ANALYSIS AND PROJECTIONS OF CARBON DIOXIDE (CO_2) EMISSIONS IN THE US, EU, AND CHINA: A COMPARATIVE STUDY

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Abstract. Considering the significant effects of carbon-dioxide (CO_2) emissions on the environment, analysis of historical emission levels and prediction of future levels are of huge importance in managing climate change. This study focuses on predicting CO_2 emissions in the United States (US), European Union (EU), and China based on the data collected from the World Bank's database. The time series were modelled using the ARIMA methodology, while the analysis was conducted in R. The findings indicate that by 2030, the EU is projected to experience a decline of 23.70% in emissions compared to 2019 levels, while the United States is expected to witness a decrease of 21.95%. However, China's projections are discouraging, with an anticipated increase of 26.83% in emissions. These projections serve as valuable tools to assess the achievement of imposed CO_2 emission targets in specific economies, informing the necessary adjustments to existing policies or the implementation of new ones. This study underscores the significance of analysing historical data and forecasting future CO_2 emissions to manage climate change and develop energy-related policies effectively.
Keywords: *time series analysis, carbon-dioxide emission, energy efficiency, climate changes, ARIMA modelling*

Introduction

Starting from the 1950s, one can notice a constant increase in greenhouse gases concentration levels as a consequence of human activities, among which energy production and consumption have a significant role (Malhi and Grace, 2000). After centuries of speculations about the relation between *humans* and *climate change and due to strong and growing empirical affirmation, considerable progress has been made in examining how these anthropogenic actions lead to climate change* (Rosa and Dietz, 2012). Today, when it comes to scientific research, there is almost a unanimous consensus on the harmful effects of energy consumption on the environment, emphasising the fact that energy sources which are non-renewable, such as fossil fuels, do more harm than renewable energy sources (UCSUSA, 2008).

Negative consequences of abnormally high levels of greenhouse gas emissions are numerous and present in various areas. Ecological impact includes extreme weather events, conditions, and natural disasters (such as floods and droughts), which inevitably lead to substantial financial losses (Osman et al., 2023). Health impacts range from direct and immediate, which occur as a result of air pollution and extreme weather

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conditions, to indirect, which are an outcome of disrupted water systems, food production, bacterial growth rates, et cetera. Researchers also accent the need to recognise deferred health impacts associated with mental health issues due to natural disasters (McMichael et al., 2012).

Current CO_2 emission predictions and trends are not favourable: the emissions are expected to rise by around 52% by 2050, with the assumption that none of the adaptive strategies will be successfully implemented (Usman et al., 2023). Furthermore, energy demand is expected to increase by 56% by 2040. If the status quo is maintained in predominant reliance on fossil fuels, rising energy demand will undoubtedly lead to the increase in greenhouse gas emissions (Osman et al., 2023).Knowing the dramatic consequences of using energy from fossil fuels, climate trend prediction is of great importance in determining the actions to adapt to the impacts of climate change and in defining objectives to reduce emissions of greenhouse gases (Collins, 2007). Furthermore, uncertainty in the aspects of scale, occurring time, and regional patterns of climate changes enforces the need for predictions, on national, regional, and global level (Herzog et al., 2000). The crucial negative consequences of burning fossil fuels are high CO_2 emissions (Ritchie, 2020). Therefore, this study focuses on CO_2 emissions, which are seen as the primary driver of global warming (Tiseo, 2020).

This paper aims to analyse and estimate the time series of CO_2 emissions for the United States, European Union, and China. The reason behind putting these economies into the center of the analysis is that they are the world's top ranked greenhouse gasses (GHG) emitters, whereas China is ranked first, US second, and EU27 fourth. Interestingly, although India is ranked as the third biggest global emitter, its per capita GHG emission value is significantly lower than any other country within the top 10 (WRI, 2023). In the latest EDGAR (Emissions Database for Global Atmospheric Research) report, it is stated that China, the United States, the EU27, India, Russia, and Japan are accountable for 67.8% of global CO_2 emissions (European Commission, 2022a). The strength of their impact on the global level is clearly visible in the fact that the top 1% emitters have a carbon footprint that is 1000 times greater than those of the bottom 1% emitters (IEA, 2023). Therefore, bearing in mind these serious disparities, one cannot expect any improvements at the global level without the participation of these three economies: hence the importance of determining their future emission trends. Furthermore, this study attempts to forecast CO_2 emissions for the selected time series in a reliable time period. Our predictions' results could be useful for supporting policy analysis and designing future actions for CO_2 emissions. To encapsulate, this study aims to provide insights into the future levels of CO_2 emissions in the US, EU, and China, and to inform policymakers about the potential outcomes of their current climate policies in these regions.

The second chapter consists of three sections, including a brief review on the importance and methods of measuring carbon-dioxide emissions, standards, and policies related to CO_2 emissions, and a time series analysis of CO_2 emissions, where the results of other eminent studies are presented. The third chapter explains the research methodology, whereas the results are presented in the chapter that follows, including descriptive analysis of collected data, modelling of CO_2 emissions in these three economies, and models comparison. Finally, the last chapter presents the analysis of obtained results, study limitations, and directions for future research.

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Literature review

Measurement of CO_2 emissions

The atmosphere is determined as "*a mixture of gases surrounding the Earth, retained by the Earth's gravity*" (UCAR, 2021). Gases in the Earth's atmosphere include Nitrogen (78%), Oxygen (21%), Argon (0.93%), Carbon dioxide (0.04%), and other gases, such as Neon, Helium, as well as traces of water vapor (NASA, 2023).

Carbon dioxide, one of the greenhouse gases, supports life on Earth as it prevents the Sun's heat from escaping to space and so has the effect of heating up the atmosphere. Nevertheless, the problem arises when the concentrations of carbon dioxide and other greenhouse gases (methane, nitrous oxide, and fluorinated gases) are higher than the naturally occurring levels, thus leading to greenhouse effect augmentation and global warming enforcement (Günel, 2016). Methane is emitted during the production and transport of coal, natural gas, and oil; nitrous oxide is emitted during agricultural, land use, industrial activities, combustion of fossil fuels and solid waste, treatment of wastewater; fluorinated gases: hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride are synthetic, powerful greenhouse gases that are emitted from a variety of household, commercial, and industrial applications and processes (IPCC, 2013). As previously stated, increased greenhouse gases concentration is a consequence of certain human activities. Anthropogenic carbon dioxide emissions are those "*stemming from the burning of fossil fuels and the manufacture of cement; they include carbon dioxide produced during consumption of solid, liquid and gas fuels and gas flaring*" (World Bank, 2023). These emissions are responsible for the largest percentage of greenhouse gas emissions, which are strongly correlated with global warming – increased concentration of carbon dioxide in the atmosphere increases global warming and causes climate changes. The importance of carbon dioxide can be seen in the fact that it is the reference gas against which other greenhouse gases are quantified. However, to get a precise image of a country's impact on climate change, other gases such as methane or nitrous oxide should also be included in the analysis (World Bank, 2023). Today, CO_2 emissions are globally at record-breaking levels, generating the largest calculated concentration of CO_2 in the atmosphere in modern times (Smith and Myers, 2018). According to Intergovernmental Panel on Climate Change (IPCC), atmospheric CO_2 concentrations in 2019 were already higher than at any time in at least 2 million years, while concentrations of some of the other greenhouse gases, methane and nitrous oxide, were higher than at any time in at least 800,000 years (IPCC, 2023).

The IPCC concludes that "*undiminished climate change would in the long term be likely to exceed the capacity of the natural, managed, and human systems to adapt*" emphasising that action is inevitably needed in order to strengthen adaptive capacities (Calbick and Gunton, 2014). In many concerning forecasts, researchers showed that without mitigation efforts CO_2 emissions are expected to rise dramatically by the end of the 21st century (Smith and Myers, 2018).

In order to reduce the negative impacts of climate changes, such as droughts, inundations and other natural disasters (Warner et al., 2010), one must reduce the concentration level of greenhouse gases, especially carbon dioxide, given its most significant influence on global warming (Budyko, 1993). Relevant deceleration of global warming could be achieved if emissions are reduced by dozens of percent, thus implying high costs which some countries are not capable of bearing. Furthermore, the IPCC finds that the impacts of climate change are not evenly distributed; countries and

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societies that will be affected the most are probably the ones with weak adaptive capacities (Adger et al., 2003). Accordingly, climate changes inevitably lead to social, political, and economic challenges (Bellamy and Hulme, 2011). Keeping in mind that climate changes are a global phenomenon, each country must address these issues carefully and establish adequate mechanisms for problem-solving.

Clearly, coping with climate change and building sustainability strategies should be conducted based on the fundamental quantitative analysis of environmental issues, including carbon dioxide emissions, hence the importance of the topic presented in this paper. Adequate and comprehensive measurement of greenhouse gas emissions is undoubtedly a solid foundation for the implementation of any kind of adaptive strategy.

Addressing climate change is one of the crucial elements of sustainability policies. There is a diversity of measurements and instruments available to national authorities, such as laws and standards, taxes and charges, agreements, tradeable permits, and physical and social infrastructure (Fernández González et al., 2014). Some of the mentioned approaches will be presented in the following section.

In regard to carbon dioxide emissions measurements and its approaches and methods, a common practice that countries use to calculate and report emissions is known as a 'bottom-up' approach, where emissions on a national level are estimated by combining data on types of activities and carbon dioxide emitted from these activities (Kulkarni, 2019). In other words, emissions are derived by consumption data and emission factors. However, obtaining estimates using a 'bottom-up' method is often challenging due to many assumptions on which the estimate relies on. Uncertainties mainly come from the lack of information regarding parameters such as import, export, and product sales (Flerlage et al., 2021). On the other hand, a 'top-down' approach uses measurements of CO_2 concentrations in the atmosphere to model the trajectories of carbon dioxide and identify emission sources. Considering that both approaches have their limitations and advantages, researchers suggest using their combination (Zhou et al., 2021) to obtain more precise and informative estimates (CSIRO, 2021).

There is a variety of measurement techniques used in research of CO_2 and other greenhouse gas emissions. Their application and corresponding accuracy depend on the environment and available resources (McGinn, 2006). Techniques commonly used in GHG studies are:

1. *Chamber techniques*. The basic principle of these methods is to measure emissions from a particular source inside a chamber during a specific time period and under controlled circumstances.
2. *Micrometeorogical techniques*. These techniques "*focus on the flux of gas in the atmosphere and relate these fluxes to the emission source*" (Harper et al., 2011). Compared to chamber techniques, this method is more representative of real conditions since it does not alter the behaviour of the emission source (Scotto di Perta et al., 2020). They are especially useful if emissions from larger monitoring areas should be integrated, which results in eliminating spatial variability issues, one of the negative aspects of chamber techniques. Nevertheless, micrometeorological techniques are highly priced and require deep expertise and special measurement instruments.

Numerous studies focused on the measurement of carbon dioxide emissions through implementing various methods or the analysis of emissions already calculated by another institution.

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In regard to China, for instance, Wu et al. (2015) developed a method to determine CO_2 emissions from tourism in 2009 and 2011 in typical Chinese provinces and cities. In another study by Meng et al. (2017), the aim was to quantify direct and indirect CO_2 emissions from the Chinese tourism industry sector using a 'top-down' approach. Chang and Lin (2018) estimated CO_2 emissions from urban traffic in Taichung city, Taiwan, and measured the relationship between CO_2 emitted from traffic and building development scale. Zhou et al. (2014) proposed an approach for measuring carbon dioxide emissions of the Chinese transportation sector. Zha et al. (2016) proposed a method for measuring carbon dioxide emissions and regional efficiency in China based on a data envelopment analysis (DEA) approach. Wang et al. (2013) investigated CO_2 emission performance in Chinese provinces using a parametric approach and, additionally, emission diminution potential and the impact of regulation and law.

Regarding the United States, several studies will be acknowledged hereby. Ramseur (2007) observed emissions of carbon dioxide as part of greenhouse gases group and analysed the results at the state level to make a comparison, arguing that state policies should be aligned with their performance. Interestingly, a group of researchers from Bond University reviewed household carbon dioxide emissions, including measurement methods, determinants, and mitigation anticipation (Zhang et al., 2015). In an insightful review of tools for managing and measuring greenhouse gas emissions done by Miller et al. (2009), it is pointed out that there is a lack of methods that have the capacity to be applied on a both regional and local levels.

