlated features.

information, they are still limited in size, can be expensive and time-consuming to conduct, and participants may drop out of the study. The All of US Research Program (AoURP) [34] is a unique effort in the US recruiting over 1 million participants to study precision population health. However,

despite its size, AoURP still might face limited representativeness, and the success of the program will depend on long-term engagement and retention of participants. In summary, exhaustive health outcomes data are often of limited scope and granularity, and are prone to a variety of biases.

D.4.2 NHS Medical Prescriptions

The practice-level prescribing data in England has been published monthly by the National Health Services (NHS) Business Services Authority since 1998. This data provides information on the quantity and cost of prescribed medications for each *general practitioner (GP) practice* in the country. Although freely accessible, it is provided in individual files for each year, and is difficult to combine in order to analyze spatial or temporal trends. The OpenPrescribing service [10] enables the exploration of trends in items, cost, price per item, and quantity per item for each medical prescription and GP practice from 1998. However, a single GP practice can cater to patients from multiple nearby administrative areas (e.g., LSOAs). Consequently, this service does not directly provide insights into the spatial prevalence of prescriptions across these areas. The PrAna R package [21] allows the calculation of prescribed quantities of active pharmaceutical ingredients (APIs) by postcode. However, a single API or medical drug can be used to treat various conditions (e.g., selective serotonin reuptake inhibitors (SSRIs) are used for treating depression, anxiety disorders, and certain eating disorders), and a specific medical condition is typically treated using multiple drugs or APIs (e.g., depression is treated with both SSRIs and tricyclic antidepressants (TCAs)). This limits the ability of such a tool to understand the prevalence of prescriptions for specific conditions. As a result, previous studies using prescribing data in England have mainly focused on a small number of drugs manually aggregated for bespoke analyses, primarily examining temporal trends (e.g., [20, 30, 8, 45, 12]), with a few studies investigating also spatial trends (e.g., [35, 18]). Despite the valuable insights provided by previous studies using prescribing data, to the best of our knowledge, there is currently no approach that generalizes across various medical conditions to calculate spatial and temporal trends from this data.

Original NHS Practice-Level Prescribing Data The monthly practice-level prescribing data in England, provided by the National Health Services (NHS) since July 2010 [31], constitutes the foundation of our analysis. The dataset consists of four files visualized in Figure 6 containing the following information:

1. *GP monthly prescriptions* – Anonymized prescriptions across General Practitioner (GP) practices in England for a given month. Each prescription entry includes details such as the drug name, British National Formulary (BNF) code [31], practice code, total number of items, total cost, and individual item quantities.
2. *Drugs* – A comprehensive list of drugs with their unique BNF codes [31].
3. *GPs* – Information on GP practices, including practice codes, names, and full addresses. Our dataset encompasses 6,924 GPs located across England, excluding closed or prison-hosted practices.
4. *Patients* – Contains practice codes, census Lower-layer Super Output Area (LSOA) codes, and the number of patients registered with each practice in a particular area. By aggregating this data, we calculated the total number of primary care patients residing in a specific area using the equation:

$$n_{\text{pat}}(a) = \sum_{\text{gp}} n_{\text{pat}}(\text{gp}, a) \quad (1)$$

Here, $n_{\text{pat}}(\text{gp}, a)$ represents the number of patients registered with a particular GP residing in area a . The strong correlation ($r = .92$) between the number of patients and residents in an LSOA validates our probabilistic approach of assigning patients to areas. Additionally, we computed the fraction of a GP practice’s patients associated with a specific area a using the equation:

$$f(\text{gp}, a) = \frac{n_{\text{pat}}(\text{gp}, a)}{n_{\text{pat}}(\text{gp})} \quad (2)$$

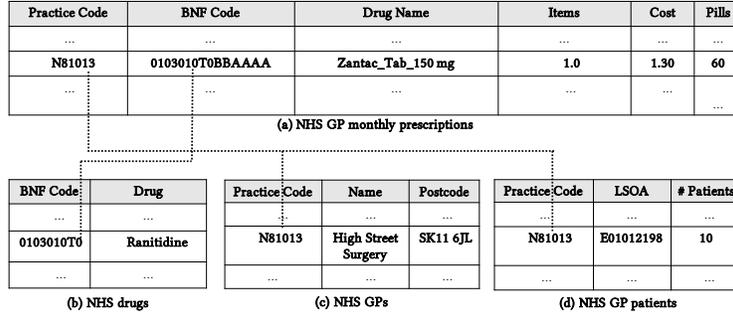


Figure 6: The four NHS Datasets: (a) GP (general practitioner) monthly prescriptions; (b) Drugs; (c) GPs; and (d) Patients. Each monthly prescription in dataset (a) was translated into a drug name based on the BNF code for which dataset (b) offered the corresponding drug (preparation name). The prescription was also geographically mapped using the GP code for which dataset (c) provided the location. To then map the prescription at the level of census LSOAs, we computed the fraction of the GP’s patients who lived in each LSOA from dataset (d).

D.4.3 DrugBank Network

We show here the lists of drug names extracted automatically from DrugBank for two conditions, i.e., diabetes (Table 3) and anxiety (Table 5), and the pre-existing list from the literature [16] for depression (Table 4). For anxiety, we also visualize the corresponding DrugBank network subset (Figure 7). For the other lists of drugs, please refer to our GitHub repository: https://github.com/sanja7s/MedSat/tree/master/code/collate_data/NHS_prescription_parser/drug_names.

The correlation between prevalence scores based on the list of drug names extracted automatically from DrugBank and based on the pre-existing list from the literature are .94 for anxiety and .99 for diabetes, attesting to the high quality of automatically generated output from DrugBank.

Table 3: List of drug names associated with **diabetes**.

