EPRA

EUROPEAN PUBLIC REAL ESTATE ASSOCIATION

ACADEMIC RESEARCH

Value of ESG contributions by investing in European public real estate companies

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Final Report

EXECUTIVE SUMMARY

In recent decades, climate change has forced governments and communities to take action. The COP21 meetings in Paris and COP22 meetings in Morocco organized by the United Nations (UN) reflect the increasing importance given to environmental issues, and particularly, carbon emissions. The UN adopted 17 sustainable development goals (SDGs) on September 25, 2015 in order to protect the environment and society. At least 8 of these goals (SDGs 3, 6, 7, 9, 11, 12, 13, and 15) are directly related to environmental and social issues, one of which is the Sustainable Cities and Communities initiative. The real estate industry has the largest potential to contribute to such actions and achieve these goals. According to the European Commission, in the European Union (EU), real estate is responsible for 40% of energy consumption and about 36% of carbon emissions. These figures reflect the direct environmental consequences.

The aim of this project is to contribute to the practice and academic literature on the ESG activities of property companies. There is no concrete valuation reflecting the ESG activities of companies in the real estate industry, which is considered to be the most potential contributor to climate actions and the UN's SDGs. In this project, we aim to estimate the euro value of contributions to ESG activities conducted by publicly listed companies in Europe through social contributions and reducing environmental impact. The data we create will help investors understand how much of their €1 investment in property companies or, how much of property companies' investments, will equivalently contribute to ESG activities.

Our analysis is based on annual and sustainability reports of publicly listed companies in Europe covered by EPRA. Most European public real estate companies report their annual carbon emissions, energy consumption, sources of energy, water consumption, and waste. Companies take environmental actions such as using renewable energy, LED lights, isolation technologies to decrease energy consumption, alternative technologies to decrease water consumption, recycling waste, etc. Companies also take an active role in society. Real estate companies contribute to local communities through social events, training programs, and collaboration with local charities. They also organize internal employee training programs.

Using algorithms and hand-collection of data, we create a dataset of ESG activities by publicly listed European real estate companies. We first create keywords based on potential ESG activities by property companies and filter the text in the annual and sustainability reports using algorithms. Then, we create ESG categories based on the filtered text and create ESG variables. In the end, we model each ESG category and apply machine-learning techniques wherever necessary to obtain a euro value of the contribution from each ESG category.

Among the environmental activities, the main activities are to reduce carbon emissions (encompassing energy consumption), water consumption, and waste. We base our model on the environmental performance of buildings at corporate level. Basically, we compare carbon emissions and water consumption per m^2 relative to a benchmark of conventional buildings. However, the main challenge here is that at the building level, the owner of a property and tenants are jointly responsible for carbon emissions and water consumption. The distribution of the environmental responsibility is based on contracts signed between the two entities. Real estate owners have operational control in regard to carbon emissions and water consumption while tenants are typically responsible for their rental areas. Some companies do not have access to tenants' consumption figures, which creates a major challenge for companies and for us to determine the environmental performance of a property company's portfolio based on building-level data.

For this purpose, we create two measures for carbon emissions (water consumption): *Building Carbon (Water) Intensity* and *Operational Control Carbon (Water) Intensity.* For companies for which we do not observe *Building Carbon (Water) Intensities,* we develop a machine-learning model to estimate the *Building Carbon (Water) Intensity.* Although the sample size is small, we propose a dynamic model to help overcome the data challenges. Furthermore, the ESG data are expected to accumulate as companies continue to report their environmental impact. In a sense, our dynamic machine-learning model will improve itself. After the estimation procedure, we develop a basic approach, where we calculate total carbon emission and water consumption of buildings in a portfolio of a property company net of a global benchmark. Then, we multiply it by a euro value per m^2 of ESG contributions through reducing carbon emissions and water consumption to obtain a euro value of contributions for these categories.

We follow a similar procedure for other categories. For waste, we use total tons of waste recycled and multiply it by a euro-value factor per ton of waste recycled. The main categories in social and governance activities are the economic value of internal spending (such as for employee training) and the spending on community donations.

Overall, we find that an average European property company contributes to ESG activities through reducing carbon emissions at a value of €4,75 millions annually. The value of contributions to ESG activities through reducing water consumption is estimated to be €2.0 millions. The contributions to ESG activities through waste recycled is predicted to be €0.66 million. The value of employee training and community donations are annually €0.42 and €0.56 million, respectively. In total, an investor can contribute to ESG activities by investing in a European public property company by €8.40 millions. This value corresponds to a ratio of contributions to Capex on investment property, NOI, and total equity at around 9.50%, 4.60%, and 0.25%, respectively.

Our main contributions in this project are twofold. Firstly, our project is the first one to create a value model to determine the value of contributions to ESG activities through investing in property companies. The measure we create is critical for the real estate industry and its participants, such as asset owners, property managers, pension fund managers, and institutional investors. Our measures on the value of contributions to ESG activities through social contributions and reducing environmental impact help investors understand how much of every euro they spend on a property company contributes to ESG activities. Our measures help improve the understanding of how ESG activities affect financial performance of property companies, particularly on a long-term basis. It is also very critical to quantify such ESG activities by property companies as they have the highest potential to help protect the environment and improve societies. Secondly, we propose a machine-learning model to provide an estimation of carbon emissions and water consumption datasets by converting the data from an operational control level to a building control level. Our model is dynamic in nature and will improve as more data become available.

Content Table

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Introduction

Real estate professionals and academics have largely concentrated on green certifications such as LEED, Energy Star, and BREEAM to support the cause for environmental actions. In academic literature, a number of studies discuss the economic value of green certifications. Eichholtz, Kok, and Quigley (2010) find that green certified buildings are sold at 11-13% premiums and generate rents by 6-8% premiums. This study is followed closely, and their findings have been confirmed by others (Fuerst and McAllister 2011; Wiley et al. 2010). Some other benefits of green buildings are supported by literature. For example, green buildings generate higher occupancy (Eichholtz, Kok, and Quigley 2013; Devine and Kok 2015), lower energy expenditures (Eichholtz, Kok, and Quigley 2013), and higher occupant satisfaction (Devine and Kok 2015).

While these studies analyze the economic benefits of green certifications, there is limited research on the impact of sustainable investments at the corporate level for property companies. Eichholtz, Kok, and Yönder (2012) use the annual share of green buildings in a property portfolio of US REITs to proxy their environmental activities. Authors then relate this *Green Share* to financial performance of US REITs and document that *Green Share* is positively associated with operating performance measured by ROA, ROE, and FFO share and negatively associated with market beta, which indicates lower firm risk. This study is followed by Eichholtz, et al. (2019), who evaluate the impact of *Green Share* on the cost of debt. The authors find that *Green Share* and green certification decrease the spread on US REIT bonds and mortgages, respectively. A recent EPRA-funded project by Devine, Steiner, and Yönder (2017) also evaluate the UK REIT market and show that *Green Share* has a positive impact on the financial performance of the UK REITs. Their findings demonstrate that *Green Share* does not only contribute to operating performance but also attracts stock market investors and enhances Price/NAV ratio beyond the operating benefits.

