Geomatics and Epidemiology: Associating Oxidative Stress and Greenness in Urban Areas

DOI:10.1016/j.envres.2021.110999

Environmental Research

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--Manuscript Draft--

Manuscript Number:	
Article Type:	Research paper
Section/Category:	Environmental Health & Risk Assessment
Keywords:	Urban Vegetation; Remote Sensing; Public Health; Isoprostane
Corresponding Author:	Samuele De Petris University of Torino ITALY
First Author:	Samuele De Petris
Order of Authors:	Samuele De Petris
	Giulia Squillacioti, Dr.
	Roberto Bono, Prof.
	Enrico Borgogno-Mondino, Prof.
Abstract:	Green spaces may benefit human health mainly by mitigating noise and air pollution, promoting physical or social activities and improving mental health. Based on the influence that green space exposure seems to exert on Public Health and using a multidisciplinary approach, we investigated, the association between oxidative stress (OS) and green exposure in children. Overall, 207 subjects (10-13 yrs.) living in Torino (NW- Italy) were involved in this study. Each participant provided a urinary sample, used to quantify a reliable OS biomarker (15-F2t-IsoP), and their residence addresses, used for geocoding. Green exposure was characterised by calculating i) the Soil Adjusted Vegetation Index (SAVI) within fixed buffers around each participant's home, using remotely-sensed data; ii) Tree Map accounting for evergreen/broadleaf species; iii) The percentage of green cover (PGC). Significant negative correlation (Pearson's $r = -0.758$, $p < 0.001$) between PGC and 15-F2t-IsoP was found. Greater SAVI was associated with lower OS (Pearson's $r = -0.717$, $p < 0.001$). Noticeably, evergreens seemed to determine a significant OS reduction compared to broadleaves (slope = -0.12 and -0.02, respectively; Warton-test $F = 12.48$, $p = 0.0011$). Finally, a spatial distribution of 15-F2t-IsoP estimates map, overlying with 2011 Census Data on same-aged dwellers of Torino, was generated. Predictive models accounting for green spaces influence on OS can be useful tool derived from geomatic employ in Public Health field. Future developments of such a multidisciplinary approach should be considered in urban planning and policy-makers decisions to better define priority zones to requalify in urban settings.
Suggested Reviewers:	Andrea Lessio andrea.lessio@ithaca.polito.it
	Alessio Calantropio alessio.calantropio@polito.it
	Piero Boccardo piero.boccardo@polito.it
	Eija Parmes eija.parmes@vtt.fi
	Carmen de Keijzer carmen.dekeijzer@isglobal.org

UNIVERSITY OF TURIN, ITALY
Department of Agricultural, Forest and Food Sciences
Largo P. Braccini 2, 10095, Grugliasco (TO), Italy

October 14th, 2020

Dear Editor of *Environmental Research,*

Please find attached the manuscript "*Geomatics and Epidemiology: Associating Oxidative Stress and Greenness in Urban Areas*". In my view, the relevance of the results can be summarised as follows. Firstly, the evidence that urban green spaces are able to influence oxidative stress in youths living in urban areas. Secondly, evergreens show a greater impact on this association compared to broadleaf species. Thirdly, the analysis on spatial distribution of oxidative stress can be a useful tool derived from GIS and remote sensing employ in Public Health, serving urban planning and policy-makers decisions to define potential priority zones to requalify in urban settings. Further key information about the presented manuscript:

- the manuscript is an original work, has not been previously published, and is not under consideration for publication elsewhere;
- the participation of all human subjects did not occur prior their informed consent was obtained;
- all authors have disclosed any potential competing interest regarding the submitted article;
- all authors have read the manuscript, agreeing on the submission to *Environmental Research*, and accepting the responsibilities for the manuscript's contents;
- all authors have read and approved the paper and it has not been published previously nor is it being considered by any other peer-reviewed journal;

The multidisciplinary approach of this manuscript involves: biosphere, anthroposphere, atmosphere. In my point of view, this manuscript may deserve Your considerations because it fits some of subject areas included in the journal:

- Environmental risks assessment and management
- Air pollution quality and human health
- Risks and public health
- Environmental management and policy
- Environmental risks assessment and management

Please find below some suggestions for potential reviewers, as requested.

1. Andrea Lessio - andrea.lessio@ithaca.polito.it
2. Alessio Calantropio - alessio.calantropio@polito.it
3. Piero Boccardo - piero.boccardo@polito.it
4. Eija Parmes - eija.parmes@vtt.fi.
5. Carmen de Keijzer - carmen.dekeijzer@isglobal.org

Hoping that the manuscript may fulfil the scientific standards of *Environmental Research*.

Best Regards,
Samuele De Petris

Contacts:
e-mail: samuele.depetris@unito.it

Highlights

1. Oxidative stress and green exposure association was investigated in children
2. Green exposure was analyzed by geomatic techniques
3. Spectral vegetation index and tree census data were used to map oxidative stress
4. Evergreens trees determine a significant oxidative stress reduction
5. Geomatics can support urban planning to improve public health

Geomatics and Epidemiology: Associating Oxidative Stress and Greenness in Urban Areas

DE PETRIS SAMUELE[A*], SQUILLACIOTI GIULIA[B*], BONO ROBERTO[B], BORGOGNO-MONDINO ENRICO[A]

[A]Department of Agriculture, Forest and Food sciences, University of Torino, 10095 Grugliasco (TO), Italy; samuele.depetris@unito.it (S.D.P.); enrico.borgogno@unito.it (E.B.M.)

[B]Department of Public Health and Pediatrics, University of Torino, 10121 Torino, Italy;

giulia.squillacioti@unito.it (G.S.); roberto.bono@unito.it (R.B.)

*these two authors equally contributed to the conceptualization and execution of the manuscript

Corresponding author: Samuele De Petris, samuele.depetris@unito.it

Declarations of interest: none.

Geomatics and Epidemiology: Associating Oxidative Stress and Greenness in Urban Areas

Abstract: Green spaces may benefit human health mainly by mitigating noise and air pollution, promoting physical or social activities and improving mental health. Based on the influence that green space exposure seems to exert on Public Health and using a multidisciplinary approach, we investigated, the association between oxidative stress (OS) and green exposure in children. Overall, 207 subjects (10-13 yrs.) living in Torino (NW- Italy) were involved in this study. Each participant provided a urinary sample, used to quantify a reliable OS biomarker (15-F2t-IsoP), and their residence addresses, used for geocoding. Green exposure was characterised by calculating i) the Soil Adjusted Vegetation Index (SAVI) within fixed buffers around each participant's home, using remotely-sensed data; ii) Tree Map accounting for evergreen/broadleaf species; iii) The percentage of green cover (PGC). Significant negative correlation (*Pearson's* $r = -0.758$, $p < 0.001$) between PGC and 15-F2t-IsoP was found. Greater SAVI was associated with lower OS (*Pearson's* $r = -0.717$, $p < 0.001$). Noticeably, evergreens seemed to determine a significant OS reduction compared to broadleaves (slope = -0.12 and -0.02, respectively; *Warton-test* $F = 12.48$, $p = 0.0011$). Finally, a spatial distribution of 15-F2t-IsoP estimates map, overlying with 2011 Census Data on same-aged dwellers of Torino, was generated. Predictive models accounting for green spaces influence on OS can be useful tool derived from geomatic employ in Public Health field. Future developments of such a multidisciplinary approach should be considered in urban planning and policy-makers decisions to better define priority zones to requalify in urban settings.

