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A Support Vector Machine approach for predicting progress toward environmental sustainability from information and communication technology and human development

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Abstract
Human activities are increasingly affecting the planet and its sustainability by degrading and damaging the environment. The literature on this topic has demonstrated that Information and Communications Technology (ICT) and human development (HD) are important promoters of progress towards environmental sustainability. The impact of these factors is most often examined by using standard regression analysis which suffers from the problems of multicollinearity and non-linear dependency. In order to resolve this problem, a non-parametric method is proposed. To be specific, a Support Vector Machine (SVM) model for predicting environmental performance growth has been developed, based on various predictors- ICT and HD indexes, population growth, and an economic development indicator. The prediction is made at the macro level using a sample of 139 countries. The model was created by a prediction procedure consisting of the optimization of the SVM learner parameters using the grid-search method, as well as k-fold cross-validation. A predictive accuracy of the SVR model of 80.4% was achieved. The model predicts growth in environmental performance of 1.5% for each 1% increase in the ICT index, while an increase of the HD index of 1% produces an environmental performance increase of 4.3%. The results of the sensitivity analysis confirm that the effects of both predictors are enhanced when they operate in interaction. This the first study to apply the predictive machine learning method to the analysis of the impact of ICT and HD on environmental performance and empirically confirmed its efficiency. The obtained results contribute to the existing literature and could be beneficial to policy makers working in sustainable development.

Keywords Environmental performance · Human development · ICT · Sensitivity analysis · Support vector regression

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1 Introduction

The concept of sustainability is a complex subject and it is very demanding as a research area, since it covers broad topics (health, the economy, the environment, and so on). Therefore, it has received considerable attention from scholars who have produced numerous research papers on sustainable development in various areas. However, the rapid exhaustion of natural resources and concerns over the environmental impact of human activities has prompted additional interest in this research field.

The Sustainable Development Goals (SDG) consists of 17 goals, five of which concern environmental issues, which shows the significance of this dimension for the overall development of society (UN General Assembly 2015). Greenhouse gas emissions (GHG) have been recognized as a major factor in influencing global warming, climate change and environmental sustainability. Human activities are increasingly becoming a significant factor in the growth of GHG emissions, especially carbon dioxide (Wu and Raghupathi 2018). The application of information and communication technologies can significantly contribute to reducing the levels of GHG in a variety of ways. Directly, ICT can influence increasing efficiency in production, as well as a reduction in and saving of electricity consumption, for example by controlling heating and cooling systems using ICT (Budde 2013) or by using intelligent transportation systems (National Research Council 2012; Funk 2015) and smart power distribution networks (Moretti et al. 2017). Systems for the automatic control of irrigation and land use contribute to the preservation of natural resources and the sustainability of agrarian development (Gouvea 2015). However, the indirect effects of ICT are also significant, achieved through the behaviour of individuals and the form of operation of businesses based on ICT solutions. The use of the Internet and telecommunication technologies for private and business communication considerably reduces the consumption of electricity and the emissions originating from traffic. E-commerce, e-banking and supply chains (marketing, ordering, payment and delivery of products and services using ICT) contribute to greener economies (Qiang and Rossotto 2009; Chen 2018), while systems of e-government contribute to greener state administrations (Raghupathi et al. 2014; Møller et al. 2019). The ability to remotely read and control connected devices (via the Internet of things) in order to monitor environmental parameters (but also in other applications) can significantly contribute to sustainability (Manyika et al. 2015). ICT enables the efficient management and exchange of our accumulated knowledge on environmental sustainability, which significantly contributes to the development and promotion of regulations at the international level (Murugesan 2008; Forge 2009). This is of particular importance for countries in transition and developing countries that have not adopted their own policies on environmental sustainability. In recent times, cloud computing and "big data" services have notably reduced the negative impact of electronic waste and energy consumption by computers (Liang et al. 2012; Song et al. 2017).

The 2030 Agenda emphasizes the importance of ICT for all of the 17 Sustainable Development Goals. Moreover, many recent studies have confirmed the link between ICT and sustainable development (Hilty 2008; Neves and Krajewski 2012; Wang et al. 2015; Funk 2015; Wu and Raghupathi 2018 and others). The Global e-Sustainability Initiative (GeSI) emphasizes the importance of e-health, e-learning, and smart building for achieving the goals of economic, environmental and social sustainability. ICT stimulates the development of a knowledge-based society where information and knowledge are prerequisites for economic growth and sustainability (El-Sherbiny 2005; Forge 2009). ICT technologies have been recognized and confirmed many times in the literature as the drivers of economic development and other macroeconomic performances (Fors and Moreno 2002; James and Hills 2003; Avgerou 2010; Gigler 2011; Hanclova et al. 2015 and so on). However, fewer papers have investigated the impact of ICT on environmental sustainability (Hilty et al. 2006; Wang et al. 2015; Özcan and Apergis 2017; Gouvea et al. 2018).

However, certain alternative findings should not be neglected. Thus, Hilty et al. (2006) state that ICT may have the opposite effect on the environment. According to Posani et al. (2018), ICT accounts for 10% of the world's total energy consumption. Digital waste has grown exponentially over the last decade, while the demand for electricity due to cloud computing has increased significantly. The increase in the generation of data and documents requires a huge amount of energy, without considering the fact that some of it is digital waste. The energy required for the annual exchange of e-mails alone involves electricity sufficient to power two million homes or produce three million cars. (Schmidt 2010). According to Higón et al. (2017), ICT production and use have a negative impact on the environment through increases in both electricity consumption and CO_2 emissions, but only up to a certain level of ICT development, at which point that impact is transformed into a positive one (via an inverted U-shaped relationship).

Economic growth and population growth are considered to be major anthropological environmental stressors (Dietz et al. 2007). The growth of the economy in developing countries leads to an accelerated growth of revenues and trade, structural changes and the accumulation of capital, which given the lack of environmental awareness and regulations, contributes to a rapid growth in CO_2 emissions (Panayotou et al. 2000). Tóth and Szigeti (2016) point out that population growth in itself is not a major factor in environmental degradation; rather the issue is the type and the level of consumption, multiplied by the number of consumers. According to Dietz et al. (2007), increases in the level of education and life expectancy are not significant environmental stressors, hence these aspects of human development can be achieved without negative consequences for the environment. In order to counteract the negative effects of economic growth and population growth, it is necessary to increase the efficiency of the use of resources, which can be best achieved by using innovative technologies, primarily ICT, and by increasing the ability of the population to competently use these technologies, that is, by increasing the level of human development. This suggests that human development and the development of ICT jointly can have a significant positive impact on environmental sustainability (Gouvea et al. 2018). Some recent research has established a positive correlation between human development and environmental sustainability (Popescu et al. 2017). In the literature it has also been shown that there is a difference between developed and developing countries in terms of the relationship between human development and environmental sustainability (Samimi et al. 2011). Developing countries largely depend on the exploitation of natural resources and the assets created from this are not sufficiently invested in programmes and projects for human development (Neumayer 2012).

