Forecasting European Union Carbon Prices: A Boosted Regression Trees Learning Method

Ahmed H. Elsayed[1]
Department of Economics and Finance, United Arab Emirates University, Al Ain, United Arab Emirates
ahmed.elsayed@uaeu.ac.ae

Zied FTITI
EDC Paris Business Schoo, OCRE Research Lab, Paris (France)
zftiti@edcparis.edu

Rabeh Khalfaoui
ICN Business School, CEREFIGE, Université de Lorraine, Nancy, France
rabeh.khalfaoui@gmail.com

You Zhou
Leeds University Business School, University of Leeds, Leeds, LS2 9JT, UK.
Email: busyzh@leeds.ac.uk

This version: April 2025

Abstract

The European Union Emissions Trading System (EU ETS) stands as the pioneering global emissions trading system, with carbon trading prices, especially EU carbon allowance prices, assuming a pivotal role in achieving carbon neutrality and advancing low-carbon initiatives. The fluctuating EU carbon price has emerged as a vital reference point for shaping policies and informing decisions among firms, policymakers, and investors. Yet, the precise forecasting of carbon prices holds significant implications for national energy resilience and sustainability policies. Machine learning techniques offer enhanced accuracy, hence heightened ability to identify irregularities and increased adaptability and versatility. In this study, we utilize the boosted regression trees (BRT) learning technique to predict the EU carbon emissions trading price and evaluate the influence of predictor variables on the system's response. Our analysis incorporates key determinants of ETS prices, encompassing oil, natural gas, coal, and European stock market. Additionally, we consider financial and economic factors, such as global uncertainties, geopolitical risks, pandemic-related concerns, bond market uncertainty, and financial stress factors. The findings demonstrate the robust predictive capability of BRT in forecasting EU carbon prices. The STOXX Europe 600 index and pandemic-related uncertainty emerge as primary factors influencing carbon emissions. Policymakers should integrate economic policies with climate goals to enhance investor confidence in carbon markets. They should also bolster crisis response and risk management strategies to mitigate the impact of global health crises and other shocks on carbon pricing.

Keywords*:* Carbon Emissions; Economic Policy Uncertainty, Financial Stress, Pandemic Uncertainty, Bond Market Uncertainty, Forecasting; Boosted Regression Trees

JEL classification: O1, Q4, Q5

[1] Corresponding author: Ahmed Elsayed (ahmed.elsayed@uaeu.ac.ae)

1. Introduction

Understanding the intricacies of carbon pricing within the European Emissions Trading System (ETS) is of paramount importance in the contemporary context of climate change and global economic uncertainties. This urgency is underscored by international efforts of the Kyoto Protocol and the Paris Agreement, which represent pivotal milestones in global climate policy. The Kyoto Protocol, effective from February 16, 2005, set binding targets for 37 industrialized countries to reduce greenhouse gas emissions by a minimum of 5% during the 2008-2012 period, acknowledging their historical responsibility due to over 150 years of industrial activity (Zhao et al., 2016; Adekoya, 2021). To support compliance with these commitments, the European Union established the EU ETS, aiming to facilitate CO2 allowance trading among governments and industries, thereby encouraging emissions reductions and the development of low-carbon technologies (Arouri et al., 2012). Subsequently, the Paris Agreement, ratified in April 2016, introduced new mitigation strategies for addressing climate change from 2020 onwards, promoting the marketization of carbon emissions through mechanisms of the EU ETS (Hintermann et al., 2016; Brink et al., 2016).

The impetus for this study arises from the urgent need to investigate how various market dynamics, particularly pandemic uncertainty, influence emissions pricing. As highlighted in the literature, significant drivers such as energy prices and stock market performance play crucial roles in carbon pricing, yet a deeper analysis is required to elucidate how these factors interact under conditions of heightened uncertainty. While past agreements have laid the groundwork for emissions trading and reducing carbon footprints, evolving challenges like economic disruptions from global crises necessitate a comprehensive understanding of how these elements converge in today's rapidly changing environment (Adekoya, 2021; Arouri et al., 2012).

Building on this framework, the establishment of the European Emissions Trading System (EU ETS) represents a landmark initiative aimed at controlling carbon dioxide emissions across Europe by implementing a market-based pricing mechanism. In response to international climate agreements like the Kyoto Protocol, the EU ETS was launched in 2005 as part of efforts to help member states comply with their emissions reduction commitments (Convery, 2009). By facilitating the trade of CO2 allowances among governments, industries, and financial institutions, the EU ETS incentivizes the adoption of clean energy solutions and fosters the transition towards less fossil-fuel-intensive production processes (Zhao et al., 2016). The trading system enables firms that find it costly to reduce emissions to purchase allowances from those with lower abatement costs, thus achieving emissions targets at a minimal cost (Verbruggen et al., 2019).

Moreover, the EU ETS has grown into the largest carbon market globally, featuring extensive trading by private investors, financial institutions, and governments, with financial institutions alone accounting for a significant share of trading volume (Adekoya, 2021; Wang and Zhao, 2021). This growth has positioned the EU ETS as an attractive platform for portfolio diversification, hedging, and speculation, offering a stable alternative amid the volatility typical of other financial markets. Additionally, the linkage between spot and futures markets within the EU ETS provides a crucial mechanism for risk mitigation and price discovery (Chen et al., 2020; Liu et al., 2021; Rittler, 2012; Arouri et al., 2012), offering valuable tools for companies to manage their carbon emission strategies effectively.

Through the EU ETS, policymakers aim to refine carbon pricing predictions, enhancing their ability to adjust climate policies and emissions caps in line with economic and energy market developments (Zhao et al., 2016). By providing a framework to accurately forecast carbon prices, the EU ETS facilitates the integration of carbon financial products such as futures and options, thereby strengthening the overall resilience and efficiency of the carbon market. Consequently, the EU ETS serves as a critical instrument in advancing global efforts to mitigate climate change through market-driven solutions.

In this context, research on forecasting EU carbon allowance prices has become increasingly significant due to the complex interplay of various market and policy dynamics. A key focus has been on identifying the primary drivers of carbon market prices, which are influenced not only by energy prices but also by market uncertainties and broader economic indicators. Adekoya (2021) notes that energy prices have consistently been identified as significant factors affecting carbon allowance prices, with prior research establishing their critical role in market predictions (Chevallier et al., 2019; Mansanet-Bataller et al., 2007). Additionally, Zhao et al. (2016) emphasize that traditional linear model like the autoregressive integrated moving average (ARIMA), often fail to capture the nonlinear characteristics of carbon pricing dynamics, necessitating the adoption of more sophisticated forecasting techniques like GARCH and machine learning methodologies. These models aim to more accurately predict movement within the carbon markets by accounting for the inherent volatility and external shocks impacting prices, aligning with the findings of Arouri et al. (2012). Furthermore, recent studies, including those by Dutta (2018), Hao et al. (2020), and Tan et al. (2023), explore the predictive power of various external factors while recognizing a gap in the literature regarding the integration of these influences into comprehensive forecasting models, by employing advanced techniques such as boosted regression trees, current research endeavors to improve the accuracy of carbon price forecasting, providing essential insights for policymakers and investors in navigating the complexities of emissions trading.

The motivation for this study is rooted in the imperative need to understand the intricate dynamics of carbon pricing within the European Emissions Trading System (ETS), especially in light of the growing uncertainties stemming from global crises such as the COVID-19 pandemic. As highlighted in existing literature, such as Adekoya (2021) and Jiménez-Rodríguez (2019), the influence of energy prices and stock market performance on carbon allowances is well-documented, yet there remains a significant gap in exploring how various types of uncertainties, like economic policy uncertainty (EPU) and geopolitical uncertainty (GPU), interact with these predictors during volatile periods. Prior studies (Dou et al., 2024; Chang et al., 2022) have begun to address pandemic-related uncertainties but often focus on historical data without leveraging modern forecasting techniques that can accommodate the emerging complexities of carbon markets.

This research aims to fill these gaps by employing advanced machine learning methodologies, specifically boosted regression trees (BRT), to evaluate the predictive capabilities of key indicators, including the STOXX 600 index, crude oil prices, and pandemic-related uncertainties. This boosted regression tree (BRT) offers enhanced accuracy, adaptability, and versatility in predicting carbon emissions trading prices. First, the findings of this study reveal that the proposed models exhibit robust forecasting performance for ETS emissions prices, with the STOXX 600 index emerging as the primary driver of carbon price predictions. This aligns with Sadorsky (2012) and Madaleno et al. (2022) regarding the need for increased investment in cleaner technologies in response to strong stock market performance. Second, the study underscores the crucial roles of various uncertainties in enhancing the accuracy of carbon price forecasts. It identifies the Europe 50 derivatives index and pandemic-related uncertainties as significant contributors to carbon pricing dynamics, reinforcing insights from Chang et al. (2022) and Li et al. (2022) about the pandemic-related uncertainty.

By highlighting the effectiveness of the BRT learning technique, the study not only meets the precision standards necessary for carbon forecasting but also contributes to ongoing discussions (Zhang and Wu, 2022; Zhu et al., 2022; Nibbering and Paap, 2024; Xiao and Liu, 2025) about the integration of advanced predictive models in climate risk management. Ultimately, the study aims to inform policymakers and market participants on how best to navigate periods of uncertainty, thus enhancing market stability and aligning investment practices with climate goals in an increasingly unpredictable economic environment.

The objective of this study is to investigate the forecasting capabilities and key predictors of emissions prices within the European Emissions Trading System (ETS), particularly focusing on the influence of pandemic uncertainty alongside energy prices and stock market performance. Given the findings from existing literature (Adekoya, 2021; Betz et al., 2016), which demonstrate the significance of energy prices and equity market performance on carbon allowances, this research aims to deepen the understanding of how these factors interact with pandemic-related uncertainties. Additionally, the study builds on the insights from Dou et al. (2024) and Chang et al. (2022), which highlight the impact of economic policy uncertainty and climate-related risks on carbon pricing dynamics during the COVID-19 pandemic. The methodology will employ advanced modeling techniques, including machine learning, to evaluate the predictive capabilities of key indicators, such as the STOXX 600 index, crude oil prices, and pandemic-related uncertainties, while drawing on the frameworks established by Zhang et al. (2023) and Liu et al. (2023). Ultimately, this research aims to inform policymakers and market participants about the critical intersections of these variables, especially in developing strategies that can enhance market stability and align investment practices with climate goals in an increasingly volatile environment.

Despite extensive research on the determinants of carbon prices, significant gaps remain in understanding how pandemic-related uncertainties influence emissions pricing dynamics within the European Emissions Trading System (ETS). While prior studies such as those by Oberndorfer (2009) and Adekoya (2021) have identified strong correlations between energy prices and equity market performance on carbon allowances, they often do not incorporate the evolving landscape of uncertainties brought about by global crises like the COVID-19 pandemic. Literature primarily focuses on traditional economic indicators without fully addressing the collective impact of various types of uncertainties—such as economic policy uncertainty (EPU), geopolitical uncertainty (GPU), and climate-related risks—on carbon pricing.

Furthermore, existing models have not sufficiently explored the interactive effects of these uncertainties during periods of market volatility and how they affect investor behavior and decision-making within carbon markets. Studies like those from Dou et al. (2024) and Chang et al. (2022) have initiated discussions on pandemic-related uncertainties but largely concentrate on historical data without providing comprehensive forecasting models that incorporate new machine-learning techniques.

This study contributes to the literature by offering a multifaceted analysis that integrates diverse predictors—such as energy prices, stock market performance, and various uncertainties—to enhance the understanding of their collective influence on carbon prices. By employing advanced modeling techniques, including boosted regression trees (BRT), we provide robust forecasting capabilities that meet industry standards for carbon price predictions. Importantly, the BRT learning technique offers enhanced accuracy in predictions, resulting in a heightened ability to identify irregularities in carbon pricing dynamics and increased adaptability and versatility in responding to market changes. The results reinforce findings from Dou et al. (2024) and Chang et al. (2022) regarding the critical role of pandemic-related uncertainties and economic policy uncertainties in shaping the behavior of market participants, providing actionable insights that can better inform policy decisions.

The findings highlight the significant roles of the STOXX 600 index and pandemic-related uncertainties, which have not been thoroughly explored in prior research. Additionally, the study emphasizes the need for policymakers to strengthen crisis response mechanisms and enhance market flexibility to promote resilience in carbon trading.

