nature mental health

Perspective

https://doi.org/10.1038/s44220-024-00318-x

Linking neuroimaging and mental health data from the ABCD Study to UrbanSat measurements of macro environmental factors

Received: 6 November 2023

Accepted: 20 August 2024

Published online: 30 October 2024

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Although numerous studies over the past decade have highlighted the influence of environmental factors on mental health, globally applicable data on physical surroundings such as land cover and urbanicity are still limited. The urban environment is complex and composed of many interacting factors. To understand how urban living affects mental health, simultaneous measures of multiple environmental factors need to be related to symptoms of mental illness, while considering the underlying brain structure and function. So far, most studies have assessed individual urban environmental factors, such as greenness, in isolation and related them to individual symptoms of mental illness. We have refined the satellite-based 'Urban Satellite' (UrbanSat) measures, consisting of 11 satellite-data-derived environmental indicators, and linked them through residential addresses with participants of the Adolescent Brain Cognitive Development (ABCD) Study. The ABCD Study is the largest ongoing longitudinal and observational study exploring brain development and child health, involving 11,800 children, assessed at 9–16 years of age, from 21 sites across the USA. Here we describe linking of the ABCD Study data with UrbanSat variables, including each subject's residential address at their baseline visit, including land cover and land use, nighttime lights and population characteristics. We also highlight and discuss important links of the satellite-data variables to the default mode network clustering coefficient and cognition. This comprehensive dataset provides an important tool for advancing neurobehavioral research on urbanicity during the critical developmental periods of childhood and adolescence.

The idea of spatially mapping diseases to understand how they relate to the human and physical environment has a rich history of urban applications, going back to the pioneering work of John Snow, who, in 1854, mapped the locations of cholera cases in London to identify the source of the disease around a pump at Broad Street[1]. Since then, many studies have highlighted the complex inter-relationships between the urban environment and public health[2,3]. Recent studies emphasize the link between environmental factors and mental disorders[4], with 12–20% of conditions such as depression and anxiety attributed to environmental influences[5].

According to the United Nations (UN), more than half the world's population live in cities, and it is estimated that by 2050. seven out of ten people will probably live in urban areas[6]. Urbanization has substantial impacts on public health[7], including mental health issues[8]. Higher prevalences of common psychopathological symptoms are reported in cities[8], including depression and substance abuse[9]. Urbanization is also

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associated with changes to land use and land cover (LULC) patterns. It is often accompanied by the expansion of built-up land cover, together with the conversion of farmland, wetlands or lakes into urban areas[10] and the transformation of natural surfaces into impervious ones[11]. Together, these changes produce a complex urban environment that gives rise to different environmental profiles, which may affect mental health in distinct ways[2]. Many aspects of the urban environment and LULC changes can be captured by sensors on satellites, which provide synoptic coverage at various spatial and temporal resolutions and enable us to understand many aspects of Earth's surface, water and atmospheric systems. Remote-sensing satellite data thus enable the registration of not only the individual environmental measures (for example, greenness and so on) that are typically found in urban settings, but also the very complex patterns of the urban environment that reflect real life-exposure.

We have refined the 'Urban Satellite' (UrbanSat) variables originally developed by Xu and colleagues[2], which feature 11 environmental factors, calibrated to measure population density as a proxy for urbanicity. Each environmental factor can be analyzed individually or in combination with other factors to assess distinct environmental profiles that contribute to population density and that may affect mental health in different ways. To provide a tool for mechanistic investigations of the impacts of environmental profiles on brain, cognition and mental health, the refined UrbanSat data were then linked to the Adolescent Brain Cognitive Development Study (the ABCD Study), the largest ongoing US study on child brain development. This was carried out across 21 sites[12], encompassing a cohort of over 11,000 children 9–10 years of age, with extensive measures on physical and mental health, neurocognition, social and emotional functions, culture, environment and multimodal brain imaging[13] ascertained during a critical developmental period, which is thought to be particularly sensitive to environmental impact[14,15].

In the following sections, we review recent studies on UrbanSat attributes relating to mental health and neuroimaging data and describe our developed variables linking satellite imagery with a US-wide longitudinal neuroimaging cohort of adolescents. We provide examples of studies correlating satellite measurements of individual environmental factors, such as green spaces, the density of urban areas and water bodies, with measures of mental health and illness, both cross-sectional and longitudinal. We then describe in detail the composition of UrbanSat and present a use case in which we relate socioeconomic status (SES; household income and parental education) with UrbanSat indicators. By providing evidence for the relevance of individual factors of the urban environment for mental health, the existing studies lay the groundwork for more comprehensive mechanistic investigations of complex, real-life measures of the urban environment, as are being enabled by the linking of UrbanSat with the ABCD Study.

Linking environment features and mental health—academic literature trends

LULC measurements and their relation to mental health

Different methods can be used to measure green spaces in the urban environment, including remotely sensed spectral indices (for example, the normalized difference vegetation index (NDVI)), green space delineation, inventory, usage, their spatiotemporal evolution, characteristics and fragmentation[16]. Although exposure to green spaces may have positive effects on physical health (for example, decreasing the risk for obesity, diabetes and cardiovascular diseases) and mental health[17,18], exposure to green spaces does not have universally positive or negative effects on human health. In some cases, due to the complex relationship between green spaces and other environmental, social and ecological indicators, the health effects of green space may contradict one another[16].

Although discussions surrounding the environmental determinants of physical health are well established[19–21], the association between LULC and mental disorders has emerged as an increasingly crucial area of research.

Urbanization has been linked to a higher prevalence of mental disorders[8]. Conversely, the density of green spaces and access to nature within urban environments have shown an inverse relationship with stress levels and the incidence of mental disorders[22].