The aim of this research is to determine whether environmental performance can be predicted, at the global level, based on ICT and human development, including population growth, with regard to the level of economic development. A sample of 139 countries was considered, which was divided into developed countries, countries in transition and developing countries, in accordance with the World Economic Situations and Prospects (WESP) classification (United Nations 2018).

There are many indicators at the international level to measure the changes in the economic, social and environmental aspects of sustainable development. With regard to the environment, the ESI (Environmental Sustainability Index), the EPI (Environmental Performance Index), the EF (Ecological Footprint), the HDI (Human Development Index), the HPI (Happy Planet Index), among others are the most widely used in the literature [more details can be found in Mally (2011)]. All of these indices have some limitations that reflect the difficulty in capturing the complexity of sustainable environmental development, but which enable the possible assessment and ranking countries in relation to environmental degradation. Recent research has tried to overcome the limitations of existing indexes through the continuous introduction of new ones that offer better comparative analysis; the DBI—Development Balance Index is one example (Mally 2011). The others propose a different approach by relating a country's impact and the availability of their resources, for example the proportional impact on the environment (Bradshaw et al. 2010). The EPI is an indicator that shows the extent to which environmental policies are being implemented and how much these practices vary from the target outcome. Environmental performance prediction aims to create appropriate policies for environmental sustainability. Given that the EPI is seen as a good basis for effective policymaking (Yale Center for Environmental Law and Policy 2018), this index is taken as a measure, bearing in mind that high EPI values do not necessarily mean reduced pressure on the environment.

Different methods have been used to examine the empirical linkage between ICT, human development and environmental performance, depending on the subject of research. The most commonly used methods are multiple linear regression methods (either cross-sectional or panel). However, the correlation and multicollinearity of regressors are very common problems in these methods. Between ICT and human development, there exist mutually causal linkages, which may affect the consistency of the parameters in the regression models. Furthermore, previous studies have shown a nonlinear relationship with an inverted U shape between economic development and the environment (Panayotou et al. 2000), and between ICT and the environment (Higón et al. 2017).

In order to overcome the problems of multicollinearity and the specification of corresponding nonlinear functional form, this paper uses the SVM method which does not face these issues. Basak et al. (2007) point out that this method represents "state-of-the-art tools for nonlinear input–output knowledge discovery" and "a powerful technique for predictive data analysis". The SVM is applied in various research areas with "noisy and risky" predictions (Christmann 2004; Li et al. 2008; Azeez et al. 2018; Nazemi et al. 2018).

The subsequent sections of this paper are organized as follows: The next section gives the conceptual framework for predicting environmental sustainability (measures and hypotheses). The data used are described and finally the applied SVM method and the predictive procedure are explained. Section 3 presents the results of the predictive analysis, which are discussed together with their implications. Section 4 offers concluding observations, where key research contributions, certain limitations and areas for further research are discussed.

2 Materials and methods

To achieve the defined goal of the study, we broadened the framework provided by Gouvea et al. (2018) which investigated the impact of these factors on environmental performance using linear regression. As pointed out in the previous section, the literature confirmed divergence because of the different levels of economic development. For that reason, we introduced a control variable, as an indicator of economic development, which makes a deeper analysis possible. In order to determine the expected level of increase in environmental sustainability as a result of a given increase in the considered factors, a prediction model was created, rather than an estimation model. The first step was the determination of the measures for environmental sustainability and predictors.

2.1 Measures

As the measures, we chose indices formed by reputable international and national institutions on the basis of a great number of environmental, economic and technological indicators, which have already been implemented in other research (Gouvea et al. 2018). The control variable was defined based on the WESP (United Nations 2018) classification of countries by economic development. A detailed description of the chosen measures is provided in the following paragraphs.

2.1.1 Environmental performance

We used the 2018 Environmental Performance Index (EPI) (Yale Center for Environmental Law and Policy 2018), a broadly accepted measure of environmental trends and progress, developed by Yale University and Columbia University in collaboration with the World Economic Forum. The EPI is based on 24 performance indicators across ten categories (air quality, water and sanitation, heavy metals, biodiversity and habitat, forests, fisheries, climate and energy, air pollution, water resources and agriculture) that are then aggregated into two main policy objectives: environmental health and ecosystem vitality and finally into the overall EPI.

Across the policy objective of environmental health, air quality continues to be the leading environmental threat to public health. The problem is particularly severe in cases where greater levels of economic development contribute to higher pollution. As the development of a country progresses, and as its industrial production, population and transportation increase, people are more exposed to higher levels of air pollution. The overall situation with water and sanitation is improving since investment in sanitation infrastructure has increased and government regulations have been strengthened when compared to previous eras. However, in some countries, notable efforts are still needed to ensure safe drinking water and functional sanitation services. The presence of polluting heavy metals remains a severe threat to environmental health. Thus, economic development should be carefully examined alongside pollution regulation, in order to diminish the health impact of, for example, exposure to lead.

Across the ecosystem vitality policy objectives, many challenges remain. The presence of a higher-quality habitat free from human pressures continues to be an important goal. In terms of forests, losses in global tree coverage are increasing due to fires, illegal logging, agricultural clearing and so on. Global trends in fishing are worrying because of the increasing overexploitation of fish stocks. The indicators that cover climate and energy show an improvement in gas emissions over the past decade. However, the positive trend needs to demonstrate that it is both stable and long-lasting. Air pollution scores for all countries have improved despite vast differences in starting points between developed and developing countries.

Environmental health and ecosystem vitality, as the two main pillars of the Environmental Performance Index are sometimes in conflict, since economic growth usually increases environmental health while placing the ecosystem is under pressure from urbanization and industrialization. Therefore, a good balance is crucial to maintaining environmental sustainability.

When all these aspects of environmental sustainability are united in one index, the basic idea is to weigh how close a specific country is to its defined environmental policy goals. For comparison purposes, score for indicators are measured on the scale from 0 (the worst rating) to 100 (the best rating). The EPI is a composed index and a more detailed explanation of its construction is given by Nardo et al. (2008) and Hsu et al. (2013).

While the EPI represents a great analytical tool to assess and measure environmental sustainability, some severe problems related to the data must be taken into consideration. Data collection and reporting, as well as missing data, especially in areas of water resources and management remain a significant challenge for future projects.

2.1.2 Information and communication technology

The Networked Readiness Index is a leading indicator of how a country is performing in the digital world. The NRI was launched by The World Economic Forum in 2011 with the main purpose of identifying common factors that help countries to use technology effectively. Therefore, the NRI measures how well an economy is using information and communication technologies to boost its competitiveness and well-being (World Economic Forum 2016).

The NRI is a very complex index derived from 53 indicators which are based on the network readiness framework. The basic idea is to identify a country's main drivers which reflect its capacity to use ICTs in order to increase competitiveness and deliver overall economic benefits. The drivers are classified into three basic subindices: environment (political and regulatory; business and innovation), readiness (which includes infrastructure, affordability and skills) and usage (broken down into individuals, business and government). The impact is examined as a separate sub-index and measured in terms of both its economic and social impact.