Finally, there is a diversity of research studies concerning the European Union. Gonzalez et al. (2014) conducted research to determine aggregate carbon dioxide emissions by tracking five distinctive factors: population, fuel mix, production per capita, carbonisation, and energy intensity. One of their findings that should be accented is a number of differences between individual countries, resulting in country-specific recommendations. Loo (2009) proposed a methodology for calculating CO_2 emissions in the transportation sector and evaluated the impact of emission-related policies. Further, in their report on measuring and managing carbon dioxide emissions from European chemical transport, scientists from Heriot-Watt University evaluate a range of existing methods for quantifying carbon emissions, accenting that there is no definitive methodology in this area. They also suggested two basic approaches to the calculation: an energy-based approach and an activity-based approach, appropriate in the absence of energy use data (McKinnon and Piecyk, 2010).

Initiatives, standards, and policies related to CO_2 emissions

Energy efficiency is becoming an essential element of energy and environmental policy worldwide, so efforts to achieve energy efficiency goals through regulations and supporting standards are growing. Moreover, as the efforts to stabilise the global effects of climate change are increasing, countries start to find mutual language regarding energy efficiency in joint agreements.

The Kyoto Protocol was the most significant international agreement, where signatory countries have agreed to set targets to limit and reduce GHG emissions under agreed individual targets (Pata and Ertugrul, 2023). The Kyoto Protocol was negotiated in 1997 and was agreed upon to enter into force in 2005. It also contains legally binding commitments for developed countries to reduce their overall GHG emissions by 5% throughout 2008-2012, compared to 1990 levels (UNFCCC, 1997). Moreover, individual targets were negotiated and agreed upon, ranging from cuts of 8% agreed by

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the EU and its Member States to growth caps of 10% compared to 1990 levels (Delbeke et al., 2019). Also, it requires industrialised countries, as listed in its Annex B, to limit their emissions of GHGs, most notably CO_2, from fossil-fuel combustion; more specifically, countries committed to reducing their GHG emissions by 5.2% on average below aggregate 1990 emission levels during the commitment period 2008-12 (UNFCCC, 1997). For some parties, these represented significant reductions against business as usual emissions levels. For other, especially former soviet-union countries, the targets measured against historically high baseline levels of emissions in 1990 known as "hot-air", allowed them to sell the extra assigned amounts or increase emissions without an actual reduction in emission levels (Maamoun, 2019). However, its failure to accomplish set targets led to a new protocol signed in Paris in 2015, where parties agreed to reduce the adverse effects of climate change based on National Determined Contributions (NDC) (Västermark, 2021). These NDCs detail the emissions reduction and adaptation efforts each nation intends to undertake. The agreement emphasises the principle of common but differentiated responsibilities, recognising historical emissions, and varying capacities of developed and developing countries in addressing climate change. The Paris Agreement emphasises international cooperation and transparency, promoting regular reporting on emissions and progress toward NDC goals. It establishes a mechanism for a Global Stocktake every five years to assess collective progress and enhance the ambition of climate targets. The agreement also encourages financial support from developed nations to aid developing countries in their mitigation and adaptation efforts, as well as technology transfer and capacity-building initiatives. The Paris Agreement aims to keep the global temperature rise to "well-below 2°C pre-industrial level" (United Nations, 2015). This climate agreement is important because it was adopted by the European Union and India, by China, the US, and Island states. Countries that in history had disagreements now work together on the global problem of climate change (Dimitrov, 2016).

Initiatives, standards, and policies related to CO_2 emissions in the EU

Countries worldwide set legislative frameworks to accomplish their climate and energy targets. For example, the European Union has adopted rules under the Regulation on the Governance of the Energy Union and Climate Action to assure planning, monitoring, and reporting progress toward its 2030 climate and energy targets and its international commitments under the Paris Agreement. In 2012, the European Commission set up the Energy Efficiency Directive, requiring Member States to set national energy efficiency targets to ensure that the EU reached its headline target of reducing energy consumption by 20% by 2020 (European Parliament, 2012). A common method and approach have yet to be established, however, most of the National Energy Efficiency Action Plans (NEEAPs) referenced the contribution to the EU level 2020 target of 20% savings from baseline (European Commission, 2022b). Also, only a limited number of Member States set additional energy efficiency (or more general climate) targets. Their main target is reducing GHG emissions above EU-level targets, decarbonising residential heating and transport, or targets for energy efficiency in buildings above Energy Performance of Buildings Directive requirements (Economidou et al., 2022).

Also, the directive declares that Member States should encourage small and medium-sized enterprises to endure energy audits, which should be mandatory for large companies to achieve energy savings. Further, energy audits should consider relevant

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European or International Standards, such as EN 16247-1 (Energy audits) and EN ISO 50001 (Energy Management Systems). The comprehensive, integrated climate and energy policy, adopted by the European Council in 2014 and revised in 2018, set out the 32.5% Union's energy efficiency target for 2030 (European Commission, 2023a). Standards are recognised as the best practice examples for increasing energy efficiency investments in the industry (European Commission, 2022c). Implementation of Energy Management Systems ensures a clear management commitment to improve energy efficiency. Energy audits bring external specialist expertise to identify energy savings opportunities across diverse company operations areas (European Commission, 2022c). The European Green Deal is the EU's plan to become a climate-neutral region by 2050 (European Commission, 2019). In 2021, the European Commission presented a package of legislation named 'Fit for 55' to meet the European climate and energy targets (European Parliament, 2021). As a result, EU countries have the legal power to acknowledge energy efficiency in policy, planning, and decisions for investments in the energy sector and beyond (European Commission, 2023b).

Furthermore, to ensure that enough efforts are deployed up to 2030, the contribution of net removals to the Union 2030 climate target shall be restricted to 225 million tons of CO_2 equivalent (European Parliament, 2021). This target is given in the European Climate Law and the legally binding commitment to reduce net greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels (European Parliament, 2021). In addition, many Member States have Voluntary Agreement (VA) schemes for energy-intensive industries or other parts of the industrial sector. A VA scheme is based on government and industry contracts on an individual enterprise or sector level. Energy management systems like ISO 50001 and systematic working procedures are important cornerstones in all VA schemes (European Commission, 2022c).

Initiatives, standards, and policies related to CO_2 emissions in the US

The United States (US) have established several regulatory actions for various aspects of the energy system which is governed by different laws that direct regulatory actions for its multiple aspects (International Energy Agency, 2019). Energy efficiency and renewable energy are becoming more important as they contribute more to US economic growth each year. Lowering oil consumption and increasing gas usage transformed the US approach to energy policy-making, shifting from emphasising energy security to maximising the benefits of energy abundance (International Energy Agency, 2019). Energy productivity has boosted US productivity and the overall economy by 2007: total energy consumption has fallen by 3.3%, while the economy grew by 15.5% (International Energy Agency, 2019). Shift from coal to natural gas in power generation and significant development in renewable electricity industry led to overall reduction of CO_2 emissions by 16% (International Energy Agency, 2019). Power generation had the largest impact on CO_2 emission thus switching from coal to gas contributed to decrease of 27% below 2007 levels (International Energy Agency, 2019). The energy revolution has made the US from the biggest consumer to a major producer and exporter of oil and gas as well (International Energy Agency, 2019). A new target for the US is to achieve a 50%–52% reduction from 2005 levels in economy-wide net greenhouse gas pollution by 2030 and reach net zero emissions economy-wide no later than 2050 (The White House, 2021).

As standards play a great role in energy efficacy, new landmark fuel economy standards are set by the U.S. Department of Transportation's National Highway Traffic

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Safety Administration in order to drive American leadership forward on clean cars (The U.S. Department of Transportation, 2022). It aims to make better mile/gallon efficiency and to reduce transportation emissions while saving consumers money at the pump (The U.S. Department of Transportation, 2022). Further, the U.S. Department of Energy published a set of Appliance and equipment standards which significantly reduce energy consumption (The U.S. Department of Energy, 2023).

Initiatives, standards, and policies related to CO_2 emissions in China

China updated its NDC in 2021, ahead of the UN Climate Change Conference in Glasgow (COP26), pledging to peak CO_2 emissions before 2030 and to reach carbon neutrality before 2060, submitting its mid-century long-term low greenhouse gas emission development strategy (Erbach and Jochheim, 2022). The aim is for China to decrease its carbon intensity until 2030, by more than 65% from the 2005 level. China plans to have over 1200 GW of installed wind and solar power by 2030, which will also contribute to its aim to reach 25% of the share of non-fossil fuels in primary energy consumption. Also, by 2030 China's forest stock should increase by 6 billion m^3 above the 2005 level (Erbach and Jochheim, 2022).

China's growing economy is energy-intensive. In 2021, China was 8th in the usage of energy per unit of GDP, due to several factors, one of which is a high share of heavy manufacturing, together with lack of market signals to promote energy efficiency in some sectors (Enerdata, 2023). However, China has been improving the energy intensity of its economy dramatically in past years, reducing energy use per unit of GDP by roughly 75% between 1990 and 2020 (Enerdata, 2023). In 2018, more than 60% of China's energy use was covered by mandatory energy efficiency policies—more than any other nation (International Energy Agency, 2018).

In several policy documents published in late 2021 and early 2022, the State Council featured the importance of energy efficiency. It drew attention to the needed improvements in energy efficiency in different sectors, covering heavy industry, building materials, coal, transport, appliances, and urban design (Sandalow et al., 2022). To endorse energy efficiency in different sectors, the Chinese central government, through its relevant ministries, the Ministry of Industry and Information Technology (MIIT), the Ministry of Housing and Urban-Rural Development (MOHURD), the Ministry of Commerce (MOFCOM), issued a significant number of regulations standards (Sandalow et al., 2022). Among the most important standards are (Sandalow et al., 2022):

- Efficiency standards for coal-fired power plants cover technology requirements for all new coal plants;
- Benchmarks standards for energy-intensive industries such as steel, aluminium, flat glass, cement, oil refining, chemicals, and data centers. In 2022, the National Development and Reform Commission (NDRC) followed up by declaring that all energy-intensive industries must meet minimum standards by 2025 or be slowly eliminated and that some portions of other industries should meet new benchmark standards by 2025;
- Appliance standards and labels. NDRC and MIIT publish catalogues of recommended energy-saving products, aiming to boost their use through public education. The most recent catalogue was published in 2020, where NDRC stated that 14 previous rounds of catalogues published since March 2005 covered 37 types of products and more than 1.9 million product models, resulting in more than 500 billion TWh of electricity savings. In addition,

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recognising the growing importance of air conditioning and other coolants, the government issued a Green and Efficient Cooling Action Plan in 2019. This plan covered many settings, including buildings and data centers, and addressed energy efficiency and the coolants being used and

- Building standards. MOHURD set targets relating to the energy consumption of new buildings, the renovation of existing buildings, the proportion of prefabricated buildings, renewable energy, and construction methods. All new urban residential and public buildings must meet these energy-saving design standards. MOHURD has also developed a Green Building Action Plan, with green building evaluation standards and a labelling program. Furthermore, in 2021, MOHURD issued codes for energy efficiency and renewable energy for buildings and together with its 14th Five-Year Plan for Building Energy Conservation and Green Building Development.

A lot of effort is put into achieving energy efficacy through regulations, policies, and standards in all observed countries. Accordingly, they all need the most accurate projections of energy efficiency indicators, such as CO_2 emissions, to set appropriate targets.

Time series analysis of CO_2 emissions

Time series analysis and ARIMA models have been used in previous studies in this field. For example, Sen et al. (2016) applied ARIMA in modelling energy consumption and greenhouse gas emissions for a pig iron manufacturing organisation of India to discover actual and future trends of critical environmentally conscious manufacturing indicators. Lotfalipour, Falahi, and Bastam (2013) implemented ARIMA and Grey System to predict CO_2 emissions in Iran. Their results showed that the amount of CO_2 emission will reach up to 925.68 million tons in 2020, which is significantly higher than in 2010, given 66% of projected growth. Ozturk and Ozturk (2018) forecasted the energy consumption of Turkey from 2015 to 2040 using ARIMA models. Rahman and Hasan (2014) developed different ARIMA models to model the carbon dioxide emission in Bangladesh by using a time period from 1972 to 2015. They concluded that the model showed respectable performance in its predicting capability. In a more recent study, Kour (2022) also used ARIMA methodology to model CO_2 emissions in South Africa for the period 2015-2027.