BNF Code	Drug name	BNF Code	Drug name
0601023A0	Acarbose	0601023AM	Canagliflozin
0601023AS	Albiglutide	0601023AP	Canagliflozin/Metformin
0601023AK	Alogliptin	0601021E0	Chlorpropamide
0601023AJ	Alogliptin/Metformin	0212000AD	Colesevelam Hydrochloride
0607010B0	Bromocriptine	0601023AG	Dapagliflozin
0601023AL	Dapagliflozin/Metformin	0605020E0	Desmopressin Acetate
0601023AQ	Dulaglutide	0601023AN	Empagliflozin
0601023AR	Empagliflozin/Metformin	0601023AX	Ertugliflozin
0601023Y0	Exenatide	0601021H0	Glibenclamide
0601021M0	Gliclazide	0601021A0	Glimepiride
0601021P0	Glipizide	0202010L0	Hydrochlorothiazide
0202080M0	Hydrochlorothiazide/Potassium	0601011A0	Insulin Aspart
0601012Z0	Insulin Degludec	0601012X0	Insulin Detemir
0601012V0	Insulin Glargine	0601012AB	Insulin Glargine/Lixisenatide
0601011P0	Insulin Glulisine	0601011R0	Insulin Human
0601011L0	Insulin Lispro	0601012S0	Isophane Insulin
0601023AE	Linagliptin	0601023AF	Linagliptin/Metformin
0601023AB	Liraglutide	0601023AI	Lixisenatide
0601022B0	Metformin Hydrochloride	0601023W0	Metformin Hydrochloride/Pioglitazone
0601023V0	Metformin Hydrochloride/Rosiglitazone	0601023AD	Metformin Hydrochloride/Sitagliptin
0601023Z0	Metformin Hydrochloride/Vildagliptin	0601023M0	Miglitol
0601023U0	Nateglinide	0601023B0	Pioglitazone Hydrochloride
0601023R0	Repaglinide	0601023S0	Rosiglitazone
0601023AC	Saxagliptin	0601023AV	Saxagliptin/Dapagliflozin
0601023AH	Saxagliptin/Metformin	0601023AW	Semaglutide
0601023X0	Sitagliptin	0601021V0	Tolazamide
0601021X0	Tolbutamide	0601023AA	Vildagliptin

Table 4: List of drug names associated with **depression** (source [16]).

BNF Code	Drug name	BNF Code	Drug name
040303Q0	Sertraline	0403040T0	Reboxetine
040303D0	Citalopram	0403040Z0	Agomelatine
040303E0	Fluoxetine	0402010S0	Flupentixol
040303P0	Paroxetine	0403010T0	Tryptophan
040303X0	Escitalopram	0403040N0	Nefazodone
040303F0	Fluvoxamine	0403010U0	Oxatriptan
040304M0	Mirtazapine	0403010B0	Amitriptyline
040304W0	Venlafaxine	0403010V0	Trazodone
040304Y0	Duloxetine	0403010H0	Dosulepin
040304AB	Vortioxetine	0403010L0	Lofepramine
0403010R0	Nortriptyline	0403010C0	Clomipramine
0403010J0	Imipramine	0403010W0	Trimipramine
0403010G0	Doxepin	0403010M0	Mianserin
0403010A0	Amoxapine	0403010P0	Moclobemide
0403010X0	Tranlycypromine	0403010S0	Phenelzine
0403010K0	Isocarboxazid		

Table 5: List of drug names associated with **anxiety**.

BNF Code	Drug name	BNF Code	Drug name
0401020A0	Alprazolam	0401020G0	Bromazepam
0403010B0	Amitriptyline Hydrochloride	0401020B0	Buspirone Hydrochloride
0401020D0	Chlordiazepoxide	0401020E0	Chlordiazepoxide Hydrochloride
040303D0	Citalopram Hydrobromide	0401020V0	Clorazepate Dipotassium
0401020K0	Diazepam	0704020AA	Duloxetine Hydrochloride
040303X0	Escitalopram	0408010G0	Gabapentin
0304010J0	Hydroxyzine Hydrochloride	0401020P0	Lorazepam
0401020R0	Meprobamate	0403040X0	Mirtazapine
0401020T0	Oxazepam	0403030P0	Paroxetine Hydrochloride
0402010Q0	Perphenazine	0406000T0	Prochlorperazine Maleate
0204000R0	Propranolol Hydrochloride	0402010AB	Quetiapine
0402010X0	Trifluoperazine	0403040W0	Venlafaxine

E Benchmarks Results

E.1 Detailed Health Inequalities

In Figure 8, we present the MEDSAT data, providing insights into healthcare accessibility disparities across regions. Our analysis focuses on comparing the total number of registered patients with the population at the LSOA level, revealing significant spatial deviations, indicative of inequalities.

First, interestingly, we find a prevailing pattern where the number of registered patients exceeds the census population in most areas of the country. This aligns with previous investigations by UK authorities [42]. Second, although the correlation ($r = .87, p \approx 0$) is strong, certain LSOAs exhibit disproportionate patient-to-population ratios. For instance, Forest of Dean and Shropshire, located near the Welsh border, show lower patient numbers, likely due to residents being registered with Welsh GPs. Similarly, Richmondshire, housing a military base in Catterick Garrison, and Forest Heath in Suffolk, hosting RAF Mildenhall, exhibit lower patient-to-population ratios. Conversely, Oxford and Cambridge have higher patient-to-population ratios, attributed to students registered with local GPs but not counted as residents (the LSOA with highest residual is Oxford 006F, featuring student housing for Oxford Brookes University, as well as an International Language Campus).

Additionally, our analysis highlights broader factors contributing to healthcare inequalities. The residual values, representing deviations from the linear fit, correlate with deprivation levels ($r = .16, p \approx 0$ for mid-deprived areas; $r = .22, p \approx 0$ for highly-deprived areas), suggesting a greater burden on healthcare access in socioeconomically disadvantaged regions (e.g., one of the areas with the highest patient-to-population ratio is near Bolton, a highly deprived region in Greater Manchester). Moreover, the residual values exhibit a negative correlation ($r = -.40, p \approx 0$) with the percentage of White population, indicating disparities associated with ethnic backgrounds. These findings underscore the presence of healthcare access inequalities across the country, as corroborated by prior