The environment sub-index assesses the extent to which a country's political, regulatory, and business and innovation environment supports ICT development. It measures the conditions that facilitate business activities and competition that would lead to innovation in ICTs. The readiness sub-index measures a country's development of infrastructure that would support the use of ICTs. It measures ICT infrastructure through the development of mobile network coverage, secure internet servers and electricity production. An important dimension of this sub-index is its examination of the affordability of ICTs through mobile telephony and internet subscription costs. The final component of the environmental sub-index is related to skills. It assesses the effectiveness of the usage of ICTs through different measures, such as the enrolment rate in secondary education, the adult literacy rate, the quality of the education system, and so on.

The Usage sub-index estimates how well the government, businesses, and individuals adopt ICTs. The main indicators in this pillar are mobile telephony penetration, personal computer ownership, the availability and quality of government online services, and so on. The wide economic and social impact obtained from ICTs is covered by the impact sub-index.

Each of the sub-indices is calculated on the basis of individual indicators. The overall NRI score is computed after the aggregation of the sub-index scores.

The main providers of data for the NRI are the International Telecommunication Union (ITU), the World Bank, the United Nations Educational, Scientific and Cultural Organization (UNESCO) and other UN agencies. In addition, national sources are used to fill the data gap in some cases.

Networked readiness is improving across the world, with a significant increase in its performance especially in developed countries, but also in many emerging and developing countries. Today, we are able to witness the enormous impact of ICT's not only on the economy, but also on forms of working and lifestyle globally.

2.1.3 Human development

Measuring human development has until recently constituted a huge challenge. However, a significant turning point was made when national development ceased to be understood only in terms of income per capita, and as health and education began to be taken into consideration. Therefore, the distinctions in human development between countries reflect their different levels of development in education, health, employment, income disparities and other areas.

Over the years, the Human Development Index (HDI) (produced by the United Nations Development Programme) has served as a reliable platform and a useful tool for analysing the distribution of human development between countries, and we use this tool in our study. It is a composite index quantifying average achievements in three basic dimensions: a long and healthy life (assessed by life expectancy at birth), knowledge (measured by mean years of schooling for adults aged 25 years and over and expected years of schooling for children of school-entering age) and a decent standard of living (measured by gross national income per capita). The HDI is the geometric mean of the normalized indices for each of the three categories.

The HDI serves as a summary measure of human development, covering both social and economic development. Even though it is considered to be one of the most widely-used measures of well-being, it has some weaknesses. The main one is that it does not consider the aspect of sustainability, especially within its environmental component. For this reason, Maccari (2014) proposes a new index named EHDI (Environmental Human Development Index) and explains the process of its construction. For the purpose of this analysis, HDI, and not EHDI, is used to test for its impact on environmental performance.

2.1.4 Population

All the data on population size were downloaded from the United Nations, Department of Economics and Social Affairs. All measurements are in millions of people.

2.1.5 Country classification

There are many different classifications of countries with respect to development, depending on the criteria for the measurement of development that different organizations use. For the purposes of this analysis we used the classification presented in World Economic Situations and Prospects (United Nations 2018) and published by the Development Policy and Analysis Division (DPAD) of the Department of Economic and Social Affairs of the United Nations Secretariat (UN/DESA). According to this United Nations (2018), all countries are classified into one of three broad categories, based on their economic conditions: developed economies, economies in transition and developing economies. Although several countries that belong to the "economies in transition" category have characteristics that could place them in more than one category, they are grouped in one category only, based on the principle of mutually exclusive groupings.

2.2 Data

The necessary data, in line with the predefined measures, were downloaded from publicly available sources Environmental Performance Index for 2018; Human Development Index for 2018; World Economic Forum, 2016; WESP-World economic situation and prospects, 2018.

Our initial dataset comprised 180 countries available from the database of the EPI index. Then we assembled the remainder of the data (on the above described measures) for all the countries. However, due to missing data for some of the variables, we completed our sample using 139 countries, beginning from Albania and ending with Zimbabwe. Since the variables' scales and units differed significantly, we normalized the data for each variable. The main reason for this was to improve the data fitting and prediction, but also because it was a requirement for SVM regressions. The main descriptive statistics are summarized in Table 1.

Table 1 Summary of variables' descriptive statistics

	Minimum	Maximum	Mean		Std. deviation	Variance	Coef. of var.
	z = 0	z = 1	Statistic	Std. Error	Statistic	Statistic	Statistic
EPI	Burundi	Switzerland	0.51	0.02	0.22	0.05	0.42
NRI	Chad	Singapore	0.47	0.02	0.25	0.06	0.52
HDI	Chad	Norway	0.61	0.02	0.26	0.07	0.44
Pop	Seychelles	China	0.04	0.01	0.12	0.01	3.33

2.3 Hypotheses

The environmental effects by human activity coupled with the consumption of energy and materials can be significantly reduced by using ICT. The use of these technologies leads to changes in the processes of production, transportation, consumption, communication, power transmission and construction, and in the way of life and work in general (Servaes 2012). For example, transatlantic flights can be replaced by videoconferencing; travel to work can be replaced by working from home; classic traffic patterns can be altered by intelligent traffic systems; standard construction is replaced by smart buildings; the normal transmission of power becomes smart grids; physical products can be replaced by e-services, and so on. ICT contributes to the accumulation and exchange of knowledge on environmental performance, which accelerates and encourages the production and application of regulations in this area (Michener 2015). Special intelligent tools allow the analysis, simulation and forecasting of ecological processes (for example, monitoring air quality and other environmental indicators, predicting environmental disasters, and so on) (Michener and Jones 2012). The SDG promote ICT as one of the main drivers of environmental sustainability. The positive effect of ICT on environmental sustainability has been demonstrated in various recent papers (Özcan and Apergis 2017; Gouvea et al. 2018). Following on from this finding, in order to determine whether and to what extent it is possible to predict the growth of environmental performance at the macro level based on the increasing use of ICT, the following hypothesis is defined:

H1 An increase in the NRI causes an increase in the predicted value of the EPI.

In developed countries, ICTs have greatly influenced profound changes in life habits, while in developing countries these changes are just beginning to have an effect. Many developing countries do not have a sufficiently developed ICT infrastructure, nor a sufficient average level of education, for its wider use. The economies of these countries are largely dependent on the exploitation of natural resources, and a significant proportion of global production has moved to these countries (due to their cheaper labour forces); hence, they now account for a greater share in the emission of harmful gasses compared to developed countries. According to Özcan and Apergis (2017), Brazil, China, India and South Africa are among the world's largest carbon emitters. These countries are also large ICT producers which can somewhat reduce the positive effect due to electronic waste. For these reasons, it is expected that there will be a less positive impact of ICT technologies in developing countries than in developed countries. This is despite the fact that developing countries are increasingly investing in the production and use of technologies that are less energy demanding, such as laptops and mobile phones, which can lead to higher savings. The penetration of the Internet and mobile phones in these countries has been rapidly increasing in recent years (World Bank 2018), so it is expected that ICT technologies will have a stronger positive impact. For this reason, it is important to predict to what extent the increase in use of these technologies can contribute to a higher degree of progress toward sustainability in developing countries. Taking into account all of the above, the following hypothesis is defined:

H1.1 An increase in the NRI causes a larger increase in the predicted value of the EPI in developed countries than it does in transition and developing countries.