Keywords: Urban Vegetation, Remote Sensing, Public Health, Isoprostane

1. Introduction

Green spaces are thought to benefit human health mainly through i) mitigation of noise and air pollution exposure ii) promotion of outdoor exercise and social activities iii) improvement of mental health. Participation in physical activity is significantly higher for people living close to parks, or green areas, determining a reduction of overweight, obesity and, in general, a lower body mass index (Bell et al., 2008). Physical activity is also showing a positive impact on health by reducing risk of diabetes (Dalton et al., 2016) and cardiovascular diseases (Fong et al., 2018; Pereira et al., 2012). Green space exposure proves to positively affect mental health and social engagement by reducing stress (Gong et al., 2016; Markevych et al., 2017), depressive symptoms (Gariepy et al., 2015), aggressive behaviour (Younan et al. 2016), and contributing in decelerating the cognitive decline (de Keijzer et al., 2018). Moreover, maternal exposure to green space is positively associated with greater new-born's birthweight; this is mainly due to environmental pollution mitigation, opportunity of socialisation, and to exercise in contact with nature.

Studies addressing greenness and respiratory health possible association are still inconsistent. Some authors referred about a positive effect of higher exposures to greenness finding risk reduction of asthma and respiratory symptoms (Lovasi et al., 2008; Sbihi et al., 2015; Squillacioti et al., 2019b). On the other hand, some authors found adverse effect of green space exposure on asthma, rhinitis and respiratory health in general (Fuertes et al., 2014; Parmes et al., 2020).

Based on the influence that green space exposure seems to exert on Public Health, we speculated that greenness might also be involved in oxidative stress (OS) induction.

OS is a pre-pathological condition characterised by an imbalance between pro-oxidant and anti-oxidant species, in favour of pro-oxidants. OS does not represent a pathology itself (Sies, 2015), but a risky condition related to the pathophysiological mechanisms behind several health impairments, such as Cardio Vascular Diseases (CVDs), diabetes and respiratory diseases. Furthermore, it is susceptible to those environmental risk factors able to act as pro-oxidants (e.g. air pollutants and tobacco smoke)(Milne et al., 2015).

At the meantime, OS may be influenced by individual characteristics of subjects like obesity, health *status*, tobacco smoking exposure and exercise training (Nikolaidis et al., 2011; van 't Erve et al., 2017). Within this context, we focused on the potential association between OS and urban green spaces, being this type of knowledge still lacking (Woo et al., 2009; Yeager et al., 2018). We operated by a multidisciplinary approach aiming at investigating strength of this potential association, specifically evaluating usefulness of geomatic tools in epidemiological studies. Many epidemiological studies investigating the relationship between green space and health benefits are already based on remotely-sensed data. Specifically, the Normalised Difference Vegetation Index (NDVI) is widely used in epidemiological research as spectral metric (Fong et al., 2018). NDVI does not provide any information about species characterisation (Fong et al., 2018). Few works, alternatively, have tried to characterise exposure with reference to land cover maps (Egorov et al., 2017; Parmes et al., 2020; Tsai et al., 2019) or tree *census* data, with the aim of taking into account type and shape of green spaces, or vegetation fraction cover (Browning and Rigolon, 2018; Lovasi et al., 2013; Pilat et al., 2012).

2. Materials

2.1. Study Area

The study area corresponds to the municipality of Torino (NW Italy, E: 396027 N: 4991913 reference frame WGS84 UTM32N), sizing about 130 Km^2 (Fig.1). In 2019 green areas covered 43% of the whole city, addressing Torino as one of the most relevant greenest cities (Baycan-Levent and Nijkamp, 2009; Li et al., 2015). With reference to green patches, the following metrics were computed: minimum and maximum patch size are 0.015 and 108 ha, respectively; patch size mode is 0.63 ha; 25^{th} percentile is 0.38 ha; 75^{th} percentile is 3.76 ha.

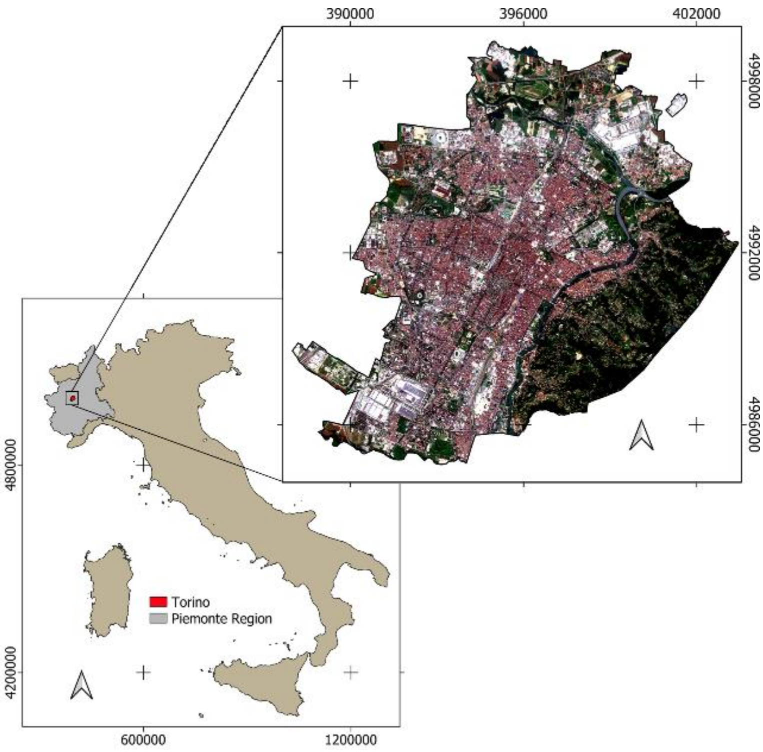

Figure 1 – Torino area localization (Reference frame: WGS84 UTM32N).