Although these studies have important contributions to our understanding of environmental activities of REITs in the US and the UK, they lack the exploration of other issues. Firstly, these studies rely on green certifications. While green certifications guarantee a standard level of environmental activities by property companies, they do not completely cover environmental actions undertaken by firms. Furthermore, from an ESG perspective, green certifications are mainly related to environmental activities but do not reflect property companies' actions on social activities and governance. Considering the UN's SDGs, there is a need for a better understanding of the ESG activities of property companies. The properties of real estate companies are at the core of human life and business activities. This focus on buildings also brings social responsibilities to property companies as they can potentially contribute to societies with the actions they take in their buildings and within local communities.

Alternative to property certifications, GRESB evaluates property companies with respect to their environmental actions. The analysis of GRESB is based on voluntary self-reporting and the responses of companies to GRESB's questionnaires. GRESB create a benchmark index and score property companies. EPRA's initiative, the sBPR database, creates sustainability data and serves as a potential milestone in the real estate industry.

In this project, our aim is to quantify the euro value of ESG contributions through environmental activities, which also help companies to obtain environmental certifications, and social activities. The environmental activities are mainly through reducing the environmental impact such as decreasing carbon emissions, water consumption, and waste. Companies make capital expenditures such as installing solar panels to produce electricity, LED lights, implementing isolation technologies to decrease energy consumption and alternative technologies to decrease water consumption, recycling waste, etc. We do not observe how much companies spend on such activities. Instead, in this project, we aim to measure euro contributions to ESG from such actions.

We follow a similar procedure to the European Commission's cap-and-trade model. In this model, a cap is set on the carbon emissions of companies. Companies receive allowances according to their caps. They can trade their allowances depending on whether they emit less than the cap or exceed the cap. For instance, assume that Company 1 is allowed to emit 100 units of carbon but emits 70 units. Company 2 is allowed to emit 90 units of carbon but emits 120 units. Company 1 sells 30 units at the market price p of carbon to Company 2 creating a value of 30 x p although having a negative impact of 70 units of carbon (if benchmarking against zero carbon). The price of allowances is determined in the secondary markets based on the demand and supply of allowances. One important tool in the system is that the cap on carbon emission declines over time and this way, emissions are reduced continuously.

Inspired by the cap-and-trade model developed by the European Commission, we compare the carbon and water intensity per m^2 of companies' properties with a benchmark measure – similar to a cap – mainly obtained from alternative sources on Europe. We then calculate how much carbon emission (water consumption) is reduced relative to the benchmark and calculate the portfolio-level reduction multiplying it by the total m^2 of the property portfolio of a company. Then, as in the cap-and-trade model, we determine a price factor (euro value per m^2) and calculate the euro value of contributions to ESG through reducing the environmental impact at portfolio level. Regarding waste, we focus on the waste recycled and multiply it with a price factor as in the carbon and water categories.

One concern in our approach could be that the European Commission and many developed countries promote zero carbon. Firstly, zero-carbon companies will get the highest euro value of contributions as the difference from the benchmark will be at most for those companies as potentially in the cap-and-trade model. Secondly, the zero-carbon target proposed by the European Commission is for newly constructed properties. According to the European Commission, 35% of the EU's buildings are over 50 years old and 75% of the building stock in the EU is energy inefficient. Thirdly, there is no zero-carbon property company among the property companies covered by EPRA as they own older properties. According to our calculations, only 12% of the properties owned by companies in our sample are built after 2010. In this regard, the efforts to reduce carbon emissions by European property companies are very important considering the old property stock in the EU.

Among social activities, we quantify euro value of donations and employee training conducted by property companies. The value of donations is straightforward as companies directly report how much they donate. We collect total hours of employee training from company reports and multiply it by a standard cost of employee training per hour.

In addition to these activities that we classify, property companies conduct other environmental, social, and governance activities. Biodiversity and air quality are important environmental activities implemented by property companies. However, there is no standard reporting practice across property companies. Some companies take other approaches in environmental activities. For instance, two companies set up hives for bees. For example, if we assume that a company reports that there are between 500,000 and 750,000 bees in the summer months in their hives, this will help us estimate the euro value of the activity.

While the real estate industry is considered to be the largest potential contributor to environmental issues, real estate companies are also at the core of societies and local communities. The activities conducted in buildings such as in retail properties can greatly contribute to local community development. With such a responsibility, most property companies actively engage with local communities. One company provides training to prisoners to help them join the workforce. There are many activities to train young people or students. Community programs are very important to the development of local communities in the training of young people or school leavers, etc. Due to data limitations, we do not cover such activities.

The report continues as follows: The next section explains data and methodology. Then, we discuss our findings and in the final section, we conclude and suggest implications and further research.

Data and Methodology

TEXT EXTRACTING ALGORITHM

The biggest challenge in quantifying ESG contributions is creating the dataset. In the last few years, European public real estate companies report more structured ESG data in their annual or sustainability reports. Overall, companies' annual sustainability reports cover total values for each category and/or intensity measures per square meter, employee, etc.

We first create an algorithm which filters and automizes annual and sustainability reports based on a set of keywords. Our algorithm finds the relevant keywords and paragraphs in the company reports and highlights important parts of each report. Depending on the size of the keyword, the algorithm reduces the data gathering process by up to 90%. The algorithm simply gets a keyword file and the PDF folder containing company reports as inputs. Then, the algorithm finds where these keywords are located in the PDF files and marks their positions, including the paragraph containing the keyword. The algorithm uses an external library to highlight these paragraphs and outputs the highlighted copy of the PDF file and a text file which includes all of the paragraphs containing the identified keywords and page numbers.

We use a large number of keywords to have a better reading of each report in order to understand any potential ESG activity that a property company can perform. In addition to highlighting PDF files, we extract text from the company reports and create text files containing highlighted text. We give full reads to the filtered text and create a narrowed sample of keywords in order to establish our ESG categorization of activities and database.

We use the algorithm to read 215 company reports of 107 European publicly listed property companies, which are among the EPRA index constituents. To evaluate the performance of the search and highlighting algorithm, we take into consideration 40 random company reports. These reports are read manually and through the algorithm without highlighting to determine the keywords. Testers are divided into two subcategories. The first set consists of five readers. Depending on the keywords, the readers try to find relevant paragraphs within each company report. The second set is the algorithm that was developed for this project. Overall, the algorithm identifies the keywords and corresponding paragraphs 4% better than the average score of five individual readers. Using the algorithm, we also count the appearance of some important keywords and use the count variables in the estimation models.