There are also studies that combine ARIMA with other methodologies. For instance, Wang and Meng (2012) proposed a hybrid methodology that combined ARIMA and artificial neural network models to forecast energy consumption in Hebel province in China. The authors concluded that forecasting accuracy was improved owing to the implementation of a hybrid methodology. Another study that uses a hybrid methodology was conducted by Zhao et al. (2018) – they forecasted carbon dioxide emissions in the US using a hybrid of mixed data sampling regression model and back propagation neural network.

The above-listed studies indicate that the ARIMA model has been a verified methodology for modelling CO_2 emissions in different economies, providing satisfying predictions and results. Therefore, in our research, we also opted for the application of ARIMA models.

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Research methodology

In this paper, we observed CO_2 emissions in the European Union, United States, and China from 1960 to 2019. Data were retrieved from the World Bank database (World Bank, 2023) and given in metric tons per capita. It is important to emphasise that data on CO_2 emissions include gases from fossil fuel consumption and cement manufacture but exclude emissions from land use such as deforestation. Additionally, estimates do not include emissions from fuel consumption in ship and aircraft international transport due to difficulties in allocating fuels among countries. These emissions are calculated annually by the U.S. Department of Energy's Carbon Dioxide Information Analysis Center from the United Nations Statistics Division's World Energy Data Set. One should be aware of the fact that although it is estimated that global emissions are seemingly accurate within 10%, country estimates may have larger error bounds (World Bank, 2023).

Before focusing on the applied statistical methodology used to model the time series analysis of the CO_2 emissions, we must elaborate on the observed EU emissions. Commencing with six member states in the 1960s, the membership progressively expanded to 15 by 1995, followed by increments to 24 in 2005, culminating with 28 in 2013. Notably, the most recent alteration occurred in 2020, marked by the stepping out of the United Kingdom from the EU. What does this mean for the data on CO_2 emissions in the EU? How is the inclusion of newly joined countries taken into consideration, and what are the impacts? The World Bank does not provide insights on the measurement methodology, but it probably took the enlargement into account. Different research approaches have been taken to tackle the issue. De Araújo and associates (2013) divided EU member states into Old and New, and conducted separate analyses on each group of countries. Other authors made subsets depending on the data availability, as Horobet et al. (2021) who analysed data for 24 EU member states. Herein, we used the data for all EU member states at the moment of measurement.

In order to estimate and forecast the trends of carbon dioxide emissions for the EU, US, and China, we applied ARIMA (p,d,q) models and Box Jenkins methodology (Makridakis and Hibon, 1997). ARIMA model is widely used to predict and forecast future values of time series data. It estimates future values of a time series as a linear combination of its own past values and/or lags of the forecast errors (Ozturk and Ozturk, 2018). An ARIMA (p,d,q) model consists of 3 parameters. Parameter p is defined as the order of the autoregressive process (AR model), parameter d refers to the order of difference needed to obtain a stationary series if the original series is non-stationary, and parameter q refers to the order of the moving average process (MA model) (Ozturk and Ozturk, 2018).

ARIMA methodology could be summarised in four steps (Chen et al., 2008): (1) identification of ARIMA structure – model identification, (2) estimation of the coefficients – model estimation, (3) fitting test on the estimation residuals – model checking, and (4) forecasting future values. Applying the ARIMA methodology encompasses conducting several statistical tests, as well as calculating metrics and graph plotting. In the lines below, we list the tests and metrics we applied within the ARIMA methodology:

1. Augmented Dickey-Fuller test (ADF). The ADF test is one of the standardly used statistical tests to explore the stationarity of the time series (Harris, 1992). The null hypothesis of the test is that the time series has a unit root and is not stationary, while the alternative hypothesis is that the time series does not have

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a unit root and is stationary. The acceptance of the null hypothesis indicates that the series is not stationary and that it should be integrated at least once. The level of integration detected by the ADF test indicates the value of the parameter *d*.

2. Autocorrelation function (ACF) and Partial autocorrelation function (PACF). The ACF graph displays the autocorrelation coefficients at different lags. According to the pattern of the ACF, one can decide on the moving average (MA) part of the model. On the other hand, the PACF graph shows the partial autocorrelation coefficients at different lags. According to the pattern of the PACF, one can decide on the autoregressive (AR) part of the model. ACF and PACF are used to detect the possible values of p and q parameters of the ARIMA model (Wirawan et al., 2019).
3. Akaike information criterion (AIC). The criterion upon which we have selected the best fit model among proposed models was the Akaike information criterion (Makridakis and Hibon, 1997). AIC determines both model fit and model unreliability; the lower the AIC value, the better the model. Hence, the model with the lowest AIC value is considered to be the closest to the real data (Mondal et al., 2014).
4. Z test. Z test is a classical test used to inspect the statistical significance of coefficients. A Z-Score in absolute values above 2 indicates that a particular coefficient or constant is said to be significant at the 5% level. In time series analysis, this test explores whether p, d, q, or constant is statistically significant.
5. Test of autoregressive conditional heteroskedasticity (ARCH test). The ARCH test analyses volatility in time series in order to forecast future volatility. Also, the test detects the presence of fat tails in the underlying distribution. The null hypothesis of the test is that homoskedasticity is present in the model, while the alternative hypothesis of the test is that heteroskedasticity is present in the model.
6. Box-Ljung. The Box-Ljung test is used to inspect the presence of autocorrelation in the model. The null hypothesis assumes no autocorrelation exists in the model, while the alternative hypothesis states that autocorrelation is present in the model (Ljung and Box, 1978).

Modelling and forecasting time series was done by using R and the packages tseries (Trapletti et al., 2023), FinTS (Graves, 2022), and lmtest (Hothorn and et al., 2022).

Research results

Descriptive analysis of the collected data

The data collected for this study encompassed CO_2 emission (metric tons per capita) for EU, US, and China from 1960 until 2019. As it can be noted, the data lags are available for a significant number of years, considering that the analysis was conducted in 2023. The descriptive statistics of the European Union, United States, and China time series data is provided in *Table 1*. Among the three time series, the US has the highest mean of 18.789 CO_2 emission in metric tons per capita, followed by the EU, with mean emissions of 7.815, and lastly, China, with mean emissions of 2.898. Standard deviation and inter quartile range (IQR) have been used to inspect the variability of the time

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series. The highest standard deviation and IQR have been measured for China, indicating that the measured values of CO_2 emission have varied the most among the three economies in the observed period. The US stands out with a median of 19.164, indicating that in half of the observed period, the CO_2 emissions in metric tons per capita have been higher than 19.164. The median is visibly lower in the EU (7.959) and China (2.057). Coefficients of skewness and kurtosis can be used to assess the normality of the observed data. The coefficient of kurtosis indicates that all three time series are leptokurtic, while the coefficient of skewness indicates that EU and US emissions are skewed to the left, opposed to China's emissions, skewed to the right.

Table 1. *Descriptive statistics of European Union, United States, and China time series*

Descriptives	European Union	United States	China
Mean	7.815	18.789	2.898
Standard deviation	1.264	2.017	2.262
Minimum	4.729	14.673	0.574
1^{st} quartile	6.789	17.085	1.190
Median	7.959	19.164	2.057
3^{rd} quartile	8.922	20.158	4.335
IQR	2.133	3.073	3.145
Maximum	10.133	22.511	7.606
Skewness	-0.399	-0.402	0.993
Kurtosis	2.597	2.273	2.534

In the next stage of the descriptive analysis, we present line graphs of the three time series with a brief elaboration on how the values within the time series for each economy changed in the observed period (*Fig. 1a-c*).

Figure 1a clearly shows the sharp increase in CO_2 emissions since the 1960s, which was a consequence of the significant economic growth of the EU member states in that period. Such growth, according to some authors, was a consequence of the introduction of regulations that encouraged a higher rate of investment and the spread of the use of technology developed in the US (Crafts, 2012). One of the important moments that impacted the EU's emission level was the second oil crisis in 1979. The crisis led to a significant increase in the price of energy, which subsequently resulted in lower consumption of highly polluting fuels (Rafaj et al., 2015). In the 1990s, there was a drop in CO_2 emissions in the EU. Drastic structural changes in the eastern countries of the EU, which caused temporary stagnation and decline in GDP, as well as changes in the energy system, are cited as one of the possible reasons (Rafaj et al., 2015). In the research aimed at analysing the key drivers of carbon dioxide emissions in the energy sector of the EU, from 2000 to 2007, it was found that carbon dioxide emissions increased by about 12% in most member countries, along with an increase in electricity production. Regarding the impact of energy efficiency, the results showed its very limited contribution to reducing and increasing CO_2 emissions. The impact was more significant in countries that recently joined the EU and had a high potential for technological improvements (Karmellos et al., 2016). The same research, for the period from 2007 to 2012, showed that the level of CO_2 emissions decreased by about 10%, to the greatest extent, thanks to the imposed changes in used fuels. Also, the factor that

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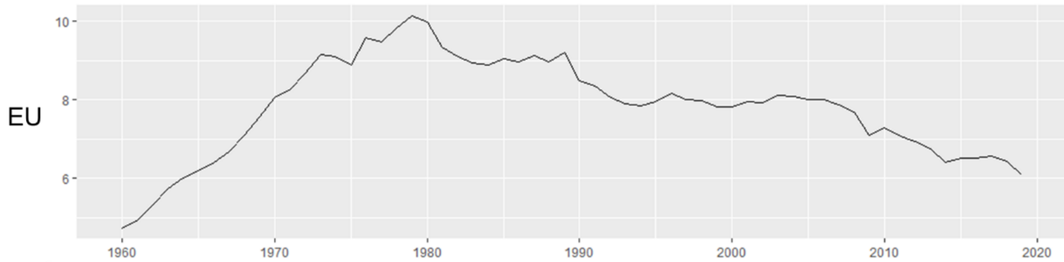
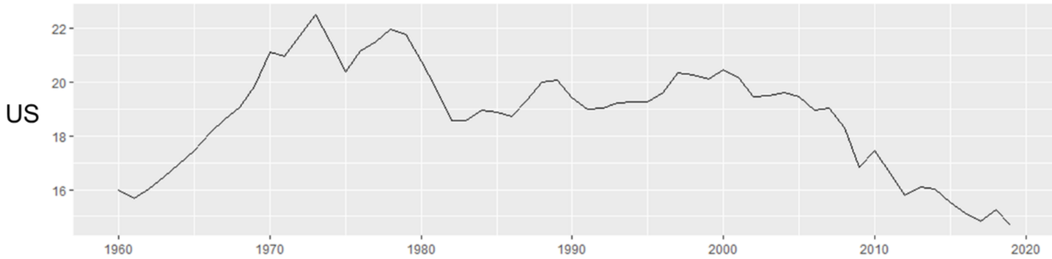
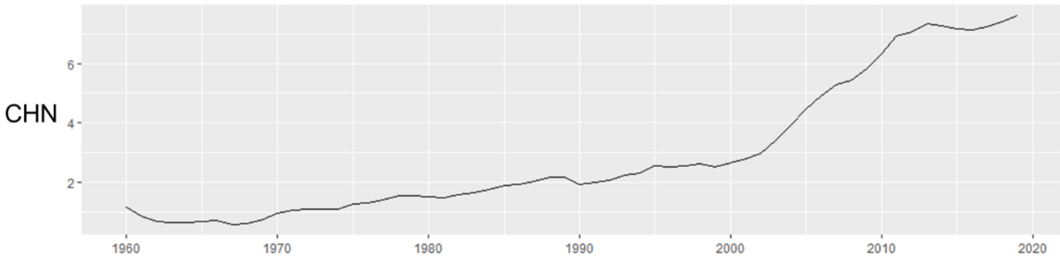
most contributed to such a sequence of events was the economic crisis that affected most European countries (Karmellos et al., 2016). In the last years of the observed period, a decline in the emission can be detected.