The study presents several key findings regarding the forecasting capabilities and predictors of emissions prices within the European Emissions Trading System (ETS). Firstly, all proposed models demonstrate strong forecasting performance for ETS emissions prices, as evidenced by favorable Mean Absolute Error (MAE) and R-squared values. Model 1 identifies the STOXX 600 index as the most significant contributor to predicting carbon prices, followed by the coal market, indicating the importance of monitoring financial and energy markets in relation to carbon emissions trading. This finding parallels the work of Sadorsky (2012), Kocaarslan and Soytas (2019), and Fahmy (2022), who note that improved stock market performance correlates with increased investments in cleaner technologies. The results suggest that policymakers should enhance transparency and oversight in these markets to ensure that carbon pricing reflects underlying dynamics and environmental considerations while also promoting sustainable investment practices, consistent with the recommendations outlined by Newell et al. (2013), Ameli et al. (2020), and Fu et al. (2023).

Second, partial dependence analysis reveals that while some predictors may have low individual importance, their collective contributions significantly enhance the accuracy of carbon price forecasts. Model 2 emphasizes the pivotal roles of economic policy uncertainties, as well as oil and gold market uncertainties, including pandemic-related uncertainties, in predicting European carbon allowance prices. This finding is supported by Li et al. (2022), Liu et al. (2023), and Adediran et al. (2023), which indicates that various forms of economic policy uncertainty positively influence carbon emissions trading prices. These insights underscore the need for policymakers to encourage risk mitigation measures and diverse investments across sectors less sensitive to economic shifts to foster stability and resilience in carbon trading markets.

Third, Models 3 and 4 identify the Europe 50 derivatives index as the most influential predictor of carbon prices, with pandemic-related uncertainties ranking as the second most significant factor (Chang et al., 2022; Li et al., 2022). These results are reinforced by Raza et al. (2024), who demonstrate that climate policy uncertainty significantly raises volatility in sustainability indices, suggesting that policymakers should strengthen crisis response mechanisms and risk management strategies to alleviate the impact of global health crises and systemic shocks on carbon pricing. Enhancing market flexibility and agility in adapting to unforeseen events could further bolster stability and investor confidence in carbon markets.

Lastly, the study highlights the effectiveness of boosted regression trees, a machine learning method, as a valuable tool for predicting EU ETS prices. This aligns with the findings of Yahşi et al. (2019), Zhang et al. (2023), Nadirgil (2023), and Zhu et al. (2022), which emphasize the importance of robust forecasting models. The results indicate that the boosted regression trees approach meets the precision standards necessary for carbon forecasting, aiding investors in making informed decisions within carbon emission trading markets, thereby contributing to broader efforts in achieving climate goals and enhancing sustainable investment strategies.

The rest of this paper is organized as follows: Section 2 reviews the relevant literature and presents the proposed hypotheses; Section 3 outlines the methodologies and describes the sample; Section 4 details the main results; and Section 5 concludes the paper.

2. Related Literature Review and Hypothesis Development

2.1 Literature Review for Hypothesis One

The influence of energy prices and equity market performance on carbon allowance prices within the European Union Emissions Trading System (EU ETS) has been a focal point of research, as understanding these relationships is essential for effective policy-making and market predictions.

2.1.1 Energy prices

In recent years, the relationship between energy prices and carbon allowance prices has been the subject of extensive research, highlighting nuanced interactions across different energy markets. Several studies have established a strong correlation between energy prices and carbon allowance prices, revealing both short-term dynamics and potential long-term predictors.

For instance, Adekoya (2021) underscores the significant influence of energy prices on carbon allowance prices, with asymmetric models for oil and coal outperforming their symmetric counterparts. Findings suggest that asymmetries in natural gas prices become pertinent only with smaller sample sizes. These insights extend to policy recommendations geared towards carbon emissions mitigation and strategic investments. Earlier research by Nazifi and Milunovich (2010) examines the temporal links between EU carbon allowance prices and other energy sources, finding short-term connections absent from long-term relationships. This temporal nuance is equally explored by Hammoudeh et al. (2014), who utilize a quantile regression framework to reveal distinct price variation effects: rising crude oil prices tend to lower carbon prices when high, while electricity and natural gas prices play varying roles depending on their distribution levels.

Adding to this discourse, Zeng et al. (2017) explore the Beijing carbon allowance market, finding minimal direct influence from crude oil and natural gas prices. Instead, past allowance prices hold greater sway. García-Martos et al. (2013) address methodological gaps by using a multivariate model, demonstrating enhanced predictive accuracy through common volatility factors, particularly amidst geopolitical instability affecting commodity markets. Further, Batten et al. (2021) focus on the European Union Emissions Trading Scheme, revealing that energy prices drive carbon prices post-2013, albeit the models explain only a fraction of carbon price variability. This highlights the critical role of unexpected temperature changes, aligning with broader climate change discourses. Lastly, Abadie and Chamorro (2008) assess the viability of deploying carbon capture technology in coal-fired plants. Their findings indicate that prevailing carbon permit prices insufficiently justify immediate investments without significant market or policy shifts.

Collectively, these studies illustrate a complex interplay between energy prices and carbon markets, emphasizing the need for sophisticated modeling approaches and adaptive policy frameworks in the context of dynamic and evolving global energy markets.

2.1.2 Stock market performance

The performance of the STOXX Europe 600 index, a broad measure of European stock market performance, is another significant factor influencing carbon prices. As businesses and investors react to changes in market conditions, a correlation often emerges between stock performance and carbon market dynamics. As businesses and investors respond to shifting market conditions, a notable correlation often emerges between stock performance and carbon market dynamics.

Betz et al. (2016) highlight this connection, demonstrating that improved stock market performance typically correlates with increased investment in cleaner technologies and carbon markets, subsequently driving up carbon prices. This relationship is further examined by Qiu et al. (2023), who investigate the evolving interconnections between carbon, stock, and renewable energy markets within a low-carbon framework. Their Time Varying Parameter - Vector Auto Regression (TVP-VAR) analysis reveals that, in the short term, shocks in the carbon market positively influence the renewable energy sector, though this effect diminishes over time. Interestingly, they find that the COVID-19 pandemic amplified positive correlations between the carbon and stock markets. Additionally, while Brexit positively affected spillovers from carbon prices to renewable energy prices, the pandemic notably intensified the negative impacts on renewable energy from the carbon market. Ramos-García et al. (2023) contribute to the discourse by assessing climate factors' effects on default risk among major companies listed on the STOXX Europe 600 from 2010 to 2020. Their factorial panel data model reveals significant fluctuations in default risk before and during the Paris Agreement, underscoring the necessity of considering climate-related risks when evaluating credit risk. The emphasis on market performance as an indicator for climate-related credit risk changes further intertwines the financial and environmental narratives.

Complementing these insights, Coeslier et al. (2016) explore the potential of low-carbon financial indices as a strategic approach to mitigate climate-related financial risks and support companies that facilitate the energy transition. Their evaluation of low-carbon stock indices highlights the need for improved methodologies to align financial instruments with ambitious climate objectives, emphasizing that traditional strategies often fail to address underlying challenges effectively. In a related vein, Ye and Xue (2021) investigate the impact of news sentiment on carbon prices through their innovative carbon tone index, which gauges sentiment using a specialized vocabulary. Their study finds a significant correlation between the carbon tone index and price fluctuations, particularly following the introduction of the Market Stability Reserve (MSR) policy in 2018, which boosted market confidence and trading volume. This suggests an improvement in market efficiency, showcasing the carbon tone index's forecasting capability across various predictive models.

Together, these studies illuminate the intricate relationships between stock markets, carbon pricing, and climate-related factors, emphasizing the importance of integrating financial performance and sentiment into the broader narrative of climate strategies and carbon market dynamics.

2.1.3 Hypothesis One(H1)

The literature reviewed underscores the multifaceted relationships between energy prices, stock market performance, and carbon allowance prices, providing a solid foundation for Hypothesis One (H1). Adekoya (2021) highlights the significant impact of energy prices on carbon allowances, demonstrating that variations in oil and coal prices can substantively influence carbon pricing dynamics. This relationship is complemented by Nazifi and Milunovich (2010), who identify short-term correlations between EU carbon allowance prices and energy sources, pointing to the variability within these connections. Moreover, the performance of the STOXX Europe 600 index emerges as a critical factor influencing carbon prices, as evidenced by Betz et al. (2016), who suggest that strong stock market performance fosters investments in cleaner technologies, further driving up carbon prices. Qiu et al. (2023) advance this understanding by showing that fluctuations in the carbon market can positively affect the renewable energy sector, amplifying the interplay between stock performance and carbon pricing, particularly during periods of significant external shocks like the COVID-19 pandemic. In this context, Ramos-García et al. (2023) reinforce the notion that market performance must be considered when evaluating climate-related risks, thereby intertwining financial metrics with environmental outcomes. The collective findings from these studies affirm the complexities of the relationships among energy prices, stock market movements, and carbon allowance prices. This multi-dimensional nature supports Hypothesis One by suggesting that standard predictors, including oil, coal, natural gas prices, and the performance of the STOXX Europe 600, play a crucial role in determining the price of carbon allowances in Europe.

Hypothesis One(H1)*: The price of carbon allowances in Europe is influenced by standard predictors, including the prices of oil, coal, natural gas, and the performance of the STOXX Europe 600 market.*

Model 1: $EUA = f(BRENT, COAL, Natural\ Gas, STOXX\ 600)$

This hypothesis will be investigated through empirical analysis using machine learning techniques to assess the predictive capability of these variables on carbon pricing within the context of the EU ETS.

2.2 Literature Review for Hypothesis Two

The relationship between pandemic-related uncertainties and carbon emissions prices has gained increased attention, particularly in the context of the COVID-19 pandemic. This literature review synthesizes existing research that underscores the correlation between heightened uncertainty during pandemics and fluctuations in carbon emissions prices.

Dou et al. (2024) delve into the impact of Economic Policy Uncertainty (EPU) on the carbon futures market, employing quantile Granger tests and quantile regression methods to explore spillover effects across various market conditions. Their findings indicate that while EPU shocks do not predict daily carbon futures volatility, they negatively influence long-term returns, highlighting an asymmetric relationship across the distribution of carbon futures returns. Importantly, the COVID-19 pandemic amplifies this interconnectedness, affecting short- and medium-term market performance. This underscores critical policy implications for both investors and regulators in navigating the complexities of carbon markets during periods of uncertainty. In a complementary study, Chang et al. (2022) examine the asymmetric impact of pandemic-related uncertainty on CO2 emissions across the world's ten most polluting economies. Their innovative use of Quantile-on-Quantile (QQ) analysis reveals that pandemic uncertainty generally leads to improved environmental quality by reducing CO2 emissions, with stronger effects observed in economies such as India, Germany, and South Korea. However, results for Japan remain inconclusive, suggesting a need for further exploration of local factors affecting emissions. The varying degrees of asymmetry in the relationship among these economies highlight the necessity for tailored policy interventions that consider national contexts amid global uncertainties. Dong et al. (2022) investigate the disruptions faced by the European Union Emissions Trading System (EU ETS) during the pandemic, elucidating how these disruptions have led to volatile carbon prices. Using methodologies such as the Bai–Perron structural break test, they reveal significant structural changes prompted by both the pandemic and the €750 billion green recovery plan. While their findings demonstrate a short-term negative correlation between economic development levels and carbon prices, the overall effectiveness of the recovery plan in stabilizing the carbon market invites further inquiry into long-term sustainability and resilience strategies. Khan et al. (2022) extend this discussion by analysing the impact of the COVID-19 epidemic on energy prices. Their analysis from January 2020 to May 2021 reveals substantial reductions in energy prices due to uncertainties tied to global lockdowns and economic slowdowns. They identify that these price reductions are particularly pronounced within the medium to upper quantiles for oil, natural gas, and heating oil, emphasizing the need for exhaustive analyses to fully grasp the varying impacts of the pandemic on energy markets and the consequent implications for carbon pricing. In contrast, Hemrit and Benlagha (2021) focus on the renewable energy index, offering a fresh perspective on the broader impacts of pandemic uncertainties. Their analysis shows a significantly positive correlation between pandemic uncertainty and the renewable energy index, indicating potential opportunities for growth in this sector. Conversely, economic policy uncertainty negatively affects this index, particularly at lower quantiles, suggesting that proactive policy measures could leverage pandemic-related challenges into growth opportunities, promoting diversification for investors. Finally, Mintz-Wooe et al. (2021) explore how the COVID-19 crisis has reshaped the justification for climate measures, particularly regarding carbon pricing strategies. They argue that the lowered oil prices during the pandemic enhance the argument for carbon pricing, as the immediate costs to consumers decrease. Additionally, the pandemic spurred a search for new revenue sources amid strained tax revenues, underpinning the relevance of discussions surrounding carbon pricing in recovery efforts. This indicates a critical juncture for policymakers as they navigate post-pandemic recovery while aiming to uphold environmental objectives. In summary, these studies collectively illustrate the intricate dynamics between pandemic-related uncertainties and carbon emissions prices. While they emphasize varying impacts across different markets and economies, they also highlight the pressing need for tailored policy interventions and strategic frameworks to manage risks and capitalize on opportunities presented by these global challenges.