CATEGORIZATION OF ESG CONTRIBUTIONS

We start by analyzing environmental activities to reduce environmental impact. In general, companies follow EPRA's guidelines and report carbon emissions, energy consumption, water consumption, and waste generation. Among these, we combine carbon emissions with energy consumption. Companies execute different initiatives and use various technologies to reduce energy consumption and subsequent carbon emissions. We consider *"Carbon Emissions"* as the final outcome as a unique category. Any energy saving initiative or usage of renewable energy decreases carbon emissions so energy consumption is not separately categorized. As described in the next section, we model carbon emissions and calculate the euro contribution through reducing carbon emissions.

We then classify *"Water Consumption"* and *"Waste,"* as separate categories. With a similar logic, any recycling activity reduces waste generation as a final outcome variable, therefore recycled waste is considered in the waste generation category. Under social and governance activities defined as social contributions, it is more difficult to estimate euro values of activities. Some companies conduct internal training programs and report the number of hours of training per employee as part of EPRA's guidelines. These activities are categorized as *"Employee Training Activities."* Additionally, companies collaborate with local charities and organizations. We categorize such community programs and donations to such charities as *"Community Donations."* Table 1 presents the ESG activities categorized and created for the purpose of calculating the euro contribution to ESG activities through investments in European public property companies.

Table 1: Categorization of ESG Activities

ESG Activity	Description
Carbon Emissions	Reducing Environmental Impact
Water Consumption	Reducing Environmental Impact
Waste	Reducing Environmental Impact
Employee Training Activities	Social Contributions
Community Donations	Social Contributions

Based on our categorization, we narrow down our keywords and go through our filtered text in a second round of reading for 215 company reports. In the second round of reading, we create our ESG variables and manually collect data for those variables. The variables cover outcome variables such as carbon emissions, water consumption as well as independent variables to estimate outcome variables such as keyword scores, etc. We also follow a two-round process in finalizing the ESG variables. In the first round, we manually extract a large set of data and information. In the second round, we clean up the information we gather and standardize our ESG variables.

ESTIMATION BY ESG CATEGORY

In this section, we discuss our methodology to calculate euro contributions of property companies to each ESG activity. Companies mainly report their energy consumption, carbon emissions and savings as a result of ESG investments such as solar panel installation. In this project, our analysis and measurements are mainly based on euro contributions of European public property companies to ESG activities through social contributions such as employee training or reducing impact i.e. carbon emissions or water consumption.

Among the activities presented in Table 1, we treat carbon emissions and water consumption differently from other ESG activities. Carbon emission and water consumption are negative outcome variables because they occur mainly from usage and consumption. An investor interested in property company stocks mainly considers relative carbon emissions or water consumption. More specifically, a typical investor can consider the carbon emission of the buildings owned by Company A relative to conventional buildings. It potentially represents the amount of carbon emission reduced by Company A through making environmental activities.

In other words, if an investor invests in Company A, the potential contribution is equivalent to the difference between the total carbon emission (or water consumption) of the property portfolio of Company A and the potential carbon emission (or water consumption) of conventional properties of the same size, same type, and same location assuming that Company A's properties have lower carbon emissions and less water consumption. We use the following equation for carbon emissions and water consumption following a procedure similar to the cap-and-trade model of the European Commission:

(1) Contribution Value in an ESG Category = (ESG Variable Intensity – Benchmark Intensity)

x Total m^2 x Euro Contribution per unit ESG Variable

We collect information from leading institutions to determine an average carbon and water intensity for a standard building. The benchmark we use varies based on property type. The Carbon Risk Real Estate Monitor report by CRREM focusing on the EU states that carbon intensity is 112-114 $kgCO_2/m^2$. According to a report by Carbon Trust focusing on the UK market, annual carbon emission of an average building is globally 115 $kgCO_2/m^2$, which is similar to CRREM's estimation. Following these reports, we assume a benchmark carbon intensity value approximately 110-120 $kgCO_2/m^2$. In the next step, we collect information on the variations in carbon intensity across different types of properties.

The European and global sources of carbon emissions by property type are limited. We gather relative carbon intensity information from City of Cambridge Getting to Net Zero Action Plan Progress Report (2019) and the Chicago Energy Benchmarking Report (2017), where carbon intensities by property types are reported. We then compare and normalize relative intensities based on the average carbon intensity by each property type using the data we collect for European public property companies. Table 2 presents predetermined benchmark carbon intensities by property type. We use these benchmark values to calculate carbon contributions (as in Equation 1) in the next section.

Table 2: Benchmark Carbon Intensities by Property Type

Property Type	Benchmark Carbon Intensity ($kgCO_2/m^2$)
Multifamily	110
Office	115
Retail	145
Industrial	90
Lodging	125
Self-Storage	70
Specialty	110
Global Mean	110

To obtain benchmark values across property types, we distribute relative carbon intensities normalized around a mean of 110 $kgCO_2/m^2$, which is approximately the European and global benchmark assumed to be around 110-120 $kgCO_2/m^2$. When we use Equation 1 for each company, we calculate a weighted average benchmark intensity using property type shares in a given portfolio of a property company. As a result, the benchmark value is different for each company based on their property type weights.

Following EPRA's guidelines, companies report the total annual carbon emissions and/or carbon emission intensity (per square meter used in our calculations) from their buildings and activities. Accordingly, in Equation 1, we obtain the value of ESG outcome variables from company reports. We collect carbon intensity and water intensity measures per square meter that are reported by companies. For the analysis of each building, we use total carbon emission and water consumption for areas both operationally controlled by the property company and areas that tenants use.

There are two obstacles here. First of all, it is not straightforward to collect carbon and water data for areas controlled by tenants for property companies. Some companies can only report emissions and water consumption based on the areas in which they have operational control. This brings another analytical obstacle. The total energy and water consumption of a building may be distributed between the owner and the tenant differently for one building (or a company) to another building (or a company). Such differences in the rental contracts can result in very different carbon and water intensity values across companies when companies report carbon emissions and water consumption based on their operational control.

To analytically overcome such difficulties that property companies face when reporting ESG activities, we propose a machine-learning model to estimate the total carbon emissions and water consumption covering tenants' energy and water consumption for the total property portfolio of a property company. For the sake of this project, one limitation that we have is limited data. However, the dynamic machine-learning model that we propose in this project will improve as more ESG data are accumulated.