(a) European Union



(b) United States



(c) China

Figure 1. *CO_2 emissions (metric tons per capita) – Time series line graph for the period 1960-2019*

The time series of CO_2 emissions in the US (*Fig. 1b*) in the 1960s saw an increase in the annual growth rate. Some of the causes cited in the literature are rising incomes, electrification, and a renewed reliance on coal for energy production. After the historical peak, carbon dioxide emissions fell drastically in 1973 due to the oil crisis (Tol et al., 2006). In contrast to the period 1949-1972, when the level of CO_2 emissions largely followed the movement of GDP, since 1973, their movements have not coincided – some of the potential reasons for such an occurrence are technological innovations, the application of more energy-efficient methods in production, as well as structural changes in the US economy in terms of the continuous shift from manufacturing to providing services (Shahiduzzaman and Layton, 2015). A significant drop in CO_2 emissions can also be observed after 1979, which is linked to the second oil crisis (Shahiduzzaman and Layton, 2015). Since 1995, the structure of energy sources has been significantly modified in the US, with an increase in the share of renewable sources, such as wind and solar energy. It is believed that the change in the energy mix contributed to the reduction of CO_2 emissions in the period from 1995 to 2009 (Sesso et al., 2020). In the same research, the authors observed the CO_2 emissions in the period

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2000-2009, when the Kyoto Protocol was in force, and they determined that the US reduced its emissions by 5.9% in most sectors even though it did not ratify the Kyoto Protocol. Also, it was shown that the technological effect - changing the combination of inputs used in production, had an impact on reducing the level of harmful gas emissions (Sesso et al., 2020). As in the case of the EU, the economic crisis of 2008 affected the level of CO_2 emissions, causing a sharp decline. However, the decrease in emissions was temporary since a new leap was recorded in 2010, which some researchers explain through the increase in energy intensity and carbon use.

In China, until 1978, CO_2 emissions rose gradually, as did GDP. However, after China's economic reforms and opening up in 1978 with the introduction of the concept of a socialist market economy, the growth of emissions became faster, in line with the pace of economic development (Long et al., 2015). As can be concluded from *Figure 1c*, since the beginning of the 2000s, China has recorded a high level of CO_2 emissions. In research that analysed the level of emissions in China from 2000 to 2009, it was determined that the structure of energy sources does not contribute to the reduction of emissions and that the change in the structure if energy sources would undermine the good results achieved in the production chain itself. In addition, the increase in demand in developing countries, including China, had a negative impact on the emissions level. However, the increase in emissions should not be interpreted as a consequence of the lack of efforts to reduce them - the efforts made to reduce emissions were less effective than the increase due to economic growth (Sesso et al., 2020). A study that aimed to examine the implications of economic factors on CO_2 emissions in China found that the huge growth of the industry in the period 2000-2013, with an average double-digit annual GDP growth, caused an unusual increase in coal consumption, which subsequently led to extremely high air pollution in China (Green and Stern, 2017). The increase in CO_2 emissions from 2005 to 2010 was caused not only by economic growth but also by China's inadequate energy mix, bearing in mind that the consumption of coal, which is its crucial source of energy, produces more carbon dioxide than other fossil fuels (Wang et al., 2015). A high degree of urbanisation, social inequalities, poverty, and environmental threats are some of the reasons why the China's economic model has been gradually changing since 2014. Such changes also implied a slowdown in GDP growth and coal consumption as a result, which is one of the reasons which led to a reduction in CO_2 emissions (Green and Stern, 2017). In the last couple of years of the observed period, according to the assessment of the International Energy Agency, improvements in energy efficiency have contributed to a significant reduction in the emission of all harmful gases in 2017 (IEA, 2017).

The line graphs of the three observed time series indicate that they might not be stationary and that there is a trend in the data. To explore the stationarity of the collected data ADF and Box-Ljung tests have been performed. The results are presented in *Table 2*.

The results of the ADF test for the time series of EU emissions indicate that the series should be integrated twice. In the level and the first difference, the ADF statistics was not statistically significant, indicating the need for integration. In the second difference, the ADF statistics was statistically significant, indicating that the series should be integrated twice and that the value of the parameter d of this time series is 2 or that the trend it the data should be modelled. The Box-Ljung statistics indicates presence of autocorrelation. In case of US's emissions, the series should be integrated only once, as the ADF test is statistically significant in first difference. This time series shows a lesser presence of

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autocorrelation. However, as the p-value was close to the 0.05 threshold, we performed the ADF test in the second leg just for inspection. Namely, we believe that in the process of model testing and identification, second difference might be a better solution. The time series of China's emissions also had to be integrated twice. The value of the ADF test was significant in the second difference. This time series did not show presence of autocorrelation except in a few first lags.

The correlograms, which present the ACF and PACF of the integrated time series are presented in *Figure 2a-c*. As can be seen, the ACF values decay rapidly and become insignificant after a few lags, which indicates little or no autocorrelation in all three observed time series. The ACF and PACF for EU series indicate a value of $p = 0$ and $q = 1$. For the US time series, the suggested values of model parameters are $p = 2$ and $q = 3$, while for the time series of China's emissions, the suggested values of the parameters are $p = 1$ and $q = 1$ due to big differences spikes.

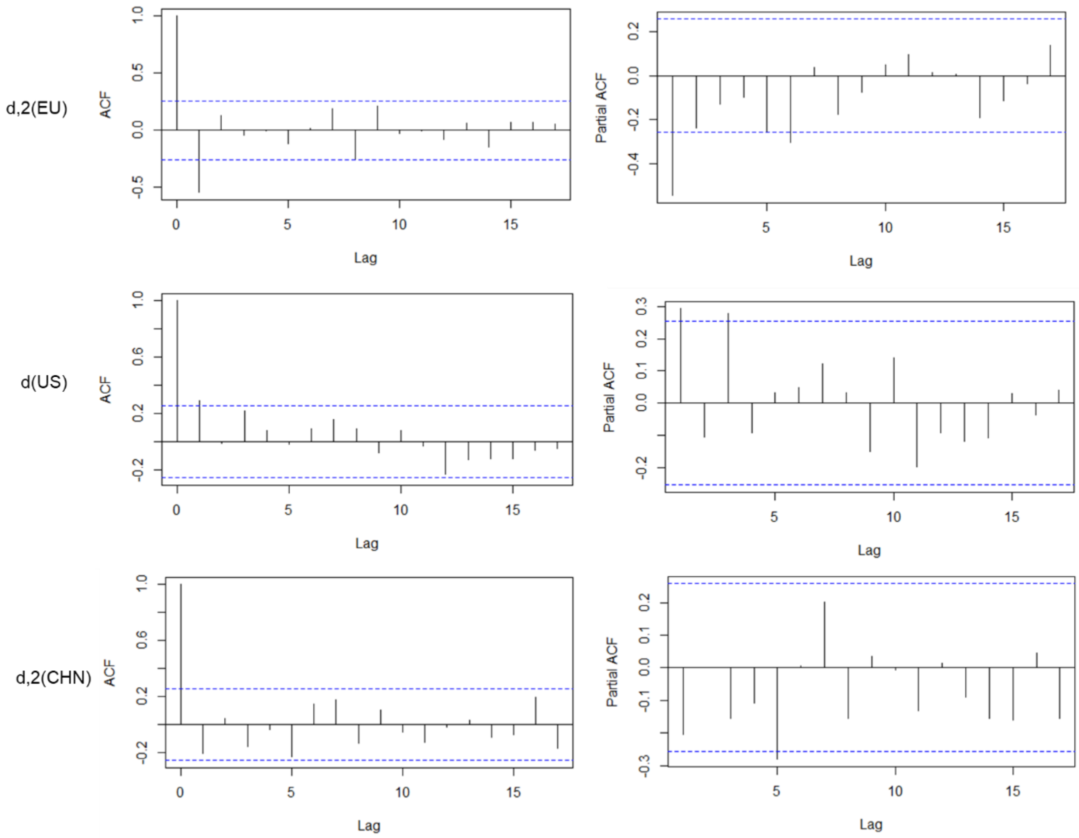

Figure 2. *ACF and PACF for d,2(EU), d(US), and d,2(CHN)*

Modelling the CO_2 emissions of the European Union

First, we modelled the CO_2 emissions of the EU. Seven ARIMA models were tested and the comparison is given in *Table 3*. The best model was chosen according to the AIC. The AIC of the tested models ranged from 11.23 to 38.69. The model with the lowest AIC was ARIMA(0,2,1) and this model was chosen for further analysis.

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Table 2. *ADF and Box-Ljung test for European Union, United States, and China time series, in level, first, and second difference*

Time series	ADF	Box-Ljung 1st lag	Box-Ljung 20th lag	Box-Ljung 40th lag	Box-Ljung 50th lag
EU	-2.489	52.480***	237.33***	377.52***	420.72***
d(EU)	-3.2961	5.832*	48.149***	60.904**	101.59***
d,2(EU)	-4.963***	18.207***	43.266***	56.030*	57.088
US	-2.565	51.644***	192.380***	346.37***	457.03***
d(US)	-3.709*	5.345*	21.135	47.895	68.319*
d,2(US)	-5.649***	4.248*	28.566	83.666***	92.413***
CHN	-1.282	57.347***	352.74***	483.99***	803.19***
d(CHN)	-3.078	25.972***	58.626***	73.600***	149.120***
d,2(CHN)	-4.741***	2.546	29.113	48.663	64.169

*p < 0.05, **p < 0.01, ***p < 0.001

Table 3. *Comparison of the EU time series ARIMA models*

Model	AIC
ARIMA(2,2,2)	17.49914
ARIMA(0,2,0)	38.69000
ARIMA(1,2,0)	20.50118
ARIMA(0,2,1)	**11.23206**
ARIMA(1,2,1)	13.39123
ARIMA(0,2,2)	13.40549
ARIMA(1,2,2)	15.48178

The chosen EU ARIMA model is presented below:

$$X_t'' = \varepsilon_t - 0.8018\varepsilon_{t-1} \quad \text{(Eq.1)}$$

where X_t'' is a second difference of the EU time series. Since

$$X_t'' = X_t - 2X_{t-1} + X_{t-2} \quad \text{(Eq.2)}$$

our model can be presented as follows:

$$X_t = 2X_{t-1} - X_{t-2} + \varepsilon_t - 0.8018\varepsilon_{t-1} \quad \text{(Eq.3)}$$

where X_t refers to forecasted emission level in year t and ε_t indicates random error in year t.

In the following stages of the analysis, the model was inspected. We observed the statistical significance of the coefficients in the model, the Ljung-Box statistics as a test for autocorrelation and the ARCH test for inspecting the presence of heteroskedasticity. The analysis of the residuals for the selected model is given in *Table 4*. The Z test for the MA coefficient is statistically significant in the model with the value of -10.242, which is satisfactory. The Ljung-Box and ARCH test indicated no presence of

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autocorrelation and presence of homoskedasticity in the model. The same conclusion can be made by looking at the model residuals in *Figure 3*. Residuals show no autocorrelation patterns and are Normally distributed.

Table 4. *Analysis of the ARIMA(0,2,1) model for the EU time series*

Test	Item	Statistics
Z test of coefficient MA(1)	$\beta 1$ = -0.802	-10.242***
Ljung-Box	Residuals - Autocorrelation	9.170
ARCH test	Residuals - Heteroskedasticity	11.252

*p < 0.05, **p < 0.01, ***p < 0.001

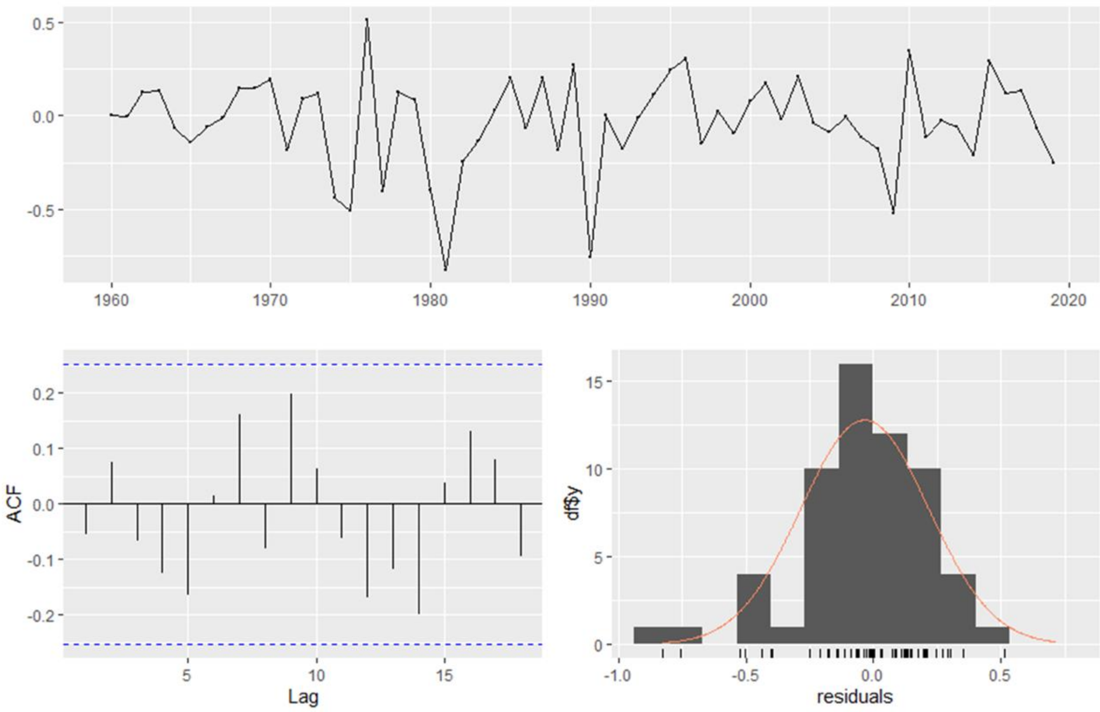

Figure 3. *Analysis of ARIMA(0,2,1) model residuals for EU time series*

Having in mind that ARIMA(0,2,1) model has the best fit, assumptions of autocorrelation and homoskedasticity are fulfilled, and the model is considered to be adequate for forecasting time series. The forecast graph is presented in *Figure 4*.