While the problem of high electricity consumption, the growth of the economy being based on natural resources and the problem of population growth is pronounced in developing countries, in countries in transition, which includes the countries in the Balkans, the major problem is the absence or insufficient awareness of and lack of regulations concerning sustainable development, as well as insufficient investment in this area. The development of ICT infrastructure and the opportunity to apply these technologies is better in most countries in transition than it is in developing countries (World Bank 2018). Therefore, it is expected that there will be a higher positive impact of ICT technologies on environmental performance in countries in transition than in developing countries. In order to determine whether and to what extend the development of ICT predicts higher performance in countries in transition compared to developing countries, the following hypothesis is defined:

H1.2 An increase in the NRI causes a larger increase in the predicted value of the EPI in countries in transition than in developing countries.

Environmental sustainability largely depends on the ability of the population to efficiently use resources, and on the readiness of the state to act in accordance with environmental regulations. A higher degree of human development, by itself or in interaction with the development of ICT, has been linked to sustainability in some recent research (Popescu et al. 2017; Gouvea et al. 2018). Developing countries devote more attention to economic growth (poverty reduction) than to human development. Hanushek (2013) points out that human development (especially the development of the educational system) is one of the fundamental requirements for economic growth in developing countries, and that the rapid expansion of digital technologies and their integration with the system of education can increase the chances of development in these countries. However, these countries do not approach the issue of improving education and other aspects of human development with due care. It is therefore to be expected that the positive effect of human development on progress toward sustainability in these countries is lower than in developed countries. In much the same way as the use of ICT, countries in transition are in a somewhat better position regarding human development, population growth, poverty, the dependence of the economy on the exploitation of natural resources, and increased production (World Bank 2018);

hence, a somewhat higher positive impact on progress toward sustainability is to be expected. In order to determine, at the macro level, whether and to what extent it is possible to predict higher environmental performance based on higher human development, and whether there are differences in the intensity of this impact depending on the degree of country's development, the following hypotheses are defined:

H2 An increase in the HDI causes an increase in the predicted value of the EPI.

H2.1 An increase in the HDI causes a larger increase in the predicted value of the EPI in developed countries when compared to countries in transition and developing countries.

H2.2 An increase in the HDI causes a larger increase in the predicted value of the EPI in countries in transition than in developing countries.

The effectiveness of ICT applications largely depends on human development, that is, on the ability and competences of individuals, their level of education and their income level. On the other hand, one of the main drivers of human development is the application of ICT in industry, education and health. There is a strong interdependence between these two factors, which is logical and has been demonstrated in the literature (Wu and Raghupathi 2018). In order to determine the interactive effect of these two predictors on environmental performance, and whether and to what extent this interactive effect is stronger than the individual effect, the following hypothesis is defined:

H3 Both the NRI and the HDI interact positively and increase the predicted value of the EPI, enhancing the individual prediction effects.

For predicting changes in environmental performance as a result of changes in the NRI, the HDI, population size or economic development, this study features the SVM method. As noted earlier, this method outperforms classical regression models as well as other predictive methods regarding nonlinear modelling, especially when the problem of the multicollinearity of factors is present. A detailed elaboration about the applied method and its predictive procedure is presented in the following section.

2.4 The SVM method and predictive procedure

SVM is a machine learning method introduced by Cortes and Vapnik (1995). The SVM that deals with classification is known as Support Vector Classification (SVC), while the version of SVM estimating and predicting continuous dependent variable is known as Support Vector Regression (SVR).

The fundamental idea of the SVR method is to have N training data consisting of n regressors observed as N vectors in n-dimensional space (input space). In cases where the function between the regressors and the dependent variable is non-linear, the vectors are mapped into higher dimensional space (feature space) where it is possible to find the optimal hyperplane which linearly models this relationship. On one hand, SVR tends to minimize errors in the estimation of the dependent variable, while on the other, it seeks to keep the feature space model as flat as possible, in order to increase its generality, that is, the precision of its estimation on an unknown data set. In order to keep the model as flat as possible, we have to minimize the norm of the hyperplane vectors so that the deviation of the dependent variable obtained by the model from its actual value is at most ε. In other words, during minimization, errors that are less than ε are tolerated (ε-intensive loss function), as we set out to have a level of deviation which is less than the limit defined in this way. Therefore, the SVR method tries to solve a convex optimization problem.

The insensitive ε zone (containing those points for which the estimation error is less than ε) can be slightly expanded by introducing an allowed deviation for ε. The elasticity of the ε zone is controlled by the C parameter, which achieves the trade-off between the flatness of the model and ε precision. Higher values of the C parameter allow the model to become less flat, that is it forms according to the data in the training set (overfitting), decreasing its generality in this way (while the deviations of ε stay small, that is, ε precision is achieved). Smaller values of the C parameter decrease the number of support vectors, and thus the complexity of the model, and increase its flatness and thereby its generality (while allowing for greater deviations of ε, that is, decreasing its precision).

The SVR method solves the original optimization problem using the following dual formulation:

$$\min\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)\varphi(x_i)\varphi(x_j)+\varepsilon\sum_{i=1}^{N}(\alpha_i+\alpha_i^*)-\sum_{i=1}^{N}y_i(\alpha_i-\alpha_i^*)$$
$$\text{subject to } \sum_{i=1}^{N}(\alpha_i-\alpha_i^*)=0$$
$$0\le\alpha_i,\alpha_i^*\le c \tag{1}$$

where αi, αi* are Lagrange multipliers; N is the number of training examples; x_i are training data points (vectors from the input space); y_i is the dependent variable; φ is the function between the input space and the feature space and ".“is the inner product in the feature space. Considering that the function φ is not explicitly known, the inner product in the feature space is calculated using the kernel function in the input space (kernel trick). The most commonly used kernel is RBF which is used for the purposes of this research:

$$K(x_i,x_j)=\exp(-\gamma\left\|x_i-x_j\right\|^2) \tag{2}$$

Solving the quadratic programming problem (1) gives the optimal parameters αi and αi* for i = 1…N. For every training data point, there exists the appropriate pair αi, αi*; however for some of them these parameters are equal to zero (for the ones belonging to the ε-insensitive zone). Those training points with parameters which are different from zero are support vectors.

Finally, the model which is the result of the SVR method takes the following form:

$$y(x) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x, x_i) + b \tag{3}$$

While for the summation only support vectors are considered. The model which is flatter and more general is also less complex, that is, the sum consists of a smaller number of support vectors, while an over-fitted model usually contains almost all of training data points.