In the carbon emissions category, we collect two carbon intensity measures (if available) for each company. The first carbon intensity measure covers carbon intensity occurring from the space that the owner has operational control – mostly Scope 1 and Scope 2 carbon emissions.[1] We call this measure *"Operational Control Carbon Intensity."* The second measure covers carbon emissions from tenants' usage and consumption in addition to operationally controlled space by the owner/property company, where tenants' carbon emissions are in general listed under Scope 3 carbon emissions. We call the second measure *"Building Carbon Intensity."*

In total, we collect 156 firm-year observations for carbon intensity, where we have at least one each for *Operational Control Carbon Intensity* and *Building Carbon Intensity*. Among those, we have 73 observations for *Building Carbon Intensity*. Among 33 of those 73 firm-years, we also observe *Operational Control Carbon Intensity*. Using these 33 observations where we have observations for both carbon intensity measures, we predict *Building Carbon Intensity* for 71 firm-years, where we only observe *Operational Control Carbon Intensity*, using a machine-learning model. We estimate the following equation:

$$(2)\ Building\ Carbon\ Intensity = f\left(\begin{array}{c} Operational\ Control\ Carbon\ Intensity, \\ Property\ Type\ Weighted\ Carbon\ Intensity\ Prior, \\ Location\ Weighted\ Climate, Economic, Demographic\ Factors, \\ Carbon\ Keyword\ Score \end{array}\right)$$

[1] As most companies report location-based carbon emissions, we collect data on location-based carbon emissions to have consistency across companies. This is relatively a conservative approach as market-based carbon intensity is in general lower than location-based carbon intensity.

We normalize all control variables with the mean and standard deviation of each parameter i.e. we calculate the z-score of each control variable. To eliminate outliers, we detect and eliminate outliers that are not in the range of 2.5 standard deviations.

To calculate property type weights and location weights, we use property portfolio data from SNL Financial. Using each property type, we determine the share for a property company in a given year. We categorize property types for multifamily (residential), office, retail, industrial, healthcare, lodging, self-storage, and specialty properties. Location weights are mainly calculated based on NUTS2 of each property. We determine NUTS2 of each property by reverse geocoding the coordinates of properties gathered from SNL Financial. We also use country and city weights wherever NUTS2 information is missing.

The goal of the machine-learning model proposed in Equation 2 is to convert *Operational Control Carbon Intensity* to *Building Carbon Intensity*. In the estimation model, our main determinant is the *Operational Control Carbon Intensity*, which is collected from company reports. Additionally, we create Property Type Weighted Carbon Intensity Prior as a control variable to estimate *Building Carbon Intensity*. For each company in a given year, we multiply benchmark carbon intensity of each property type in Table 2 by the weight of that property. Then, we calculate a carbon intensity prior as the average benchmark carbon intensity weighted by property type.

We also develop location-based control variables. Our aim is to benefit from potential locational determinants of carbon emissions such as weather conditions or environmental literacy proxied by education to better estimate the building-level carbon intensity. Among those, we create weighted average climatological controls for each company in a given year. We use weather station data from the National Centers for Environmental Information's (NOAA) 'Global Summary of the Month' (GSOM) dataset. The GSOM dataset has 114,789 stations available. To note, stations that do not have data available after the year 2000 have been eliminated from the list. Additionally, we only keep station data if we have observations every year. After cleaning, the number of available stations decreases to 53,257.

We then determine the closest station to a property in property companies' portfolio. From the matched stations, we use annual climatological variables such as minimum, maximum and average temperatures, precipitation, cooling degree days, and heating degree days. In Figure 1, we map the locations of properties owned by European public property companies that we cover and their corresponding weather stations.

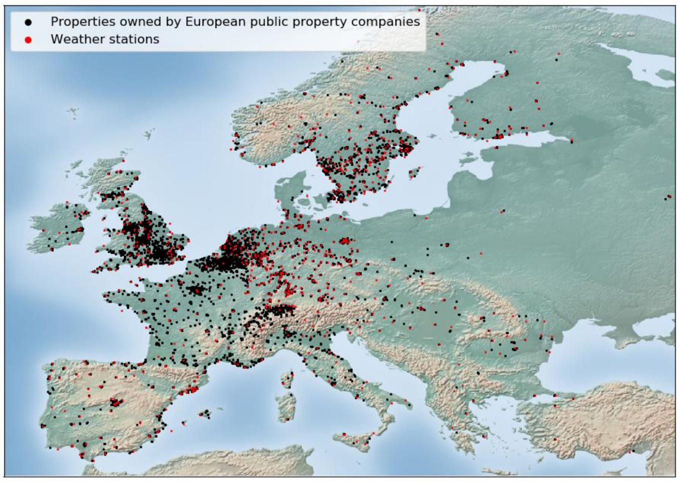


Figure 1: Properties Owned by European Public Property Companies and Selected Stations in Europe

More than 50% of weather stations that are matched with properties in the portfolios of property companies are within the range of 10 km to property locations: 2.4% are in a 1-km range, 7.4% are in a 2-km range, and 13.8% are in a 3-km range. As final control variables, we calculate weighted average maximum, minimum, average temperature values, total annual precipitation, and annual heating and cooling degree days for each firm-year observation. We expect that these climatological variables will help us predict the impact of climate on carbon emissions especially due to the energy consumption required.

We also use weighted average local economic and demographic factors. To capture the potential impact of environmental literacy proxied by education on carbon emission, we use the share of the population between 25 and 64 years old with a tertiary level of education out of the total population in a region. Our logic here is that on average, there may be a greater level of environmental awareness among highly educated people, which may contribute to lower carbon intensity policies. With a similar intuition, we expect that income is negatively correlated with carbon intensity. To control for income, we use GDP per capita. The list of variables obtained from Eurostat are reported in Table 3. For Norway and Switzerland, GDP data are not available for NUTS2 regions. We obtain the GDP data for the locations in Norway and Switzerland from the OECD database.

Table 3. Economic and Demographic Factors

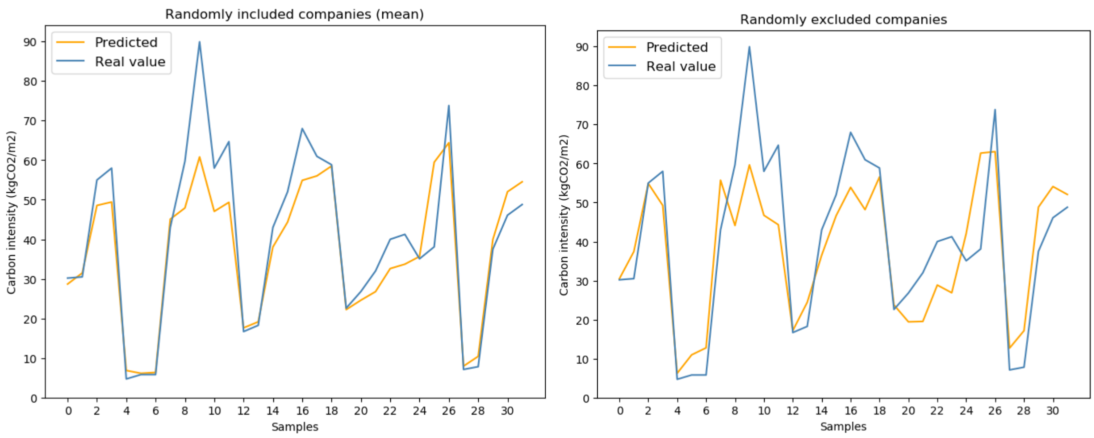
Factor	Variable Description	Eurostat Code
GDP	Gross domestic product (GDP) at current market prices by NUTS 2 regions	nama_10r_2gdp
EDU	Population aged 25-64 by educational attainment level, sex and NUTS2 regions	edat_lfse_04
Population	Population on 1 January by age group, sex and NUTS2 region	demo_r_pjangroup