2.2.1 Hypothesis Two(H2)

The literature reviewed illustrates a complex interplay between pandemic-related uncertainties and carbon emissions prices, providing a compelling foundation for our Hypothesis Two (H2). Studies such as those by Dou et al. (2024) and Chang et al. (2022) suggest that heightened uncertainties during the COVID-19 pandemic have indeed influenced market dynamics, demonstrating both direct and indirect impacts on carbon emissions and pricing. Dou et al. highlight the spillover effects of Economic Policy Uncertainty on carbon futures, indicating that while daily volatility may not be predicted by these shocks, long-term returns are negatively affected. This aligns with Chang et al.'s findings that pandemic uncertainty can lead to reduced CO2 emissions across various economies. Furthermore, the disruptions faced by the EU ETS, as noted by Dong et al. (2022), indicate that significant external shocks can prompt volatility in carbon prices, underscoring the potential for increased prices amid heightened uncertainties. Collectively, these insights suggest that as pandemic uncertainty rises, market behaviors may adapt in ways that create upward pressure on carbon emissions prices, thus supporting the proposition of Hypothesis Two. This hypothesis invites further empirical exploration to quantify the relationship and to understand its broader implications for policy and investment strategies in the context of future uncertainties. Given the insights provided by the literature, we propose the following hypothesis:

Hypothesis 2 (H2)*: Increased pandemic uncertainty correlates with higher carbon emissions prices.*

Model 2: $EUA = f(IDEMV, UKEPU, USEPU, GVZ, OVX, VIX)$

This hypothesis posits that as uncertainty arises during pandemic events, it creates volatility in the carbon market, potentially leading to higher carbon emissions prices. The rationale behind this hypothesis is that heightened uncertainty may drive investors towards sustainable asset classes, thus increasing demand for carbon allowances and, subsequently, raising their prices. Furthermore, the implementation of recovery policies aimed at mitigating pandemic impacts could allocate additional resources towards carbon pricing mechanisms, amplifying this relationship. This hypothesis warrants empirical investigation to better understand the dynamics between pandemic-related uncertainties and carbon pricing mechanisms.

2.3 Literature Review for Hypothesis Three

The interplay between financial stress, bond market uncertainty, and fluctuations in carbon emissions prices has garnered increasing attention in recent research, particularly as market dynamics and economic conditions evolve. This literature review highlights key findings that support the hypothesis that financial stress and bond market uncertainty positively contribute to fluctuations in carbon emissions prices.

Wang et al. (2023) explore the relationships among climate policy uncertainty (CPU), energy costs, the green bond index, and carbon emissions trading prices using a quantile connectedness approach. Their findings indicate that the interdependence among these variables is more pronounced at extreme quantiles, particularly during significant global events, such as the U.S. withdrawal from the Paris Agreement and the COVID-19 pandemic. This dynamic spillover analysis shows that CPU acts as a risk recipient, emphasizing the need for a comprehensive understanding of its impact on energy, green finance, and carbon markets. Similarly, Li et al. (2022) focus on the influence of economic policy uncertainty (EPU) on carbon emissions trading prices in China. Their application of a nonlinear Autoregressive Distributed Lag (ARDL) model reveals that trade policy uncertainty (TPU) and monetary policy uncertainty (MPU) positively impact carbon emissions trading market prices, while exchange rate policy uncertainty (ECPU) exerts a negative influence. These findings support Bloom's (2009) assertion regarding the asymmetric effects of uncertainty shocks, suggesting that regulatory authorities should implement measures to mitigate volatility in the carbon emissions trading market. Also, Agliardi and Agliardi (2021) present a structural model of defaultable bonds that incorporates corporate earnings uncertainty and climate-related risks. Their model elucidates how sudden climate policy shocks influence bond values, highlighting that green bonds can enhance issuers' credit quality by reducing climate-related risks and systemic financial distress. They advocate for policy interventions to stimulate green bond markets, which is critical for reinforcing capital allocation toward environmentally friendly investments and supporting a transition to a low-carbon economy. Mar'I et al. (2024) further investigate the effects of financial stress and uncertainty on the returns of both green and conventional bonds. Their use of nonlinear analyses reveals that financial stress significantly impacts the returns of conventional bonds, with financial uncertainty exerting a more pronounced negative effect on upper quantiles. They introduce a risk assessment pyramid for financial assets, assisting investors in evaluating vulnerabilities and advocating for governmental support for green investments. Additionally, Wang et al. (2023) analyze the influence of geopolitical risk, financial uncertainty, and oil price volatility on global green bond investment from 1985 to 2020. Their findings indicate a long-term relationship between these variables, with oil price fluctuations positively impacting green investments, whereas financial stress and geopolitical risk present significant challenges. While their study emphasizes the need for broader regional analyses, it confirms the interconnections among financial factors and emphasizes the importance of understanding green bond investment trends.

Collectively, these studies illustrate the complex interactions between financial stress, bond market uncertainty, and carbon emissions prices, underscoring the necessity for continued examination of these relationships to inform policy and investment strategies in the evolving landscape of financial and environmental markets.

2.3.1 Hypothesis Three(H3)

The literature examined provides a strong basis for proposing Hypothesis Three (H3), which asserts that financial stress and bond market uncertainty positively contribute to fluctuations in carbon emissions prices. Wang et al. (2023) illustrate that climate policy uncertainty (CPU), particularly during critical global events such as the COVID-19 pandemic and the U.S. withdrawal from the Paris Agreement, heightens the interconnectedness between energy costs, the green bond index, and carbon emissions trading prices. This dynamic relationship indicates that financial stressors can enhance volatility within carbon markets. Furthermore, Li et al. (2022) support this notion by demonstrating that various forms of economic policy uncertainty, such as trade and monetary policy uncertainties, positively influence carbon emissions trading prices in China, aligning with Bloom's (2009) findings on the asymmetric impacts of uncertainty. Additionally, Agliardi and Agliardi (2021) contribute to this discussion by highlighting how climate policy shocks can significantly affect bond valuations, with green bonds offering potential benefits in terms of credit quality and reducing systemic financial risks. Mar'I et al. (2024) further reinforce this connection as they reveal that financial stress significantly influences returns on both green and conventional bonds, underscoring the broader implications for carbon pricing dynamics. The comprehensive analysis provided by these studies suggests that fluctuations in carbon emissions prices can be distinctly traced to underlying financial stress and market uncertainties, thereby necessitating deeper exploration of these relationships as formalized in Hypothesis Three.

Hypothesis Three(H3): *Financial stress and bond market uncertainty positively contribute to fluctuations in carbon emissions prices.*

Model 3:$EAU = f(GPR, MOVEBOND, FSI, BEZ50N)$

This hypothesis aims to be tested through empirical analysis, utilizing machine learning techniques to evaluate the relationship between indicators of financial stress, bond market fluctuations, and carbon price movements. The results will enhance our understanding of how economic factors influence carbon markets and inform strategies for risk management and investment decisions in the context of carbon emissions trading.

2.4 Literature Review for Hypothesis Four

The notion that pandemic uncertainty significantly contributes to predicting carbon prices, particularly during periods of market volatility and global uncertainties, has garnered substantial scholarly attention. This literature review aims to elucidate key findings that support the hypothesis that pandemic uncertainty plays a pivotal role in influencing carbon price dynamics.

Adediran and Swaray (2023) investigate the effects of Economic Policy Uncertainty (EPU) and Geopolitical Uncertainty (GPU) on volatility and risk in the carbon trading market. Their research utilizing daily data from the European Union Emissions Trading Scheme reveals that instability in policies and geopolitical tensions increases carbon market risk by heightening information asymmetry and risk premiums, ultimately leading to delays in investment decisions. They advocate for future discussions among parties to the United Nations Framework Convention on Climate Change to focus on strategies aimed at reducing global uncertainty while promoting decarbonization and the adoption of clean technologies. Contributing to this discourse, Olubusoye et al. (2021) analyze the impact of various uncertainties on energy pricing during the COVID-19 pandemic, employing multiple uncertainty measures such as COVID-Induced Uncertainty (CIU) and Economic Policy Uncertainty. Their findings show significant responses of energy prices to these uncertainty metrics, with a pronounced effect of Economic Policy Uncertainty on different energy types during the pandemic, emphasizing the predictive capabilities of the Volatility Index (VIX) and other uncertainty indicators. Similarly, Mintz-Woo et al. (2021) investigate the impact of various uncertainties on energy pricing, utilizing five different uncertainty measures: CIU, EPU, Global Fear Index (GFI), Volatility Index (VIX), and Misinformation Index of Uncertainty (MIU). Their study reveals that energy prices respond significantly to these uncertainty metrics, particularly noting the strong effect of Economic Policy Uncertainty on the pricing of various energy sources during the pandemic. They also underscore the predictive capabilities of indices such as VIX, CIU, and MIU concerning global energy resources, highlighting the interconnectedness between uncertainty and energy pricing dynamics. Zhang et al. (2023) introduce a novel two-stage framework for forecasting carbon prices that optimally balances economic growth with climate impacts, particularly within the European Union's Emissions Trading System (ETS). Their approach utilizes machine learning techniques to enhance predictions of carbon prices and demonstrates effectiveness even when accounting for the impacts of the COVID-19 pandemic, illustrating the framework's robustness in fluctuating conditions. Liu et al. (2023) further investigate the relationships among crude oil prices, natural gas prices, and carbon emissions allowances, along with climate policy uncertainty (CPU). Their analysis, which includes bootstrap rolling-window Granger causality tests, reveals complex interdependencies, indicating that rising fossil fuel prices influence both carbon prices and levels of uncertainty within the market. Building on this, Raza et al. (2024) provide empirical evidence of the significant impact of climate policy uncertainty on forecasting volatility in green and sustainable financial markets. By employing a new news-based climate policy uncertainty index through advanced econometric methods, they find that climate policy uncertainty heightens volatility in key indices, reinforcing the notion that such uncertainty can be a critical predictor of market dynamics, particularly in the context of carbon pricing.

Together, these studies illustrate the multifaceted relationships between pandemic and policy uncertainties and their substantial influence on carbon price dynamics, underscoring the necessity for ongoing research to inform effective policy and investment strategies in an increasingly volatile global market.

2.4.1 Hypothesis Four(H4)

The literature reviewed supports the assertion that pandemic uncertainty plays a critical role in predicting carbon prices, particularly during times of market volatility and global uncertainties, thereby laying the groundwork for Hypothesis Four (H4). Adediran and Swaray (2023) highlight how Economic Policy Uncertainty (EPU) and Geopolitical Uncertainty (GPU) elevate risks in the carbon trading market, leading to greater market volatility and delayed investment decisions. This acceleration of uncertainty is echoed in the findings of Olubusoye et al. (2021) and Mintz-Woo et al. (2021), both of which emphasize how various uncertainty metrics—including COVID-Induced Uncertainty (CIU) and Economic Policy Uncertainty—significantly affect energy pricing dynamics, further illustrating the influence of these uncertainties on market reactions. Moreover, Zhang et al. (2023) demonstrate that their novel forecasting framework for carbon prices remains resilient even amidst the impacts of the COVID-19 pandemic, implying that pandemic-related uncertainties can be effectively integrated into predictive models. Liu et al. (2023) expand this discussion by examining the interrelations among fossil fuel prices and carbon allowances, finding that increases in these prices can exacerbate levels of uncertainty within the market. Additionally, Raza et al. (2024) provide empirical evidence showing that climate policy uncertainty significantly raises volatility in sustainability indices, reinforcing the premise that these uncertainties are vital predictors in volatile markets. Collectively, these studies underscore the necessity of acknowledging pandemic uncertainty as a significant factor influencing carbon price dynamics, thus supporting the formulation of Hypothesis Four, which posits that pandemic uncertainty contributes significantly to predicting carbon prices, especially in the presence of market volatility and global uncertainties. With the insights drawn from the literature, we propose the following hypothesis:

Hypothesis Four(H4): *Pandemic uncertainty contributes significantly to predicting carbon prices, especially in the presence of market volatility and global uncertainties.*

Model 4: $EUA = f(GPR, FSI, IDEMV, MOVEBOND, BEZ50N, UKEPU, USEPU, GVZ, OVX, VIX)$

This hypothesis will be empirically tested using quantitative methods to assess how pandemic-related indicators, alongside measures of market volatility and global uncertainties, relate to fluctuations in carbon prices. The findings will enhance our understanding of the predictive dynamics within carbon markets and inform stakeholders on how best to navigate periods of uncertainty.