Training of the SVR model consists of the choice of the optimal combination of the parameters C, ε and γ (from the kernel function). Higher values of the C parameter and lower values of the ε parameter lead to smaller errors in the estimation of the dependent variable on training data, but decrease the generality of the model, that is, its predictive power on an unknown data set. The γ parameter depends on the distribution of the training data.

In this research, a SVM learner was used which was implemented using LIBSVM software (Chang and Lin 2011) within RapidMiner.

For the choice of the SVR parameters (C, ε and γ), a grid-search technique is used, in combination with k-fold cross-validation. The initial set of data is divided into k subsets of equal size. From those k subsets, k-1 subsets are used for model training (the training set), while the one remaining subset is used for testing the predictive performance of the model on unknown data (the test set). The process of cross-validation is repeated k times, so that each of the k subsets becomes a test set. The indicators of predictive performances obtained during each of the k iterations are averaged, in order to obtain the predictive performance of the model.

3 Results

In this section we describe the predictive performance of the SVR model and the results of the sensitivity analysis to establish the predictive effect of the considered factors. In addition, the section contains the results of our hypothesis testing.

3.1 The predictive performance of the SVR model

The preliminary analysis, before estimating any models, consists of testing for multi-collinearity. The correlation coefficients reported in Table 2 indicate a potential risk of multi-collinearity, since the correlation between the NRI and the HDI is both very high and significant.

Therefore, we computed the variance inflation factors (VIF). The results are summarized in Table 3. There is a lot of divergence in the literature regarding which VIF value should be used as the threshold for collinearity.

Table 2 Correlation matrix for the selected variables

	EPI	NRI	HDI
NRI	0.811**		
HDI	0.852**	0.889**	
Pop	− 0.177*	− 0.013	− 0.041

*Correlation is significant at the 0.05 level (2-tailed)
**Correlation is significant at the 0.01 level (2-tailed)

Table 3 Variance inflation factors (VIF)

	GVIF	DF	GVIF^(1/(2*Df))
POP	1.017	1	1.008
HDI	5.082	1	2.254
NRI	5.049	1	2.247
WESP	1.951	2	1.182

GVIF, generalized variance inflation factor, *DF* degrees of freedom

Table 4 The performance of SVR model

	Fitting	Prediction—threefold cross-validation
RMSE	0.086	0.096
R-square	0.928	0.804

Some papers argue that a VIF of less than 10 is acceptable (Hair et al. 2009), but there is a disagreement between researchers with respect to this, as some believe that 5 should be the maximum level of the VIF (Kline 2010; Ringle et al. 2015). It is obvious that the aforementioned depends to a significant degree on the criteria of the researcher and that on the other hand it also implies the possible superiority of SVR in comparison to linear regression.

In the next step, using a grid-search technique in combination with a threefold cross-validation procedure, a predictive SVR model was trained with the following parameters: $\varepsilon = 0.024$, $C = 80000$ and $\gamma = 0.001$.

The results are shown in Table 4. We utilized the root mean squarer error (RMSE) and R-square for the performance of the fitting and prediction by the SVR model. This table indicates that the predictive accuracy (R-squared of the unknown data set) of the SVR model was 80.4%. Likewise, the goodness-of-fit values (R-square) are higher for the SVR model (92.8%) compared to the linear regression model (84%) achieved in the study by Gouvea et al. (2018).

In the next section the means by which the SVR model was used for sensitivity analysis is described.

3.2 Sensitivity analysis and hypothesis testing

As discussed previously, SVR models do not have a specified functional form or estimated coefficients. For that reason, as an increasingly widely-used machine learning method, SVR models are sometimes criticized and compared with neural networks, in the sense that they both fail to generate interpretable parameters for explanatory variables. However, Fish and Blodgett (2003) introduced a procedure, known as sensitivity analysis, to overcome or at least to lessen the problem of interpretability (frequently

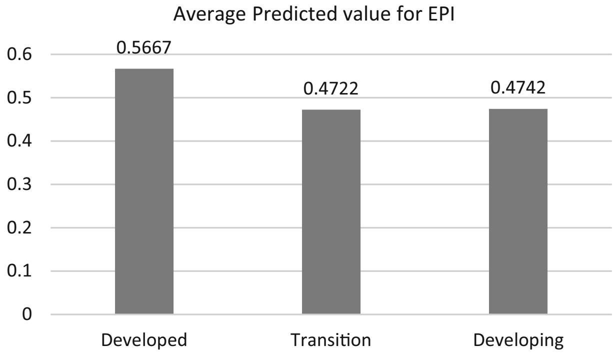

Fig. 1 Average predicted EPI by groups of countries

called "black box"). Afterwards, this methodology was adopted by others, such as Li et al. (2008) and (2012). The basic idea behind sensitivity analysis is to evaluate the effects of explanatory variables by changing each explanatory variable within a reasonable interval while the other variables remain unchanged. Then, the SVR models were recalculated with the changed datasets and the changes were recorded every time for further comparison. The same procedure was conducted for each explanatory variable, one at a time. The average predicted values of the EPI was used to detect a positive or negative relationship with the explanatory variables.

We applied sensitivity analysis to the control variable and by changing its value through including various different groups of country we obtained the results presented in the Fig 1.

The results indicate that a continued increase of EPI may be expected in developed countries. A 10% weaker increase is expected for developing countries when compared to developed countries.

To test hypothesis H1, we conducted a study of the functional relationship between the NRI, on the one hand, and EPI, on the other, by assigning changing NRI units from 0 to 1 with a 0.1 step, while keeping the other variables at their original values. We then estimated the effects of the input variable on the EPI as the average predicted changes for the index for every one unit change to the input variable. Figure 2 shows the results of the sensitivity analysis for the predictor NRI.

It is obvious that there is a clear positive association in the relationship, meaning that as the NRI increases, the mean predicted EPI increases. A quadratic relationship was found between EPI and NRI changing units (nevertheless, it could be noted that the relationship is almost linear).

Within the sensitivity analysis, it can be noticed that based on NRI growth of 1%, the predicted environmental performance increase at a macro level amounts to 1.5%, which confirms Hypothesis H1.

We have already established that the predicted values of the EPI differ depending on the value of the controlled variable (the three group of countries: developed, transition and developing). Hence, additional information could be obtained after an investigation of the dependence between the EPI and the NRI across the different groups of countries.