With regard to *Figure 4,* the blue line shows projected CO_2 emission levels in tons per capita in the period from 2020 to 2030, the black line indicates historical values upon which the forecast was built, light blue intervals indicate a 99% confidence interval, while dark blue intervals indicate the 95% confidence interval. According to the prediction, in the next seven-year period, CO_2 emissions in the EU will continue to decline.

Modelling the CO_2 emissions of the United States

We further modelled CO_2 emissions of the US. Again, seven ARIMA models were tested, and the comparison is given in *Table 5*. The AIC of the tested models ranged

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from 105.72 to 110.23. The model with the lowest AIC was ARIMA(0,2,3) and this model was chosen for further analysis. According to AIC, models in which the data was integrated two times produced better results than models in which the data was integrated once.

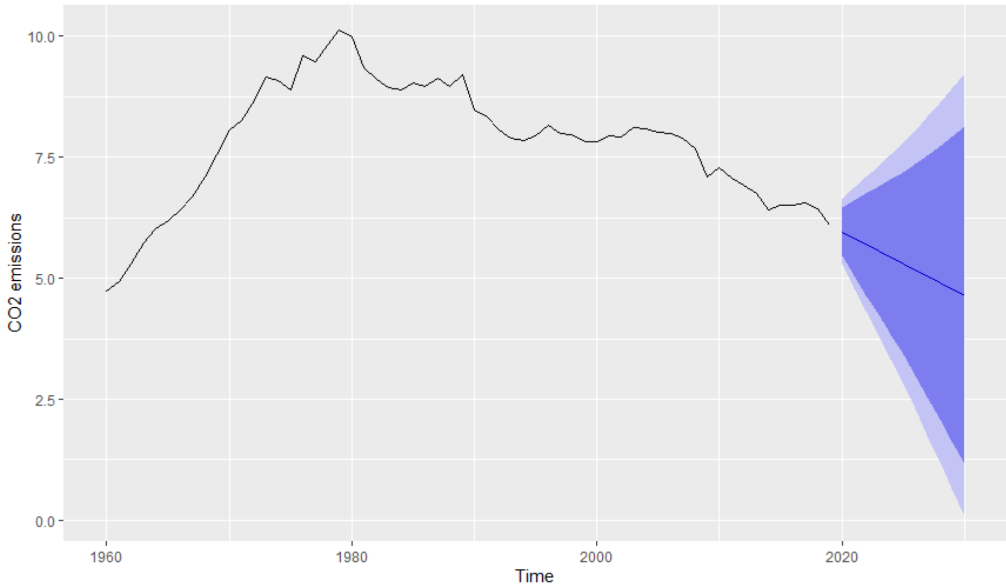

Figure 4. *European Union - historical and predicted values of the CO_2 emissions and confidence intervals*

Table 5. *Comparison of the US time series ARIMA models*

Model	AIC
ARIMA(2,2,2)	107.6541
ARIMA(1,2,2)	105.9960
ARIMA(0,2,2)	105.9887
ARIMA(0,2,3)	**105.7251**
ARIMA(1,2,3)	108.0435
ARIMA(0,2,4)	107.8946
ARIMA(1,2,4)	110.2265

The chosen US ARIMA model is given below:

$$X_t^{''} = \varepsilon_t - 0.5481\varepsilon_{t-1} - 0.5108\varepsilon_{t-2} + 0.1906\varepsilon_{t-3} \quad \text{(Eq.4)}$$

$$X_t = 2X_{t-1} - X_{t-2} + \varepsilon_t - 0.5481\varepsilon_{t-1} - 0.5108\varepsilon_{t-2} + 0.1906\varepsilon_{t-3} \quad \text{(Eq.5)}$$

The model was inspected using Z test, as well as Ljung-Box and ARCH tests. The results of the selected model are given in *Table 6*. The Z test for the coefficients MA(1) and MA(2) are statistically significant in the model, while the MA(3) is not. However, this was not observed as an issue. The Ljung-Box and ARCH test indicated no presence of autocorrelation and the presence of homoskedasticity in the model. The same

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conclusion can be made by looking at the model residuals in *Figure 5*. Residuals show no autocorrelation patterns and are Normally distributed.

Table 6. *Analysis of the ARIMA(0,2,3) model for the US time series*

Test	Item	Statistics
Z test of coefficient MA(1)	$\beta 1 = -0.548$	-4.2926***
Z test of coefficient MA(2)	$\beta 2 = -0.510$	-3.9466***
Z test of coefficient MA(3)	$\beta 3 = 0.190$	1.6119
Ljung-Box	Residuals - Autocorrelation	4.5766
ARCH test	Residuals - Heteroskedasticity	12.111

*p < 0.05, **p < 0.01, ***p < 0.001

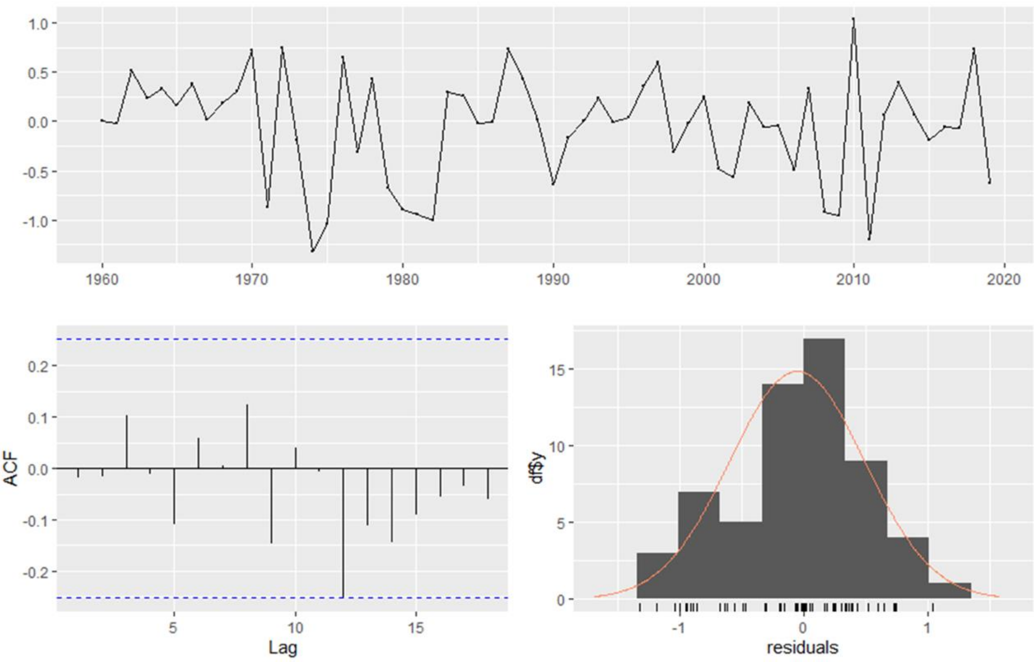

Figure 5. *Analysis of ARIMA(0,2,3) model residuals for US time series*

Regarding the model's statistical significance, best fit compared to other suggested models and the fact that assumptions are met, using ARIMA(0,2,3) for the purpose of forecast is acceptable. The forecast graph is presented in *Figure 6*. According to the projection presented in *Figure 6*, a slight decline in the CO_2 emission level is expected in the United States.

Modelling the CO_2 emissions of China

Finally, we modelled CO_2 emissions in China. Again, seven ARIMA models were tested and the comparison 'is given in *Table 7*. The AIC of the tested models ranged from -60.6 to -56.84. The model with the lowest AIC was ARIMA(1,2,1) and this model was chosen for further analysis.

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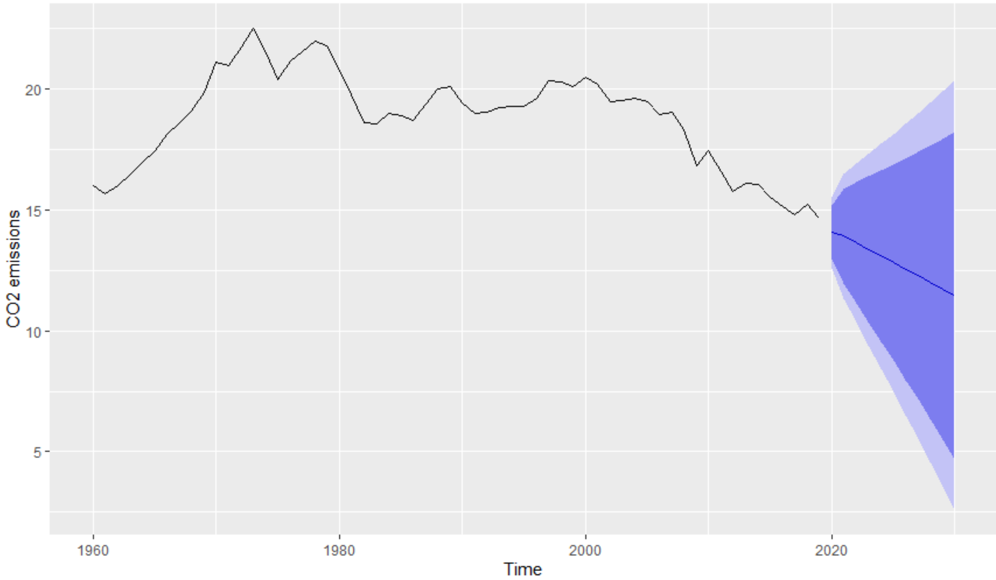

Figure 6. *United States - historical and predicted values and confidence interval*

Table 7. *Comparison of the China time series ARIMA models*

Model	AIC
ARIMA(2,2,2)	-56.84226
ARIMA(0,2,0)	-59.03755
ARIMA(1,2,0)	-59.28346
ARIMA(0,2,1)	-59.4025
ARIMA(1,2,1)	**-60.60172**
ARIMA(2,2,1)	-58.41911
ARIMA(2,2,0)	-57.05786

The China ARIMA model is given below:

$$X_t^{''} = 0.6464X_{t-1} + \varepsilon_t - 0.9196\varepsilon_{t-1} \quad \text{(Eq.6)}$$

$$X_t = 2.6464X_{t-1} - X_{t-2} + \varepsilon_t - 0.9196\varepsilon_{t-1} \quad \text{(Eq.7)}$$

The same model inspection procedure was conducted as in the previous two models. We observed the statistical significance of the coefficients in the model, the Ljung-Box statistics, and the ARCH test. The analysis of the residuals for the selected model is given in *Table 8*. The Z test showed that both AR and MA coefficients are statistically significant. The Ljung-Box and ARCH test indicated no presence of autocorrelation and presence of homoskedasticity in the model. The same conclusion can be made by looking at the model residuals in *Figure 7*.

Having in mind that ARIMA(1,2,1) model has the best fit, assumptions of autocorrelation and homoskedasticity are fulfilled, and the model is considered to be adequate for forecasting time series. The forecast graph is presented in *Figure 8*.