Evidence suggests that a higher vegetation index and residential greenness, including greenness surrounding schools and kindergartens, may reduce symptoms of attention-deficit/hyperactivity disorder[23]. Green spaces may also positively influence development from an early age. For instance, Engemann and colleagues[22] demonstrated that childhood residence in low-green areas elevated the risk of mental illness by up to 55% in Danes[22], with both genetic predisposition and green-space exposure influencing schizophrenia risk[24]. Similar positive effects on cognitive development[25], partly attributed to a decrease in air-pollution levels, and reduced problematic behaviors in children were observed in studies from Barcelona and South Korea, using high-resolution satellite data and the modified soil-adjusted vegetation index, respectively, highlighting the benefits of green environments for children's mental development[26]. Longitudinal evidence shows that short- and long-term green-space exposure near residences reduces adolescent aggressive behaviors, with even slight vegetation increases causing notable behavioral improvement. These associations remained unaffected by sociodemographic and neighborhood quality factors, suggesting green space to be a preventive measure for urban externalizing problems[27]. Interestingly, the protective effects of green space might be particularly relevant for certain subgroups; for example, children from lower-income households experience greater stress from artificial light at night than do those from higher-income households [28].

The benefits of green spaces extend beyond early development. A comparison of street-view and satellite methods assessing green and blue spaces in Beijing revealed an inverse association with geriatric depression[29], and satellite-based vegetation measurements of green space were found to reduce somatization and anxiety symptoms among mothers in a Spanish birth cohort[30]. Furthermore, Brown and colleagues[31] confirmed the link between green surroundings, measured using the NDVI, and mental health in elderly people, showing 18% and 28% lower risk of Alzheimer's disease and depression, respectively, demonstrating that green environments may boost mental wellbeing in older adults, especially in disadvantaged areas.

When delving into such relationships, it becomes apparent that ecological and economic factors intertwine in distinct ways across countries. Thus, urban green space and gross domestic product (GDP) have been linked to a nation's happiness level, with urban green space influencing happiness in wealthier countries and GDP in less wealthy ones. Social support mediated the relationship between urban green space and happiness, whereas GDP moderated this connection[32].

Although numerous studies have highlighted the positive impacts of green spaces on mental health, it is essential to approach this subject with a nuanced perspective, taking into account critical mediators of this relationship. A recent Dutch study delved into the long-term relationship between residential greenery exposure and adult suicide mortality, emphasizing individual-level risk factors in this association[33]. Likewise, the presence and severity of affective disorders were found to be associated not just with population density, but also with the quality of a neighborhood's socioeconomic, physical and social characteristics[34]. Further evidence for such indirect pathways was provided by Wang and colleagues[35], who found that 62% of the relationship between streetscape greenery and mental wellbeing is mediated by factors such as physical activity, stress, air quality, noise and social cohesion, whereas NDVI greenery is partially mediated by physical activity and social cohesion, explaining 22% of the association. This suggests that factors beyond urbanization, including elements such as SES, noise levels, social cohesion and safety, may substantially influence mental health outcomes.

https://doi.org/10.1038/s44220-024-00318-x

The impact of green spaces on mental health varies considerably across the different types of space, such as tree canopies, grassy areas and low-lying vegetation. Research has consistently shown that tree canopies have greater beneficial effects on psychological distress[36], postpartum depression[37] and general mental health[38] than grasslands, which may not consistently support mental health[36,37]. These differential effects may stem from a general human preference for denser green spaces with moderate vegetation complexity[39] and enhanced biodiversity[40], which offer greater restorative benefits[41]. Additionally, tree canopies help mitigate heat during the summer, further supporting their health advantages[42]. Therefore, the choice of exposure indicators, as well as the methodology used to measure and define green spaces and mental health indicators, substantially influences the relationship between green space and mental health outcomes[18], highlighting the utility of combining satellite-based and street-view-based data to better characterize green-space types in future research[37].

Furthermore, the methods used to measure exposure should also be considered. For instance, people's exposure to green spaces can be measured in different geographic contexts, including using residence-based and mobility-based methods. Manifesting the uncertain geographic context problem, mobility-based measurements of people's exposure to green spaces may better represent the impact of green spaces on health outcomes than residence-based measurements[43].

The spatial configuration, composition and fragmentation of LULC may also impact mental health. For instance, Bertram and colleagues[44] have shown that although LULC fragmentation has little impact on people's wellbeing at an aggregate level, wellbeing is positively affected by lower average degrees of soil sealing and larger shares of vegetation, especially in areas with above-average population density. In a study conducted across large metropolitan areas in the USA, Tsai and colleagues[45] examined the relationships between mental health and the characteristics (amount and patterns) of urban green land cover, showing that more spatially dispersed forests have the most positive bivariate association with lower prevalence of frequent mental distress, while more connections between forest and built features are associated with lower mental distress.

Other types of LULC have also been found to be associated with mental health, with several studies suggesting a positive linkage between exposure, proximity or visibility to 'blue spaces' and mental health[46–48], which can be explained by the contribution of such spaces to increased physical activity, enhanced restoration and improved environmental factors[49]. 'Gray spaces' and 'brown spaces' have also been shown to be related, at least to some extent, to mental health. For example, Nazif-Munoz and colleagues[50] evaluated the effects of LULC on depression using a continuous measure of 'grayness' (that is, buildings, roads, parking lots and other impervious surfaces) and 'brownness' (arid pervious natural settings without vegetation), suggesting a protective association between 'brownness' and depression and an adverse association between 'grayness' and depression[50]. Moreover, although it is not always measured by means of satellite observations, studies have shown that living near vacant land and accessibility to abandoned areas such as waste or leftover land impact mental health issues, such as anxiety[51], as well as life satisfaction[52].

Remotely sensed nighttime light measurements and mental health

Artificial light at night (ALAN), emitted from stationary and non-stationary sources across outdoor environments associated with human activity[53], may also affect human health. Exposure to ALAN has been linked to mental disorders[54], including depressive symptoms, suicidal behaviors[55] and anxiety disorders[56]. ALAN may act as a social determinant of human health affecting physical and mental health directly and indirectly, positively and negatively. For example, although exposure to ALAN may have positive impacts on human health (for example, with light-based interventions), it also imposes extra stress on human health by disturbing human circadian rhythms and sleep, which in turn impacts various aspects of mental health[57].

Despite some inherent challenges associated with measuring the relationship between ALAN and human health using satellite-measured nighttime light (NTL)—for example, contextual settings, sensor configurations and spatial resolution[58]—NTL, which can act as a proxy for urbanization, economic and industrial activity, and population distribution, has demonstrated relationships with a variety of mental health outcomes.