We also create variables that can potentially capture the impact of companies' environmental practices on lowering carbon emissions. For this purpose, we create a keyword score. Some of the keywords include: "planted roof, renewable, clean energy, LED light, solar energy, solar, solar panel, Photovoltaic, and PV." Based on these keywords, we create a *"Carbon Keyword Score,"* which is the normalized sum of the occurrence of the keywords in the company reports.

In our estimations, we use a machine learning model, specifically, a multilayer perceptron (MLP) with one input, one output, and three hidden layers to analyze and predict *Building Carbon Intensity* for the companies that we do not observe. In the model, approximately 85% of the input dataset are reserved for training and the remaining 15% is used for testing. We follow two approaches. Firstly, we feed the model by all feature sets (12 individual parameters). Secondly, we use a Principal Component Analysis (PCA). The PCA is an efficient dimension-reduction method commonly used in machine-learning applications. This method is particularly useful, when the input dataset has many features and the sample size is comparably small such as our case. In our model, PCA is used as a feature-extraction and dimension-reduction method with a criteria based on the performance of the extracted features. In PCA, features are extracted by their ability to explain at least 90% of the variance of the original data. Overall, PCA-preprocessed MLP performs better than MLP alone.

K-fold cross-validation method is used for training and testing of the models. K-fold shuffles the dataset randomly and splits the dataset into k number of groups. Then, for each group, it takes a group as a test dataset where the remaining groups are used as the train dataset. Then, model is trained and evaluated for the relevant groups. We choose 6 for k in the model. In Figure 2, the estimations for randomly included companies (train datasets for each training) and randomly excluded companies (test datasets for each training) are presented.

The proposed model is trained 6 times with different dataset pairs. Each unique group of train datasets are merged and shown with their predicted values in Panel A of the Figure 2. Since each sample is used in the training 5 (k-1) times, there are multiple predictions for each train sample. In Panel B of Figure 2, observed carbon intensity values of the samples and the average of the predictions for the test samples are presented. Although the sample size is limited, the model performs well to predict out-of-sample excluded observations.



Panel A. Model Train *Panel B. Model Test*

Figure 2. Carbon Model Performance

To calculate total value of contributions through reducing carbon emissions, we use the price of CO_2 European Emission Allowances, which is used for the cap-and-trade model. Currently, the price of carbon is €25.56/tonneCO_2 (close price on Sep 19, 2019). We believe that this is a conservative valuation. According to a report by Carbon Tracker Initiative, the price of carbon may double by 2021 and quadruple by 2030. Additionally, in an academic paper published in Nature Climate Change, Ricke et al. (2018) ascertain that the global social cost of carbon is €380/kgCO_2 on average. The global social cost of carbon estimated by the authors is more than tenfold the carbon price. However, we stick to the price of carbon in the EU as it is determined in the capital markets. We obtain total m^2 of each property company portfolio from SNL Financial.

We model water consumption similar to carbon emissions. As companies conduct efforts to decrease water consumption, they will diverge from the global water consumption benchmark. We again use Equation 1 to calculate contributions from water consumption.

To our knowledge, there is no reliable source for water consumption benchmark across different property types in Europe. We benefit from the Chicago Energy Benchmarking Report (2017) and the City of Boston's Energy and Water Use in Boston's Large Buildings Report (2013) to determine our benchmark water intensities across property types after normalizing by the data we collect from

European public property companies' reports. The benchmark values across property types are shown in Table 4.

Table 4: Benchmark Water Intensities by Property Type

Property Type	Benchmark Water Intensity (m^3/m^2)
Multifamily	1.55
Office	0.65
Retail	0.70
Industrial	0.90
Lodging	1.90
Self-Storage	0.60
Specialty	0.85
Global Mean	1.00

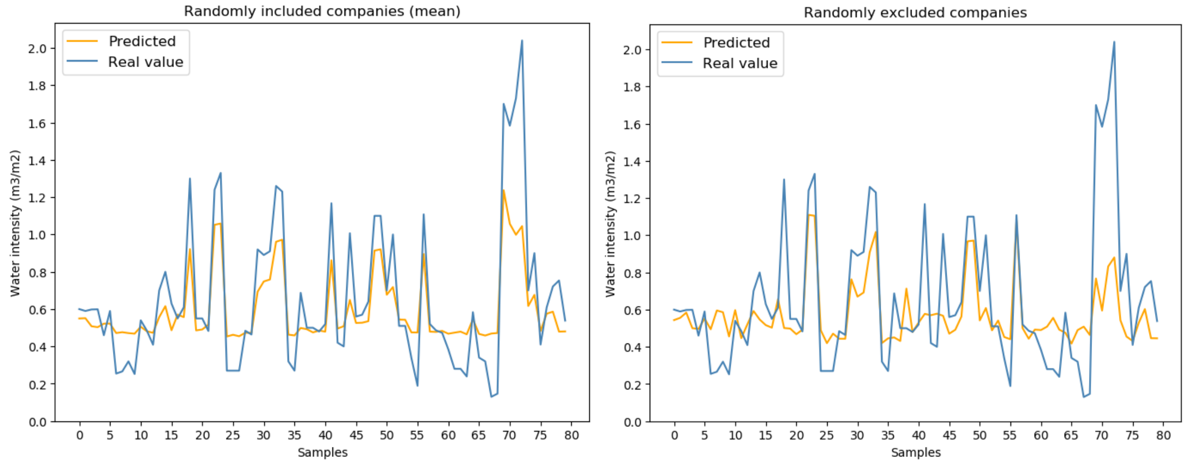
$$(3)\ Building\ Water\ Intensity = f\begin{pmatrix} Property\ Type\ Weighted\ Water\ Intensity\ Prior, \\ Location\ Weighted\ Economic \\ and\ Demographic\ Factors, \\ Water\ Keyword\ Score \end{pmatrix}$$

We normalize all control variables with the mean and standard deviation of each parameter i.e. we calculate the z-score of each control variable. To eliminate outliers, we detect and eliminate outliers that are not in the range of 2.5 standard deviations.