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Table 8. *Analysis of the ARIMA(1,2,1) model for China time series*

Test	Item	Statistics
Z test of AR coefficient	$\alpha 1$ = 0.646	4.540***
Z test of MA coefficient	$\beta 1$ = -0.919	-11.772***
Ljung-Box	Residuals - Autocorrelation	9.215
ARCH LM-test	Residuals - Heteroskedasticity	8.977

*p < 0.05, **p < 0.01, ***p < 0.001

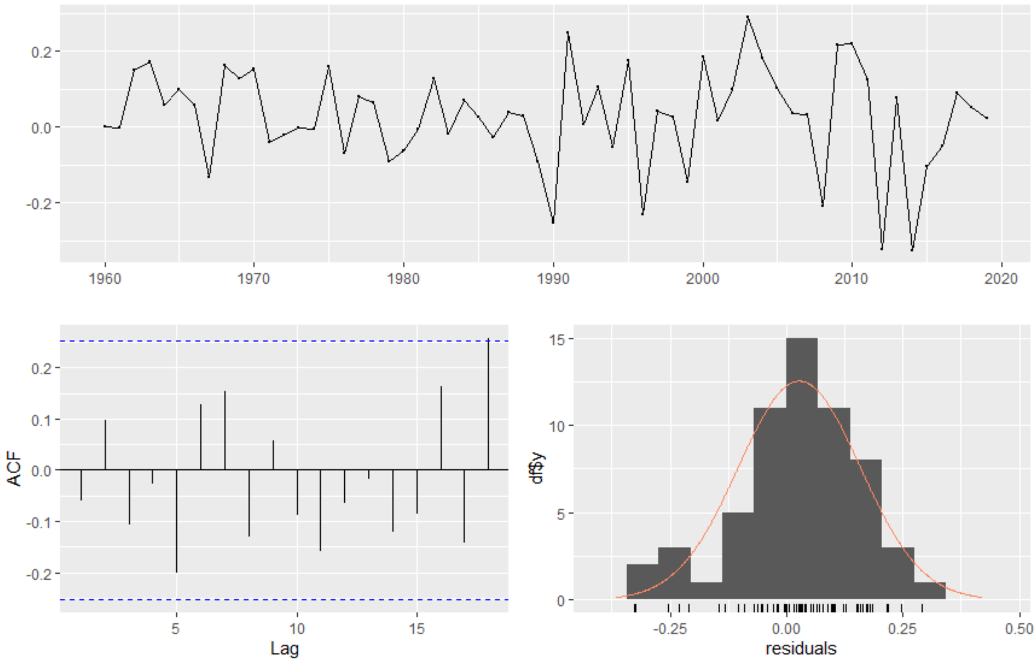

Figure 7. *Analysis of ARIMA(1,2,1) model residuals for China time series*

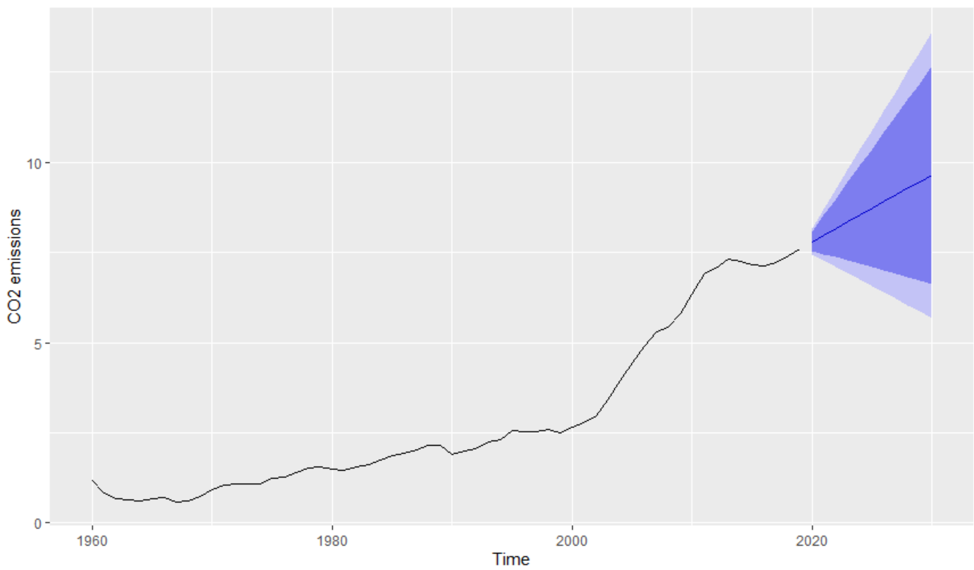

Figure 8. *China - historical and predicted values of the CO_2 emissions and confidence intervals*

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As seen in *Figure 8*, the expectations are the least favourable for China since it is projected that the emission level will rise.

Model comparison

In order to compare the obtained results, it is advisable to observe them parallelly and in more detail. *Table 9* shows projected quantities of CO_2 emissions in metric tons per capita in the EU, US, and China in the period 2020-2030. Besides the predicted values, we present the percentage of change in emissions compared to 2019 and the average emission in 2020-2030.

Table 9. *Projection results for the EU, US, and China CO_2 emissions*

Projection year	EU	EU - % change to 2019	US	US - % change to 2019	China	China - % change to 2019
2020	5.9599	-2.15%	14.0615	-4.17%	7.8002	2.55%
2021	5.8287	-4.31%	13.9075	-5.22%	7.9903	5.05%
2022	5.6974	-6.46%	13.6347	-7.08%	8.1778	7.52%
2023	5.5662	-8.62%	13.3619	-8.94%	8.3635	9.96%
2024	5.4349	-10.77%	13.0891	-10.80%	8.5481	12.39%
2025	5.3037	-12.93%	13.8163	-12.66%	8.7319	14.80%
2026	5.1725	-15.08%	12.5435	-14.52%	8.9153	17.22%
2027	5.0413	-17.23%	12.2707	-16.37%	9.0985	19.62%
2028	4.9100	-19.39%	11.9979	-18.23%	9.2814	22.03%
2029	4.7788	-21.54%	11.7251	-20.09%	9.4641	24.43%
2030	4.6476	-23.70%	11.4522	-21.95%	9.6468	26.83%
Average emission (2020-2030)	5.3037		12.8055		8.7289	

Based on the projections shown above, emissions in the EU should decline compared to 2019. Therefore, the projected decrease of the carbon-dioxide emissions in the EU are close to the values for the period between 1965 and 1967. The predicted emissions should decline from 5.96 to 4.65 mt per capita by 2030. The average CO_2 emission in the EU in the observed period should be 5.30. However, considering the width of the confidence interval, the estimate should be taken with reservation.

Indeed, IPCC reports that many countries have signalled an intention to achieve net zero greenhouse gasses or net zero CO_2 by around mid-century, but pledges differ across countries in terms of scope and specificity, and limited policies are to date in place to deliver on them (IPCC, 2023). Predictions of the US emissions are similar to the EU predictions: the emissions should decline compared to 2019. The predicted emissions should decline from 14.06 to 11.45 mt per capita by 2030. The average CO_2 emission in the US in the observed period should be 12.81. The results are affirmative, as the emissions are expected to decline. Still, the level of CO_2 emissions in the US per capita is twice as much as in the EU. The efforts to decrease these emissions should be higher, because, as IPCC reports, global warming will continue to increase in the near term (2021–2040) mainly due to increased cumulative CO_2 emissions in nearly all IPCC scenarios and modelled pathways. Global warming is more likely to reach than not to reach 1.5°C even under the very low greenhouse gasses emission scenario and likely or

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very likely to exceed 1.5°C under higher emissions scenarios (IPCC, 2023). Also, it should be mentioned that the obtained confidence interval is wide, so the results should be interpreted with reservation.

The predictions of the China's emissions are not so promising: the emissions would rise compared to 2019. The predicted emissions would rise from 7.80 to 9.65 mt per capita by 2030. Although the emissions in China are predicted to increase, they will still be below the emissions per capita in US. The average CO_2 emission in China in the observed period would be 8.73. The same as with previous predictions, the obtained confidence interval is wide, so the results should be interpreted having that in mind.

Discussion of the results and concluding remarks

CO_2 emissions have been related to the industry, services, gross-fixed capital formation (Mitić et al., 2020), GDP (Marjanović et al., 2016), health expenditures and economic growth (Chaabouni et al., 2016), and other social and economic phenomena. Therefore, it is of utmost importance to adequately, timely, and continuously measure CO_2 emissions and impose policies that will lead to its decrease. Having in mind that in 2023, according to Wisevoter (2023), the global average of CO_2 emission was 180 mt, and that the largest emitters were China (10.7 mt), US (4.7 mt), India (2.4 mt), and Russia (1.6 mt), analysis and predictions of CO_2 emission are needed.

Since the last estimated year in the World Bank database is 2019, it is possible to compare forecasted values from 2020, 2021, and 2022 with other disponible sources which use similar statistical methods so as to get a general image on the time series trends. However, a direct comparison of projections made by different institutions would be methodologically incorrect considering their potentially different aggregation methods, types of emissions included in the estimate, datasets, estimate precision, and others.

Concerning EU, in 2022, International energy Agency (IEA)evaluated a decline, which is consistent with this research results (International Energy Agency, 2023). On the other hand, our research findings are in contrast with the study by Akashi et al. (2018), who stated that considering the introduction of technologies with specific reduction costs, emissions would increase by 17% in EU15 between 2005 and 2030. However, these results should be interpreted carefully, given the fact that the analysis was based on technologies available in 2011. Even though the forecast can be considered favourable, additional efforts are needed to achieve carbon neutrality by 2050. Our results show a decrease in CO_2 emissions by about 15% in the examined period, which makes IPCC's very low greenhouse gas emissions scenario (SSP1-1.9) not so achievable, since in IPCC's modelled pathways that limit warming to 1.5°C (>50%), global CO_2 emissions are reduced by 48 [36-69] % by 2030 relative to 2019 (IPCC, 2023). The limitation of warming to 2°C requires a reduction of CO_2 emissions by 22%. Some of the EU countries are highly successful in lowering their CO_2 emissions, while others are inefficacious in meeting their climate-related objectives. For that reason, one useful action could be upgrading climate policy and its implementation in countries where results are inadequate.

When it comes to US projections, study results are partly aligned with the findings of IEA. Namely, IEA expects an increase by 7.1% in 2021 and 1.5% in 2022 after a 11.1% decrease in 2020. Nevertheless, starting from 2023, an emission decline is forecasted as a consequence of higher renewable energy's share in the energy mix. Study results are in

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accordance with forecasts by Wang et al. (2020), who concluded that US emission levels could remain stable from 2019 to 2030, with an average annual growth rate of -0.87%. In the matter of the US, projected stagnation of emission level cannot be viewed as a success, regarding the country's ambitious objectives that should be attained. Suggested solution is similar to one proposed for the case of European Union.

Regarding the People's Republic of China, our findings are levelled with a study done by Fang et al. (2018), who projected that China would have a higher growth rate than any developed country, such as the US. In previously mentioned research by Wang et al. (2020), China's CO_2 emissions could grow with an average annual rate of 1.6%, which is significantly lower than our projection of 11.376%. However, the authors explained that the emission rise could diminish as a result of improving the climate policy. Due to its unfavourable projections, the most significant changes should be made in China. In spite of the fact that the regulation which affects climate change and the environment is in constant progress, its contribution to CO_2 emissions is apparently lower than the negative ecological consequences of economic growth. Therefore, supplementary measures should be implemented. For instance, stricter regulation of coal consumption indicates a huge space for improvement since coal is China's number one cause of carbon emissions (U.S. Energy Information Administration, 2020).