2.2.Multispectral Data

Multispectral imagery are widely used to detect and characterise vegetation in urban contexts, permitting to locally map vegetated areas (Mudele and Gamba, 2019; Rosina and Kopecká, 2016). We assumed that the maximum of vegetation vigour, in the area, occurs in the summer period (June-July, Zhou et al. 2016; De Petris S. et al. 2019;

Borgogno-Mondino, Sarvia, and Gomarasca 2019). Consequently, a Sentinel-2 Level 2A image (S2), acquired by the Copernicus Sentinel-2 MSI (Multi Spectral Instrument) sensor on 14th June 2016, was obtained from the Theia CNES geoportal (https://www.Theia-land.fr/en/product/sentinel-2-surface-reflectance/, Baetens, Desjardins, and Hagolle 2019; Revel et al. 2019)). In summer time, vegetation-related biomass expresses its maximum in Torino. This assumption also relies on the observed inter-annual phenological behaviour of vegetation in urban context. Since anthropogenic green areas show no expansion dynamics, if compared with natural ones, and vegetation density does not change significantly, due to the human-management (i.e. pruning, mowing), biomass shows inter-annual flat behaviour (Li et al., 2017). S2 Level 2A data are supplied already calibrated in at-the-ground-reflectance. Nominal radiometric accuracy is about 0.01 reflectance units (European Space Agency/Centre National d'Eudes Spatiales (CNES), 2019). Technical features S2 image are reported in Table 1. It is worth to remind that the minimum mapping unit from S2 imagery is 100 m^2; this size was retained appropriate if compared with the average dimension of green areas in Torino.

[Here Table 1]

2.3.Epidemiological Data

Available epidemiologic sample refers to an on-going cohort whose subjects were recruited in 2010 as part of a research project funded by the Piedmont Regional Council focusing on the effects of environmental factors. This cross-sectional study involved 207 healthy children (10–13 years old) from secondary schools located in Torino. All subjects gave the assent to participate along with their parents, who signed an informed consent. Since the study involved human subjects, the study protocol required the Ethics

Committee approval (protocol number 826/13/08). Parents filled out a questionnaire to provide general information and their home address; participants provided a sample of urine that was used for quantification of a reliable biomarker of OS, namely 15-F2t-isoprostane (15-F2t-IsoP). At this concern, 15-F2t-IsoP was quantified to measure OS by a specific enzyme-linked immunosorbent assay (ELISA) kit (Oxford, MI, USA), according to the manufacturer's instructions. To achieve better accuracy each sample was diluted 1:4, as reported in previous works (Romanazzi et al., 2013; Squillacioti et al., 2019a). Urinary creatinine (crea) was quantified in each urinary sample in order to normalise urinary excretion rate and dilution. 15-F2t-IsoP was finally referred as ng/mg crea. Collected home addresses (Fig. 2) were used to geocode each subject by means of MMQGis QGIS plugin; positioning accuracy achieved by MMQGis is declared lower than 25m (Cetl et al., 2018).

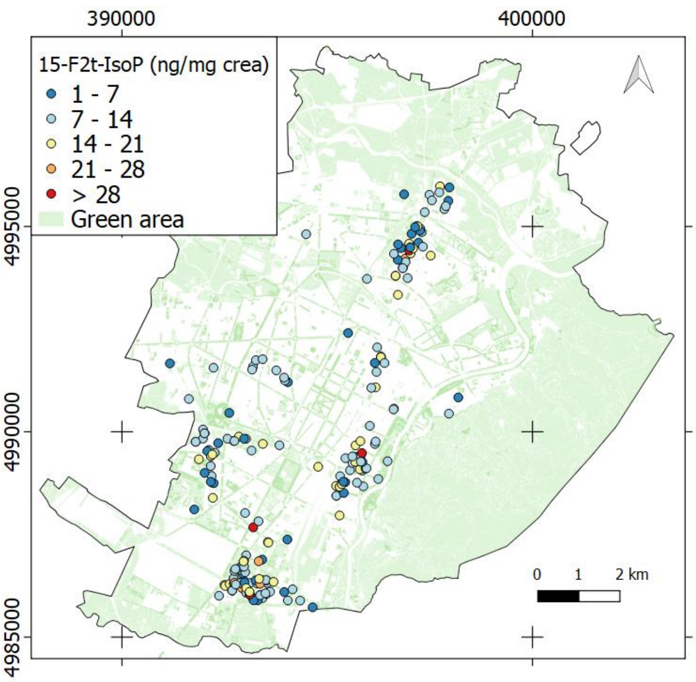

Figure 2 – Position (accuracy < 25 m) of sampled subjects (207) children aged between 10 and 13) within the study area. Reference frame is WGS84 UTM 32N.

2.4. Auxiliary data

Auxiliary data, provided by institutional geoportals, were supplied in vector format. A Tree Map (TM), updated at 2019 with a nominal scale 1:1000 was obtained as point layer from the Torino Geoportal. TM contains more than 160,000 individuals divided in evergreen and broadleaf species (Fig. 3). Main evergreen genera are: *Abies spp., Picea spp., Pinus spp., Thuja spp., Cedrus spp., Cupressus spp., Ilex spp., Magnolia spp.* representing the 5% of the trees*;* while the broadleaf genera are: *Platanus spp., Tilia spp., Aesculus spp., Celtis spp., Acer spp., Ulmus spp., Carpinus spp.,* representing the 95%.

Census data (*CD*, 2011) were obtained from the ISTAT (Italian Statistics Institute) geoportal; *CD* has a nominal scale of 1:5000 and contains census sections (polygons) and the correspondent features of surveyed people, included the number of children aged between 10 and 13 years. *CD* was used to describe the spatial distribution of potential targets that was retained a driving factor to address future urban policies eventually aimed at mitigating OS effects.

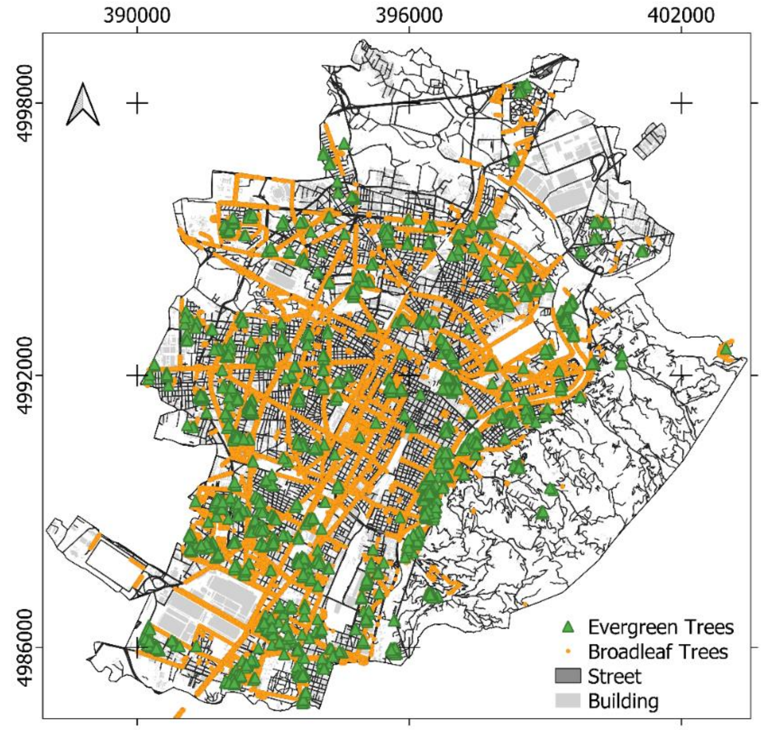

Figure 3 - Tree Map (TM) providing position of trees within the study area. It was obtained from Torino Geoportal. Nominal scale is 1:1000 and reference frame WGS84 UTM 32N.