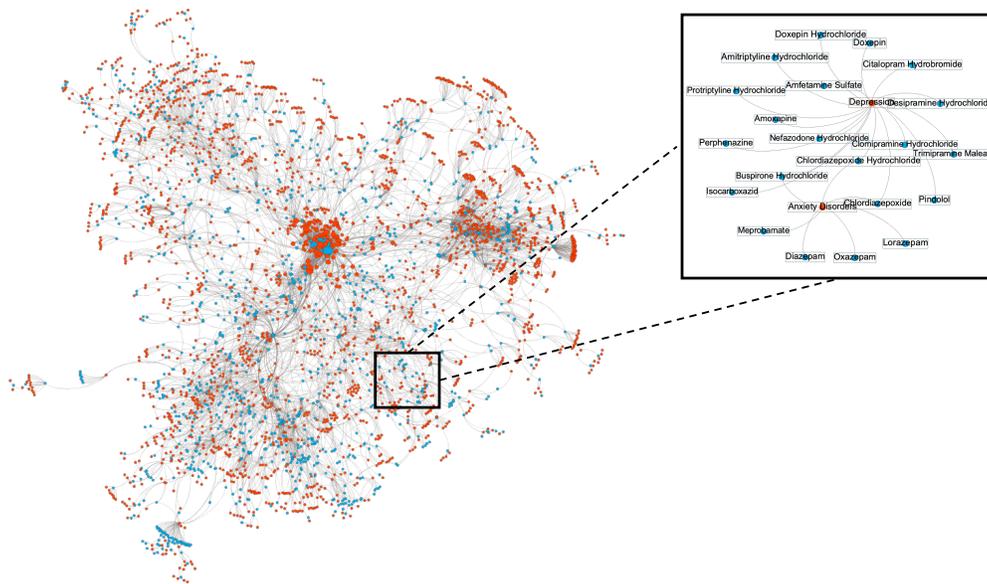


Figure 7: **Visualization of the Drugbank network:** showcasing the comprehensive interconnections between various drugs; the inset provides a zoom-in view to the subset specifically associated with *anxiety* prescriptions.

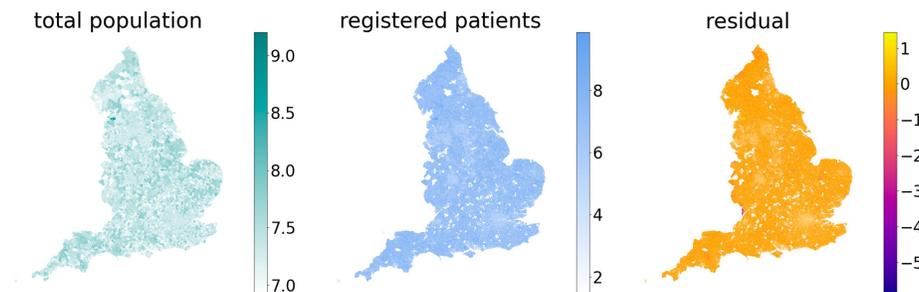


Figure 8: **Health access disparity analysis using MEDSAT.** We present a quick analysis of health access disparities by examining the relationship between the population and the number of registered patients (log-transformed), revealing a strong correlation ($r = 0.87, p \approx 0$). However, the residual values from a linear fit between the two highlight a clear rural-urban pattern, with urban areas showing a higher patient-to-population ratio, which correlates with the percentage of White population ($r = -0.40, p \approx 0$). Furthermore, the residuals show associations with mid- ($r = 0.16, p \approx 0$) and highly-deprived areas ($r = 0.22, p \approx 0$), indicating a potentially greater health-access burden in these areas. Details of the analysis are found in Appendix.

research examining various healthcare system aspects, including NHS data on waiting times, staffing, hospital activity, outcomes, and the GP Patient Survey [41], or COVID-19 hospitalisations and deaths [28].

E.2 Predicting Prescriptions

E.2.1 Spatial Lag Model (SLM)

The Spatial Lag Model (SLM) [3, 4], differs from the Ordinary Least Squares (OLS) model by the inclusion of the spatial lag term ($\rho W y$):

$$y = \rho W y + X\beta + \epsilon,$$

where y is the outcome, X is the matrix of features, and ϵ is the error term. W is a matrix of the shape $N \times N$ and it contains spatial weights capturing the spatial interaction among variables, and the coefficient of spatial autocorrelation is captured by ρ . We fed in input to SLM the LSOA shapefiles to calculate the spatial lag term.

Table 6: **The spatial R^2 scores resulting from the Spatial Lag Model (SLM).** These scores are computed across various prescription types and combinations of dataset features specifically for the year 2020.

input	metabolic		mental		respiratory	opioids	total
	diabetes	hypertension	depression	anxiety	asthma		
Image	0.04	0.23	0.23	0.19	0.25	0.28	0.11
Env.	0.13	0.34	0.41	0.37	0.34	0.49	0.25
Soc.	0.33	0.44	0.50	0.48	0.38	0.52	0.31
Env. + Soc. + Image	0.38	0.49	0.54	0.55	0.43	0.63	0.38

The SLM results are presented in Table 6.

E.2.2 Machine Learning Models

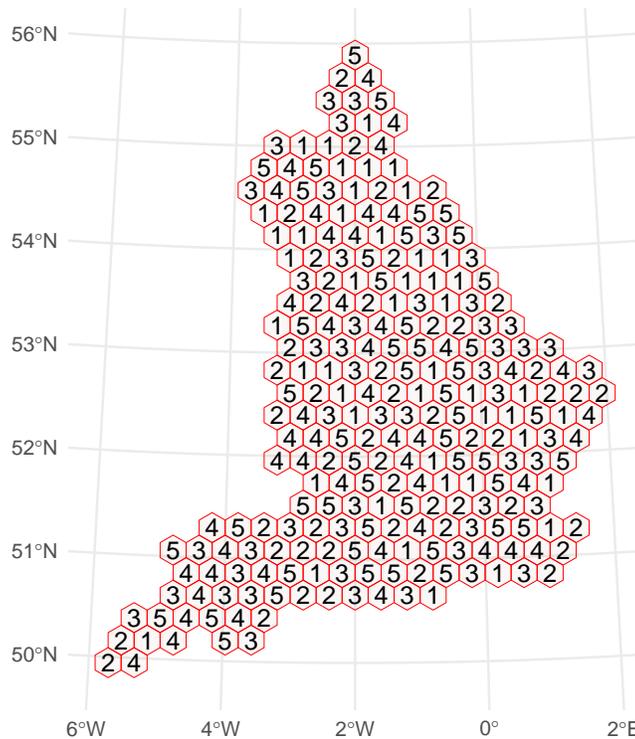


Figure 9: **Visualization of an example spatial fold created using blockCV spatial blocking:** we chose hexagonal blocks and randomly assigned those blocks to 5 folds consisting of an equal number of blocks. The numbers specify the fold assignment of the blocks.

Spatial Cross-Validation In spatial data scenarios, traditional random cross-validation methods can inadvertently undervalue prediction errors which can lead to suboptimal model choices. Recognizing this challenge, specific validation techniques tailored for spatial modeling, such as spatial blocks

and buffers, have been introduced [23, 43]. We utilized the R package `blockCV`, which facilitates the creation of spatially or environmentally separated folds. We used `cv_spatial` function to create spatial blocks (hexagons) and relied on the interactive tool `rangeExplorer` withing `blockCV` to visualise the blocks and assess the impact of block size on the number and arrangement of blocks in the landscape. For our experiments, we chose the block size of 28km x 28km.