The proposed empirical models:

Model 1: $EUA = f(BRENT, COAL, Natural\ Gas, STOXX\ 600)$

Model 2: $EUA = f(IDEMV, UKEPU, USEPU, GVZ, OVX, VIX)$

Model 3:$EAU = f(GPR, MOVEBOND, FSI, BEZ50N)$

Model 4: $EUA = f(GPR, FSI, IDEMV, MOVEBOND, BEZ50N, UKEPU, USEPU, GVZ, OVX, VIX)$

3. Econometric Approaches and Synopsis

3.1. Variables and dataset

This paper utilizes the daily futures price of European Union Allowances (EUAs), ….XXX

See Table 1

[Insert Table 1 here]

[Insert Table 2 here]

3.2. The Boosted Regressions Trees Learning Method

In this subsection, we introduce the learning technique used to forecast EU ETS prices. The goal of this work is to determine the impact of each covariate on dam behavior and to understand the dynamics of dam response over time by investigating the influence of variable feature loads on the system. There are numerous machine learning (ML) tools available (Hastie et al., 2009). Boosting stands out as one of the most influential learning techniques introduced in the past two decades. Leathwick et al. (2006), through a comparative study, demonstrated that boosted regression trees, as an ensemble model, are among the most suitable learning algorithms for predicting dam response. Therefore, we have selected this ML framework after comparing its forecasting accuracy with well-known and robust ML algorithms such as neural networks, support vector machines, random forests, and multi-adaptive regression splines (Salazar et al., 2024).

How does the boosted regression trees algorithm works?

It is an ensemble method in which each individual process (commonly known as base learners) is trained on the error of the prior ensemble. In contrast to the random forest ML technique, where ensemble forecasting is determined by averaging, boosted regression trees use the weighted sum of responses of the base learners to compute the overall prediction.

The learning process of boosted regression trees incorporates two components to prevent overfitting. Firstly, each learner is trained on a distinct random subset of the training set, ensuring each subset is unique and used only once in the training model. Consequently, boosted regression trees enhance diversity among learners and reduce the computational burden by focusing on smaller, more manageable parts of the data. By utilizing smaller subsets, training time and overall computational cost are minimized without compromising the learning effectiveness of the ensemble. Secondly, boosted regression trees use a shrinkage operator λ applied in the algorithm, which falls within the interval $[0,1]$.

Following Leathwick et al. (2006), the boosted regression trees algorithm possesses the following key properties: (i) It is robust against extreme outliers and the inclusion of irrelevant predictors, (ii) it involves minimal data pre-processing, (iii) is capable to managing both numerical and categorical covariates, and (iv) It is suitable for modeling nonlinear relationships, which is a key feature of our data of interest.

The proposed models are developed by combining two algorithms (Salazar et al., 2024): decision trees and boosting. Initially, a series of individual models is created using decision trees (Breiman et al., 2017).

Subsequently, the outputs from these models are integrated to generate overall predictions through boosting (Friedman, 2001).

Algorithm 1: decision trees

Breiman et al. (2017) introduced regression tree learning algorithms, which derive from iterative partitioning of the training data sample into clusters of similar features. Specifically, the result of this algorithm is the average of the target variable within each cluster. When multiple predictors are used, the algorithm calculates the optimal split point for each predictor, selecting the one that results in the greatest reduction of residual error. Consequently, irrelevant predictors are automatically excluded because the reduction in residual error from partitioning on less relevant predictors is significantly lower than from partitioning on informative ones. One disadvantage of the decision trees algorithm is its instability, which arises from small variations in the training dataset.

Algorithm 2: boosting

Boosting learning was developed by Friedman (2001) to create ensemble forecasting methods. This approach involves training "weak learners" on modified versions of the training dataset. The general prediction process entails computing a weighted sum of the individual model results within the ensemble. The rationale behind this algorithm is that the average prediction of multiple simple learners can outperform that of a single complex learner. However, the algorithm operates by fitting each learner to the prior ensemble error.

Salazar et al. (2024) summarize the key steps of boosted regression trees and the squared-error loss function by:

Step 1: Begin prediction using the mean of the observations (fixed value):

$$G_0(W) = g_0(W) = \bar{y}_j$$

Step 2: Iterate over m from 1 to M.

(i) Calculate the error of predictions on the training set:

$$\tilde{y}_j = y_j - G_{m-1}(W_j)$$

(ii) Randomly select a portion of the training set (Ω_m).

(iii) Use Ω_m and built a new regression tree based on the residuals of the existing ensemble:

$$\tilde{y}_j \approx g_m(W), j \in \Omega_m$$

(iv) Revise the ensemble:

$$G_m(W) \Leftarrow G_{m-1}(W) + g_m(W)$$

Step 3: G_m stands as the ultimate model.

Michelis (2012) argues that it is widely acknowledged that this ML approach is susceptible to overfitting, as the training error reduces with each iteration. To address this issue, it is beneficial to include a regularization operator $\lambda \in [0,1]$, consequently stage (iv) in step 2 turns into:

$$G_m(W) \Longleftarrow G_{m-1}(W) + \lambda \times g_m(W)$$

Several studies have revealed that employing value of λ less than 0.1 substantially enhances generalization capability (Salazar et al., 2024).

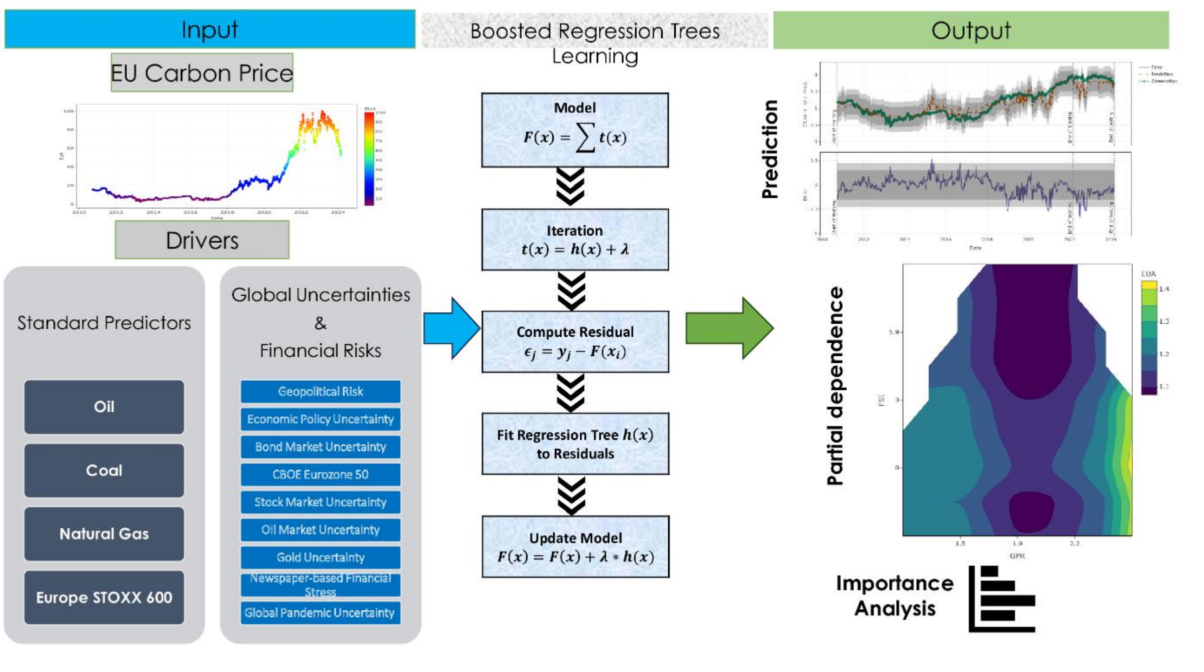


Fig.1. The main workflow of the proposed ML forecasting method.

4. Results and discussions

4.1 Forecasting performance metrics

To assess the accuracy of the forecasting performance of our proposed models, we adopt the loss function Mean Absolute Error (MAE) and the coefficient of the determination (R^2) (Makridakis et al., 1979). Typically, the smaller the MAE, the superior the prediction will be. The formula of this performance criterion is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

Where n defines the samples' number for training set, the variable Y_i denotes the real observations and the predicted observations are shown by $\hat{Y}_i$.

The goodness of fit of the model is measured with R^2. The higher the R^2, the better the prediction of the model is. The formula of this indicator is given by:

$$R^2 = \frac{\sum_{i=1}^{n}\left(\hat{Y}_i - \bar{Y}\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

To illustrate the predictive influence of the selected predictors on EUA, the models were fitted following the division of the dataset into two segments: the training set and the testing set. The suggested Boosted Regression Trees ensemble model relies on trees, hence we experimented with different tree counts: 750 and 500. Regarding the other parameters integrated into the model, we designated a shrinkage value of 0.01 (tree learning rate), an interaction depth of 2 (tree partition count), and a bagging fraction of 0.5 (sampling ratio at each step).

4.2 Precision assessment results

4.2.1 Assessment outcomes of Model 1

The predictive analysis utilizing Model 1 is presented in Table 3 and Figs. 4 and A1. The figures illustrate the real-world carbon allowance price alongside the model predictions. As evidenced by both the figures and Table 3, Model 1 exhibits a strong forecasting capability for ETS emissions data spanning from September 17, 2010, to January 3, 2024. Based on the MAE accuracy metric, it is evident that Model 1 utilizing 750 trees outperforms (MAE = 0.11, 0.19, 0.04) its counterpart using 500 trees (MAE = 0.13, 0.20, 0.05) across both panels. The R-squared values are consistently high, ranging from 77% to 99% in both panels, underscoring the efficacy of BRENT, GAS, COAL, and STOXX600 as robust predictors for European carbon emissions. The predictors' contributions are depicted in Fig. 8. It is evident from the figure that STOXX600 holds the greatest relative influence, accounting for over 60.19% of the variance in EUA, followed by COAL at 18.69%. This suggests a strong correlation between European carbon emissions prices and the STOXX Europe 600 stock market. However, the relative influences of BRENT (10.19%) and GAS (10.94%) are less discernible from Fig. 8, indicating their contributions to carbon price prediction are comparatively minor.

[Insert Table 3 here]

[Insert Figure 4 here]

[Insert Figure 8 here]

To further explore the significance analysis, we broaden our examination of predictive performance to partial dependence, which offers insights into the combined impact of the predictors. While Fig. 4 delineates the individual influence of each predictor, Fig. 9 portrays their combined effect through heatmap diagrams. The findings reveal compelling patterns: instances such as low/high BRENT coupled with low natural gas (Fig. 9a) significantly influence EUA. Moreover, scenarios involving low BRENT alongside high STOXX600 or low COAL paired with low GAS (Fig. 9b) tend to correlate with escalating European carbon emissions prices. Furthermore, both COAL and BRENT exhibit considerable influence on EUA, as demonstrated in Fig. 9c. This finding may suggest that the combination of high COAL and high BRENT serves as a reliable predictor of ETS emissions prices.

[Insert Figure 9 here]

Further analysis, which can serve as a helpful instrument in model validation, involves graphical examination of residuals. Residuals represent the disparities between real-world data and predicted values. In Fig. A5, the residuals for Model 1 in the training data are displayed alongside a convex hull, representing the envelope of values within the bounds of the training set. It is apparent that unusual combinations—such as high BRENT and COAL, high BRENT and GAS, high BRENT and STOXX600, high COAL and GAS, high COAL and STOXX600, and high COAL and STOXX600—resulted in significant errors, despite not being observed during training.

4.2.2 Assessment outcomes of Model 2

The evaluation of forecasting results based on Model 2 is presented in Table 4 and Figs. 5 and A2. Both panels (P1 and P2) demonstrate Model 2's strong ability to forecast carbon allowance prices in Europe, as indicated by the assessment metrics. The training and testing Mean Absolute Errors (MAE) are consistently low, ranging from 0.12 to 0.45, while the R-squared values are high, ranging from 0.68 to 0.80. These results signify the model's significant predictive performance regarding ETS emissions. It's noteworthy that global uncertainties, such as economic policies, pandemics (IDEMV), and uncertainties related to oil and gold, have played a crucial role in predicting European carbon prices during the analyzed period.