3. Methods and data processing

Spatial analyses were operated by *SAGA GIS vs.7.1* and *QGIS vs. 3.4.12;* statistical analyses were performed using *Past vs. 3.6.6* (Hammer et al., 2001).

3.1. Detection and characterization of urban vegetation

In urban contexts soil background makes remotely sensed pixels not pure, i.e. mixed (Small and Lu, 2006; Song, 2005). In fact, background exerts considerable influence on the average pixel spectrum, thus influencing the accuracy of detection of green areas. To minimize such an effect while mapping vegetation within urban environments (Huete, 1988), the Soil Adjusted Vegetation Index (SAVI) was calculated by eq. 1:

$$SAVI = \frac{1.5\,(\rho_{NIR} - \rho_{RED})}{\rho_{NIR} + \rho_{RED} + 0.5} \tag{1}$$

where ρ_{NIR} and ρ_{RED} are S2 band 4 (665 nm) and band 8 (840 nm), respectively.Not-vegetated areas (buildings, streets etc.) were masked out by SAVI thresholding: pixel showing SAVI values < 0.45 were labelled as not-vegetated (Borgogno-Mondino et al., 2016; Burgan, 1993; Gao, 1996; Ormsby et al., 1987; Zhang et al., 2003). A map showing only vegetated areas was, therefore, generated (Fig.4), making possible to obtain preliminary information about spatial distribution of biomass in the area. Biomass is well-known to be related to spectrally derived vegetation indices (SAVI included).

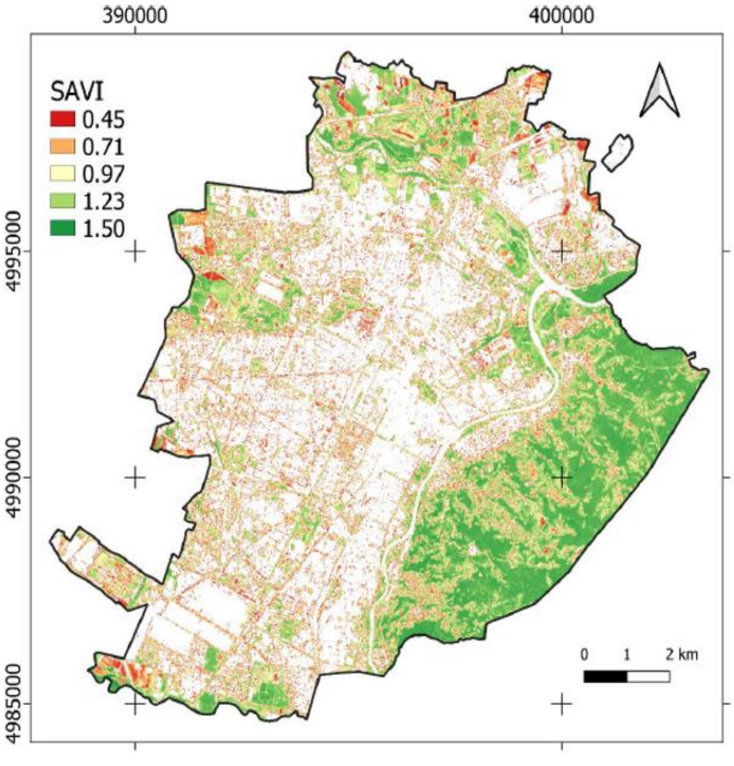

Figure 4 – SAVI map obtained by S2 image. Not-vegetated pixels were masked out by SAVI thresholding (SAVI < 0.45). Reference frame is WGS84 UTM32N.

3.2. Green Exposure Assessment

Many studies attested that green spaces may positively contribute to children's health (McMorris et al., 2015; Thiering et al., 2016). Greenness positive effects are assumed to decay with distance and increase with exposure time. Consequently, a first reasonable approach to quantify greenness exposure level is the characterisation of vegetated areas falling in a buffer zone surrounding subject' houses (James et al., 2015). Considering that children aged between 10 and 13, they can be supposed having an independent mobility pattern that ranges between 500 and 1000 m from their houses (Fagerholm and Broberg, 2011; Mavoa et al., 2011; Tillberg Mattsson, 2002). Consequently, buffers having a fixed radius of 500 m (B_{500}) were mapped around geocoded addresses. Different metrics, useful to measure and characterise green space falling in each buffer, were then calculated.

With reference to the masked SAVI map pixels were counted falling in B_{500} and the related SAVI mean value (mSAVI) computed. The percentage of green cover (PGC) was also calculated comparing the vegetation fraction with the whole area of the buffer. mSAVI was then multiplied by PGC, assuming the latter as a sort of weight. A new metric, hereinafter called *Unitary SAVI* (uSAVI) was finally obtained to somehow measure biomass density. Using TM, two more variables accounting for the number of evergreen and broadleaf tree falling in B_{500} were calculated, namely NET (Number of Evergreen Trees) and NBT (Number of Broadleaf Trees).