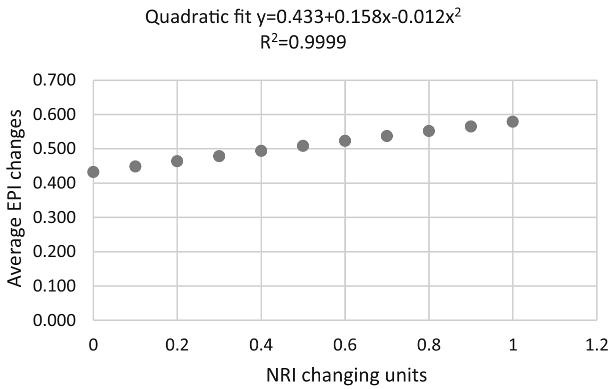

Fig. 2 Sensitivity analysis for the NRI

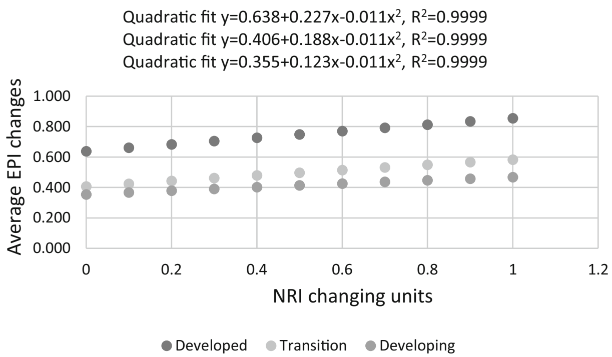

Fig. 3 Sensitivity analysis for the NRI by the groups of countries

To achieve this, we conducted a sensitivity analysis for the interaction effects of the NRI and the control variable. Figure 3 demonstrate various liaisons between environmental performance and the NRI predictor for different groups of countries. The quadratic fits are estimated for each relationship and the estimated parameters of the quadratic equations clearly indicate distinctions in the degree of influence between the variables.

Based on Fig. 3, a unit increase in the NRI would most significantly benefit developed countries, while it would impact developing countries the least. To be specific, a unit change (of 1%) in the NRI causes a 2.27% increase in the predicted EPI for developed countries, a 1.88% increase for economies in transition and a 1.23% increase in the predicted EPI for developing countries. Therefore, the expected differences in the predicted EPI values are confirmed, depending on the economic development of the countries concerned, i.e. both Hypotheses H1.1 and H1.2 are confirmed.

The results obtained by the sensitivity analysis for the HDI are displayed in Fig. 4. On the other hand, the results obtained by analysing the interaction between the control variable and the HDI are showed in Fig. 5.

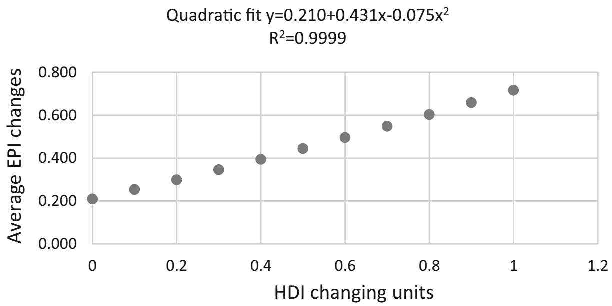

Fig. 4 Sensitivity analysis for the HDI

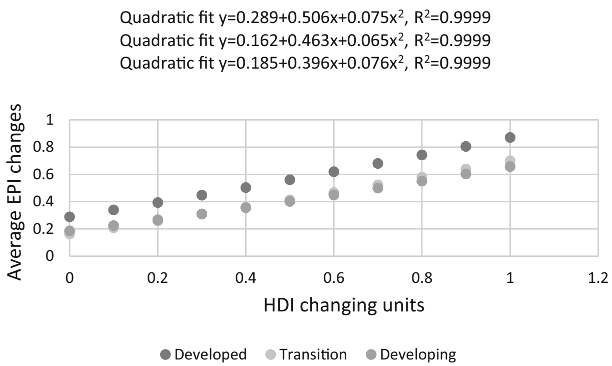

Fig. 5 Sensitivity analysis for the HDI by groups of countries

At the macro level, based on HDI growth of 1%, an increase in the political response to sustainability issues of 4.3% may be expected. The predicted EPI values growth differences are confirmed depending on economic development. Therefore, based on HDI growth of 1%, an environmental performance increase of 5% may be expected in developed countries, in transition countries we find an increase of 4.6% and in developing countries there should be an increase of 3.9%. Hence, it can be concluded that Hypotheses H2, H2.1 and H2.2 have all been confirmed.

Population growth by 1% involves a decrease in the expected value of EPI of 2.48% (Fig. 6), while this trend is not more dominant among developing countries (Fig. 7).

The interaction between ICT and HD was also examined using sensitivity analysis. We used a simulation for a low (value 0.2) and a high (value 0.8) level and their joint impact on the prediction of the average EPI. A summary of the results is presented in Table 5.

Low levels for both HDI and NRI predict an average overall value of EPI at 0.253, with the highest being for developed countries (0.279) and the lowest for transition economies (0.211). On the other hand, high values for both HDI and NRI predict an average EPI of about 0.644 for the whole sample, with 0.753 for developed countries, and figures that are significantly lower for other countries.

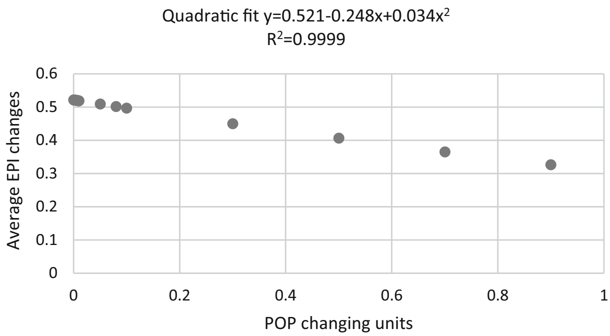

Fig. 6 Sensitivity analysis for POP

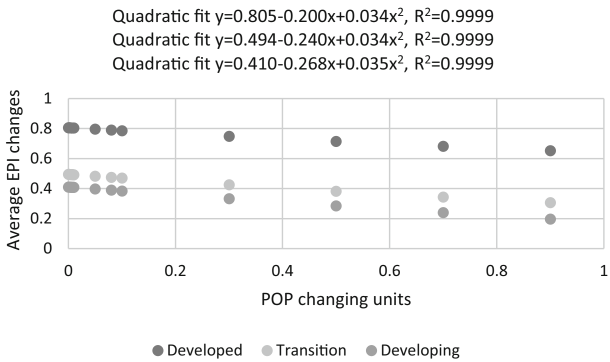

Fig. 7 Sensitivity analysis for POP by groups of countries

Table 5 Average EPI due to the interaction between the NRI and the HDI

HDI level	NRI level	Overall	Developed	Transition	Developing
Low	Low	0.2529	0.2799	0.2110	0.2486
High	Low	0.5548	0.6241	0.5318	0.5304
Low	High	0.3376	0.4041	0.3134	0.3145
High	High	0.6442	0.7532	0.6389	0.6010

The insufficient development of ICT (measured by a low level of NRI) predicts an average EPI of 0.464, but in interaction with high human development, the average predicted value increases to 0.554. This is especially evident in developed countries, where the average EPI amounts to 0.624 due to this interaction.

For countries with a low level of human development (a test value of 0.2) the average predicted value equals 0.299, rising to 0.337 in interaction with a high development of ICTs (a test value of 0.8). There is no major difference between economies in transition and developing countries under these conditions, whilst developed countries stand out from the rest.