The findings of this study could be beneficial for relevant institutions and environmental organisations, which should provide support to these economies in the field of CO_2 reduction. Monitoring and reducing CO_2 emissions is crucial for creating a sustainable society (Maricic et al., 2014). Nevertheless, the findings of this study must be seen in the light of some limitations. Namely, as mentioned before, the World Bank's database has not included the data for the period 2020-2022 yet. Considering the COVID-19 global crisis of which negative economic impacts are strongly associated with greenhouse gas emissions, forecast precision would have been higher if 2020 had been included. It mplyes that when that data becomes disponible, the forecast should be revised in future research. Another problem is the limited ability to compare research findings with other sources, given the fact that relevant institutions use more or less different measuring methodologies (JRC, 2011). A as an illustration, some institutions measure only carbon-dioxide emissions, other analyse all greenhouse gas emissions, some of them include cement manufacturing while others do not, etc. Additionally, a fact that the World Bank's emission data does not include all CO_2 emissions sources, such as land use, leads to a presumption that actual emissions are even higher than presented. A future direction of the study also emerges, which encompasses the application of other time series models and algorithms. For instance, the grey method is a relevant forecasting method applied in the field (Lotfalipour et al., 2013). The approach taken by Dobrota et al. (2021), which encompassed creating a large number of different models (R(p), MA(q), ARMA(p,q), ARCH, GARCH, BMMR, BMMRJD, GBM, GBMJD) could be of interest. Also, one possible future research is the observation of CO_2 time series per EU member-state. Namely, in the presented study, we observed the EU as one entity, but it would be valuable for European policy-makers to have more precise information and country-level predictions to arrange and align their energy policies (Pao and Chen, 2022). In the same sense, another future direction of the study could be to provide the assessment and prediction of CO_2 per capita for other large emitters such as India, Russia, and Japan. Also, datasets which take into account CO_2 emissions from land use, deforestation, and fuel consumption in ship and aircraft international transport can be taken into consideration.

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REFERENCES

[1] Adger, W.N., Huq, S., Brown, K., Conway, D., Hulme, M. (2003): Adaptation to climate change in the developing world. – Prog. Dev. Stud. 3(3): 179-195.

[2] Akashi, F., Bai, S., Taqqu, M. S. (2018): Robust regression on stationary time series: a self-normalised resampling approach. – J. Time Ser. Anal. 39(3): 417-432. DOI: 10.1111/jtsa.12295.

[3] Bellamy, R., Hulme, M. (2011): Beyond the tipping point: understanding perceptions of abrupt climate change and their implications. – Weather. Clim. Soc. 3(1): 48-60. DOI: 10.1175/2011WCAS1081.1.

[4] Budyko, M. I. (1993): Global Warming. – In: Nakicenovic, N. et al. (eds.) Integrative Assessment of Mitigation, Impacts, and Adaptation to Climate Change. IIASA, Laxenburg, pp. 87-92.

[5] Calbick, K. S., Gunton, T. (2014): Differences among OECD countries' GHG emissions: Causes and policy implications. – Energy Policy 67 895-902. DOI: 10.1016/j.enpol.2013.12.030.

[6] Chaabouni, S., Zghidi, N., Ben Mbarek, M. (2016): On the causal dynamics between CO 2 emissions, health expenditures and economic growth. – Sustain. Cities Soc. 22 184-191. DOI: 10.1016/j.scs.2016.02.001.

[7] Chang, C.-T., Lin, T.-P. (2018): Estimation of carbon dioxide emissions generated by building and traffic in Taichung City. – Sustainability 10(1): 112. DOI: 10.3390/su10010112.

[8] Chen, P., Yuan, H., Shu, X. (2008): Forecasting Crime Using the ARIMA Model. – In: 2008 Fifth International Conference on Fuzzy Systems and Knowledge Discovery. IEEE, pp. 627-630. DOI: 10.1109/FSKD.2008.222.

[9] Collins, M. (2007): Ensembles and probabilities: a new era in the prediction of climate change. – Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 365(1857): 1957-1970. DOI: 10.1098/rsta.2007.2068.

[10] Crafts, N. (2012): Western Europe's Growth Prospects: An Historical Perspective. – https://ec.europa.eu/economy_finance/events/2011/2011-11-21-annual-research-conference_en/pdf/session012_crafts_en.pdf.

[11] CSIRO (2021): How are greenhouse gases measured, estimated, and reported? – https://www.csiro.au/en/research/environmental-impacts/climate-change/climate-change-qa/measuring-ghg (accessed 5.21.23).

[12] De Araújo Junior, I. F., Jackson, R. W., Ferreira Neto, A. B., Perobelli, F. S. (2020): European Union membership and CO2 emissions: a structural decomposition analysis. – Struct. Change. Econ. D. 55: 190-203. DOI: 10.1016/j.strueco.2020.06.006.

[13] Dimitrov, R. S. (2016): The Paris Agreement on Climate Change: behind closed doors. – Glob. Environ. Polit. 16(3): 1-11. DOI: 10.1162/GLEP_a_00361.

[14] Dobrota, M., Zornić, N., Marković, A. (2021): FDI time series forecasts: evidence from emerging markets. – Manag. Sustain. Bus. Manag. Solut. Emerg. Econ. 26(2): 77-88. DOI: 10.7595/management.fon.2021.0010.

[15] Economidou, M., Ringel, M., Valentova, M., Castellazzi, L., Zancanella, P., Zangheri, P., Serrenho, T., Paci, D., Bertoldi, P. (2022): Strategic energy and climate policy planning: lessons learned from European energy efficiency policies. – Energ. Policy. 171: 113225. DOI: 10.1016/j.enpol.2022.113225.

[16] Enerdata (2023): Energy Intensity Global Energy Intensity Improvement in 2021 is below the 2000-2019 Average. – Enerdata, Grenoble.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_55655594

[17] Erbach, G., Jochheim, U. (2022): China's Climate Change Policies. – Briefing. European Parliament, Strasbourg.
[18] European Commission (2019): What is the European Green Deal? – EC, Brussels.
[19] European Commission (2022a): CO2 Emissions of All World Countries. – 2022 Report. https://edgar.jrc.ec.europa.eu/report_2022 (accessed 6.2.23).
[20] European Commission (2022b): EU Energy in Figures: Statistical Pocketbook 2022. – Publications Office of the European Union, 2022. https://data.europa.eu/doi/10.2833/334050.
[21] European Commission (2022c): Further Improvements of Energy Efficiency in Industry. – Final Report. EC, Brussels.
[22] European Commission (2023a): Energy Policy. General Principles. – WWW Document. EC, Brussels.
[23] European Commission (2023b): European Green Deal: EU Agrees Stronger Rules to Boost Energy Efficiency. – EC, Brussels.
[24] European Parliament, C. of the E.U. (2012): Directive 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on Energy Efficiency, Amending Directives 2009/125/EC and 2010/30/EU and Repealing Directives 2004/8/EC and 2006/32/EC.
[25] European Parliament, C. of the E.U. (2021): Regulation (EU) 2021/1119 of the European Parliament and of the Council of 30 June 2021 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 (European Climate Law').
[26] Fang, D., Zhang, X., Yu, Q., Jin, T. C., Tian, L. (2018): A novel method for carbon dioxide emission forecasting based on improved Gaussian processes regression. – J. Clean. Prod. 173 143-150. DOI: 10.1016/j.jclepro.2017.05.102.
[27] Fernández González, P., Landajo, M., Presno, M. J. (2014): Tracking European Union CO2 emissions through LMDI (logarithmic-mean Divisia index) decomposition. The activity revaluation approach. – Energy 73 741-750. DOI: 10.1016/j.energy.2014.06.078.
[28] Flerlage, H., Velders, G. J. M., de Boer, J. (2021): A review of bottom-up and top-down emission estimates of hydrofluorocarbons (HFCs) in different parts of the world. – Chemosphere 283 131208. DOI: 10.1016/j.chemosphere.2021.131208.
[29] González, P. F., Landajo, M., Presno, M. J. (2014): Tracking European Union CO2 emissions through LMDI (logarithmic-mean Divisia index) decomposition. The activity revaluation approach. – Energy. 73: 741-750. DOI: 10.1016/j.energy.2014.06.078.
[30] Graves, S. (2022): Package 'FinTS'. – https://cran.r-project.org/web/packages/FinTS/FinTS.pdf.
[31] Green, F., Stern, N. (2017): China's changing economy: implications for its carbon dioxide emissions. – Clim. Policy 17(4): 423-442. DOI: 10.1080/14693062.2016.1156515.
[32] Günel, G. (2016): What is carbon dioxide? When is carbon dioxide? – PoLAR Polit. Leg. Anthropol. Rev. 39(1): 33-45. DOI: 10.1111/plar.12129.
[33] Harper, L. A., Denmead, O. T., Flesch, T. K. (2011): Micrometeorological techniques for measurement of enteric greenhouse gas emissions. – Anim. Feed Sci. Technol. 166-167: 227-239. DOI: 10.1016/j.anifeedsci.2011.04.013.
[34] Harris, R. I. D. (1992): Testing for unit roots using the augmented Dickey-Fuller test. – Econ. Lett. 38(4): 381-386. DOI: 10.1016/0165-1765(92)90022-Q.
[35] Herzog, H., Eliasson, B., Kaarstad, O. (2000): Capturing greenhouse gases. – Sci. Am. 282(2): 72-79. DOI: 10.1038/scientificamerican0200-72.
[36] Horobet, A., Popovici, O. C., Zlatea, E., Belascu, L., Dumitrescu, D. G., Curea, S. C. (2021): Long-run dynamics of gas emissions, economic growth, and low-carbon energy in the European Union: the fostering effect of FDI and trade. – Energies 14(10): 2858. DOI: 10.3390/en14102858.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_55655594

[37] Hothorn, T., Zeileis, A., Farebrother, R., Cummins, C., Millo, G., Mitchell, D. (2022): Package ‘lmtest’. – https://cran.r-project.org/web/packages/lmtest/lmtest.pdf.
[38] IEA (2017): World Energy Outlook 2017: China. – https://www.iea.org/reports/world-energy-outlook-2017-china (accessed 5.1.23).
[39] IEA (2023): The world's top 1% of Emitters Produce over 1000 Times More CO2 than the Bottom 1%. – https://www.iea.org/commentaries/the-world-s-top-1-of-emitters-produce-over-1000-times-more-co2-than-the-bottom-1 (accessed 5.10.23).
[40] International Energy Agency (2018): Energy Efficiency 2018 Market Report Series Analysis and Outlooks to 2040. – IEA, Paris.
[41] International Energy Agency (2019): United States 2019 Review. – IEA, Paris.
[42] International Energy Agency (2023): CO_2 emissions in 2022 Report. – IEA, Paris.
[43] IPCC (2013): Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. – Cambridge University Press, Cambridge, United Kingdom and New York, NY.
[44] IPCC (2023): Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. – IPCC, Geneva, pp. 1-34. DOI: 10.59327/IPCC/AR6-9789291691647.001.
[45] JRC (2011): Analysis of Existing Environmental Footprint Methodologies for Products and Organizations: Recommendations, Rationale, and Alignment. – ECJRC, Brussels.
[46] Karmellos, M., Kopidou, D., Diakoulaki, D. (2016): A decomposition analysis of the driving factors of CO2 (Carbon dioxide) emissions from the power sector in the European Union countries. – Energy 94 680-692. DOI: 10.1016/j.energy.2015.10.145.
[47] Kour, M. (2022): Modelling and forecasting of carbon-dioxide emissions in South Africa by using ARIMA model. – Int. J. Environ. Sci. Technol. 11267-11274. DOI: 10.1007/s13762-022-04609-7.
[48] Kulkarni, S. D. (2019): A bottom up approach to evaluate the carbon footprints of a higher educational institute in India for sustainable existence. – J. Clean. Prod. 231 633-641. DOI: 10.1016/j.jclepro.2019.05.194.
[49] Ljung, G. M., Box, G. E. P. (1978): On a measure of lack of fit in time series models. – Biometrika 65(2): 297-303. DOI: 10.1093/biomet/65.2.297.
[50] Long, X., Naminse, E. Y., Du, J., Zhuang, J. (2015): Nonrenewable energy, renewable energy, carbon dioxide emissions and economic growth in China from 1952 to 2012. – Renew. Sustain. Energy Rev. 52: 680-688. DOI: 10.1016/j.rser.2015.07.176.
[51] Loo, R. T. (2009): A Methodology for Calculating CO2 Emissions from Transport and an Evaluation of the Impact of European Union Emission Regulations. – Technical University, Eindhoven.
[52] Lotfalipour, M. R., Falahi, M. A., Bastam, M. (2013): Prediction of CO2 emissions in iran using grey and ARIMA models. – Int. J. Energy Econ. Policy 3(3): 229-237.
[53] Maamoun, N. (2019): The Kyoto protocol: Empirical evidence of a hidden success. – J. Environ. Econ. Manag. 95: 227-256. DOI: 10.1016/j.jeem.2019.04.001.
[54] Makridakis, S., Hibon, M. (1997): ARMA Models and the Box-Jenkins Methodology. – J. Forecast. 16(3): 147-163. DOI: 10.1002/(SICI)1099-131X(199705)16:3<147:AID-FOR652>3.0.CO;2-X.
[55] Malhi, Y., Grace, J. (2000): Tropical forests and atmospheric carbon dioxide. – Trends Ecol. Evol. 15(8): 332-337. DOI: 10.1016/S0169-5347(00)01906-6.
[56] Maricic, M., Jankovic, M., Jeremic, V. (2014): Towards a framework for evaluating Sustainable Society Index. – Rom. Stat. Rev. 62(3): 49-62.
[57] Marjanović, V., Milovančević, M., Mladenović, I. (2016): Prediction of GDP growth rate based on carbon dioxide (CO2) emissions. – J. CO2 Util. 16 212-217. DOI: 10.1016/j.jcou.2016.07.009.
[58] McGinn, S. M. (2006): Measuring greenhouse gas emissions from point sources in agriculture. – Can. J. Soil Sci. 86(3): 355-371. DOI: 10.4141/S05-099.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_55655594