For example, based on 750 trees, the resulting MAE values are 0.12 and 0.14 for the training set, and 0.42 and 0.28 for the testing set, across both panels. A similar order of magnitude for MAE values is observed based on 500 trees. These findings are consistent with those reported by Quinlan (1993). Likewise, the R-squared coefficients (ranging from 0.75 to 0.80 for training and 0.68 to 0.73 for testing) align with results obtained by Nishino and Suzuki (2019). These findings confirm the robustness of the boosted regression trees algorithm and the effectiveness of the selected parameters.

[Insert Table 4 here]

[Insert Figure 5 here]

[Insert Figure 10 here]

Fig. 10 presents the individual effects of each predictor on carbon price allowances. The prediction contributions of various global uncertainties are as follows: IDEMV (53.27%), GVZ (17.81%), VIX (9.44%), OVX (9.31%), UKEPU (7.76%), and USEPU (2.41%). It's evident that IDEMV has the most significant predictive effect on EUA, accounting for over half of the total percentage in the prediction system. This suggests that pandemics, particularly the recent COVID-19 pandemic, exert a considerable influence on forecasting European carbon emissions. According to Model 2, the second-highest contributor to EUA is gold uncertainties (GVZ: 17.81% of the total share). Conversely, the lowest predictor contributor to European carbon emissions is USEPU (2.41% of the total share).

[Insert Figure 11 here]

Now, shifting our focus to the findings of the partial dependence presented in Fig.11, which illustrates the combined influence of several predictors on EUA. The findings disclose several patterns: for example, a low GVZ combined with low UKEPU significantly influences the prediction of EUA, while high USEPU combined with low or moderately high OVX results in high EUA. Overall, all the heatmaps presented in Fig.11 indicate that all pairs of predictors are likely to be effective predictors for the European carbon allowance price. The residual scatterplots for training model validation are depicted in Fig. A6. It is evident that all error distributions are normal, as indicated by the heatmaps.

4.2.3 Assessment outcomes of Model 3

To assess the accuracy and performance of Model 3, the data undergo partitioning into training and testing sets, incorporating two alternatives to ensure robustness. Model 3 evaluates the influence of the European derivatives index (Europe 50), U.S. treasury bonds represented by the Merrill Lynch Option Volatility Estimate (MOVE) index, geopolitical risk, and global financial stress on the European carbon allowance price. The evaluation metrics and predictive outcomes are presented in Table 5 and Figs. 6 and A3. Table 5 and the figures collectively indicate Model 3's robust forecasting capabilities. Notably, Table 5 showcases the model's strong prediction accuracy, with MAE values ranging from 0.14 to 0.26 for panel 1 and from 0.04 to 0.15 for panel 2, indicating good accuracy. Furthermore, the R-squared values exceed 0.70, with panel 2 exhibiting 99% for both counts of trees in the testing sets. These results suggest that the model avoids overfitting and possesses exceptional predictive skills. Moreover, Fig. A3 illustrates that Model 3's generated curves closely track real carbon price observations, underscoring its remarkable ability to learn from historical data and forecast future trends.

Regarding panel 2 evaluation performance, the error values approach zero (Fig. A3), indicating the model's capability to meet the decision-making needs of stakeholders in the European carbon market.

[Insert Table 5 here]

[Insert Figure 6 here]

[Insert Figure 12 here]

The importance factor analysis is presented in Fig. 12. Let's delve into the significance of the variables used in predicting the European carbon allowance price. Boosted regression trees assign weights to the importance of forecasting factors. In essence, Fig. 12 provides a visual representation of the boosted regression trees values for the four predictors incorporated in the model, elucidating the importance of ETS emissions market predictions. Fig. 12 showcases the relative influence of BEZ50N, MOVEBOND, GPR, and FSI on EUA. The results indicate that all predictors are likely to contribute to the European carbon price, except GPR. As depicted in the figure, the significance of each predictor is depicted by the length of the strip in the diagram. BEZ50N emerges as the most significant contributor to predicting European carbon emissions. The relative influence of BEZ50N in predicting EUA is approximately 72.15%. This finding suggests that the European derivatives index plays a crucial role in determining ETS emissions market stability.

Another noteworthy insight pertains to the impact of financial stress on predicting carbon emissions. The FSI predictor ranks second in predicting carbon price, accounting for 15.82% of the total share in the proposed model. The third-ranked contributor is the U.S. treasury bonds market with 11.61%, while GPR exhibits the smallest predictive influence (0.43%) on EUA compared to the other predictors.

[Insert Figure 13 here]

The general importance of the combined impact of predictors on predicting European ETS emissions pricing is illustrated in Fig. 13. Interesting insights are further highlighted in the joint effect of GPR and FSI on predicting EUA. While the GPR predictor individually has a negligible effect on EUA forecasting, it is observed that when low/high GPR is paired with high FSI, it strongly influences EUA predictability (Fig. 13b5). Conversely, low/high GPR coupled with low MOVEBOND shows a high correlation with EUA (Fig. 13b6). Another noteworthy finding from Fig. 13b4 is that low FSI combined with low MOVEBOND significantly contributes to predicting EUA. Fig. A7 depicts the scatterplots of error distributions. These scatterplots, when combined with convex hulls, indicate that some of the lowest errors occur under abnormal (unobserved during training) integrations of high BEZ50N and high MOVEBOND, or high BEZ50N and low FSI, or high BEZ50N and high GPR.

In sum, the aforementioned results offer a solid foundation for predicting European ETS emissions prices and provide valuable insights for interpreting the findings of Model 3.

4.2.4 Assessment outcomes of Model 4

Table 6 and Figs. 7 and A4 present the forecasting accuracy of Model 4. In this model, we examine how global uncertainties, risks, and financial stress impact the predictive ability of European carbon allowance pricing. The findings demonstrate that Model 4 exhibits strong forecast performance, as evidenced by the values of MAE and R-squared. Specifically, for both panels P1 and P2, MAE coefficients range between 0.04 and 0.15, while R-squared values range between 0.82 and 0.98. To illustrate that Model 4 can generalize well with varying training sets, Panel 1 showcases the forecasting accuracy with different sizes of test sets. Notably, the prediction performance of Model 4 demonstrates higher accuracy across various training sets. Therefore, the larger the training period, the more proficient insights and directives the forecasting model can acquire. It is evident that R-squared coefficients for panel 2 exceed 88% for the training cluster and approach unity for the testing cluster.

[Insert Table 6 here]

[Insert Figure 7 here]

[Insert Figure 14 here]

Fig. 14 illustrates the overall feature importance of each predictor on the European carbon allowance price. As depicted in the bar chart, the top three contributors demonstrating the strongest global predictive power for EUA are BEZ50N, IDEMV, and VIX, with boosted regression trees coefficients of 44.29%, 23.15%, and 13.40%, respectively. These findings offer significant insights. Specifically, BEZ50N emerges as the most influential factor affecting EUA, followed by IDEMV, representing pandemics, as the second most significant indicator. The rise in European derivatives appears to substantially contribute to increased carbon emissions. Furthermore, the emergence of new pandemics may significantly heighten carbon emissions in Europe, aligning with hypothesis 4.

Regarding the influence of oil, stock, and gold global uncertainties, an increase in carbon price is observed in response to heightened oil market uncertainty (OVX), stock market uncertainty (VIX), or gold market uncertainty (GVZ). Conversely, the feature importance of bond market uncertainty (MOVEBOND) and economic policy uncertainties (USEPU and UKEPU) is relatively low in predicting carbon emissions in Europe.

In Model 4, another visualization tool for safety evaluation is employed, which illustrates the partial dependence, indicating the contribution of joint predictor features. These findings are presented in the heatmaps shown in Fig.15. The heatmaps offer a transparent and user-friendly means of understanding how the trio of factors interact with each other. The visualization of partial dependence can aid in identifying which predictor holds the most significant feature and how two indicators correlate with the target variable (EUA).

Given that certain predictors exhibit low individual feature importance in predicting carbon allowance prices in the proposed model, let's concentrate on evaluating the combined effect of only those pairs that demonstrate low individual relative influence. Several significant outcomes are documented. For instance, when the FSI is low and paired with either low or high GPR (Fig.15c10), or when FSI is low/high along with high MOVEBOND (Fig.15c13), or low FSI is related to low/moderate UKEPU (Fig.15c15), or high USEPU is paired with any type of FSI (Fig.15c16), it positively contributes to predicting the EU Allowance (EUA) price. This suggests an increase in carbon allowance prices in the presence of high geopolitical risk, volatile bond markets, or economic policy uncertainty in the UK or US.

Additionally, combining GPR with high MOVEBOND (Fig.15c20), or with low/high UKEPU (Fig.15c22), or with high USEPU (Fig.15c23) significantly contributes to predicting carbon allowance prices. An intriguing finding from the partial dependence features is that when MOVEBOND is associated with high USEPU, it strongly influences the prediction of EUA prices. This finding implies that US bond market uncertainty, when coupled with increased US economic policy uncertainty, raises carbon emissions prices.

Regarding the predictive influence of factors such as GPR, MOVEBOND, FSI, UKEPU, and USEPU, even though their individual feature importance in Model 4 is relatively low compared to other predictors, it is evident that during periods of pandemics (IDEMV) and in the presence of high geopolitical risk (Fig.15c19), or when bond market uncertainty is high (Fig.15c31), or during financial stress (low or high), as well as when UK and/or US economic policy uncertainties are high, these predictors contribute to increasing carbon prices. The scatterplots depicting residual distributions for training data are presented in Fig.A8. Based on these diagrams, it is evident that the lowest or highest errors tend to occur under abnormal integrations of low or high feature importance of predictors.

[Insert Figure 15 here]

5. Conclusion and policy implications

The EU ETS price has a pivotal impact on the mitigation of carbon emissions and environmental preservation. However, developing a precise and consistent forecasting model for carbon allowance prices may ensure its reliable performance. In this study, we applied a novel machine learning (ML) framework developed by Solazar et al. (2024) for dam performance analysis and safety assessment, focusing on the impact of key predictors on system response.

To illustrate this, we proposed four forecasting models (Models 1-4) incorporating variables related to global uncertainties, risks, and financial stress. These predictors include economic policy uncertainties (UK EPU and US EPU), stock market uncertainty (VIX), oil market uncertainty (OVX), gold market uncertainty (GVZ), US bond market uncertainty (MOVEBOND), geopolitical risk (GPR), newspaper-based financial stress index (FSI), CBOE Eurozone 50 index (BEZ50N), and pandemics-based index (IDEMV). Additionally, we included standard predictors of carbon price such as natural gas, oil, coal, and the Europe 600 stock market index.

The primary objective of this study is to evaluate the forecasting accuracy of the aforementioned economic and financial factors in predicting EU ETS prices. Employing a boosted regression trees ML technique enables the detection of variations in dam performance and enhances comprehension of how structural loads impact system behavior. Our main findings may be summarized as follows:

(i) All the proposed models in the study demonstrate strong forecasting capabilities for ETS emissions prices, as indicated by MAE and R-squared values.

(ii) According to Model 1, STOXX 600 is the primary contributor to predicting carbon prices, followed by the coal market. This significant impact of STOXX 600 and coal stock markets on predicting carbon price sheds light on the vital role of monitoring and standardizing financial and energy markets from the perspective of carbon emissions trading. Implementation of crucial measures to boost transparency and oversight financial and energy markets could be the objective of Policymakers to secure that carbon pricing accurately mirrors fundamental market dynamics and sustainability concerns. In addition, policymakers could provide strategies to foster eco-friendly investment practices within the financial sector to strengthen the association between market behavior and climate goals.

(iii) The partial dependence analysis reveals that while certain predictors exhibit low individual feature importance, they can collectively contribute significantly to accurate carbon price forecasts when paired with other factors.

(iv) Model 2 findings suggest that economic policy uncertainties, oil and gold market uncertainties, along with pandemic-related uncertainties, have played pivotal roles in predicting European carbon allowance prices. By implementing several measures and geopolitical factors that may mitigate climate risk, policymakers can encourage market participants. This might be achieved through encouraging diversified investments in sectors that show lower sensitivity to economic policy change and commodity market shifts, thereby boosting stability and durability in the carbon trading market. In addition, to enhance predictability and certainty for market participants and investors in carbon trading, policymakers might prioritize the alignment of economic strategies with climate targets. For instance, long-run policy strategies that account for climate uncertainty and financial/commodity market interactions may boost market stability and help eco-friendly investment choices.

(v) The boosted regression trees machine learning method employed in this study proves effective and valuable for predicting EU ETS prices. Our findings show that this ML tool meets the precision criteria required for carbon forecasting, providing a benchmark for investors and market participants in making informed investment decisions within carbon emission trading markets.