3.3. Statistical Analysis and Data Processing

Outliers detection in the 15-F2t-IsoP dataset was performed looking for values greater than Q3+1.5*(Q3-Q1), where Q1 is the 25th percentile and Q3 is the 75th percentile of 15-F2t-IsoP statistical distribution. Preliminarily, the relationship between OS and uSAVI was tested using the Pearson's linear correlation (*r*) and the correspondent linear regression was calibrated by Ordinary Least Squares (OLS). Correlation was also tested by *r* for the following relationship: 15-F2t-IsoP *vs* PGC, IsoP *vs* NET, and 15-F2t-IsoP *vs* NBT. Obtained values showed, for all the tested relationships, a weak correlation (see Results and Discussion section). Nevertheless, an envelope function (*Ev*) of these distributions was considered bounding observations clouds. *Ev* can be interpreted as the upper limit beyond which none 15-F2t-IsoP values exist referred to actual vegetation parameters values. It was computed by dividing the 15-F2t-IsoP range into 20 equiprobable classes corresponding to a class width of about 1.4 points of 15-F2t-IsoP value, starting from 3.56 ng/mg crea. With reference to the defined classes the correspondent 15-F2t-IsoP and uSAVI, PGC, NET, NBT maximum values were calculated and compared by scatterplots.Linear associations relating 15-F2t-IsoP-Ev with the other variables, were tested using Pearson's coefficient and correspondent linear regression modelled. Namely, NET-Ev and NBT-Ev slope values were compared according to the Warton method (Warton et al., 2006) in order to evaluate if evergreen trees determined a significant difference in OS reduction rate (i.e. slope value of bivariate model) with respect to broadleaf trees. Given these relationships, in order to spatialise the information generating a map of estimate of 15-F2t-IsoP-Ev, authors only focused on *uSAVI-Ev* since, among the tested metrics, from an operational point of view, it can be easily and globally computed from free satellite data. Consequently, the same procedure could be applied everywhere in spite of the existence of more specific databases containing more accurate information about local vegetation. Nevertheless, other useful information is derived from the interpretation of relationship between 15-F2t-IsoP-Ev and PGC-Ev, NET_Ev and NB-Ev for investigation purposes, solely. With these premises the linear regression model relating 15-F2t-IsoP-Ev to uSAVI-Ev was adopted to spatialise 15-F2t-IsoP-Ev estimates in the study area. For this purpose a 500x500 m squared graticule (G) was generated assuming this size consistent with a walking mobility of 10–15 minutes (Wolch et al., 2014). For each cell of G, the uSAVI maximum value was computed from the previously generated SAVI masked map. G was then rasterised to generate $uSAVI^G$. A raster map of estimates of 15-F2t-IsoP-Ev (hereinafter called 15-F2t-IsoP-Ev^G) was finally computed by grid calculation tools, implementing the previously calibrated linear regression relating uSAVI to 15-F2t-IsoP-Ev. An accuracy assessment of 15-F2t-IsoP-Ev^G was operated by a “leave-one-out” procedure (Brovelli et al., 2008) to compute the Mean Absolute Error (MAE) (Willmott and Matsuura, 2005).

4. Results and Discussions

Concerning outliers detection in the 15-F2t-IsoP dataset 4 individuals were found having a 15-F2t-IsoP value > 40 ng/mg crea and removed. With reference to the test concerning relationship between OS and uSAVI (Fig. 5) a Pearson’s linear correlation coefficient was found equal to -0.045, $p > 0.05$. A linear regression was calibrated by OLS estimation finding a slope value of -2.214 , *C.Is* 95% (upper bound =9.538 and lower bound=4.68 , p >0.05).

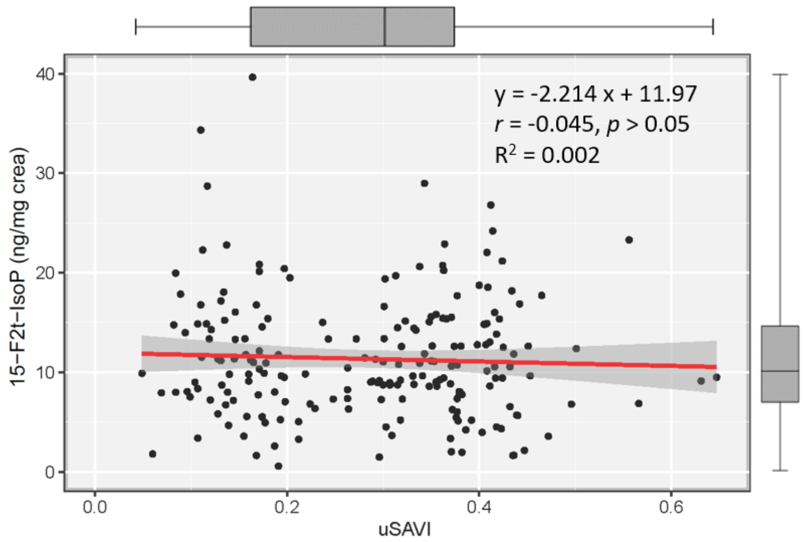

Figure 5– Linear regression model (red line, dark-grey are 95% Cis) of 15-F2t-IsoP (dependent variable) and uSAVI (independent variable). Box-plot represent respectively: minimum, Q1, median, Q3, maximum of both uSAVI (up box-plot) and 15-F2t-IsoP (right) value distributions without outliers.

It is worth to stress that some of the OLS regression assumptions were violated: residuals were not normally distributed (Shapiro-Wilk test) showing autocorrelation (Durbin-Watson test) and, more in general, both *r* and the OLS regression model showed that OS and uSAVI were poorly correlated. Such poorly correlation values were possibly due to the fact that OS is also related with other factors like air quality, personal behaviour (i.e. diet, smoking), individual pathology. Therefore, all these relationships influence the covariance and, as well, correlation coefficient. Concerning the other tested relationships (15-F2t-IsoP *vs* PGC, IsoP *vs* NET, and 15-F2t-IsoP *vs* NBT) the following values were found (Tab.2).

[Here Table 2]

It is worth to remind that OS level differences are due to several risk factors, both individual and environmental (Fig. 6). Therefore, a modelling of 15-F2t-IsoP based on uSAVI does not have the aim of producing reliable absolute 15-F2t-IsoP estimates; conversely, it is expected to produce a general overview, enhancing relative differences between different areas.

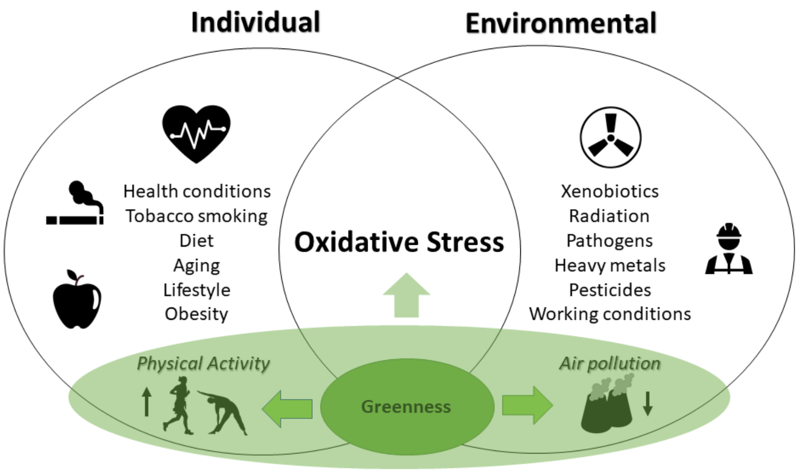

Figure 6 – OS is influenced by many individual (left ellipse) and environmental factors (right ellipse). This generates high variability in OS values if ordinary regression-based approaches are used. (Green ellipse) Interaction between OS and greenness. OS level can be influenced by green areas increasing physical activity or mitigating air pollution (Nowak, Crane, and Stevens 2006; McMorris et al. 2015)

Figure 7 graphically shows scatterplots relating 15-F2t-IsoP to uSAVI, PGC, NET and NB. Red lines define the upper bound (*envelope*) of 15-F2t-IsoP estimates, which class *maxima*, used to generate the new metrics 15-F2t-IsoP-Ev, uSAVI-Ev, PGC-Ev, NET_Ev and NB-E, have to somehow represent. Classes used for maximum value computation are reported in Tab. 3.