For instance, Ohayon and colleagues[59] used Defense Meteorological Satellite Program–Operational Linescan System observations to link higher NTL levels with delayed bedtime and wake-up time, shorter sleep duration, increased daytime sleepiness and dissatisfaction with sleep quantity and quality, raising the likelihood of a diagnosis of circadian rhythm disorder. This relationship was confirmed in a study involving US adolescents that associated higher NTL levels with later weeknight bedtimes, shorter sleep durations, as well as increased past-year mood and anxiety disorders prevalence[56]. Similarly, in children 2–18 years of age, increased NTL exposure within 500 m of their residence elevated sleep disturbances and the risk of sleep disorders, particularly among those under 12 years of age[60].

Important research has highlighted the links between higher NTL and worse mental health outcomes. In South Korea, Min and Min[55] found significant associations between NTL and depressive symptoms and suicidal behaviors in South Korean adults. Similarly, in the Netherlands, NTL exposure within 100 m of residences was found to be related to higher depressive symptoms among individuals 18–65 years of age[61]. This was confirmed by Liao and colleagues[3], who used data extracted from UK Biobank Cohort participants to associate higher NTL with increased mental problems, including depressed mood and tiredness/lethargy, and physical health problems such as obesity, as well as more air pollution, less green space, higher economic and neighborhood deprivation and higher household poverty. Leveraging this dataset, a further study established a connection between heightened NTL exposure and an elevated risk of substance-use disorder and depression, particularly in individuals with increased iron deposition in the hippocampus and basal ganglia[62].

Satellite data and neuroimaging

Despite many opportunities, research exploring the relationship between satellite data, brain features and mental health remains scarce. A seminal study by Xu and colleagues[2] provided evidence for a satellite-data-derived urbanicity factor being negatively related to medial prefrontal cortex volume and positively to cerebellar vermis volume in Chinese ('CHIMGEN' sample) and European ('IMAGEN' cohort) young adults. Urbanicity also correlated with functional network connectivity, particularly in Chinese participants, and was associated with both positive and negative outcomes, in particular improved social cognition, for example, perspective-taking, but also increased depression symptoms, mediated by brain changes, with susceptibility peaking during mid-childhood and adolescence.

Furthermore, Dadvand and colleagues[63] demonstrated that green neighborhoods may benefit brain development and cognitive function. Specifically, lifelong greenness exposure was found to be associated with increased gray and white matter in prefrontal, premotor and cerebellar regions, predicting improved working memory and reduced inattentiveness.

In conclusion, current research exhibits substantial gaps in understanding the link between the different features of satellite data—and their real-life combinations characteristic of urban life—and mental health. In particular, there is a need to uncover the biological mechanisms underlying this relationship, including brain structure and function. To address this gap, utilizing the ABCD dataset in conjunction with the UrbanSat dataset presents a unique opportunity. The ABCD study includes an extensive dataset from a large and diverse sample of

 https://doi.org/10.1038/s44220-024-00318-x

Table 1 | A description of the 11 key UrbanSat environmental indicators within the ABCD Study

	Description	Units	Source (source resolution)
1	LULC		
1.1	Percent 2017 built-up land use	Fraction of total (0–1)	CGLS (100 m)
1.2	Percent 2017 forest area	Fraction of total (0–1)	CGLS (100 m)
1.3	Percent 2017 cropland use	Fraction of total (0–1)	CGLS (100 m)
1.4	Percent 2017 grass area	Fraction of total (0–1)	CGLS (100 m)
1.5	Percent 2017 permanent inland water area	Fraction of total (0–1)	CGLS (100 m)
1.6	Percent 2017 seasonal water area	Fraction of total (0–1)	CGLS (100 m)
2	NTL		
2.1	Total monthly average 2017 night-light radiance	$nW\,cm^{-2}\,sr^{-1}$	CGLS (100 m)
3	Population		
3.1	Total 2017 population	Number of people	WorldPop (100 m)
4	Spectral indices		
4.1	Percent 2017 area with NDVI index over 0.2	Fraction of total (0–1)	Sentinel-2 (GEE) (10 m)
4.2	Percent 2017 area with NDWI index over 0.3	Fraction of total (0–1)	Sentinel-2 (GEE) (10 m)
4.3	Average 2017 NDBI index value	NDBI index value	Sentinel-2 (GEE) (10 m)

9- and 10-year-old children who are being followed up longitudinally and are currently 16 years old. This period spans a critical age of brain plasticity, allowing examination of how environmental factors impact brain development and behavior during this highly formative period. The extensive and comprehensive characterization of ABCD enables the generation of robust findings and reveals their applicability across different populations.

UrbanSat variables in the ABCD Study

Sample description

The ABCD Study's UrbanSat variables consist of 11 key environmental indicators representing land cover characteristics, NTL, population estimates and remote sensing indices in 2017 (Supplementary Fig. 1 presents a histogram), which were derived from multiple sources, including the Copernicus Global Land Service (CGLS)[64], the Earth Observation Group of the Colorado School of Mines[65], WorldPop[66] and Sentinel-2 data processed within Google Earth Engine (GEE) (Table 1). The data are available through the National Institute of Mental Health data archive as part of the ABCD Study 5.0 release (https://doi.org/10.15154/8873-zj65) and include satellite data values linked to three concurrent addresses for each participant at the baseline study visit when the participants were 9 or 10 years of age[67] (more information is provided in the Supplementary Information).

Data analysis

The UrbanSat data sources were unified into new raster files with identical parameters (extent, pixel size and pixel locations) and aggregated to an ~1-km grid covering the 48 contiguous states of the USA (a detailed methodology for calculating these UrbanSat raster products is provided in the Supplementary Information). Aggregation to a uniform raster pixel grid provides a critical level of consistency between the disparate datasets: by regularizing the pixels, the new values for LULC, NTL, population and spectral indices each represent the same land areas on Earth when sampling pixel values at given geocoordinates. Additionally, by aggregating to a new larger pixel size of 1 km, we characterize the environment of the neighborhood surrounding each study participant. Similar studies have also relied on 1-km radii around participants' residency to represent the everyday living environment when linking greenery and public health[68]. In a literature review of 260 analyses, Browning and Lee[69] demonstrated that greenness measured at larger distances from people's home environments—specifically buffers between 500 m and 999 m in size—predicted physical health better than smaller buffers[69]. However, one limitation of this 1-km fixed size aggregation approach is that although it attempts to capture the environment surrounding participant geocoordinates, it is possible that different variables instead affect subjects at different spatial scales.