Prescription Prediction To understand whether the prevalence scores for the different prescription types can be reliably predicted based on the environmental, sociodemographic indicators and the simple image features, we performed spatial cross-validation for the LightGBM [22] tree-based model and a Feed-Forward Neural Network (FNN). For this experiment, we dropped the instances having missing values. The hyperparameters used for LightGBM model and the FNN are provided in Tables 7 and 8, respectively. For both years in our dataset, we implemented the following evaluation procedure: We randomly created 5 splits consisting of 5 folds where each fold contains an equal number of the above-described spatial blocks. Figure 9 depicts one example of a spatial split consisting of 5 folds. For each split, we performed the standard cross-validation procedure such that 80 % of the spatial blocks are used in model training and the rest 20 % for model testing. This procedure ensures that the test set does not contain LSOAs from the geographical blocks used for model training. Further, we used half of the instances in the test fold as a validation set for early stopping to prevent overfitting, and the other half was used as a test set to evaluate the model performance. Additionally, in each split, we performed feature standardization such that each feature has zero mean and unit variance. Figure 10 shows the average R^2 scores over the test sets and the corresponding standard deviation per prescription type and machine learning model. These results show that for both years, the LightGBM model consistently outperforms the FNN. Moreover, we can also see that the R^2 scores are similar for the different prescription types for both years except for the total prescriptions which have lower goodness-of-fit in 2019 compared to 2020.

Table 7: LightGBM hyperparameters.

parameter	value
objective	regression
metric	rmse
boosting	gdbt
data_sample_strategy	bagging
num_iterations	100
learning_rate	0.1
tree_learner	serial
early_stopping_rounds	10

Table 8: Feed-Forward Neural Network hyperparameters.

parameter	value
hidden layers	3
embedding dimension	512
epochs	100
criterion	mse
optimizer	Adam
learning_rate	0.0001
weight_decay	0.001
early_stopping_rounds	10

Detailed SHAP results The 10 most important features as estimated by the SHAP approach [25] and the relationship between feature values and their SHAP importance for the prediction of LightGBM models for 2019, and 2020 are given in Figures 11 and 12, respectively. The LightGBM models were trained on the proposed spatial split described in Section E.2. Although these plots indicate that the majority of the relevant factors overlap for 2019 and 2020, we also see that the important factors for a condition can change in the subsequent year. For instance, the aerosols feature

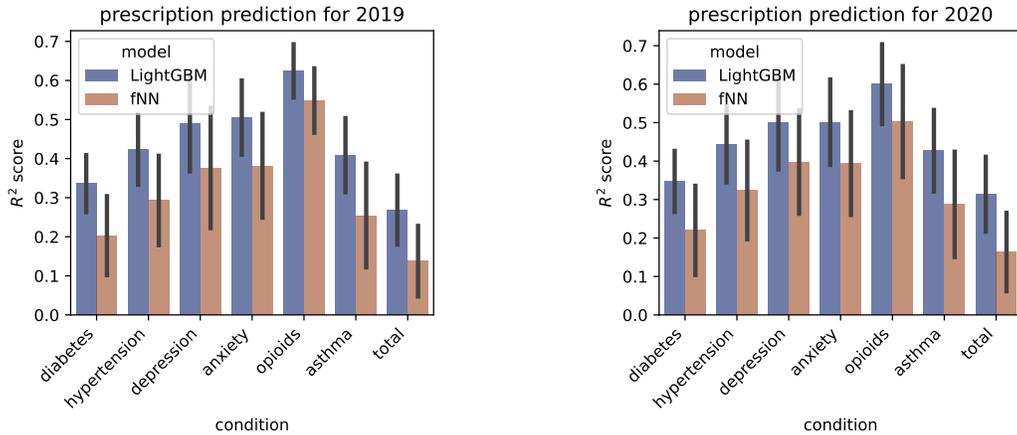


Figure 10: **Prescription prediction results on the spatial cross-validation splits of the LightGBM model and the FNN model for the different medical conditions in 2019 (left plot) and 2020 (right plot).** The error bars indicate the standard deviation per machine learning model and medical condition and they show that the R^2 scores deviate strongly for the FNN model.

that does not appear among the top-15 features for predicting opioids in 2019 is the most important feature for the same condition in 2020. Also, we observe that the contribution of a feature can vary over the years. For example, while low values of thermal radiation are related with an increase in opioids prescriptions for 2019, such a relationship is not exhibited for 2020. These insights shed light on the challenges introduced with our dataset for predicting future health outcomes based on historical data.

SHAP Dependence Plots The SHAP dependence plots explain the effect of a feature on the model predictions on the entire dataset while also revealing the interaction effects between the features [2]. In Figure 14, we show the SHAP dependence plots for the lightGBM models trained for predicting anxiety and opioid prescriptions. For creating the plots, we used the SHAP python library with the auto option for the interaction index that selects the feature which has the highest estimated interaction with the most important feature (according to the SHAP values). The left plot shows that LSOAs with a high number of White ethnicity population result in higher model predictions for anxiety. Further, the interaction of White ethnicity with work from home feature reveals that among the LSOAs with a large White population, lower prescriptions are predicted for those having a large percentage of people working from home. Next, the right plot shows that the model tends to predict lower prescription rates for LSOAs with high PM2.5 values while at the same time depicting no clear relationship between the PM2.5 and the wind component.

E.3 Temporal Analyses

As Figures 15, and 16 show, both the prescription quantities for our observed outcomes, as well as the environmental point features exhibit different distributions between 2019 and 2020. People in England were prescribed more mental health-related medications, as well as *diabetes*-associated medications, and less medications associated with *asthma* and *hypertension*. Satellite data measured significantly less *NO2*, *ozone*, and *PM2.5* across England during 2020. The changes in land cover manifested by an increase in *built* environment, and a decrease in *trees* cover. Finally, *temperatures* and the amount of *solar radiation*, as well as the amounts of *wind*, as expressed through its both components, east-west and north-south, were higher in England in 2020 compared to 2019.

References

- [1] UK Office for National Statistics. https://www.nomisweb.co.uk/sources/census_2021, 2022. [Online; accessed 26-February-2022].