[59] McKinnon, A. C., Piecyk, M. (2010): Measuring and managing CO2 emissions in European chemical transport. – European Chemical Industry Council, Brussels.
[60] McMichael, T., Montgomery, H., Costello, A. (2012): Health risks, present and future, from global climate change. – BMJ 344 e1359. DOI: 10.1136/bmj.e1359.
[61] Meng, W., Xu, L., Hu, B., Zhou, J., Wang, Z. (2017): Reprint of: Quantifying direct and indirect carbon dioxide emissions of the Chinese tourism industry. – J. Clean. Prod. 163: S401-S409. DOI: 10.1016/j.jclepro.2016.03.177.
[62] Miller, N., Cavens, D., Condon, P., Kellet, R. (2009): Policy, urban form, and tools for measuring and managing greenhouse gas emissions: the North American problem. – Univ. Color. Law Rev. 80 977-998.
[63] Mitić, P., Kostić, A., Petrović, E., Cvetanovic, S. (2020): The relationship between CO2 emissions, industry, services and gross fixed capital formation in the Balkan countries. – Eng. Econ. 31(4): 425-436. DOI: 10.5755/j01.ee.31.4.24833.
[64] Mondal, P., Shit, L., Goswami, S. (2014): Study of effectiveness of time series modeling (Arima) in forecasting stock prices. – Int. J. Comput. Sci. Eng. Appl. 4(2): 13-29. DOI: 10.5121/ijcsea.2014.4202.
[65] NASA (2023): Earth Fact Sheet. – NASA, Washington, DC.
[66] Osman, A. I., Chen, L., Yang, M., Msigwa, G., Farghali, M., Fawzy, S., Rooney, D. W., Yap, P.-S. (2023): Cost, environmental impact, and resilience of renewable energy under a changing climate: a review. – Environ. Chem. Lett. 21(2): 741-764. DOI: 10.1007/s10311-022-01532-8.
[67] Ozturk, S., Ozturk, F. (2018): Forecasting Energy Consumption of Turkey by Arima Model. – J. Asian Sci. Res. 8(2): 52-60. DOI: 10.18488/journal.2.2018.82.52.60.
[68] Pao, H.-T., Chen, C.-C. (2022): The dynamic interaction between circular economy and the environment: evidence on EU countries. – Waste Manag. Res. J. a Sustain. Circ. Econ. 40(7): 969-979. DOI: 10.1177/0734242X211057015.
[69] Pata, U. K., Ertugrul, H. M. (2023): Do the Kyoto Protocol, geopolitical risks, human capital and natural resources affect the sustainability limit? A new environmental approach based on the LCC hypothesis. – Resour. Policy 81 103352. DOI: 10.1016/j.resourpol.2023.103352.
[70] Rafaj, P., Amann, M., Siri, J., Wuester, H. (2015): Changes in European Greenhouse Gas and Air Pollutant Emissions 1960-2010: Decomposition of Determining Factors. – In: Ometto, J. P. et al. (eds.) Uncertainties in Greenhouse Gas Inventories. Springer International Publishing, Cham, pp. 27-54. DOI: 10.1007/978-3-319-15901-0_3.
[71] Rahman, A., Hasan, M. (2014): Modeling and forecasting of carbon dioxide emissions in bangladesh using autoregressive integrated moving average (ARIMA) models. – Open J. Stat. 7(4): 560-566.
[72] Ramseur, J. L. (2007): State greenhouse gas emissions: comparison and analysis. – https://www.everycrsreport.com/reports/RL34272.html.
[73] Ritchie, H. (2020): What are the safest and cleanest sources of energy? – https://ourworldindata.org/safest-sources-of-energy (accessed 5.20.23).
[74] Rosa, E. A., Dietz, T. (2012): Human drivers of national greenhouse-gas emissions. – Nat. Clim. Chang. 2(8): 581-586. DOI: 10.1038/nclimate1506.
[75] Sandalow, D., Meidan, M., Andrews-Speed, P., Hove, A., Qiu, S., Downie, E. (2022): Guide to Chinese Climate Policy 2022. – Oxford. https://chineseclimatepolicy.oxfordenergy.org/.
[76] Scotto di Perta, E., Fiorentino, N., Carozzi, M., Cervelli, E., Pindozzi, S. (2020): A review of chamber and micrometeorological methods to quantify NH 3 emissions from fertilisers field application. – Int. J. Agron. 2020 1-16. DOI: 10.1155/2020/8909784.
[77] Sen, P., Roy, M., Pal, P. (2016): Application of ARIMA for forecasting energy consumption and GHG emission: a case study of an Indian pig iron manufacturing organisation. – Energy 116 1031-1038. DOI: 10.1016/j.energy.2016.10.068.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_55655594

[78] Sesso, P. P., Amâncio-Vieira, S. F., Zapparoli, I. D., Sesso Filho, U. A. (2020): Structural decomposition of variations of carbon dioxide emissions for the United States, the European Union and BRIC. – J. Clean. Prod. 252 119761. DOI: 10.1016/j.jclepro.2019.119761.
[79] Shahiduzzaman, M., Layton, A. (2015): Changes in CO2 emissions over business cycle recessions and expansions in the United States: a decomposition analysis. – Appl. Energy 150 25-35. DOI: 10.1016/j.apenergy.2015.04.007.
[80] Smith, M. R., Myers, S. S. (2018): Impact of anthropogenic CO2 emissions on global human nutrition. – Nat. Clim. Chang. 8(9): 834-839. DOI: 10.1038/s41558-018-0253-3.
[81] The U.S. Department of Energy (2023): Appliance and Equipment Standards Program. – https://www.energy.gov/eere/buildings/appliance-and-equipment-standards-program.
[82] The U.S. Department of Transportation (2022): The U.S. Department of Transportation. – WWW Document. Veh. Fuel Econ. Stand.
[83] The White House (2021): FACT SHEET: President Biden Sets 2030 Greenhouse Gas Pollution Reduction Target Aimed at Creating Good-Paying Union Jobs and Securing U.S. Leadership on Clean Energy Technologies. – https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/.
[84] Tiseo, I. (2020): Emissions in the EU. – Statistics & Facts. – https://www.statista.com/topics/4958/emissions-in-the-european-union/ (accessed 5.15.23).
[85] Tol, R. S. J., Pacala, S. W., Socolow, R. (2006): Understanding Long-Term Energy Use and Carbon Dioxide Emissions in the USA. – No. FEEM Working Paper No. 107.06, SSRN Electronic Journal. DOI: 10.2139/ssrn.927741.
[86] Trapletti, A., Hornik, K., LeBaron, B. (2023): Package 'tseries'. – https://cran.r-project.org/web/packages/tseries/tseries.pdf.
[87] UCAR (2021): What is the atmosphere? – https://scied.ucar.edu/learning-zone/atmosphere/what-is-atmosphere (accessed 4.14.23).
[88] UCSUSA (2008): Environmental impacts of renewable energy technologies. – https://www.ucsusa.org/resources/environmental-impactsrenewable-energy-technologies (accessed 6.10.23).
[89] United Nations (2015): Paris Agreement. – UN, New York.
[90] Usman, M., Balsalobre-Lorente, D., Jahanger, A., Ahmad, P. (2023): Are Mercosur economies going green or going away? An empirical investigation of the association between technological innovations, energy use, natural resources and GHG emissions. – Gondwana Res. 113 53-70. DOI: 10.1016/j.gr.2022.10.018.
[91] Västermark, A. (2021): The United Nation and the threat of climate change: a critical security study of UNFCCC, the Kyoto Protocol and the Paris Agreement. – http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1548213&dswid=8746.
[92] Wang, Q., Chiu, Y.-H., Chiu, C.-R. (2015): Driving factors behind carbon dioxide emissions in China: a modified production-theoretical decomposition analysis. – Energy Econ. 51 252-260. DOI: 10.1016/j.eneco.2015.07.009.
[93] Wang, Q., Li, S., Pisarenko, Z. (2020): Modeling carbon emission trajectory of China, US and India. – J. Clean. Prod. 258 120723. DOI: 10.1016/j.jclepro.2020.120723.
[94] Wang, Q. W., Zhou, P., Shen, N., Wang, S. S. (2013): Measuring carbon dioxide emission performance in Chinese provinces: a parametric approach. – Renew. Sustain. Energy Rev. 21 324-330. DOI: 10.1016/j.rser.2012.12.061.
[95] Wang, X., Meng, M. (2012): A hybrid neural network and ARIMA model for energy consumption forecasting. – J. Comput. 7(5): 1184-1190. DOI: 10.4304/jcp.7.5.1184-1190.

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DOI: http://dx.doi.org/10.15666/aeer/2106_55655594

[96] Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., Julca, A. (2010): Climate change, environmental degradation and migration. – Nat. Hazards 55(3): 689-715. DOI: 10.1007/s11069-009-9419-7.

[97] Wirawan, I. M., Widiyaningtyas, T., Hasan, M. M. (2019): Short Term Prediction on Bitcoin Price Using ARIMA Method. – In: 2019 International Seminar on Application for Technology of Information and Communication (ISemantic). IEEE, pp. 260-265. DOI: 10.1109/ISEMANTIC.2019.8884257.

[98] Wisevoter (2023): CO2 emissions by country. – https://wisevoter.com/country-rankings/co2-emissions-by-country/.

[99] World Bank (2023): CO_2 emissions (metric tons per capita). – https://data.worldbank.org/indicator/EN.ATM.CO2E.PC.

[100] WRI (2023): This interactive chart shows changes in the world's top 10 emitters. – https://www.wri.org/insights/interactive-chart-shows-changes-worlds-top-10-emitters (accessed 6.1.23).

[101] Wu, P., Han, Y., Tian, M. (2015): The measurement and comparative study of carbon dioxide emissions from tourism in typical provinces in China. – Acta Ecol. Sin. 35(6): 184-190. DOI: 10.1016/j.chnaes.2015.09.004.

[102] Zha, Y., Zhao, L., Bian, Y. (2016): Measuring regional efficiency of energy and carbon dioxide emissions in China: a chance constrained DEA approach. – Comput. Oper. Res. 66 351-361. DOI: 10.1016/j.cor.2015.07.021.

[103] Zhang, X., Luo, L., Skitmore, M. (2015): Household carbon emission research: an analytical review of measurement, influencing factors and mitigation prospects. – J. Clean. Prod. 103 873-883. DOI: 10.1016/j.jclepro.2015.04.024.

[104] Zhao, X., Han, M., Ding, L., Calin, A. C. (2018): Forecasting carbon dioxide emissions based on a hybrid of mixed data sampling regression model and back propagation neural network in the USA. – Environ. Sci. Pollut. Res. 25(3): 2899-2910. DOI: 10.1007/s11356-017-0642-6.

[105] Zhou, S., Yan, Y., Yang, X. (2014): Measuring carbon dioxide emissions from the Chinese transport sector. – Proc. Inst. Civ. Eng. – Transp. 167(5): 306-321. DOI: 10.1680/tran.13.00093.

[106] Zhou, X., Yoon, S., Mara, S., Falk, M., Kuwayama, T., Tran, T., ... Vijayan, A. (2021): Mobile sampling of methane emissions from natural gas well pads in California. – Atmos. Environ. 244: 117930. DOI: 10.1016/j.atmosenv.2020.117930.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2106_55655594