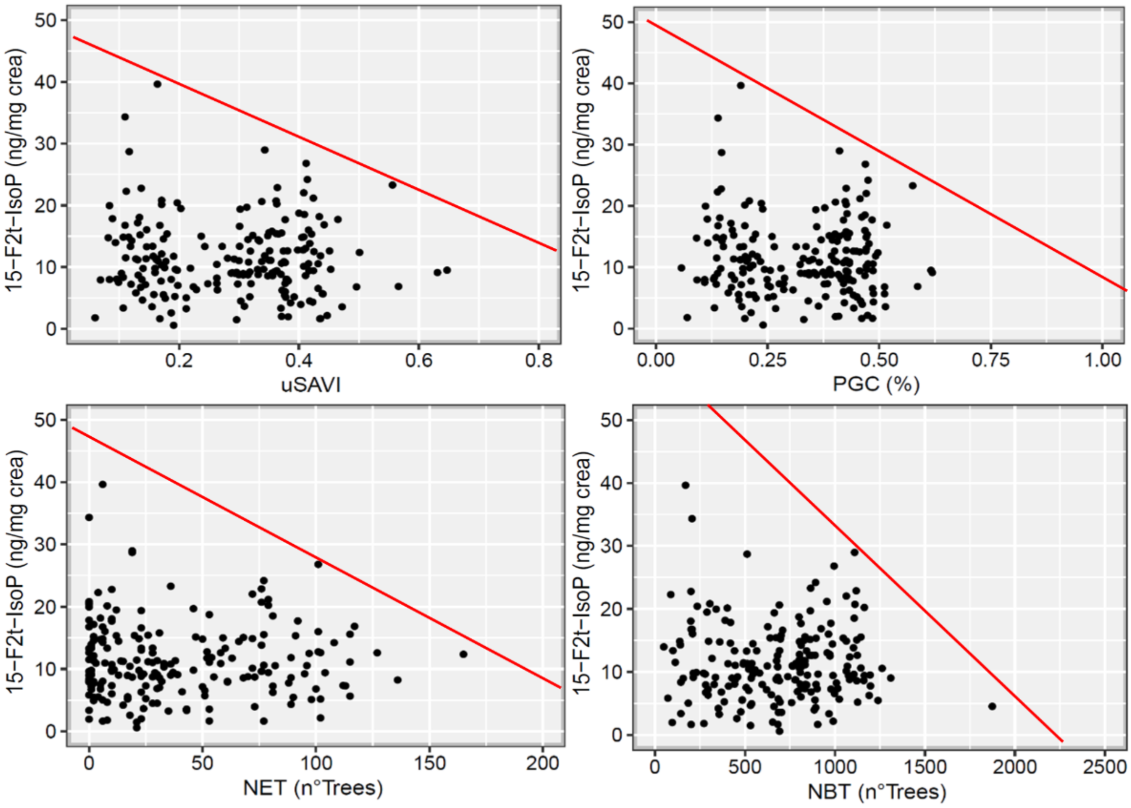

Figure 7 – Scatterplots relating 15-F2t-IsoP and vegetation parameters. A linear envelope function (Red line) can be defined for each cloud defining the upper boundary of the estimates.

[Here Table 3]

Figures 8 (a-b) and 9, and table 4 report results of the bivariate models that relate 15-F2t-IsoP-Ev to PGC-Ev, 15-F2t-IsoP-Ev and uSAVI-Ev, respectively.

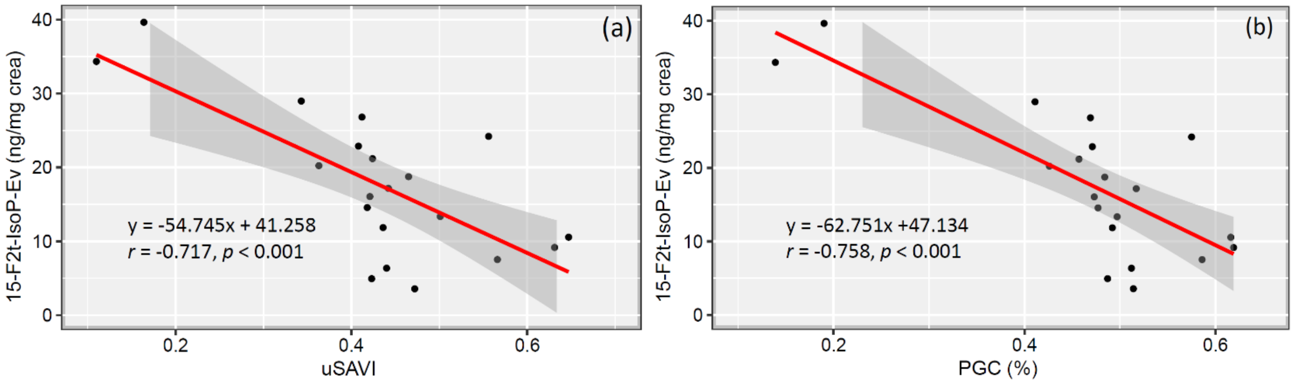

Figure 8 – (A) bivariate model between 15-F2t-IsoP-Ev and uSAVI-Ev; (B) Bivariate model between 15-F2t-IsoP-Ev and PGC-Ev. Pearson correlation coefficient (r) was reported with related significance level. Dark-grey limits are 95% CIs.

A significant negative correlation was found between 15-F2t-IsoP-Ev and PGC-Ev (r = -0.758, p < 0.001) and between 15-F2t-IsoP-Ev and uSAVI-Ev (r = -0.717, p < 0.001). Results prove that higher vegetation cover seems to significantly reduce OS. In particular, if vegetation cover is composed by trees (i.e. high uSAVI), OS tends to decrease. With respect to evergreen and broadleaf tree *genera*, the correspondent regressions were tested separately (Figure 9).