Table 6 Summary of hypothesis testing

	Hypothesis	Confirmed?
H1	An increase in the NRI causes an increase in the predicted value of the EPI	Yes
H1.1	An increase in the NRI causes a larger increase in the predicted value of the EPI in developed countries than it does in transition and developing countries	Yes
H1.2	An increase in the NRI causes a larger increase in the predicted value of the EPI in countries in transition than in developing countries	Yes
H2	An increase in the HDI causes an increase in the predicted value of the EPI	Yes
H2.1	An increase in the HDI causes a larger increase in the predicted value of the EPI in developed countries when compared to countries in transition and developing countries	Yes
H2.2	An increase in the HDI causes a larger increase in the predicted value of the EPI in countries in transition than in developing countries	Yes
H3	Both the NRI and the HDI interact positively and increase the predicted value of the EPI, enhancing the individual prediction effects	Yes

In general, for higher values of both NRI and HDI predictors, higher EPI values are expected. Low NRI in interaction with high HDI enhances the predictive effect on NRI, i.e. the predicted EPI values increase. The combination of low HDI with high NRI also increases the expected values for EPI. Therefore, Hypothesis H3 is confirmed.

Table 6 summarizes all the hypotheses tested in the study.

4 Discussion

In this section, the main findings of the research are examined and their implications are considered. In addition, the methodological contribution of the study is presented.

4.1 Discussion of the findings and implications

The analysis carried out in this study contributes to the existing research on the relationship between environmental performance, ICT and human development. Unlike previous studies that were mainly concerned with estimation, this is the first study that deals with the prediction of the environmental performance based on these two factors.

The prediction model confirmed that the further continuous growth of environmental performances is expected in developed countries, while in developing countries considerably weaker growth is expected. It should be noted that here we refer to the potential of countries to achieve environmental goals and we should bear in mind that the real environmental footprint of developed countries is still larger compared to the developing countries (Wackernagel et al. 2017; Galli et al. 2012). Biomass use is greater in high-income countries, although this is difficult to see, due to the displacement of land use in poor countries. Low-income countries produce agricultural and forestry products for export to developed countries, while their natural resources are being devastated. In that way, countries with an obligation to reduce their carbon emissions simply move part of their emissions to countries without restriction. Developed countries are saving their resources in this regard, but the global environmental impact is not reduced. Thus, the impact of international trade changes the overall picture of the share that countries have of the total ecological footprint (Weinzettel et al. 2013).

Although many relevant global institutions which are engaged in environmental issues have recognized the problems faced by developing countries, developed countries need to increase their efforts and donations in order to narrow the gap. In that respect, special attention should be paid to the effects of trade and the fact that production activities accompanied by environmental degradation in low income countries are conditioned by increased consumption in high income countries. Thus, adequate policies should encourage developed countries to reduce resource consumption and therefore decrease the consequent pressure on poor countries.

The results indicate a positive correlation between the expected environmental performances and ICT development, which is in line with the findings of previous research (Higón et al. 2017; Gouvea et al. 2018; Khan et al. 2018; Haseeb et al. 2019). However, it is predicted that the positive effects of this technology will be almost 50% less in developing than in developed countries.

These findings indicate that more investment should be directed towards the ICT sector in developing countries. Higher investment is needed in the educational system, so as to increase the ability of the population to apply ICT and change the way of life and work, by relying more on new technologies and less on material resource consumption. The use of more energy efficient ICT such as mobile phones and laptops may lead to significant environmental savings under these conditions, especially if we recall that in these countries the factor of population growth is the most dominant one. In order to reduce the negative effects of economic growth mainly based on the consumption of fossil fuels, considerably more intensive development and application of ICT is necessary. Developing strategies which establish a balance between economic growth and environmental sustainability is crucial for low-income countries. The best strategy is investment in ICT which may contribute to both of these goals (Özcan and Apergis 2017).

On the other hand, the use of ICT technologies in increasing resource efficiency can result in a reduction in the expected positive environmental effects due to rebound effects. Many studies have drawn attention to this effect. For example, Houghton (2009) points out that offices continue to handle paper despite widespread computer use; e-commerce over short distances may not save money; internet use increases energy consumption, and the demand for electronic devices is increasing, all of which indicate possible rebound effects. According to Giampietro and Mayumi (2018), technological innovation alone is not enough to deal with the sustainability challenge, but in coordination with good policies and changes in behaviour it can achieve good results.

In accordance with previous studies (Popescu et al. 2017; Gouvea et al. 2018), a positive link between human development and expected country capacity for environmental sustainability has been identified, and the expected positive effect of this factor is stronger than the effect of ICT. Moreover, the differences between developed and developing countries are lower for this impact than they are for the ICT effect.

These findings lead to the conclusion that the effect of investing in human development on the environmental performance is high in both developed and developing countries. Human development in the first place involves an income increase and that income increase involves economic growth. Economic growth in developing countries is the significant cause of environmental damage (Yao et al. 2015; Panayotou et al. 2000). It follows that for progress toward sustainability of the environment in these countries, the strategy should involve paying more attention to the development of the other two components of human development that are not such significant environmental stressors. In particular, through investment into education and health care, along with the wider application of ICT in these sectors, it is possible to encourage the population to use their resources more efficiently, become more aware of the importance of environmental sustainability, adopt ecological regulations faster, and in this way ensure that significant environmental savings are indirectly provided (Hanushek 2013).

With respect to developed countries, investing in human development leads to a disproportionate increase in the real ecological footprint, which is mainly due to increased consumption. On the other hand, many low-income countries achieve higher human development without increasing their *per capita* ecological footprint. The conclusion that can be drawn is that high-income nations have failed to adjust their consumption patterns to environmental boundaries. Wealthy individuals can reduce their consumption of goods and services without seriously threatening their quality of their life, which should be taken into consideration when designing strategies for environmental sustainability (Moran et al. 2008).

Population growth has a negative effect, which is consistent with previous findings (Popescu et al. 2017; Gouvea et al. 2018; Dong et al. 2018). This trend is not much more pronounced within developing countries.

It can be concluded from this finding that population growth in developing countries is not a more significant problem for environmental performance than it is for the developed ones. Taking into account the fact that population growth is much higher among developing countries and the effects are almost the same, it can be concluded that the cause of high emission in the countries is more to do with the way of life and behaviour of the population than population growth per se (Tóth and Szigeti 2016). However, given the accelerated economic growth and industrialization of these countries, it is expected that population growth, especially in the most populous countries such as China and India, could significantly increase their ecological footprint in the coming years (Galli et al. 2012). Therefore, in developing countries, a change in the lifestyle and work practices of the population is necessary, providing for the efficient use of resources. This can be achieved through investment in ICT and human development. Furthermore, changes in the habits and behaviour of people in developed countries are necessary. In particular, although they have a slight increase in population, they have a very high consumption of resources *per capita*, which leads to the fact that they still have a larger ecological footprint than some other more populous countries (Galli et al. 2012).

The results of this analysis confirm the recognized fact in the literature, that much better effects on sustainability can be achieved by the interactive development of ICT and human resources (Wu and Raghupathi 2018).