To estimate *Building Water Intensity*, we use a very similar model to the *Building Carbon Intensity* estimation as presented in Equation 3. In total, we collect 121 firm-year observations for water intensity, where we have either of *Operational Control Water Intensity* or *Building Water Intensity*. Among those, we have 102 observations for *Building Water Intensity*. We observe *Operational Control Water* Intensity for 19 firm-years but do not observe *Building Water Intensity*. We predict *Building Water Intensity* for those 19 firm-years, using the machine-learning model we propose.

We use a limited set of control variables for water intensity. Based on benchmark water intensity values, we create the *Property Type Weighted Water Intensity Prior* for each firm in a given year using the share of each property type in a property company's property portfolio. Water consumption is mainly determined by building efficiency and economic and demographic factors, which can be affected by local education level and income. The keywords that we use for the water category are "water, rainwater, and water efficiency." Based on these keywords, we again create *"Water Keyword Score,"* which is the normalized sum of the occurrence of the keywords in the company reports.

We follow a similar estimation procedure as in carbon intensity model using a machine-learning framework. Similar to the carbon emission model, we use k-fold cross-validation for water intensity model, where we choose 10 for k. As we have a smaller set of control variables (parameters) than the carbon model, we do not use PCA. The findings of the model are presented in Figure 3. The water model also performs well, as seen in the plot of the average predictions of out-of-sample water intensities compared to actual observations as in Panel B of Figure 3.



Panel A. Model Train *Panel B. Model Test*

Figure 3. Water Model Performance

To calculate the euro value of contributions to ESG activities through reducing water consumption, we follow the OECD's Environment at a Glance report (2015), where we collect the price of water per m^3 in the European countries. Using the data from the report, we calculate that the normalized price of water per m^3 on average is €4.00/m^3. Using Equation 1, we obtain the total value of contributions in the water category. The current value of water is also conservative by nature. Water scarcity is becoming a major issue globally, especially in major cities such as London or Paris. As the water scarcity problem worsens, the price of water will increase faster. We obtain total m^2 of each property company portfolio from SNL Financial.

Although waste generation is similar to carbon emissions and water consumption, the standard effort to decrease waste generation is recycling. From company reports, we collect total recycled waste in tons. Overall, we have 81 firm-years of observations for recycled waste. Since we directly collect total tons of recycled waste, we multiply it by a euro factor per ton of waste. While the economic benefits of recycled waste are various and not straightforward to quantify, in this project, we use landfill tax to convert recycled waste into euro benefits. We collect landfill tax for European companies from the Confederation of European Waste-to-Energy Plants. By averaging the landfill tax across European countries, we assume that the value of ESG contribution from recycled waste is €55/ton. Equation 4 presents the basic calculation:

(4) Contribution Value in Recycled Waste = Total Tons of Recycled Waste

x Euro Contribution per ton

It is a common practice among European public property companies to conduct employee training programs. The EPRA recommends that companies report hours of training per employee; this recommendation is followed by some companies. Using the available data in the company reports, we calculate the euro contributions in the employee training category, and we multiply hours of training per employee by the number of employees and the average expenditure to train employees.

According to the Association for Talent Development, $1,252 per employee for 33.5 hours accounting for approximately $37 (€34) per hour per person in the US. The figure for the UK is £1,530 per employee for 32 hours accounting for £48 (€54) per hour per person according to a report by the Department of Education in the UK. By averaging the two values, we assume that the economic contribution of employee training is €44 per hour per employee. Equation 5 reflects the calculation procedure. If companies directly report total hours of employee training, we take total value directly. In total, we collect total training hours for 36 companies.

(5) Contribution Value in Employee Training = Average Hours of Training per Employee
x Number of Employees Trained
x Euro Contribution per hour per employee

Regarding local community donations, we sum the euro value of the activities reported by companies. We observe the value of donations for 29 companies. There are also other environmental and social activities that European property companies conduct. In this project, we do not estimate the value of those activities due to the limited number of companies performing the activities and consequent limited information. As a result, the value of contributions we estimate is potentially a conservative estimate.

LIMITATIONS

In this section, we discuss potential limitations that we face in this project. One of the main limitations that we have is other potential activities that we do not classify. Although such uncategorized activities can be included in our final calculations, company reports are not sufficient to create ESG data on those activities. One important contribution that property companies can make to ESG activities is through the geographic effects of properties in regard to the society and environment. For instance, developing a mixed-type property in a region that needs economic development can help local communities grow. There are also other potential environmental and social effects through the property investment. The effects of properties on biodiversity, local transportation, the economic and social impacts of job creation, and air quality are some examples that are ignored in this project. Additionally, reducing carbon emissions and water consumption potentially have indirect community and social effects. Our estimations also potentially disregard such benefits, making our estimation results more conservative. Main reason to take no notice of such activities and effects is data limitation. The other reason that we exclude such categories is that there is no direct way of estimation of those categories as they may potentially increase the measurement error.

From a financial accounting perspective, companies' spending on investments is reported under capital expenditures. With this logic, if a company makes an investment on environmental activities to reduce impact such as solar panels for producing electricity in their own buildings, the capital expenditure for such an activity is the company's spending on the costs of solar panels themselves and installation of the panels. Although property companies explain these kinds of actions, they do not report the capital expenditures on such activities. On the other hand, companies report their energy consumption, carbon emissions and savings based on ESG investments such as solar panel installation. Due to such a data limitation on capital expenditures for such activities, our analysis and measurements are mainly based on euro contributions of European public property companies to ESG activities through social contributions or reducing environmental impact such as carbon emissions.

In the estimation of environmental categories, one of our targets is to control for a determinant, which can capture environmental activities. For this purpose, we collect information on the *Green Share* of property portfolios of companies. However, we find that the correlation between *Green Share* and carbon intensity is positive, which is against our expectations. On the other hand, Devine, Steiner, and Yönder (2017) find that operating expenses increase by *Green Share* for the US REITs in their EPRA-funded research, where an opposite relationship is expected. The authors explain this inverse relationship by the technological advancements of certified properties. Considering such an inverse relationship, we drop *Green Share* from our estimations. Based on these findings, further research is needed for the impact of certifications on building operating expenses and carbon emissions. Since this is beyond the scope of this project, we do not control for *Green Share* in our estimations. Instead, we use our keyword score measures.

Our estimations are sensitive to the selection of benchmark values. One of our aim in this project is to propose a modelling and machine-learning estimation procedure to firstly estimate euro value of contributions. The estimation procedure that we propose including the benchmark values is the first attempt to develop a value measure, which is important for our understanding of such ESG activities. The model we propose is dynamic in nature so can be improved as more ESG data are accumulated. The benchmark values in our model can be considered as the cap values proposed by the European Commission. Additionally, the benchmark values should be lowered periodically in the future in line with the zero-carbon targets.