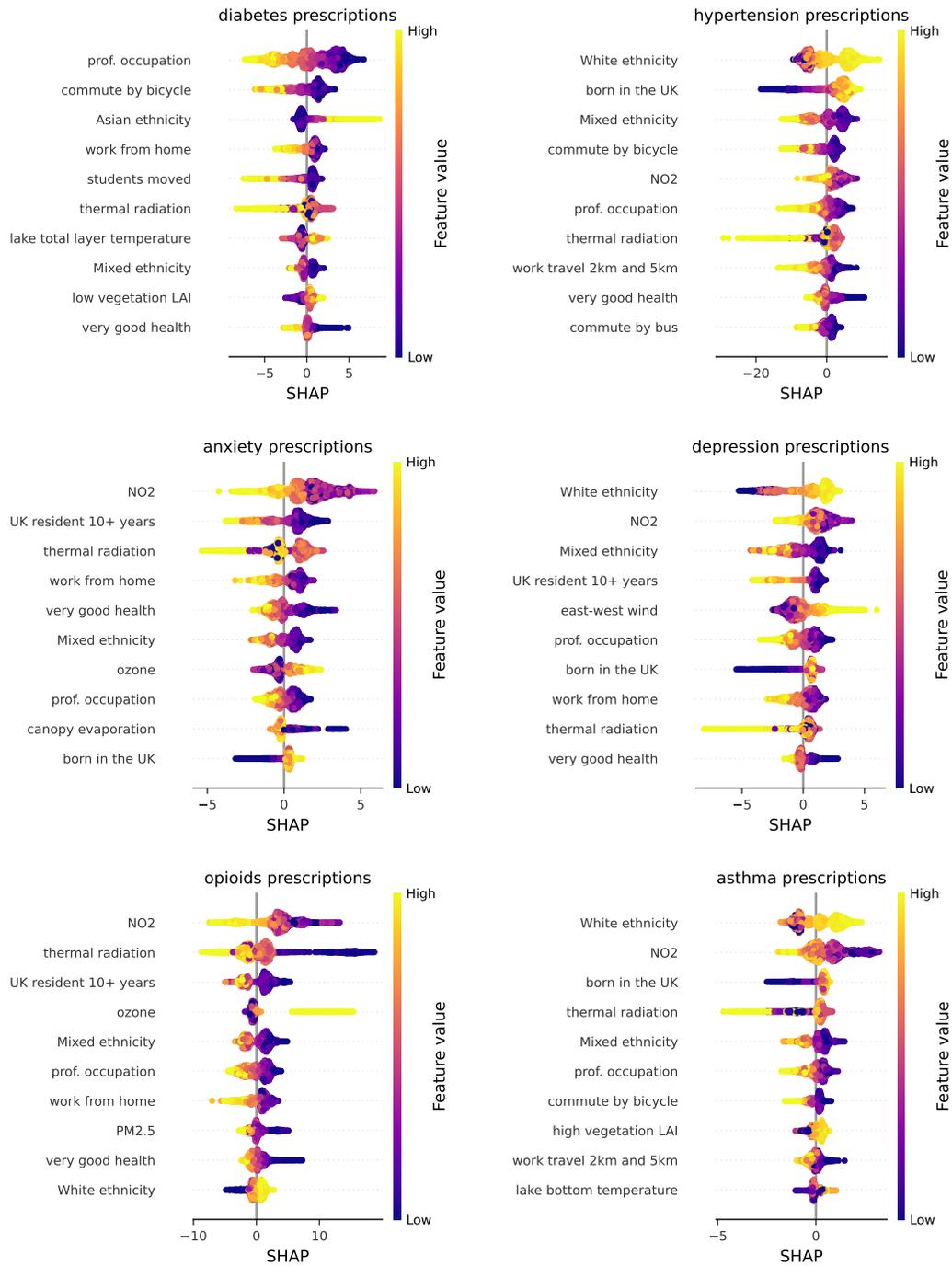


Figure 11: SHAP values for the LightGBM model used for predicting prescriptions for different conditions in MEDSAT for 2019. The SHAP value for a feature indicates its contribution towards the difference between the prediction for an instance and the average model prediction.

[2] Census income classification with LightGBM . https://shap.readthedocs.io/en/latest/example_notebooks/tabular_examples/tree_based_models/Census%20income%20classification%20with%20LightGBM.html, 2023. [Online; accessed 22-August-2023].