These findings lead to the conclusion that those countries with the insufficient application of ICT may increase the efficiency of their application of these technologies and improve their expected progress toward environmental sustainability through investment in human development (primarily education). An appropriate combination of the good technologies and their advanced usage can reduce rebound effects. Therefore, the way technology is used could in fact be more important than the technology itself.

On the other hand, countries with lower human development may expect an increase in environmental performance if they invest sufficiently in ICT. The development of ICT infrastructure in education, health care, trade, traffic, transfer systems and construction, leads to faster human development, more balanced economic growth, the more efficient use of resources and the development and wider application of ecological regulations, all of which results in better environmental performance.

4.2 Discussion of the methodological findings

From the methodological perspective, the empirical results confirmed the superiority of non-parametric SVR methods in relation to parametric regression methods for this kind of the analysis.

To begin with, higher goodness-of-fit values (R-square) are achieved compared to the results obtained by ordinary least squares regression in Gouvea et al. (2018). As one of the potential problems, the aforementioned authors, in their paper, point out the issue of multi-collinearity, due to the correlation between the ICT and HDI regressors. Considering that the highest acceptable limit for VIF is 10, they conclude that there is no evidence of multicollinearity. However, as we have already noted, there is no full consensus among researchers regarding the acceptable limit for VIF. Given the possibility of spurious correlation, the authors in the above quoted study had to make a robustness check. As opposed to this, the SVR method does not suffer from the problems of multicollinearity and spurious correlation.

Secondly, the SVR method provided a prediction instead of an estimation, i.e. the assessment of the expected environmental performance growth based on the observed predictors.

Finally, it has been confirmed that sensitivity analysis can overcome the "black-box" nature of non-parametric methods and capture the nonlinear dependencies between the predictors and the target variable. In this way, additional information about these dependencies could be extracted, which could not be detected by standard regression models. Gouvea et al. (2018) include in their model the interaction term between ICT and HDI to explore the interactive effect of these two factors. However, in the case of a large number of predictors, the functional form specification implies the inclusion of a large number of interaction terms. This could be particularly complicated with discrete type regressors (which are often the case with control variables) due to the large number of dummy variables (Kašcelan et al. 2016). For example, in this study, in order to analyze the effect of the three predictors (NRI, HDI and POP), 9 interaction terms should be included in the model (due to the WESP control variable for the 3 groups of countries). Through sensitivity analysis, using the SVR model (which is trained to predict the target variable on an unknown data set with a high level of accuracy), the different interactions of the independent variables could be easily detected, without the need for a researcher to model the interaction terms manually (Christmann 2004). In that manner, stratifying the prediction for environmental performance based on the NRI, HDI and POP predictors by group of countries, all 9 interaction terms were automatically obtained, as well as the interactive effect of the NRI and HDI predictors, without their specification in the model.

5 Conclusions

This manuscript empirically confirms that based on the greater application of ICT, human development and population growth, it is possible to predict an increase in environmental performance at the macro level, as well as depending on the degree of economic development. Human development has the greatest positive impact on the expected environmental performance, then the use of ICT, while population growth has a less negative impact. Human development and the application of ICT are mutually conditionally related. The results confirmed that the interactive effect of these two factors has a positive impact on environmental performance. A lower level of human development allied to the growth of ICT application increases the predicted values of environmental performance, meaning that developing countries can significantly increase the chance of sustainability by investing in ICT. Moreover, a low level of ICT application with higher human development leads to an increase in predicted performance. This finding may be a guideline, especially to developing countries, that investing in human development may lead to an increase in the competences of the nation in applying ICT, and thus increase resource use efficiency and create environmental savings.

The assumption that the prediction of EPI based on ICT and human development varies depending on economic development has been confirmed. Among developed countries, increases in ICT and human development predict a greater increase in environmental performance than is the case for developing countries.

Developing countries face a number of problems that diminish the positive effect of these two factors, such as the dependence of the economy on the exploitation of natural resources, population growth (the most populous countries in the world such as China and India are among them), production growth due to cheap labour (BRICS countries are among the largest air pollutants), the lack of ICT infrastructure, the low level of information literacy, and the like. There are differences between countries in transition and developing countries, but they are relatively small. However, transition countries have a better sustainability outlook when they develop an appropriate investment policy in ICT and human development.

The study contributes to literature in this field in many ways. According to the position of many important world institutions and sustainable development agenda (SDG, GeSI), ICT is one of the main drivers of environmental sustainability. However, there are only limited numbers of empirical studies confirming this recommendation in the literature. There are several recent studies that have identified a positive link between ICT and sustainable development, but very few of those relate to environmental sustainability. Furthermore, according to the available information, there has so far been no research dealing with the predictability of environmental performance based on the development and application of ICT, as well as the development of human resources.

The main contribution from the methodological perspective is the empirical confirmation that the SVR method is a very good alternative to the standard regression methods for this kind of analysis which allows for prediction instead of estimation. It has also been shown that the application of this method can overcome the problems of multi-collinearity and the correlation of regressors that are strongly expressed in this analysis (both the NRI and the HDI are mutually conditioned and dependent). The applied method also overcomes the problem of nonlinear dependencies that exist between the predictors and the target (dependent) variable. The method is a non-parametric statistical method, so it is not necessary to test its functional form and the interaction between the regressors, which themselves can be numerous, especially if a large number of control variables are introduced (Christmann 2004).

Based on the findings of this research, policy makers at the global level can draw some significant implications. To begin with, taking into account the positive impact of ICT and human development on expected environmental performance, it is necessary to change development strategies, especially those related to developing countries. The emphasis should be placed on the development and widespread use of ICT, especially those that appear as smaller consumers (mobile phones, laptop devices, and so on), as well as human development (education, awareness raising, competencies, and the like). Global institutions should direct the donations granted to these countries into the development of ICT infrastructure, so as to enable the introduction of intelligent and automatic control into production processes, transport, energy transfer and construction and accomplish environmental savings in this way. The high dependency of developing countries on fossil fuels should be reduced through investment in renewable energy sectors and innovative technologies supporting these sectors. Due to expensive technological solutions, in developing countries, the introduction of strict ecological regulations may have negative impact on economic growth. At the same time, contributions to both environmental performance and economic growth can be achieved through investment in ICT.

In addition to its contribution, it is important to highlight the limitations and disadvantages of this research. The prediction was made on the basis of cross-sectional data for 139 countries of the world, for which the data were available. Due to data deficiencies, 54 countries are not included in the analysis. In addition, the time dimension was not observed, although the changes in the indicators at the annual level were small and could not significantly affect the results. Measures taken from publicly available sites were applied. It must be said that the measures had already been applied in previous studies (Gouvea et al. 2018), so their validity may be explained in that way. The only control variable was applied for economic development. The inclusion of some additional variables relevant to environmental performance may contribute to a more precise prediction and deeper sensitivity of the analysis.

Future research may include regional analyses, since sustainability conditions can vary significantly between regions. It would also be useful to make a prediction including more factors which may be significant in relation to environmental performance.

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