Input data for each dataset were obtained for the year 2017 to align with the baseline ABCD Study visit timing (October 2016 to October 2018) and comprised LULC (Fig. 1 and Table 2), NTL and population data (Fig. 2) and spectral indices (Fig. 3), as described in more detail in the Supplementary Information.

UrbanSat characterization and association with behavioral, cognition and brain function in the ABCD Study

The UrbanSat data in ABCD release 5.0 encompass 11 variables across three baseline addresses, reflecting diverse regional environmental aspects (Supplementary Information and Supplementary Fig. 1). A strong correlation emerged between forest and built-up land cover, NDVI, normalized difference built-up index (NDBI), NTL and population, whereas normalized difference water index (NDWI) showed moderate correlations with other indicators (Fig. 4, left) (details are provided in the Supplementary Information).

Behavior and cognition. To demonstrate the influence of UrbanSat indicators on behavior, cognition and brain function, we examined associations with measures from the ABCD Study's baseline assessments at 9–10 years of age and utilized the total problem count from the Child Behavior Checklist (CBCL)[70] and the total score composite from the NIH Toolbox cognition battery[71] for our analyses. Detailed assessment methodologies and findings are presented in the Supplementary Information.

Resting-state functional MRI data. We extracted 53 intrinsic connectivity networks via a spatially constrained independent component analysis framework, organizing them into seven functional domains (Supplementary Fig. 2 and Supplementary Table 1). We computed the functional network connectivity and represented the brain as a connected graph, focusing on the default mode network (DMN) (Fig. 4, right). We focused on the DMN because it is recognized as a critical component of the whole brain's functional network architecture[72], and alterations related to the DMN have commonly been observed in a broad spectrum of mental disorders[73–76] and in response to environmental adversity[77]. As an initial step, we calculated the average clustering coefficient of DMN intrinsic connectivity networks, which gives an overall measure of how DMN regions connect to the rest of the brain[78]. Detailed methodologies and equations are provided in the Supplementary Information.

Results. We evaluated the correlation between SES (household income: total combined family income for the past 12 months, range 0–10) and parental education (never attended to doctoral degree, range 0–21) with UrbanSat indicators (Supplementary Table 2). The level of parental education was significantly and negatively correlated to built-up land, NDBI, NTL and population, and positively correlated to cropland, forest land and NDVI. Household income presented very similar associations with UrbanSat indicators and was most significantly correlated with NDBI. Therefore, due to multicollinearity, two sets of linear mixed-effect models were examined with and without SES covariates, and were implemented for UrbanSat association analyses.

Without the inclusion of SES, the UrbanSat indicators were associated with cognition and DMN clustering (except for forest land),

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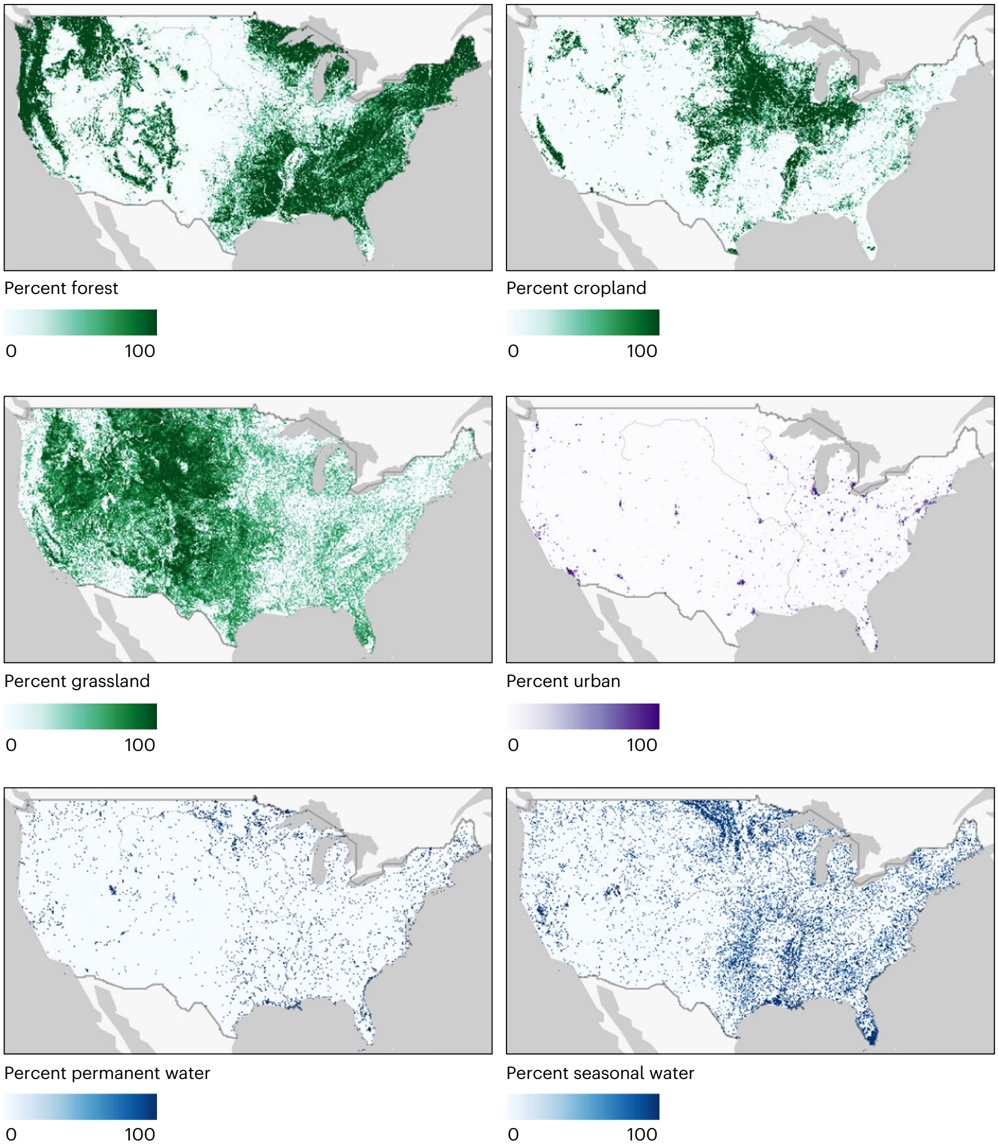

Fig. 1 | Spatial distribution and characteristics of the six LULC maps covering the 48 contiguous states of the USA incorporated in the UrbanSat indicators. Shown are plots of forest percent, crop percent, grass percent, urban percent, permanent inland water percent and seasonal water percent. Basemap credit: Esri, TomTom, FAO, NOAA, USGS.