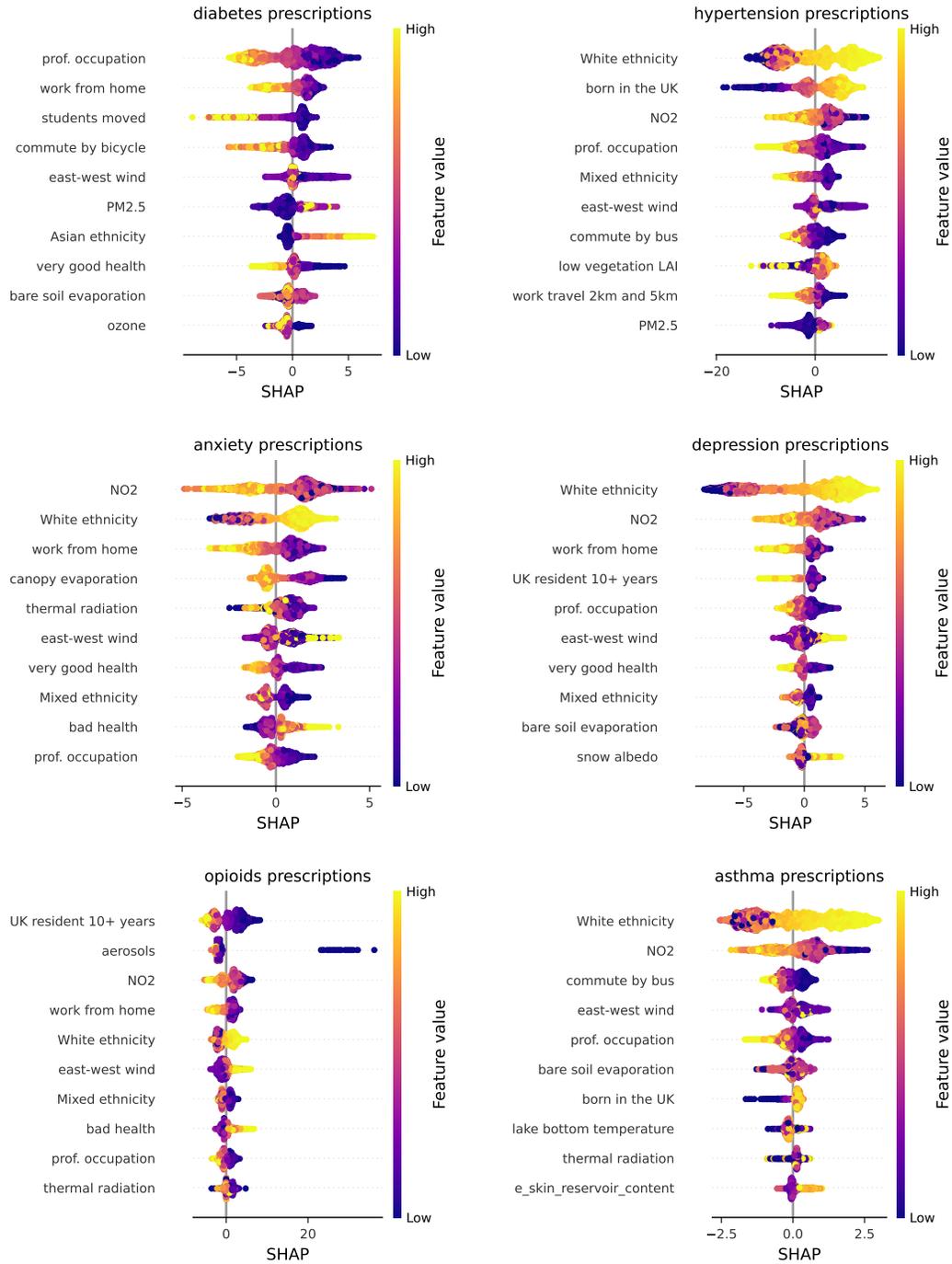


Figure 12: SHAP feature importance for the LightGBM model used for predicting prescriptions for different conditions in MEDSAT for 2020.

- [3] Luc Anselin. *Spatial econometrics: Methods and Models*, volume 4. Springer Science & Business Media, 1988.
- [4] Luc Anselin. Spatial regression. *The SAGE handbook of spatial analysis*, 1:255–276, 2009.
- [5] Evelise Pereira Barboza, Marta Cirach, Sasha Khomenko, Tamara Iungman, Natalie Mueller, Jose Barrera-Gómez, David Rojas-Rueda, Michelle Kondo, and Mark Nieuwenhuijsen. Green

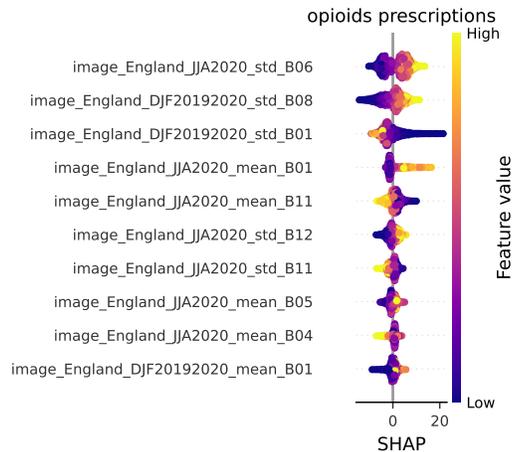


Figure 13: SHAP values for the LightGBM model trained on prescription prediction based on the mean and standard deviation simple image features.

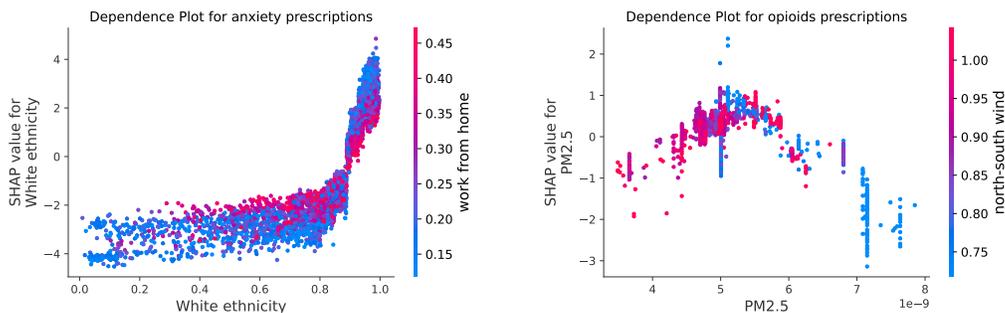


Figure 14: SHAP dependence plots for anxiety prescriptions (left) and opioids prescriptions (right).

space and mortality in european cities: a health impact assessment study. *The Lancet Planetary Health*, 5(10):e718–e730, 2021.

- [6] Marshall Burke, Anne Driscoll, David B Lobell, and Stefano Ermon. Using satellite imagery to understand and promote sustainable development. *Science*, 371(6535):eabe8628, 2021.
- [7] Kei Long Cheung, Peter M Ten Klooster, Cees Smit, Hein de Vries, and Marcel E Pieterse. The impact of non-response bias due to sampling in public health studies: A comparison of voluntary versus mandatory recruitment in a dutch national survey on adolescent health. *BMC public health*, 17(1):1–10, 2017.
- [8] AJ Connor and SG Fraser. Glaucoma prescribing trends in england 2000 to 2012. *Eye*, 28(7):863–869, 2014.
- [9] Copernicus. CAMS About Us. <https://atmosphere.copernicus.eu/about-us>, 2023. [Online; accessed 13-June-2023].
- [10] Helen J Curtis and Ben Goldacre. Openprescribing: normalised data and software tool to research trends in english nhs primary care prescribing 1998–2016. *BMJ Open*, 8(2):e019921, 2018.
- [11] Centers for Disease Control, Prevention, et al. National health and nutrition examination survey (nhanes), 2007.
- [12] Earn H Gan, Stewart Pattman, Simon HS Pearce, and Richard Quinton. A uk epidemic of testosterone prescribing, 2001–2010. *Clinical endocrinology*, 79(4):564–570, 2013.