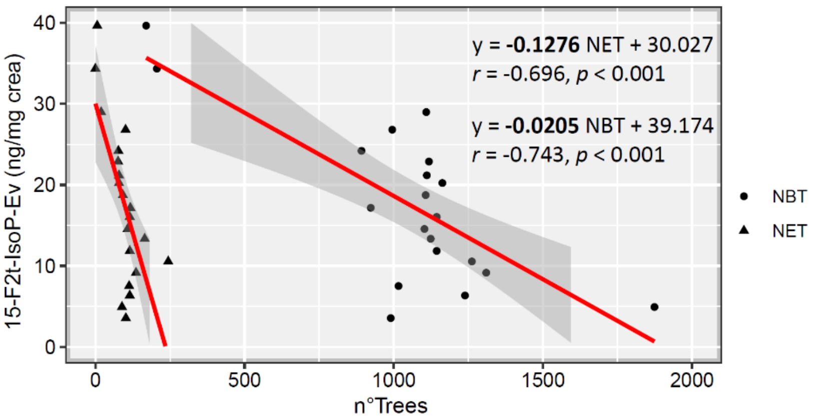

Figure 9 – (Triangle) bivariate model between 15-F2t-IsoP-Ev and NET-Ev; (Circle) Bivariate model between 15-F2t-IsoP-Ev and NBT-Ev. Pearson correlation coefficient (r) was reported with related significance level. Dark-grey limits are 95% CIs. In Bold are highlighted IsoP reduction rate (slope values) of NET and NBT. NET slope is steeper negative than NBT one and the two slopes are statistically different (p<0.01).

To test significance of slope of NET and NBT, the Warton test (Warton et al., 2006) was applied finding a F value = 12.48 , p = 0.0011. It proved that NET and NBT bivariate model gain values were significantly different. In particular, NET determines a negative steeper 15-F2t-IsoP-Ev reduction rate six-time greater in respect of NBT, suggesting that evergreen trees determine a stronger positive effect on OS. Statistic parameters of tested relationships are reported in Table 4.

[Here Table 4]

Concerning accuracy of estimates, MAE of 15-F2t-IsoP-Ev^G was computed by a leave-one-out approach. It resulted equal to 5.26 15-F2t-IsoP ng/mg crea. Results proved that green areas where evergreen trees dominate OS is lower. Consequently, urban planners could exploit this information while designing new restoration/requalification actions, possibly promoting these interventions especially in those parts of the city having a higher density of potential targets (i.e. children). In order to exemplify spatial implications of the above-mentioned relationships a 15-F2t-IsoP-Ev^G map was generated with a grid size of 10 m and coupled, by overlaying, with CD (Fig. 10). This map is intended to represent an operational tool to describe OS risk of 10-13 years old children. According to the map, if high OS estimate values were found to be associated with a low density of children, eventual economical efforts would not be completely justified. Oppositely, if high OS estimates were found where children density is high, interventions aimed at improving greenness would be proper. The map of 15-F2t-IsoP-Ev^G estimate may be useful in locating urban areas with higher or lower expected OS levels. It can be therefore considered a simulation tool useful to generate future scenarios where new green areas could be added, or old ones requalified, providing estimates of associated 15-F2t-IsoP-Ev^G resulting from the adopted choices.

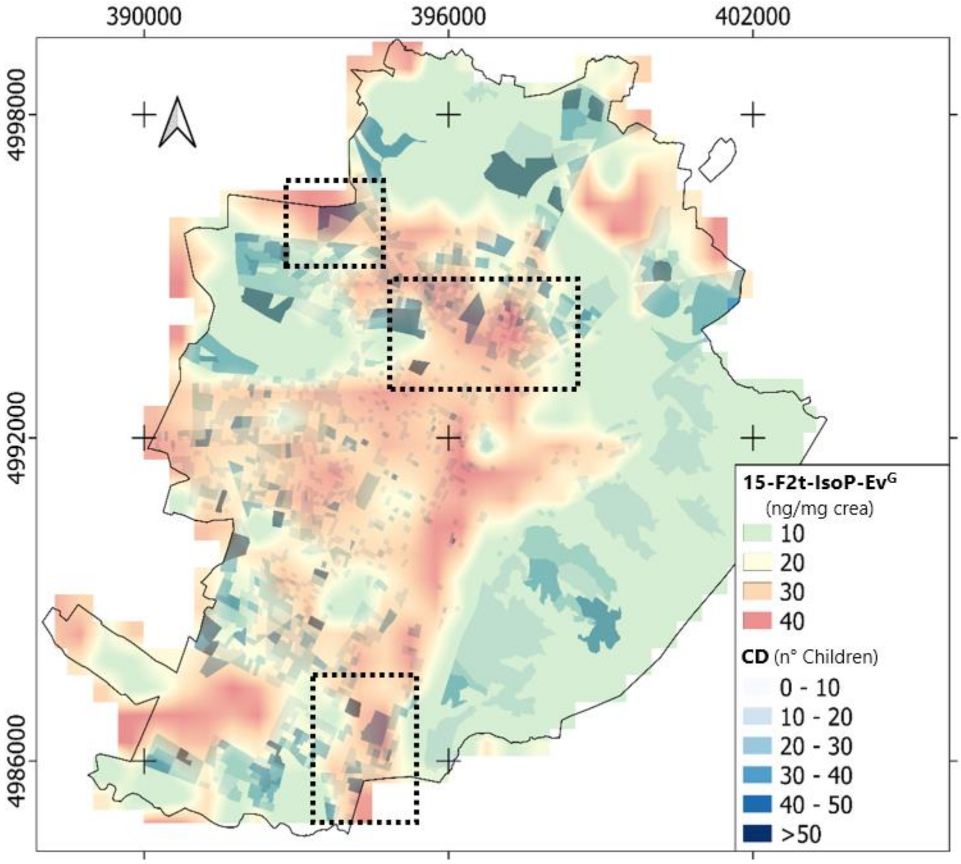

Figure 10 –Map shows spatial distribution of 15-F2t-IsoP-Ev^G estimates coupled by overlaying with 2011 Census Data (children). It could be useful to urban planners to define priority zones where creating/ requalifying green areas. Dotted rectangles are critical zones where high children density and high OS values are located. Reference frame is WGS84 UTM32N.

5. Conclusions

This study aimed at investigating and formalising the relationship between OS and greenness with reference to children living in Torino (NW Italy). Significant negative correlations (Pearson's $r = -0.758$, $p < 0.001$) between PGC-Ev and 15-F2t-IsoP-Ev were found indicating that a higher degree of green areas around children's houses determines a lower OS levels in children. One of the potential mechanisms underlying this association could be related to the presence of accessible green areas potentially used to perform physical activity.