(vi) According to Models 3 and 4, Europe derivatives (Europe 50) index emerges as the most influential predictor impacting carbon prices. Additionally, pandemic-related uncertainties emerge as the second most significant factor affecting carbon price forecasts. Therefore, to measure the influence of pandemic outbreak and other fundamental disruptions on carbon pricing, policymakers could help for advancing resilience and risk management strategies.

References

Abadie, L. M., & Chamorro, J. M. (2008). European CO2 prices and carbon capture investments. *Energy Economics*, 30(6), 2992-3015.

Adediran, I. A., & Swaray, R. (2023). Carbon trading amidst global uncertainty: The role of policy and geopolitical uncertainty. *Economic Modelling*, 123, 106279.

Adekoya, O.B., 2021. Predicting carbon allowance prices with energy prices: A new approach. *Journal of Cleaner Production*, 282, p.124519.

Agliardi, E., & Agliardi, R. (2021). Pricing climate-related risks in the bond market. *Journal of Financial Stability*, 54, 100868.

Ameli, N., Drummond, P., Bisaro, A., Grubb, M., & Chenet, H. (2020). Climate finance and disclosure for institutional investors: why transparency is not enough. *Climatic Change*, 160(4), 565-589.

Arouri, M. E. H., Jawadi, F., & Nguyen, D. K. (2012). Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS. *Economic Modelling*, 29(3), 884-892.

Batten, J. A., Maddox, G. E., & Young, M. R. (2021). Does weather, or energy prices, affect carbon prices?. *Energy Economics*, 96, 105016.

Betz, F., Hautsch, N., Peltonen, T. A., & Schienle, M. (2016). Systemic risk spillovers in the European banking and sovereign network. *Journal of Financial Stability*, 25, 206-224.

Breiman, L., Friedman, J., Olshen, R. A., & Stone, C. J. (2017). *Classification and regression trees*. Routledge.

Brink, C., Vollebergh, H. R., & van der Werf, E. (2016). Carbon pricing in the EU: Evaluation of different EU ETS reform options. *Energy Policy*, 97, 603-617.

Chang, L., Chen, K., Saydaliev, H. B., & Faridi, M. Z. (2022). Asymmetric impact of pandemics-related uncertainty on CO2 emissions: evidence from top-10 polluted countries. *Stochastic Environmental Research and Risk Assessment*, 36(12), 4103-4117.

Chen, H., Liu, Z., Zhang, Y., & Wu, Y. (2020). The linkages of carbon spot-futures: evidence from EU-ETS in the third phase. *Sustainability*, 12(6), 2517.

Chevallier, J., Nguyen, D. K., & Reboredo, J. C. (2019). A conditional dependence approach to CO2-energy price relationships. *Energy Economics*, 81, 812-821.

Coeslier, M., Louche, C., & Hétet, J. F. (2016). On the relevance of low-carbon stock indices to tackle climate change. *Journal of Sustainable Finance & Investment*, 6(4), 247-262.

Convery, F. J. (2009). Origins and development of the EU ETS. *Environmental and Resource Economics*, 43, 391-412.

Dong, F., Gao, Y., Li, Y., Zhu, J., Hu, M., & Zhang, X. (2022). Exploring volatility of carbon price in European Union due to COVID-19 pandemic. *Environmental Science and Pollution Research*, 1-12.

Dou, Y., Li, Y., Dong, K., & Ren, X. (2022). Dynamic linkages between economic policy uncertainty and the carbon futures market: does Covid-19 pandemic matter?. *Resources Policy*, 75, 102455.

Dutta, A. (2018). Modeling and forecasting the volatility of carbon emission market: The role of outliers, time-varying jumps and oil price risk. *Journal of Cleaner Production*, 172, 2773-2781.

Fahmy, H. (2022). The rise in investors’ awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus. *Energy Economics*, 106, 105738.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of Statistics*, 1189-1232.

Fu, C., Lu, L., & Pirabi, M. (2023). Advancing green finance: a review of sustainable development. *Digital Economy and Sustainable Development*, 1(1), 20.

García-Martos, C., Rodríguez, J., & Sánchez, M. J. (2013). Modelling and forecasting fossil fuels, CO2 and electricity prices and their volatilities. *Applied Energy*, 101, 363-375.

Hammoudeh, S., Nguyen, D. K., & Sousa, R. M. (2014). Energy prices and CO2 emission allowance prices: A quantile regression approach. *Energy policy*, 70, 201-206.

Hao, Y., Tian, C., & Wu, C. (2020). Modelling of carbon price in two real carbon trading markets. *Journal of Cleaner Production*, 244, 118556.

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction* (Vol. 2, pp. 1-758). New York: springer.

Hemrit, W., & Benlagha, N. (2021). Does renewable energy index respond to the pandemic uncertainty?. *Renewable Energy*, 177, 336-347.

Hintermann, B., Peterson, S., & Rickels, W. (2016). Price and Market Behavior in Phase II of the EU ETS: *A Review of the Literature. Review of Environmental Economics and Policy.*

Jiménez-Rodríguez, R. (2019). What happens to the relationship between EU allowances prices and stock market indices in Europe?. *Energy Economics*, 81, 13-24.

Khan, K., Su, C. W., & Zhu, M. N. (2022). Examining the behaviour of energy prices to COVID-19 uncertainty: A quantile on quantile approach. *Energy*, 239, 122430.

Kocaarslan, B., & Soytas, U. (2019). Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar). *Energy Economics*, 84, 104502.

Leathwick, J. R., Elith, J., Francis, M. P., Hastie, T., & Taylor, P. J. M. E. P. (2006). Variation in demersal fish species richness in the oceans surrounding New Zealand: an analysis using boosted regression trees. *Marine ecology progress series*, 321, 267-281.

Li, K., Qi, S., & Shi, X. (2022). The COVID-19 pandemic and energy transitions: Evidence from low-carbon power generation in China. *Journal of Cleaner Production*, 368, 132994.

Li, X., Li, Z., Su, C. W., Umar, M., & Shao, X. (2022). Exploring the asymmetric impact of economic policy uncertainty on China's carbon emissions trading market price: do different types of uncertainty matter?. *Technological Forecasting and Social Change*, 178, 121601.

Liu, J., Tang, S., & Chang, C. P. (2021). Spillover effect between carbon spot and futures market: evidence from EU ETS. *Environmental Science and Pollution Research*, 28(12), 15223-15235.

Liu, T., Guan, X., Wei, Y., Xue, S., & Xu, L. (2023). Impact of economic policy uncertainty on the volatility of China's emission trading scheme pilots. *Energy Economics*, 121, 106626.

Liu, X., Wojewodzki, M., Cai, Y., & Sharma, S. (2023). The dynamic relationships between carbon prices and policy uncertainties. *Technological Forecasting and Social Change*, 188, 122325.

Madaleno, M., Dogan, E., & Taskin, D. (2022). A step forward on sustainability: The nexus of environmental responsibility, green technology, clean energy and green finance. *Energy Economics*, 109, 105945.

Makridakis, S., & Hibon, M. (1979). Accuracy of forecasting: An empirical investigation. *Journal of the Royal Statistical Society: Series A (General)*, 142(2), 97-125.

Mansanet-Bataller, M., Pardo, A., & Valor, E. (2007). CO_2 prices, energy and weather. *The Energy Journal*, 28(3), 73-92.

Mar'I, M., Seraj, M., & Tursoy, T. (2024). The Impact of Financial Stress and Uncertainty on Green and Conventional Bonds and Stocks: A Nonlinear and Nonparametric Quantile Analysis. *Risks*, 12(8).

Michelis, A. (2012). Traditional versus non-traditional boosting algorithms. *Master's Thesis, University of Manchester, Manchester.*

Mintz-Woo, K., Dennig, F., Liu, H., & Schinko, T. (2021). Carbon pricing and COVID-19. *Climate Policy*, 21(10), 1272-1280.

Nadirgil, O. (2023). The relationship between the contaminating industries and the European carbon price, machine learning approach. *Journal of Cleaner Production*, 426, 139131.

Nazifi, F., & Milunovich, G. (2010). Measuring the impact of carbon allowance trading on energy prices. *Energy & Environment*, 21(5), 367-383.

Newell, R. G., Pizer, W. A., & Raimi, D. (2013). Carbon markets 15 years after Kyoto: Lessons learned, new challenges. *Journal of Economic Perspectives*, 27(1), 123-146.

Nibbering, D., & Paap, R. (2024). Forecasting carbon emissions using asymmetric grouping. *Journal of Forecasting*, 43(6), 2228-2256.

Nishino, K., & Suzuki, A. (2019). Taguchi's T- method using median- median line for small sample with outliers. *Electronics and Communications in Japan*, 102(1), 49-56.

Olubusoye, O. E., Akintande, O. J., Yaya, O. S., Ogbonna, A. E., & Adenikinju, A. F. (2021). Energy pricing during the COVID-19 pandemic: Predictive information-based uncertainty indexes with machine learning algorithm. *Intelligent Systems with Applications*, 12, 200050.

Qiu, L., Chu, L., Zhou, R., Xu, H., & Yuan, S. (2023). How do carbon, stock, and renewable energy markets interact: Evidence from Europe. *Journal of Cleaner Production*, 407, 137106.

Quinlan, J. R. (1993, June). Combining instance-based and model-based learning. *In Proceedings of the tenth international conference on machine learning* (pp. 236-243).

Ramos-García, D., López-Martín, C., & Arguedas-Sanz, R. (2023). Climate transition risk in determining credit risk: evidence from firms listed on the STOXX Europe 600 index. *Empirical Economics*, 65(5), 2091-2114.

Raza, S. A., Khan, K. A., Benkraiem, R., & Guesmi, K. (2024). The importance of climate policy uncertainty in forecasting the green, clean and sustainable financial markets volatility. *International Review of Financial Analysis*, 91, 102984.

Rittler, D. (2012). Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. *Journal of Banking & Finance*, 36(3), 774-785.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, 34(1), 248-255.

Salazar, F., Irazábal, J., & Conde, A. (2024). SOLDIER: SOLution for Dam behavior Interpretation and safety Evaluation with boosted Regression trees. *SoftwareX*, 25, 101598.

Tan, X., Sirichand, K., Vivian, A., & Wang, X. (2022). Forecasting European carbon returns using dimension reduction techniques: Commodity versus financial fundamentals. *International Journal of Forecasting*, 38(3), 944-969.

Verbruggen, A., Laes, E., & Woerdman, E. (2019). Anatomy of emissions trading systems: what is the EU ETS?. *Environmental Science & Policy*, 98, 11-19.

Wang, F., Ma, W., Mirza, N., & Altuntaş, M. (2023). Green financing, financial uncertainty, geopolitical risk, and oil prices volatility. *Resources Policy*, 83, 103716.

Wang, K. H., Wang, Z. S., Yunis, M., & Kchouri, B. (2023). Spillovers and connectedness among climate policy uncertainty, energy, green bond and carbon markets: A global perspective. *Energy Economics*, 128, 107170.

Wang, Z. J., & Zhao, L. T. (2021). The impact of the global stock and energy market on EU ETS: A structural equation modelling approach. *Journal of Cleaner Production*, 289, 125140.

Xiao, C., & Liu, Y. (2025). A Multifrequency Data Fusion Deep Learning Model for Carbon Price Prediction. *Journal of Forecasting*, 44(2), 436-458.

Yahşi, M., Çanakoğlu, E., & Ağralı, S. (2019). Carbon price forecasting models based on big data analytics. *Carbon Management*, 10(2), 175-187.

Ye, J., & Xue, M. (2021). Influences of sentiment from news articles on EU carbon prices. *Energy Economics*, 101, 105393.

Zeng, S., Nan, X., Liu, C., & Chen, J. (2017). The response of the Beijing carbon emissions allowance price (BJC) to macroeconomic and energy price indices. *Energy Policy*, 106, 111-121.

Zhang, W., & Wu, Z. (2022). Optimal hybrid framework for carbon price forecasting using time series analysis and least squares support vector machine. *Journal of Forecasting*, 41(3), 615-632.

Zhang, X., Li, Z., Zhao, Y., & Wang, L. (2023). Carbon trading and COVID-19: a hybrid machine learning approach for international carbon price forecasting. *Annals of Operations Research*, 1-29.

Zhao, X., Han, M., Ding, L., & Kang, W. (2018). Usefulness of economic and energy data at different frequencies for carbon price forecasting in the EU ETS. *Applied Energy*, 216, 132-141.