Table 2 | Description of the UrbanSat Copernicus classifications incorporated into the ABCD Study

LULC	Copernicus classification
Forest	111–116: closed forest (evergreen or deciduous, needle or broad leaf, mixed, unknown) 121–126: open forest (evergreen or deciduous, needle or broad leaf, mixed, unknown)
Grass	30: herbaceous vegetation
Crop	40: cultivated and managed vegetation/agriculture (cropland)
Urban	50: urban/built up
Water	80: permanent inland water bodies

with NTL also being associated with problem behavior (Table 3, top). With the inclusion of SES, NDBI was significantly associated with the cognitive total score, and NTL was significantly associated with the DMN clustering coefficient and associated with the cognitive score (with a trend toward significance). Further analyses on subsamples with limited collinearity between UrbanSat and SES also confirmed the association between UrbanSat indicators and cognition (Supplementary Table 4).

Discussion

Understanding the link between the urban environment and mental health requires us to account for a range of environmental factors and measures and relate them to symptoms of mental illness, while considering underlying brain structure and function. However, although there has been an exponential increase in the availability of satellite records, integrating them with mental health presents challenges due to the scarcity of large-scale datasets on brain and behavior.

So far, most studies have assessed individual urban environmental factors (such as greenness) in isolation, then related them to individual symptoms of mental illness, but the very wide range of remotely sensed satellite indicators can enable an understanding of the complex physical urban environment and its impacts on mental health. In this Perspective we refine the satellite-based UrbanSat measures (consisting of 11 satellite-data-derived environmental indicators) and link them through residential addresses with participants of the ABCD Study. The ABCD

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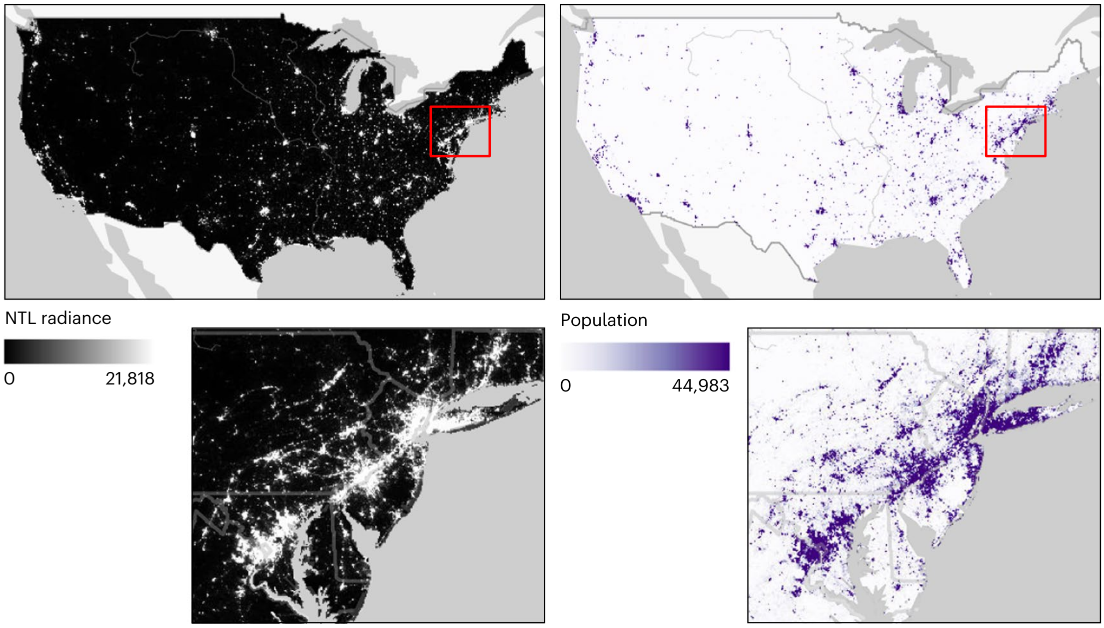

Fig. 2 | Spatial distribution and characteristics of NTL and population maps incorporated in the UrbanSat indicators. NTL data are sourced from the Earth Observation Group Annual Visible and Infrared Imaging Suite (VIIRS) Night Light version 2 (VNL 2) product[95]. These data provide an average monthly radiance at an original resolution of 15 arcsec (~500 m). The VNL 2 data are based on VIIRS satellite observations and include filtering for clouds, removal of fires and background isolation. Our aggregated NTL product (NTL radiance) provides the sum of annual NTL radiance values within each 1-km output pixel. Population data from 2017 ('population') are based on WorldPop Population Counts[96], specifically the US unconstrained top–down 100-m-resolution dataset. These data take population census counts and use other geospatial data to disaggregate census tract information into 100 × 100-m^2 pixels. Basemap credit: Esri, TomTom, Garmin, FAO, NOAA, USGS, EPA, USFWS.

database, with its deep phenotyping information encompassing mental health, cognition and other health indicators, can aid in disentangling these effects. It captures over 11,800 children with biennial brain scans, and it is considered the largest ongoing study on brain development and child health across 21 US sites.

Within the large domain of linked external data within the ABCD Study[67], this Perspective provides an opportunity to understand the interrelation of macroscale environmental factors when children are 9 and 10 years of age with brain development and health. Each environmental factor can be analyzed individually or in combination with other factors to assess distinct environmental profiles that contribute to population density and that may affect mental health in different ways.