Moreover, our results emphasised that local biomass plays a key role in OS reduction. In fact, higher values of uSAVI correspond to lower levels of OS (Pearson's $r = -0.717$, $p < 0.001$). High biomass can be generally related to a strong presence of trees: green areas where trees density was higher proved to be significantly related to lower OS values. Trees are thought to provide positive effects to health by reducing exposure to particular matter (PM_{10} or $PM_{2.5}$) or ozone (Fausto Manes et al., 2012; F. Manes et al., 2012; Nowak et al., 2006). In particular, evergreen trees seem to determine a significant 15-F2t-IsoP-Ev reduction rate in respect to broadleaves (NET slope = -0.12, NBT slope = -0.02, Warton-test $F = 12.48$, $p = 0.0011$). With respect to evergreen trees, this can be related to: (a) a higher content of cuticular resins, which have an important role in pollution absorption and mitigation (Marando et al., 2016; Sawidis et al., 2012); (b) a total leaf area greater than broadleaf that, considering the annual phenology of urban trees, provides larger absorption surfaces for pollutants. Furthermore, in northern Italy, especially in Po river watershed, air quality dramatically decreases in winter (Bigi and Ghermandi, 2014; Finardi and Pellegrini, 2004) when only the evergreen species can provide the mitigation effect on air pollution.

uSAVI and OS bivariate model (15-F2t-IsoP-Ev^G map) can be used for future developments related to urban planning strategies and policy makers decisions, making possible to define priority zones where requalification or new greenspaces should be considered. These plans might take into account the here presented results according to three main strategies: (a) green cover improvement; (b) trees or shrubs (i.e. high biomass density cover) planting in place of grass; (c) evergreen trees selection rather than broadleaves.

It is worth to remind that calibrated uSAVI-OS model describes the Ev function containing OS estimates, meaning that one can infer only about the upper limits of expected 15-F2t-

IsoP, with no possibility of knowing its exact local value. This is mainly due to the high intrinsic variability in OS-induced factors (individual and environmental). Since this study mainly refers to children, further works are expected to test the association between greenness and OS in differently aged subjects and different geographic urban areas where the sole intensity of urbanization can produce different level of OS (Squillacioti et al., 2020). Expectation is that this approach could promote the highest public health standards even with the best urban green design *criteria*.

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Table

Table 1. Technical features of the S2 images obtained from Theia CNES provider (https://www.Theia-land.fr/en/product/sentinel-2-surface-reflectance/)

Band ID	***Central wavelength (nm)***	***Bandwidth (nm)***	***Nominal Geometric resolution by Theia CNES provider***
B2	490	98	10 m
B3	560	45	10 m
B4	665	38	10 m
B5	705	19	10 m (20 m native resolution)
B6	740	18	10 m (20 m native resolution)
B7	775	28	10 m (20 m native resolution)
B8	840	145	10 m
B8A	865	33	10 m (20 m native resolution)
B11	1610	143	10 m (20 m native resolution)
B12	2200	242	10 m (20 m native resolution)

Table 2 – Coefficients of linear regression models between 15-F2t-IsoP vs PGC, IsoP vs NET, and 15-F2t-IsoP vs NBT. All dependent variables were poorly correlated with OS.

Dependent variable	***r***	***p*-value**	**R^2**	**Slope**	***p*(slope)**	**Slope (95% C.Is)**	**Intercept**
uSAVI	-0.045	0.520	0.002	-2.214	0.520	(-9.538, 4.685)	11.967
PGC	-0.046	0.519	0.002	-2.126	0.519	(-8.747, 4.819)	12.035
NBT	-0.028	0.691	0.001	-0.001	0.691	(-0.003, 0.002)	11.699
NET	-0.030	0.673	0.001	-0.005	0.673	(-0.025, 0.014)	11.523

Table 3 – Twenty equi-probable classes of 15-F2t-IsoP (divided by about 1.4 ng/mg crea step) and vegetation parameters. In order to calculate the envelope function of each scatterplot, maximum values of equi-probable class were extracted. For each equi-probable class maximum value and coefficient of variation (%) were reported. Slash sign denotes only one value within equi-probable class.

15-F2t-IsoP		**uSAVI**		**NBT**		**NET**		**PGC**	
Max	CV%	Max	CV%	Max	CV%	Max	CV%	Max	CV%
3.56	39.9	0.47	46.9	990	55.2	102	91.5	0.514	43.5
4.93	10.8	0.42	38.8	1874	58.9	89	84.3	0.487	34.6
6.35	7.7	0.44	37.5	1239	51.7	115	95.8	0.512	34.5
7.52	4.2	0.57	51.6	1016	37.6	113	94.9	0.586	46.5
9.16	5.5	0.63	46.2	1310	48.6	136	100.0	0.619	40.8
10.55	4.2	0.65	45.5	1262	45.8	244	99.4	0.616	39.9
11.85	3.2	0.44	40.3	1144	33.0	115	80.7	0.492	35.9
13.35	3.0	0.50	35.1	1124	30.2	165	91.4	0.497	31.2
14.56	3.2	0.42	45.8	1103	72.6	108	119.2	0.477	43.5
16.05	2.6	0.42	43.1	1144	41.8	115	79.6	0.473	41.1
17.17	1.2	0.44	60.6	923	60.0	117	167.9	0.517	57.6
18.74	2.2	0.47	46.1	1107	50.3	92	108.4	0.484	44.3
20.23	1.8	0.36	43.7	1163	55.5	79	105.8	0.426	42.6
21.18	1.4	0.42	36.7	1111	58.6	79	137.0	0.457	33.1
22.88	1.8	0.41	59.7	1118	88.9	76	95.8	0.471	60.3
24.2	2.7	0.56	20.7	892	2.2	77	51.3	0.575	13.5
26.81	/	0.41	/	995	/	101	/	0.469	/
28.98	0.7	0.34	69.5	1109	52.1	19	/	0.411	66.9
34.34	/	0.11	/	206	/	0	/	0.139	/
39.65	/	0.16	/	170	/	6	/	0.190	/

*Table 4 – Bivariate relationships statistics of 15-F2t-IsoP-Ev and vegetation parameters. Significance levels: * p <0.05, ** p <0.01, *** p < 0.001.*

Proxy	***r***	**R^2**	**Slope**	**Slope (95% C.I.s)**	**Intercept**
PGC	-0.758***	0.57	-62.75***	(-83.671 -34.792)	34.26
uSAVI	-0.717***	0.51	-0.01***	(-0.016, -0.005)	0.59
NET	-0.696***	0.48	-0.12***	(-0.192, -0.023)	30.02
NBT	-0.743***	0.55	-0.02***	(-0.031, -0.010)	39.17

Credit Author Statement

S.D.P.: Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft; **G.S.:** Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft, Data curation; **R.B.:** Supervision, Project administration, Writing - Review & Editing; **E.B.M.:** Supervision, Project administration, Writing - Review & Editing

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.