Lastly, it is difficult to determine a benchmark for waste that is generated by a single building due to data limitations. Most company reports cover the amount of waste recycled and accordingly, in the waste category, we concentrate on the waste recycled. On the other hand, carbon emissions from waste are mostly covered in the carbon intensity measures reported by companies so carbon emissions from waste are mainly covered in the carbon category in our estimations.

Findings on the Value of ESG Contributions

In this section, we calculate the total value of contributions to each ESG activity. We calculate *Building Carbon Intensity* for 72 companies. While for half of the companies, we collect *Building Carbon Intensity* directly, for the other half, we estimate *Building Carbon Intensity* using our machine learning model. We calculate a weighted average benchmark weighted by property type shares in each property company's portfolio for *Building Carbon Intensity* for each company. We follow a similar procedure for water consumption, as well. In total, we calculate *Building Water Intensity* for 63 companies, for 12 of which we estimate *Building Water Intensity* using the machine learning model. In the waste category, we collect information for 35 companies.

Table 5. Value of Contributions through Reducing Environmental Impact

	Panel A - Carbon ($kgCO_2/m^2$)			
	Number of Companies	Building Carbon Intensity net of Benchmark	Total m^2 per Company	Total Value of Contributions per Company
All companies	72	87.12	2,339,035	€4,754,341
Actual data	36	84.63	2,318,632	€4,828,630
Estimated data	36	89.60	2,360,039	€4,680,052
	Panel B - Water (m^3/m^2)			
	Number	Building	Total m^2	Total Value

	of Companies	Water Intensity net of Benchmark	per Company	of Contributions per Company
All companies	63	0.26	2,463,023	€2,046,447
Actual data	51	0.26	2,505,894	€1,704,296
Estimated data	12	0.27	2,268,158	€3,601,678
	Panel C - Waste Recycled (tons)			
	Number of Companies	Waste Recycled per Company	Recycle Ratio	Total Value of Contributions per Company
All Companies	35	12,113	0.48	€666,245

The findings are presented in Table 5. The mean of *Building Carbon Intensity* net of the benchmark for companies directly reporting *Building Carbon Intensity* is roughly 5 $kgCO_2/m^2$ smaller than the estimated values, where it is 84.63 $kgCO_2/m^2$ and 89.60 $kgCO_2/m^2$, respectively. We multiply *Building Carbon Intensity* net of the benchmark by the total m^2 of a company's property portfolio and euro contribution per $kgCO_2$. We present total value of contributions in the last column of Table 5. On average, we estimate that a European public property company contributes to ESG activities through reducing carbon emissions with a value of €4.75 millions annually. Our estimations using machine learning model give similar results to the value calculations based on the actual *Building Carbon Intensity*, on average.

We find similar means at around 0.26 m^3/m^2 for *Building Water Intensity* net of the benchmark for the calculations based on actual and predicted *Building Water Intensities.* The mean of total value of contributions to ESG activities through reducing water consumption is estimated to be around €2.05 millions annually. In the waste category, on average, the recycle ratio is around 0.48. Companies recycle 12,113 tons of waste on average and the value of contribution to waste is around €0.67 million annually.

Table 6. Value of Social Contributions

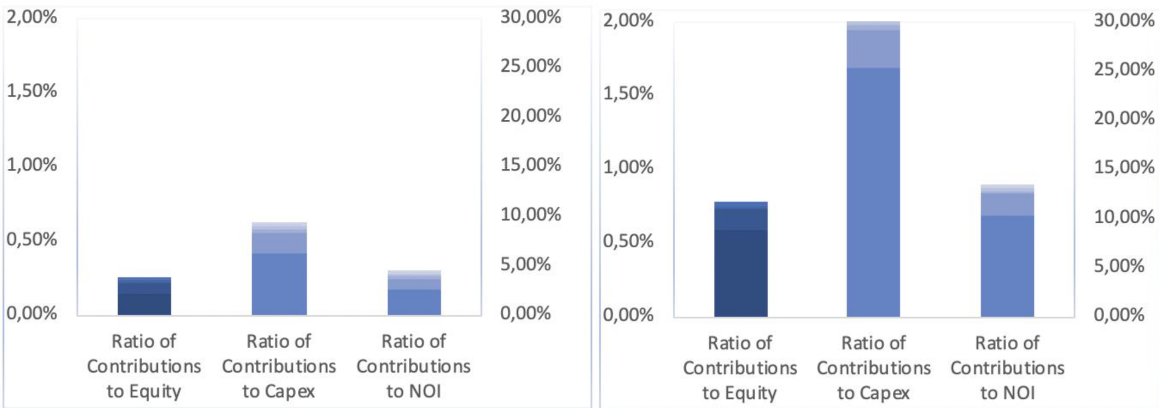
	Number of Companies	Employee Training per Company (total hours)	Total Value of Contributions per Company
Employee Training	48	9,618	€423,176
Local Community Donations	29		€555,881

We present the findings on social contributions in Table 6. Based on our text extraction algorithm and manual readings, we are able to collect data for 48 companies on employee training. The mean of total hours of employee training per company is around 9,618 hours. The total contribution in this category is €0.42 million annually. Finally, we collect data on local community donations from company reports. We obtain concrete data for 29 companies and the euro value of contributions corresponds to €0.56 million annually. Overall, for the five categories we determine, an investor can contribute to ESG activities with a value of €8.34 millions annually by investing in an average European public property company.

Table 7. Ratio of Contributions to Company Financials

Contributions by ESG Category	Ratio of Contributions to Capex		Ratio of Contributions to NOI		Ratio of Contributions to Equity	
	Mean	Max	Mean	Max	Mean	Max
Carbon Emissions	6.34%	58.98%	2.57%	35.78%	0.15%	0.62%
Water Consumption	1.93%	13.31%	1.18%	9.51%	0.07%	0.62%
Waste	0.48%	2.69%	0.21%	1.72%	0.01%	0.10%
Employee Training	0.28%	1.24%	0.18%	1.99%	0.01%	0.18%
Local Community Donations	0.44%	2.06%	0.45%	1.88%	0.02%	0.09%
Total Contributions	9.47%		4.59%		0.26%	

We collect financial data from SNL Financial to normalize contributions to ESG activities as presented in Table 7. We use Capex to investment property, NOI, and total equity. In total, an average property company contributes to ESG activities by 9.47%, 4.59%, and 0.26% as a share of Capex, NOI, and total equity, respectively. The company contributing most contributes up to 59% and 36% of Capex and NOI, respectively.