As a proof of concept, our simple analyses lend support for the interrelation of environmental factors derived from satellite images with brain and cognitive development and mental health, while also hinting at the need for careful modeling of multicollinearity between UrbanSat indicators and SES indicators. We thus provide strong evidence for NDBI negatively affecting cognitive ability when controlled for SES.

The phenotypic variance explained by SES was higher than that of the environmental measures. Although this is expected given that SES, encompassing a wide array of risk factors and closely linked to psychosocial risks, is widely recognized as a key factor influencing mental health outcomes[79], UrbanSat data still bring to light nuanced details about the environmental backdrop of mental health that SES does not fully encompass. With the precise, objective measurements of environmental aspects such as green spaces, the density of urban areas and water bodies, data from UrbanSat enrich our understanding of how physical surroundings impact mental wellbeing. This integration allows us to observe not only the static socioeconomic conditions but also the dynamic environmental changes and their impact on mental health over time, pinpointing specific interventions to boost mental wellbeing in various communities. In areas with homogeneous SES in particular, the environmental variability captured by UrbanSat data might elucidate additional variation in mental health outcomes. This integration can also enable a better understanding of the various potential confounding associations between different types of environmental feature found in urban settings and their implications for urban health[80].

Furthermore, satellite imagery, with its broad coverage and rich environmental detail, presents a largely untapped resource for socioeconomic studies, with particular value in areas lacking up-to-date census or survey data. The density of the built environment, land use patterns and the glow of NTL captured from space can serve as insightful proxies for SES. These markers can shed light on urban development, economic activities and even how densely populated an area is—all key indicators of socioeconomic health. By weaving these satellite-based insights into our research, we can deepen our grasp of how socioeconomic factors influence health and wellbeing, especially in less-studied areas. Looking ahead, harnessing this method could bridge important data voids, offering a richer, more detailed picture of how our surroundings and socioeconomic conditions intertwine to affect health outcomes.

Associations between illness and environment vary across different parts of the world. For instance, research reveals mixed effects of urbanicity on psychosis risk globally, with urban living linked to higher risk in Northern Europe but not in Southern Europe or some low- and middle-income countries, where it may even be protective. These inconsistencies suggest that factors beyond urbanicity itself, such as social cohesion and resource availability, influence mental health outcomes (for a review, see ref. 81). Satellite data offer a promising tool to explore these complex associations by providing objective, consistent measures of urbanicity and environmental factors across diverse geographical settings. This approach could help identify specific urban features that correlate with mental health risks or benefits, advancing our understanding of the relationship between urban environments and psychopathological symptoms such as psychosis.

Although research on the relationship between water bodies, or 'blue spaces', derived from satellite data and mental health is scarce, this link has increasingly been recognized in environmental health research.