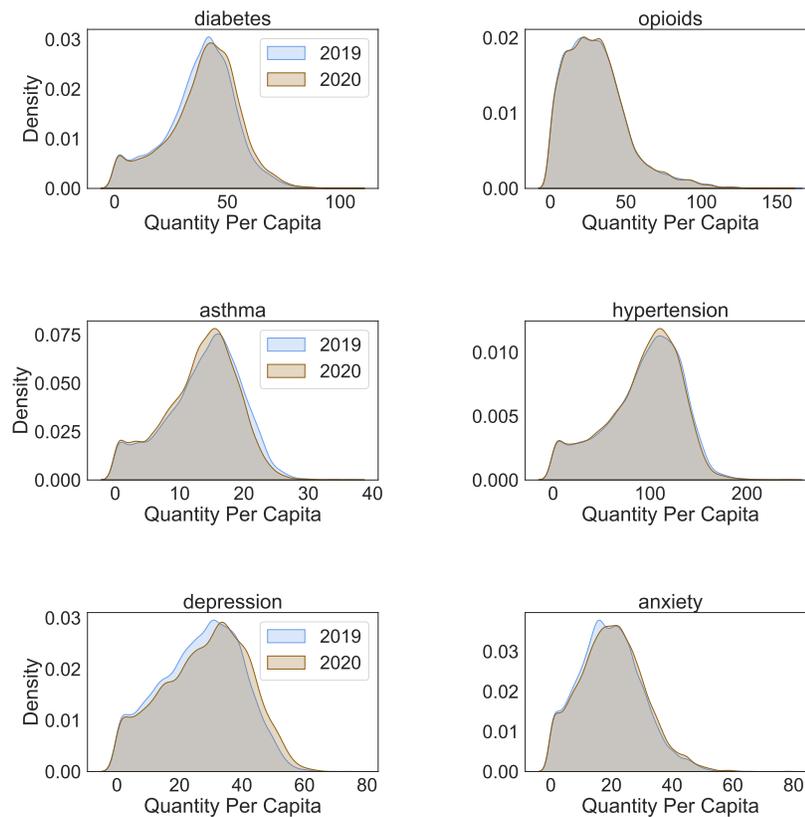


Figure 15: **Differences in distributions of MEDSAT outcomes between 2019 and 2020.** The Kolmogorov-Smirnov (KS) test [27] showed that, except for *opioids*, all the other prescription types have significantly different distributions between the two years. Notably, prescriptions associated with *hypertension* and *asthma* have decreased in 2020; while the prescriptions associated with mental conditions (i.e., *depression* and *anxiety*), as well as *diabetes* have increased.

- [13] Christopher J Gidlow, Graham Smith, David Martinez, Richard Wilson, Paul Trinder, Regina Gražulevičienė, and Mark J Nieuwenhuijsen. Research note: Natural environments and prescribing in england. *Landscape and Urban Planning*, 151:103–108, 2016.
- [14] Noel Gorelick, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 2017.
- [15] Ola Hall, Mattias Ohlsson, and Thorsteinn Rögnvaldsson. A review of explainable ai in the satellite data, deep machine learning, and human poverty domain. *Patterns*, 3(10):100600, 2022.
- [16] Adrian H Heald, Mike Stedman, Mark Davies, Mark Livingston, David Taylor, and Roger Gadsby. Antidepressant prescribing in england: patterns and costs. *The Primary Care Companion for CNS Disorders*, 22(2):26631, 2020.
- [17] Marco Helbich, Nadja Klein, Hannah Roberts, Paulien Hagedoorn, and Peter P Groenewegen. More green space is related to less antidepressant prescription rates in the netherlands: A bayesian geoaddditive quantile regression approach. *Environmental research*, 166:290–297, 2018.

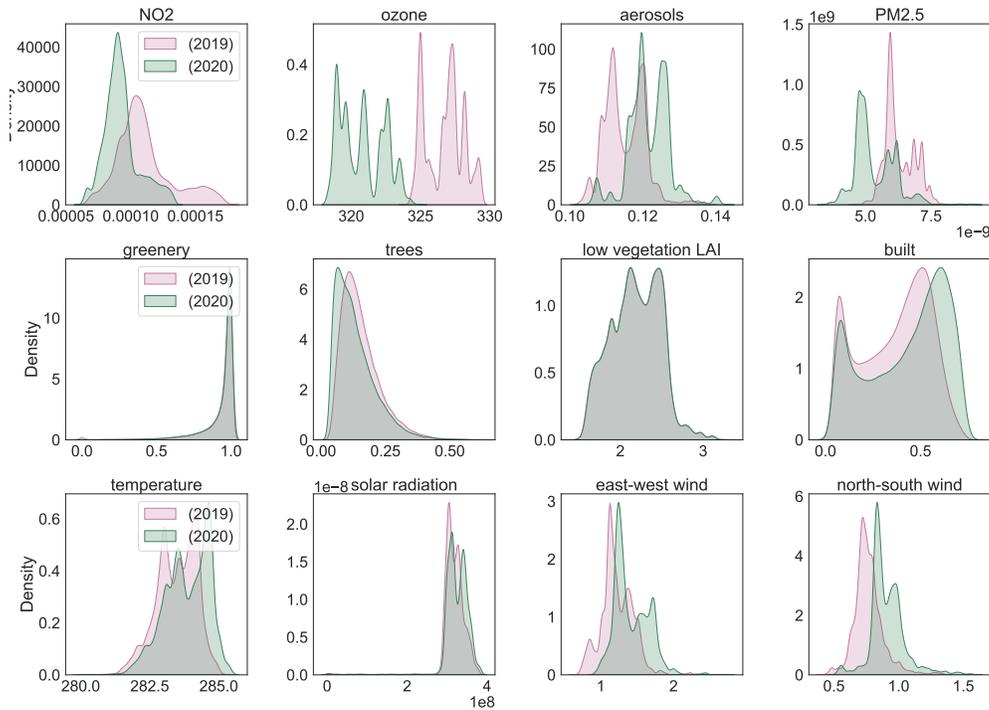


Figure 16: Differences in distributions of MEDSAT environmental features between 2019 and 2020. The Kolmogorov-Smirnov (KS) test [27] showed that, except for *low and high vegetation LAI*, all the other environmental features have significantly different distributions between the two years. Specifically, variables related to air pollution (*NO2*, *ozone*, and *PM2.5*) have significantly decreased in 2020. Interestingly, the amount of total *aerosols* has on the other hand increased. The amount of *trees* as observed from satellite imagery has decreased, while the amount of *built* environment has increased. Finally, all the climate-related variables, such as *temperature*, *solar radiation*, the two *wind components* have also exhibited increased values in 2020.