Zhu, B., Ye, S., Wang, P., Chevallier, J., & Wei, Y. M. (2022). Forecasting carbon price using a multi- objective least squares support vector machine with mixture kernels. *Journal of Forecasting*, 41(1), 100-117.

Table 1. Definition of variables.

Variable name	Symbol	
EU ETS allowances	EUA	
Natural Gas	GAS	
Global Coal	COAL	
Brent crude oil	BRENT	
STOXX Europe 600 Index	STOXX600	
United States Economic Policy Uncertainty Index	USEPU	
United Kingdom Economic Policy Uncertainty Index	UKEPU	
Geopolitical Risk Index	GPR	
Bond Market Uncertainty	MOVEBOND	
CBOE Eurozone 50 Index	BEZ50N	
Stock Market Uncertainty	VIX	
Oil Market Uncertainty	OVX	
Gold Market Uncertainty	GVZ	

newspaper-based Financial Stress Indicator	FSI	
Infectious Disease Equity Market Volatility tracker	IDEMV	

Table 2. Summary statistics.

Vars	Mean	Std.dev	Median	Min.	Max.	Range	Skew.	kurtosis	S.E.
EUA	1.18461	0.44086	1.11461	0.43933	2.00147	1.56214	0.47020	-1.13675	0.00744
GAS	1.74791	0.25631	1.73878	0.92942	2.75587	1.82646	0.66942	1.84696	0.00433
COAL	1.94933	0.20133	1.93044	1.58490	2.64246	1.05757	1.06259	1.42820	0.00340
BRENT	1.86837	0.15325	1.88058	1.28623	2.10714	0.82091	-0.50246	-0.37744	0.00259
STOXX600	2.55286	0.08176	2.56783	2.33221	2.69686	0.36465	-0.46022	-0.53263	0.00138
USEPU	2.00728	0.26584	2.00199	0.52114	3.01131	2.49017	0.05423	0.53563	0.00449
UKEPU	2.40809	0.27159	2.41440	0.26482	3.41665	3.15183	-0.33393	1.47526	0.00459
GPR	2.00220	0.17999	2.00259	0.97734	2.73306	1.75572	-0.03179	0.91361	0.00304
MOVEBOND	1.86382	0.13406	1.84572	1.56348	2.29820	0.73472	0.41104	-0.58733	0.00226
BEZ50N	2.50836	0.08261	2.51542	2.29019	2.69727	0.40708	-0.15608	-0.43155	0.00139
VIX	1.23570	0.14023	1.21511	0.96095	1.91745	0.95651	0.80896	0.88316	0.00237
OVX	1.54250	0.15206	1.53732	1.16137	2.51208	1.35072	0.73214	3.10146	0.00257
GVZ	1.21416	0.11388	1.21405	0.94841	1.69002	0.74161	0.29384	0.22432	0.00192
FSI	-1.19505	2.19064	-1.60800	-4.36400	10.26600	14.63000	1.28919	2.24854	0.03697
IDEMV	4.12653	7.92512	0.45000	0.00000	68.37000	68.37000	2.96482	11.39962	0.13375

Table 3. Assessing the forecasting accuracy: Model 1.

	Training MAE	Training R-squared	Testing MAE	Testing R-squared
Panel P1: Training set: 2010-09-17 to 2022-02-27; Testing set : 2022-02-28 to 2024-03-01				
Trees = 750	0.11	0.81	0.19	0.93
Trees = 500	0.13	0.77	0.20	0.92
Panel P2: Training set: 2010-09-17 to 2023-08-30; Testing set: 2023-08-31 to 2024-03-01				
Trees = 750	0.11	0.88	0.04	0.99
Trees = 500	0.13	0.85	0.05	0.99

Table 4. Assessing the forecasting accuracy: Model 2.

	Training MAE	Training R-squared	Testing MAE	Testing R-squared
Panel P1: Training set: 2010-09-17 to 2022-02-27; Testing set: 2022-02-28 to 2024-03-01				
Trees = 750	0.12	0.78	0.42	0.71
Trees = 500	0.13	0.75	0.45	0.68

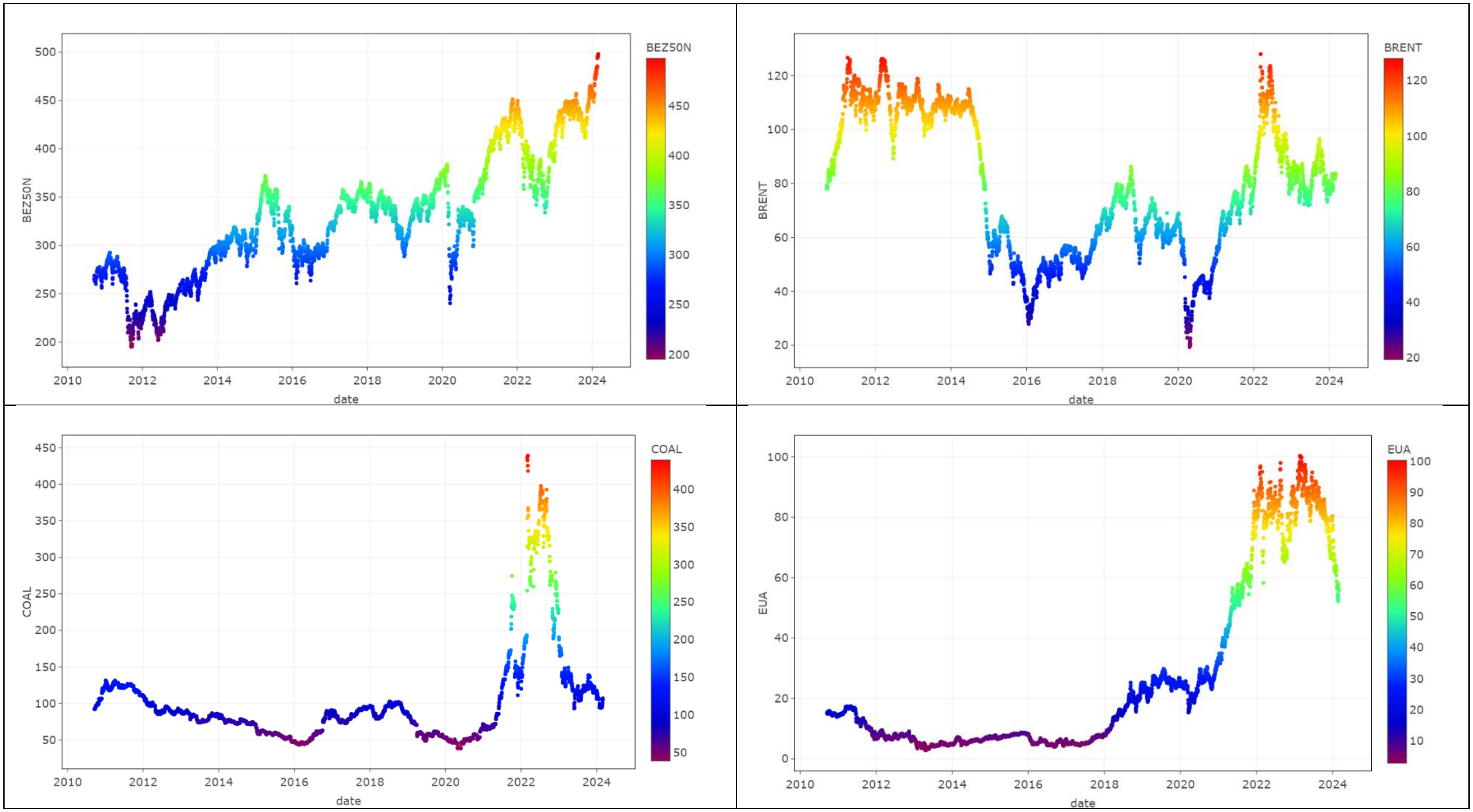
Panel P2: Training set: 2010-09-17 to 2023-08-30; Testing set: 2023-08-31 to 2024-03-01				
Trees = 750	0.14	0.80	0.28	0.73
Trees = 500	0.16	0.78	0.30	0.71

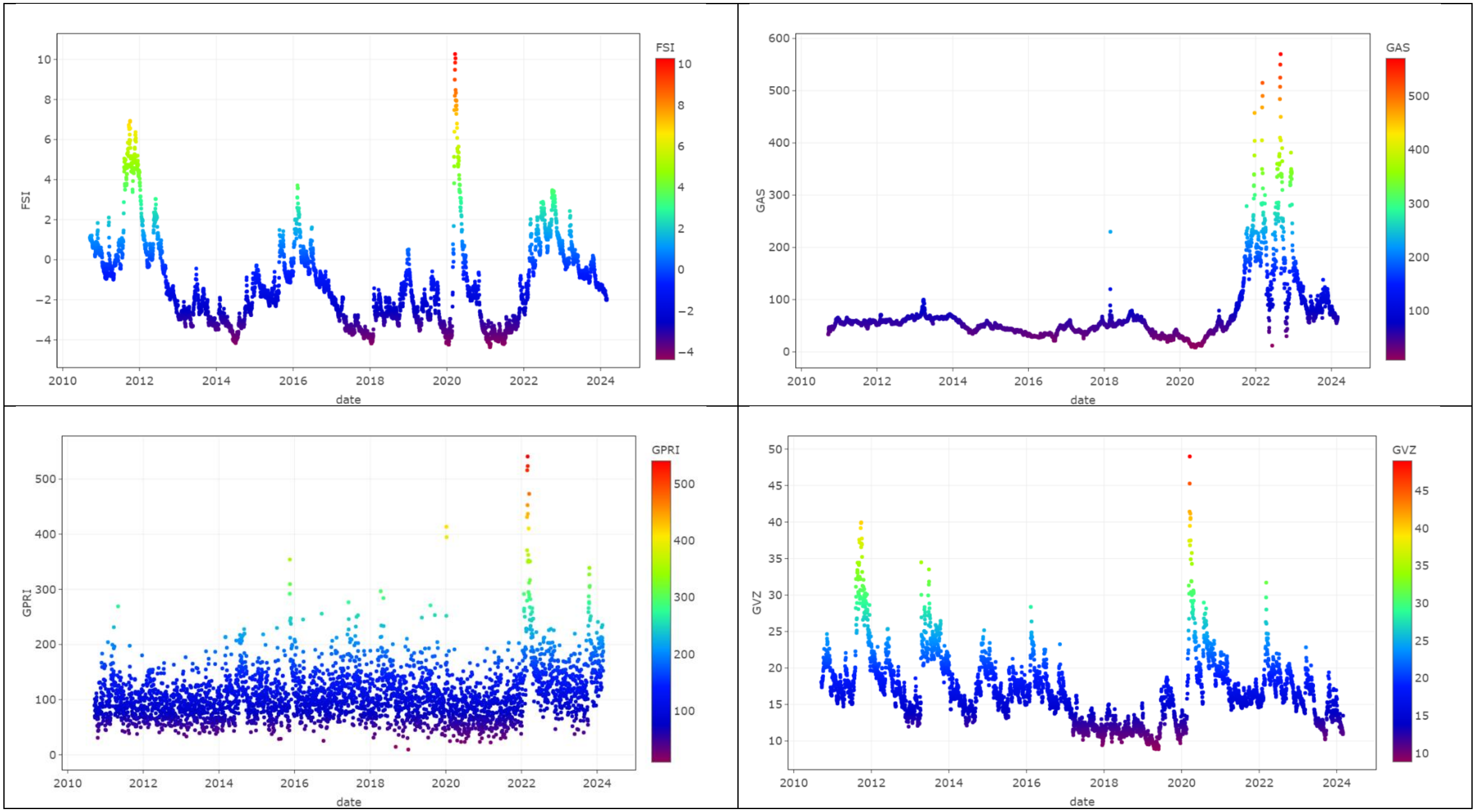
Table 5. Assessing the forecasting accuracy: Model 3.