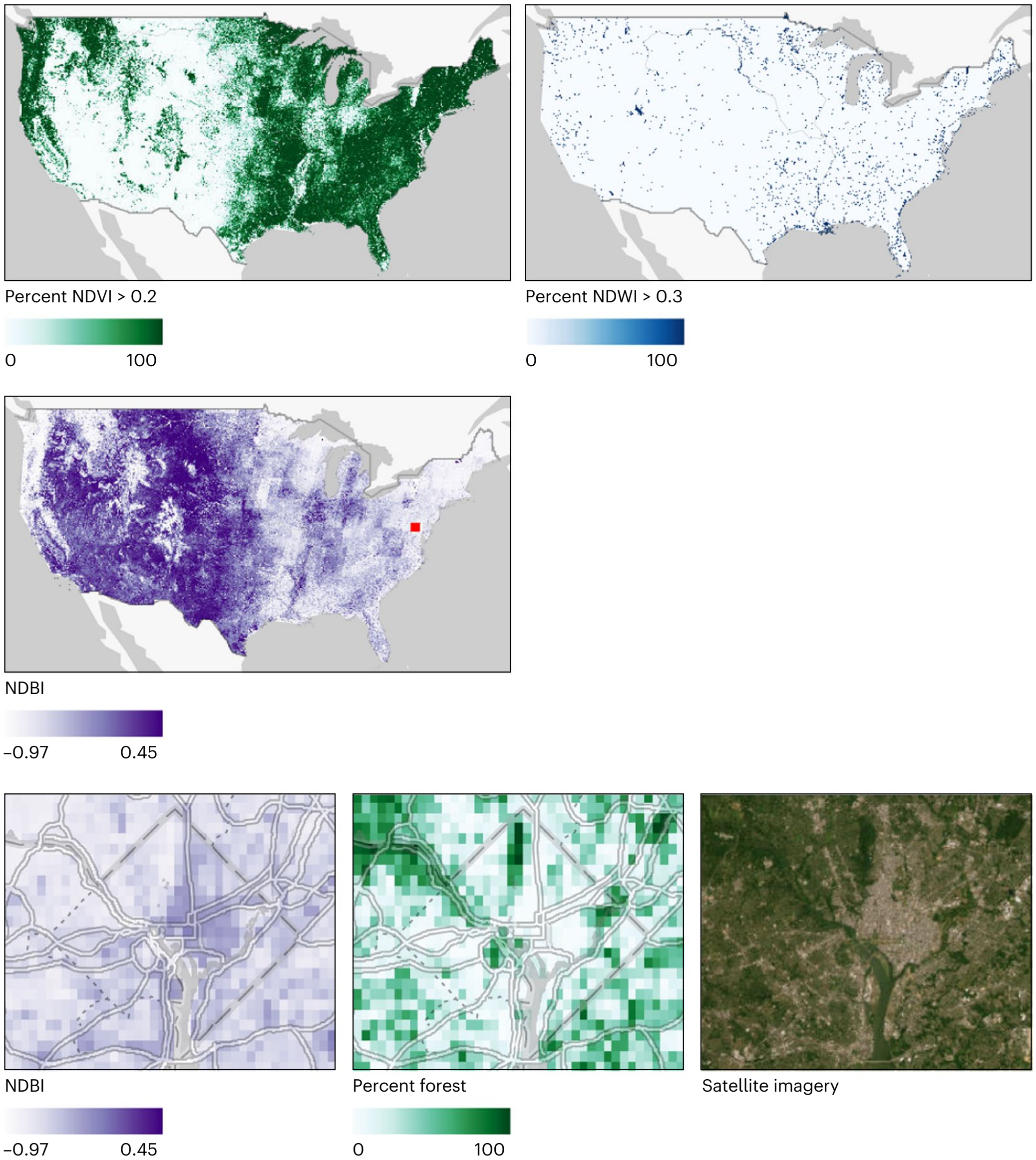

Fig. 3 | Spatial distribution of the NDVI (percent NDVI above 0.2), NDWI (percent NDWI above 0.3) and NDBI within the UrbanSat dataset. Spatial distributions were calculated using 2017 Sentinel-2 Multispectral Instrument Level-1C data accessed via GEE. Bottom row: comparison of the percentage of forest cover, NDBI and satellite imagery within the Washington DC area, demonstrating higher NDBI in urban and less vegetated areas. Basemap credit: Esri, TomTom, FAO, NOAA, USGS, Earthstar Geographics, DCGIS, Fairfax County, VA, M-NCPPC, VGIN, Garmin, SafeGraph, METI/NASA, EPA, NPS, USFWS.

Blue spaces are linked to enhanced mental health and lower distress through their support for recreational activities and their therapeutic visual and physical presence[82,83], with benefits increasing for those individuals living in urban areas and facing material deprivation[84].

The results presented here need to be understood while considering their limitations. For example, the spatial resolution of the satellite measurements may impact their ability to effectively capture the full array of environmental features people are exposed to in urban settings (for example, small green spaces people frequently visit in the city[16]), as well as their impacts on people's health[43]. Here we relied on inferred exposure from UrbanSat data, based on proximity to environmental features. To address this and enhance the accuracy of exposure assessment, future studies should consider merging UrbanSat data with passively sensed data, such as accelerometer readings for physical activity and Global Positioning System data for mobility patterns. This integration would provide a direct measure of individual engagement with the environment.

Furthermore, the relationships between environmental factors and their health effects are not always stable over space and time and may vary both across geographic areas[85] and the study's assumed contextual units, including geographical delineations and the timing and duration for which individuals experience these contextual influences. As alluded to in the uncertain geographic context problem[86], residential neighborhoods do not always accurately represent the actual areas that exert the contextual influences of the environment and other activity spaces, and people's daily mobility patterns should also be considered when defining the contextual units[87]. Environmental factors may have different health effects in different contexts, such as day and night, weekday and weekend. For instance, people are usually exposed to ALAN during the night and to green spaces during the day, introducing potential context errors that might affect the interpretation of the association between the environment and health outcomes[88].

Although initial evidence for the potential involvement of the DMN is provided, the comprehensive biological mechanisms linking environmental factors (such as those captured by UrbanSat variables) and mental health remain unclear. These connections involve complex physiological, psychological and social pathways, providing important

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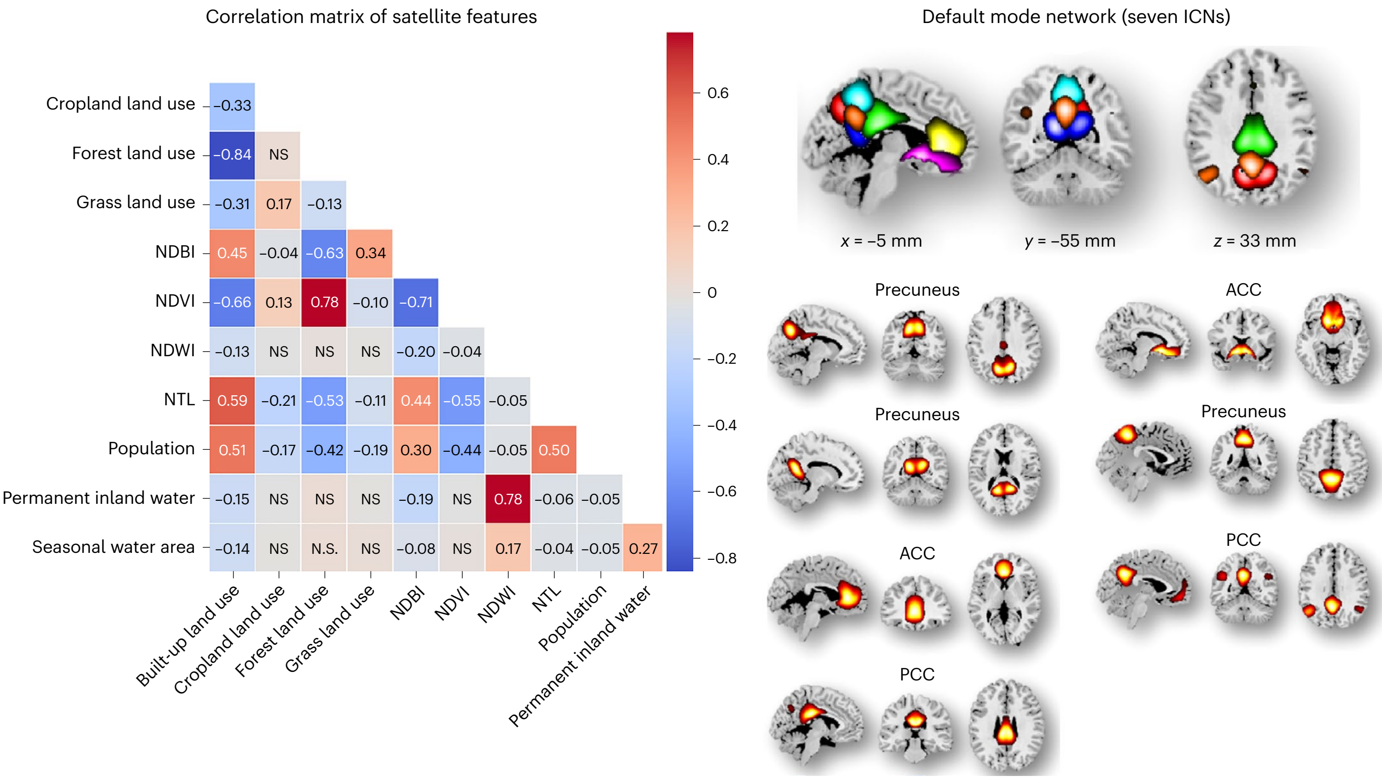

Fig. 4 | Summary of satellite variables and default mode components included in the analysis. Left: cross-correlation among 11 UrbanSat indicators in the ABCD Study. Right: seven intrinsic connectivity networks (ICNs) within the default mode network. ACC, anterior cingulate cortex; PCC, posterior cingulate cortex. NS, not significant.