Panel A. Main Estimations *Panel B. Projected Estimations*

Figure 4. Ratio of Contributions to Company Financials based on Main and Projected Estimations

We also show the share of contributions in Figure 4. Panel A presents estimations based on our main model and findings in Table 7. In Panel B, we modify the euro value of contributions per unit carbon and water. Tracker Initiative estimates that the price of carbon may quadruple by 2030. Additionally, Ricke et al. (2018) find that the global social cost of carbon is €380/kgCO_2 on average. To reflect such potential changes in the economic effects of carbon emissions, we double our per unit cost of carbon to a value of roughly €100/kgCO_2 in Panel B. In a press conference in 2019, the chief executive of the UK Environment Agency states that there will potentially be 50-80% less water in the rivers of the UK due to climate change.[2] To observe the impact of such water shortages on water prices, the price of water in our model is projected to double to a value of €8/m^3. The impact on the share of contributions due to

[2] For more information, https://www.theguardian.com/environment/2019/mar/18/england-to-run-short-of-water-within-25-years-environment-agency, latest access date: September 5, 2019.

such shocks or changes are presented in Panel B. The ratio of contributions to Capex and NOI rises to almost 30% and 15%, respectively. The ratio of contributions to total equity increases 0.8%.

Concluding Remarks

In this project, we propose and develop a model to estimate the value of contributions to ESG activities by investing in the European public property companies that an investor can make. To our knowledge, this is the first study to create and quantify the total value of contributions to ESG activities through social contributions and reducing environmental impact.

Due to difficulties in creating ESG database especially on carbon emissions and water consumption, we additionally propose a machine learning model to estimate and standardize such datasets. Our model is dynamic in nature and as the ESG data grow, the model's performance will improve accordingly. The model we develop can additionally be enhanced and improved by creating and adding new ESG categories as real estate industry offers a strong potential to contribute to ESG activities.

Real estate industry is considered to be the largest potential contributor to environmental issues and real estate companies also interact societies and local communities though their properties. The activities conducted in buildings can greatly contribute to local community development. The value of the measure we create is important for the real estate industry and its participants, such as asset owners, property managers, pension fund managers, and institutional investors to understand how much of every euro an investor spends on a property company contributes to ESG activities through social contributions and reducing environmental impact.

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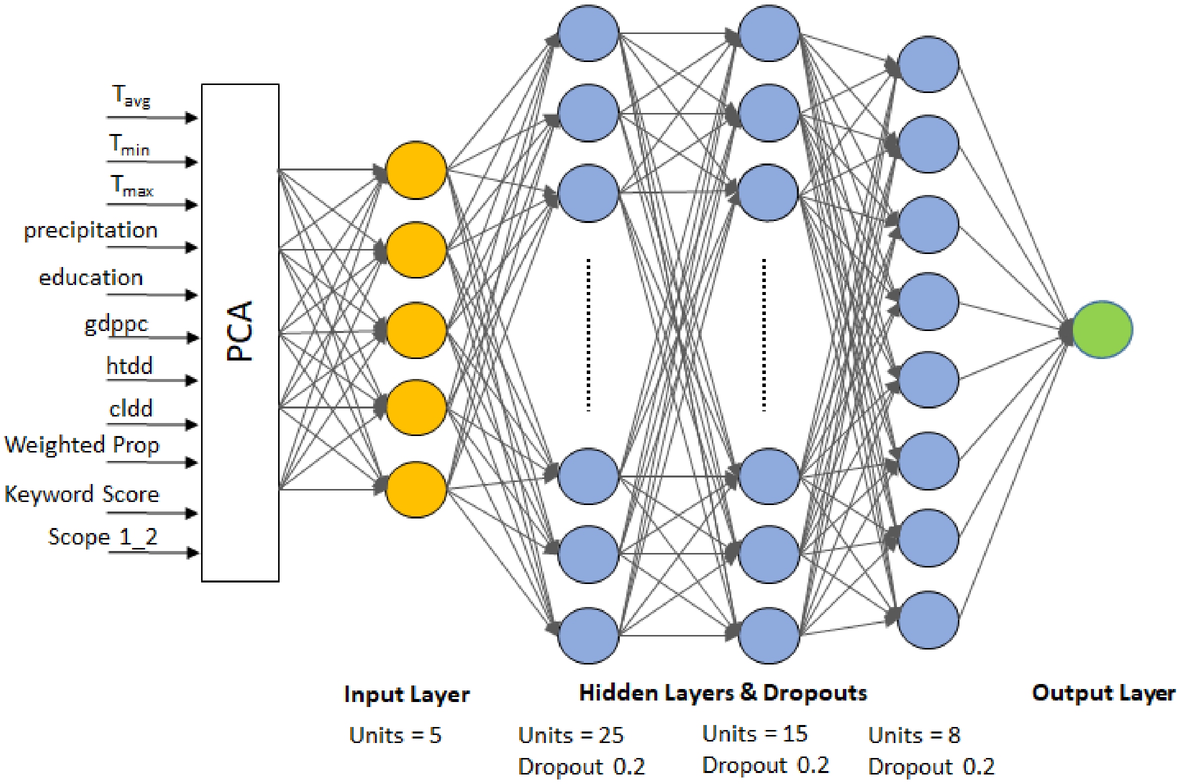
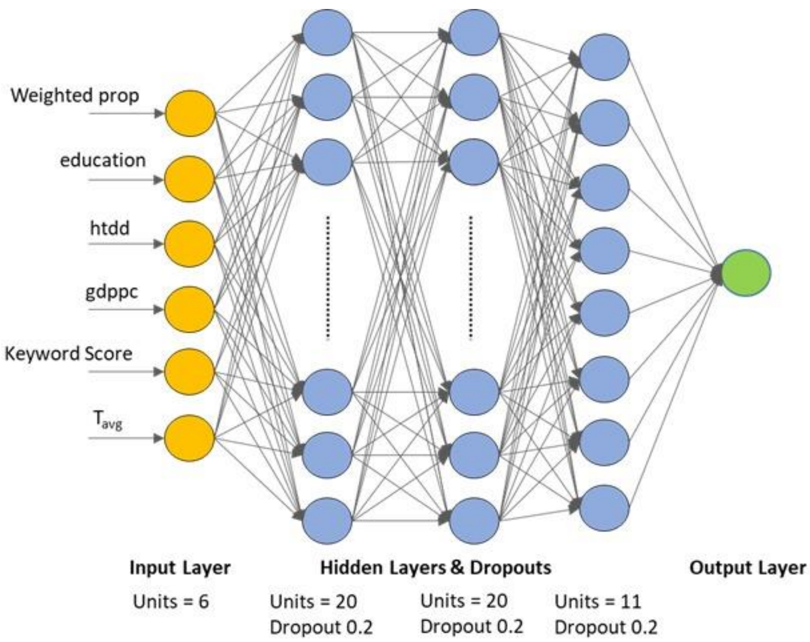
Appendix A



Panel A. Schematic Neural Network Model for Carbon



Panel B. Schematic Neural Network Model for Water

Figure A1. Schematic Neural Network Model for Carbon and Water