- [18] Lisa EM Hopcroft, Jon Massey, Helen J Curtis, Brian Mackenna, Richard Croker, Andrew D Brown, Thomas O’Dwyer, Orla Macdonald, David Evans, Peter Inglesby, et al. Data-driven identification of unusual prescribing behavior: Analysis and use of an interactive data tool using 6 months of primary care data from 6500 practices in England. *JMIR Medical Informatics*, 11:e44237, 2023.
- [19] Matthias Hunger, Larissa Schwarzkopf, Margit Heier, Annette Peters, Rolf Holle, and KORA Study Group. Official statistics and claims data records indicate non-response and recall bias within survey-based estimates of health care utilization in the older population. *BMC health services research*, 13:1–11, 2013.
- [20] Stephen Ilyas and Joanna Moncrieff. Trends in prescriptions and costs of drugs for mental disorders in England, 1998–2010. *The British Journal of Psychiatry*, 200(5):393–398, 2012.
- [21] Kishore Kumar Jagadeesan, James Grant, Sue Griffin, Ruth Barden, and Barbara Kasprzyk-Hordern. Prana: an R package to calculate and visualize England NHS primary care prescribing data. *BMC Medical Informatics and Decision Making*, 22(1):5, 2022.
- [22] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 2017.
- [23] Kévin Le Rest, David Pinaud, Pascal Monestiez, Joël Chadoeuf, and Vincent Bretagnolle. Spatial leave-one-out cross-validation for variable selection in the presence of spatial autocorrelation. *Global ecology and biogeography*, 23(7):811–820, 2014.

- [24] Alex Levering, Diego Marcos, and Devis Tuia. On the relation between landscape beauty and land cover: A case study in the uk at sentinel-2 resolution with interpretable ai. *ISPRS journal of Photogrammetry and Remote Sensing*, 177:194–203, 2021.
- [25] Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30, 2017.
- [26] Syed S Mahmood, Daniel Levy, Ramachandran S Vasan, and Thomas J Wang. The framingham heart study and the epidemiology of cardiovascular disease: a historical perspective. *The lancet*, 383(9921):999–1008, 2014.
- [27] Frank J Massey Jr. The kolmogorov-smirnov test for goodness of fit. *Journal of the American statistical Association*, 46(253):68–78, 1951.
- [28] Rohini Mathur, Christopher T Rentsch, Caroline E Morton, William J Hulme, Anna Schultze, Brian MacKenna, Rosalind M Eggo, Krishnan Bhaskaran, Angel YS Wong, Elizabeth J Williamson, et al. Ethnic differences in sars-cov-2 infection and covid-19-related hospitalisation, intensive care unit admission, and death in 17 million adults in england: an observational cohort study using the opensafely platform. *The Lancet*, 397(10286):1711–1724, 2021.
- [29] Jennifer Mindell, Jane P Biddulph, Vasant Hirani, Emanuel Stamatakis, Rachel Craig, Susan Nunn, and Nicola Shelton. Cohort profile: the health survey for england. *International journal of epidemiology*, 41(6):1585–1593, 2012.
- [30] Anna L Mitchell, Bryan Hickey, Janis L Hickey, and Simon HS Pearce. Trends in thyroid hormone prescribing and consumption in the uk. *BMC public health*, 9(1):1–9, 2009.
- [31] NHS. BNF Classifications. <https://digital.nhs.uk/data-and-information/areas-of-interest/prescribing/practice-level-prescribing-in-england-a-summary/practice-level-prescribing-glossary-of-terms>, 2019. [Online; accessed 5-October-2019].
- [32] Met Office. When does spring start? Meteorological spring. [\url{https://www.metoffice.gov.uk/weather/learn-about/weather/seasons/spring/when-does-spring-start}](https://www.metoffice.gov.uk/weather/learn-about/weather/seasons/spring/when-does-spring-start), 2023. [Online; accessed 3-June-2023].
- [33] Carol Pierannunzi, Shaohua Sean Hu, and Lina Balluz. A systematic review of publications assessing reliability and validity of the behavioral risk factor surveillance system (brfss), 2004–2011. *BMC medical research methodology*, 13(1):1–14, 2013.
- [34] Pamela L Sankar and Lisa S Parker. The precision medicine initiative’s all of us research program: an agenda for research on its ethical, legal, and social issues. *Genetics in Medicine*, 19(7):743–750, 2017.
- [35] Rossano Schifanella, Dario Delle Vedove, Alberto Salomone, Paolo Bajardi, and Daniela Paolotti. Spatial heterogeneity and socioeconomic determinants of opioid prescribing in england between 2015 and 2018. *BMC medicine*, 18:1–13, 2020.
- [36] Karen L Schneider, Melissa A Clark, William Rakowski, and Kate L Lapane. Evaluating the impact of non-response bias in the behavioral risk factor surveillance system (brfss). *J Epidemiol Community Health*, 66(4):290–295, 2012.
- [37] Copernicus Climate Change Service. ECMWF Reanalysis v5 (ERA5). <https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5>, 2023. [Online; accessed 13-June-2023].
- [38] Adrian Spoerri, Marcel Zwahlen, Matthias Egger, and Matthias Bopp. The swiss national cohort: a unique database for national and international researchers, 2010.
- [39] Cathie Sudlow, John Gallacher, Naomi Allen, Valerie Beral, Paul Burton, John Danesh, Paul Downey, Paul Elliott, Jane Green, Martin Landray, et al. Uk biobank: an open access resource for identifying the causes of a wide range of complex diseases of middle and old age. *PLoS medicine*, 12(3):e1001779, 2015.

- [40] Shane Timmons, Frances McGinnity, Cameron Belton, Martina Barjaková, and Peter Lunn. It depends on how you ask: measuring bias in population surveys of compliance with covid-19 public health guidance. *J Epidemiol Community Health*, 75(4):387–389, 2021.
- [41] Nuffield Trust. Poor areas left behind on standards of GP care, research reveals. <https://www.nuffieldtrust.org.uk/news-item/poor-areas-left-behind-on-standards-of-gp-care-research-reveals>, 2018. [Online; accessed 3-June-2023].
- [42] Parliament UK. Population estimates GP registers: why the difference? <https://commonslibrary.parliament.uk/population-estimates-gp-registers-why-the-difference>, 2016. [Online; accessed 3-June-2023].
- [43] Roozbeh Valavi, Jane Elith, José J Lahoz-Monfort, and Gurutzeta Guillera-Arroita. block cv: An r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods in Ecology and Evolution*, 10(2):225–232, 2019.
- [44] WASDI platform. Earth Observation tech for everyone. <https://www.wasdi.cloud>, 2023. [Online; accessed 3-June-2023].
- [45] Yixue Xia and Patrice Forget. Opioid and gabapentinoid prescriptions in england from 2015 to 2020. *Plos one*, 17(11):e0276867, 2022.
- [46] Christopher Yeh, Chenlin Meng, Sherrie Wang, Anne Driscoll, Erik Rozi, Patrick Liu, Ji-hyeon Lee, Marshall Burke, David B Lobell, and Stefano Ermon. Sustainbench: Benchmarks for monitoring the sustainable development goals with machine learning. *arXiv preprint arXiv:2111.04724*, 2021.