Table 3 | Significant associations of UrbanSat indicators with the CBCL total problem, cognitive total score and DMN clustering coefficient in children 9–10 years of age

UrbanSat indicators	CBCL total problem N=8,715		Cognitive total score N=8,561		DMN clustering N=6,837	
	P	Percent variance (sign[a])	P	Percent variance (sign[a])	P	Percent variance (sign[a])
Linear mixed-effect model without SES						
Built-up land	NS	NS	1.28×10^{-13}	0.81% (−)	6.90×10^{-3}[b]	0.20% (+)
Forest land	NS	NS	7.96×10^{-21}	1.89% (+)	NS	NS
NDBI	NS	NS	8.79×10^{-59}	7.21% (−)	1.92×10^{-4}	0.50% (+)
NDVI	NS	NS	7.27×10^{-38}	4.58% (+)	1.54×10^{-3}	0.34% (−)
NTL	6.40×10^{-3}[b]	0.11% (+)	1.20×10^{-38}	2.62% (−)	1.86×10^{-8}	0.60% (+)
Population	NS	NS	1.99×10^{-20}	5.06% (−)	1.76×10^{-3}	0.21% (+)
Linear mixed-effect model with SES covariates						
NDBI	NS	NS	3.91×10^{-7}	0.74% (−)	NS	NS
NTL	NS	NS	5.51×10^{-3}[b]	0.11% (−)	1.71×10^{-3}	0.20% (+)
Household income[c]	5.38×10^{-18}	1.53% (−)	5.57×10^{-74}	7.26% (+)	2.13×10^{-8}	0.84% (−)
Education[c]	NS	NS	2.05×10^{-77}	7.28% (+)	5.24×10^{-3}[b]	0.20% (−)

[a]Sign of linear effect; NS, not significant. [b]Trending significant, with $1.00\times10^{-2} > P > 4.5\times10^{-3}$ (Bonferroni correction threshold). [c]Effects are similar across different UrbanSat indicators. We report results from NDBI models.

avenues for future research. For instance, in terms of biologically plausible pathways, the strengthening of physiological systems such as respiratory health and immune function may have a crucial role in linking green space to a reduced risk of psychopathology[89]. In addition, it has been observed that environmental pollutants, especially fine particles, can breach the protective barrier around the brain, potentially causing damage to the nervous system by triggering neuro-inflammation, disrupting neural signaling and provoking immune responses[90]. In terms of indirect effects, nature exposure can enhance psychological aspects by reducing negative emotions, while promoting positive feeling[91] and replenishing cognitive resources[92], and also contributing to adaptive perceptions of stressors and the development of self-esteem and new competencies[93]. Moreover, neighborhood socioeconomic and social aspects, such as diminished social cohesion and reduced safety[34], along with physical activity[35], may mediate the relationship between urbanization and mental health. On the other hand, shared experiences in nature could potentially yield social benefits by encouraging communication, providing support and fostering cooperation[94].

We expect to see more in-depth investigations of such intricate relationships in the future by linking the UrbanSat indicators with the ABCD data from the National Institute of Mental Health's Data Archive (https://doi.org/10.15154/8873-zj65). Future research should capitalize on the longitudinal nature of the ABCD Study to examine how changes in environmental exposures, including air pollution, green space availability and urban heat islands, as well as their resulting environmental profiles over time affect mental health trajectories and brain development. This approach can provide critical insights into the temporal dynamics of environmental influences on mental health, highlighting periods of heightened vulnerability or resilience. Additionally, the effects of the physical environment can be assessed against the backdrop of a broad risk architecture that also includes social adversity levels, economic factors, genetic profiles and other levels of biological functioning, providing a comprehensive understanding of individual differences in susceptibility to environmental risks, contributing to a more personalized understanding of mental health, facilitating targeted interventions and policies.

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Acknowledgements

Data used in the preparation of this Article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the National Institute of Mental Health Data Archive. This is a multisite, longitudinal study designed to recruit more than 10,000 children 9–10 years of age and follow them over 10 years into early adulthood. The ABCD Study is supported by National Institutes of Health (NIH) grants (U01DA041022, U01DA041028, U01DA041048, U01DA041089, U01DA041106, U01DA041117, U01DA041120, U01DA041134, U01DA041148, U01DA041156, U01DA041174, U24DA041123 and U24DA041147). A full list of supporters is available at https://abcdstudy.org/nih-collaborators. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data used in this report came from https://doi.org/10.15154/8873-zj65. Additional support for this work was made possible by grants R01ES032295, R01ES031074, NSF 2316421 and R01DA049238 and NSF grant no. 2112455, as well as NSFC grant no. 82150710554 and Horizon Europe project 'environMENTAL' grant 101057429, funded by the European Union. Complementary funding was provided by UK Research and Innovation under the UK Government's Horizon Europe funding guarantee (10041392 and 10038599). Additional support for this work was made possible by The German Center for Mental Health (DZPG) and the German Research Society (DFG) 88122260. Support was also provided by the National Natural Science Foundation of China to J.X. (grant no. 82371924), National Key Project of "Inter-governmental International Scientific and Technological Innovation Cooperation" to J.X. (grant no. 2023YFE0199700), the Tianjin Applied Basic Research Diversified Investment Foundation to J.X. (grant no. 21JCYBJC01360), the Tianjin Young Talents in Science and Technology to J.X., the Tianjin Medical University "Clinical Talent Training 123 Climbing Plan" to J.X., and the Ministry of Science and Technology (MOST) of the PR China. The views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or European Health and Digital Executive Agency (HADEA). Neither the European Union nor HADEA can be held responsible for them. N.H. acknowledges grant support from the German Research Foundation (grant no. GRK2350/1, TRR379, project B05).

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s44220-024-00318-x.

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Peer review information *Nature Mental Health* thanks Yang Liu and the other, anonymous, reviewers for their contribution to the peer review of this work.

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 https://doi.org/10.1038/s44220-024-00318-x

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