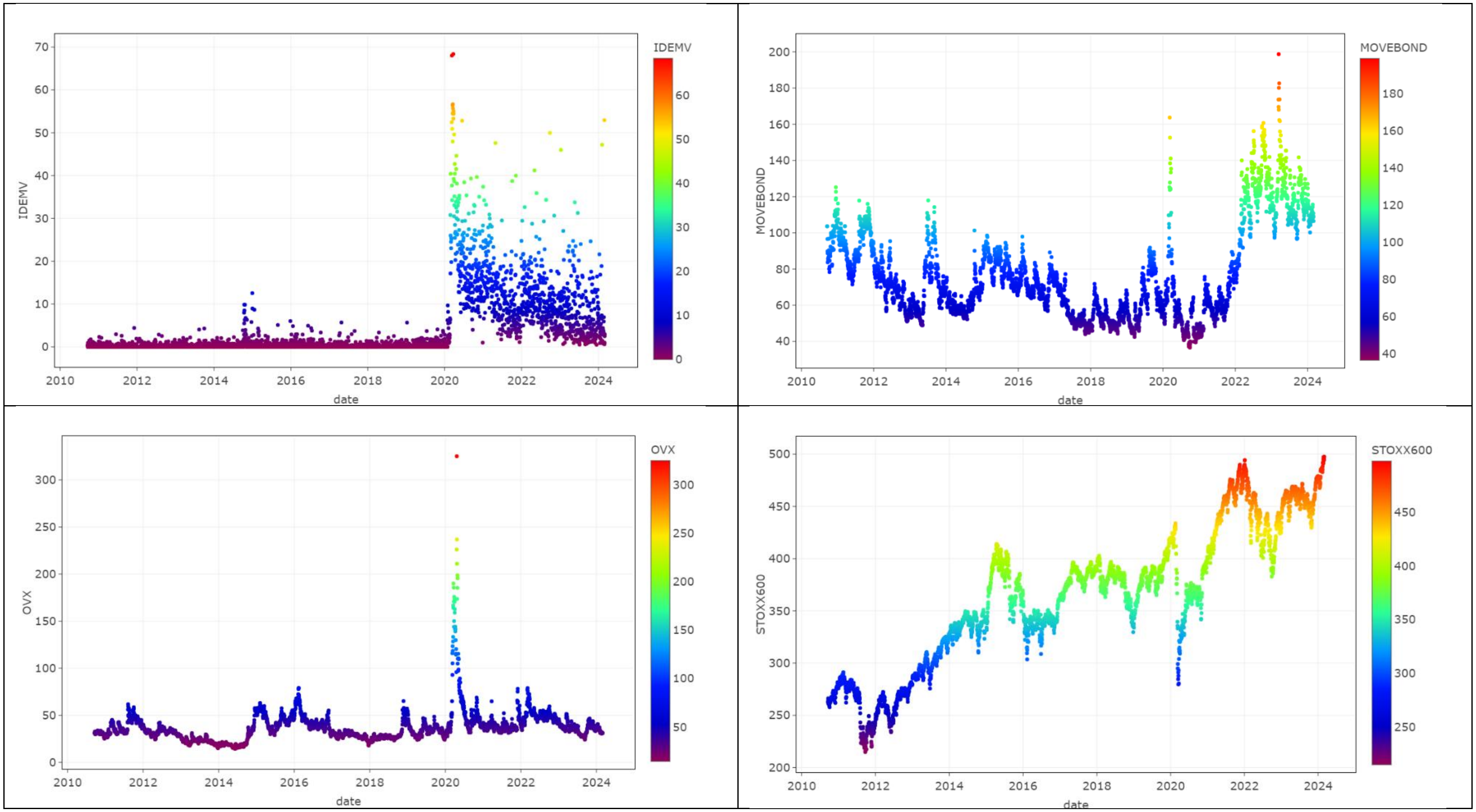
	Training MAE	Training R-squared	Testing MAE	Testing R-squared
Panel P1: Training set: 2010-09-17 to 2022-02-27; Testing set: 2022-02-28 to 2024-03-01				
Trees = 750	0.14	0.74	0.20	0.88
Trees = 500	0.15	0.70	0.26	0.84
Panel P2: Training set: 2010-09-17 to 2023-08-30; Testing set: 2023-08-31 to 2024-03-01				
Trees = 750	0.13	0.84	0.06	0.99
Trees = 500	0.15	0.81	0.04	0.99

Table 6. Assessing the forecasting accuracy: Model 4.

	Training MAE	Training R-squared	Testing MAE	Testing R-squared
Panel P1: Training set: 2010-09-17 to 2022-02-27; Testing set: 2022-02-28 to 2024-03-01				
Trees = 750	0.10	0.85	0.21	0.91
Trees = 500	0.12	0.82	0.28	0.87
Panel P2: Training set: 2010-09-17 to 2023-08-30; Testing set: 2023-08-31 to 2024-03-01				
Trees = 750	0.10	0.90	0.08	0.98
Trees = 500	0.11	0.88	0.07	0.98


BEZ50N
500
450
400
350
300
250
200
2010
2012
2014
2016
2018
2020
2022
2024
date
BRENT
120
100
80
60
40
20
COAL
450
400
350
300
250
200
150
100
50
EUA
100
90
80
70
60
50
40
30
20
10
0


FSI
date
GAS
date
GPRI
date
GVZ
date
2010
2012
2014
2016
2018
2020
2022
2024


IDEMV
date
2010
2012
2014
2016
2018
2020
2022
2024
MOVEBOND
OVX
STOXX600

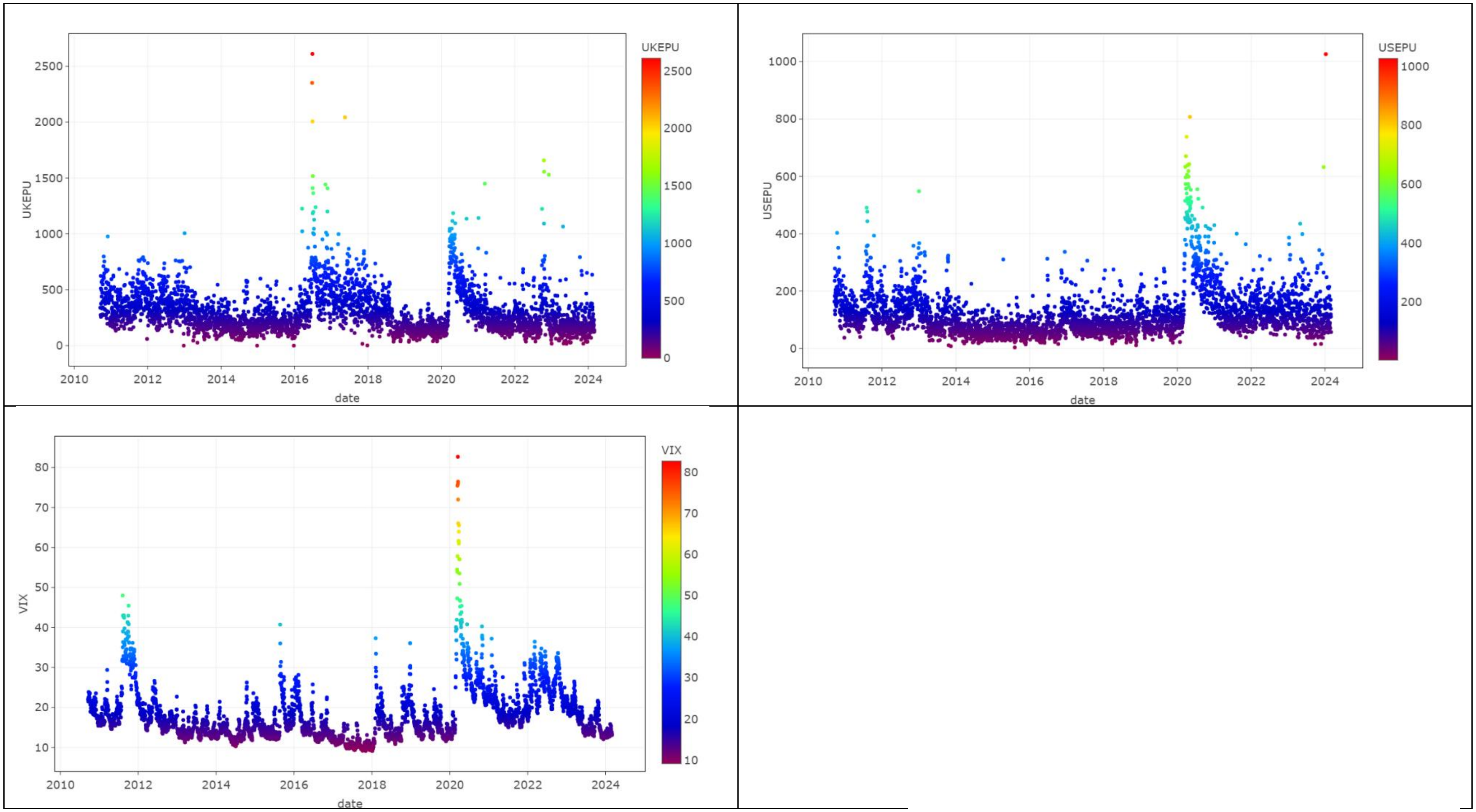


Fig.2. Scatterplot displaying the dynamics of the target variable and predictors. Please consult the online edition of this paper for explanations regarding color references.

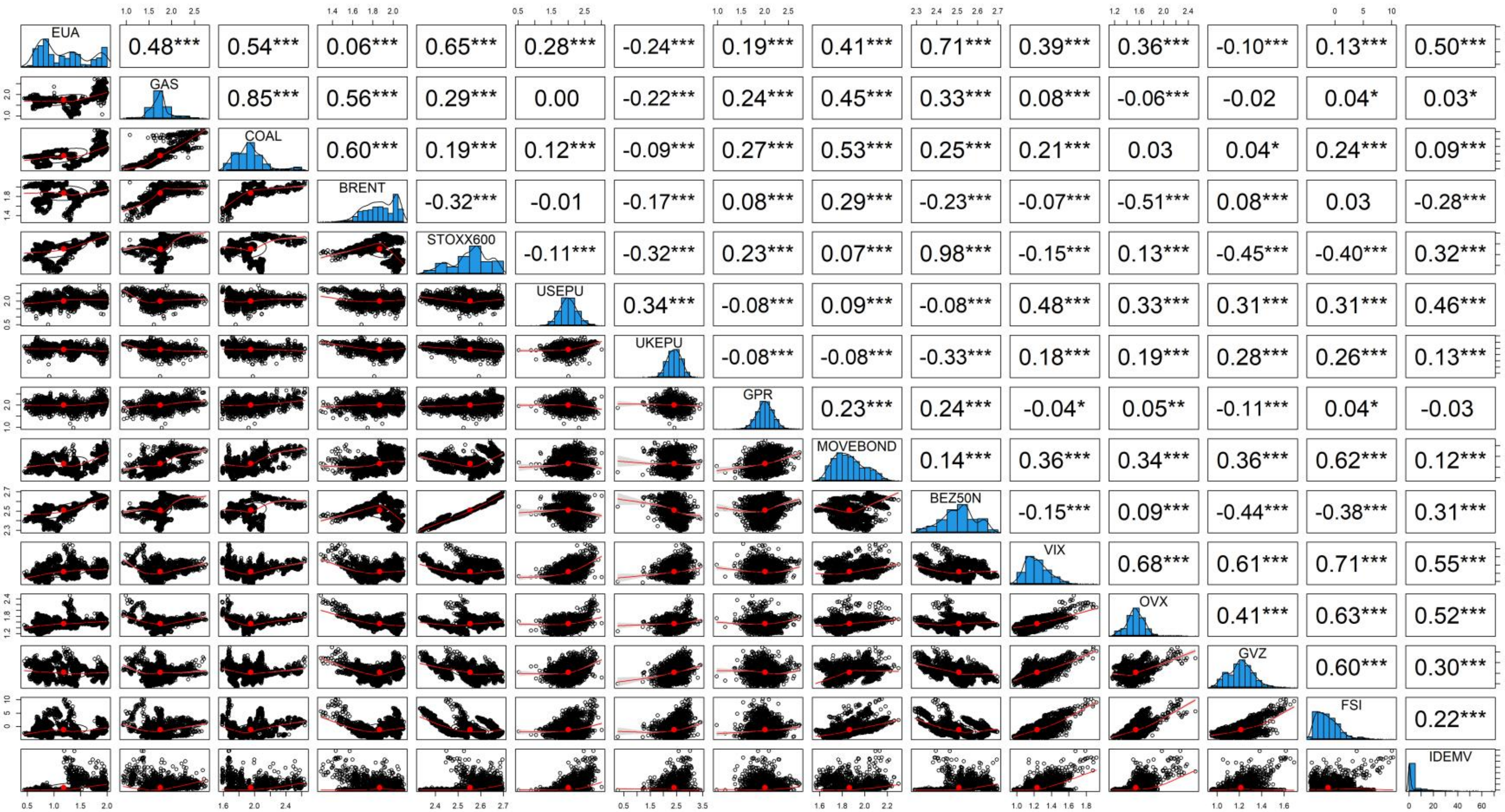


Fig.3. Heatmap correlation.

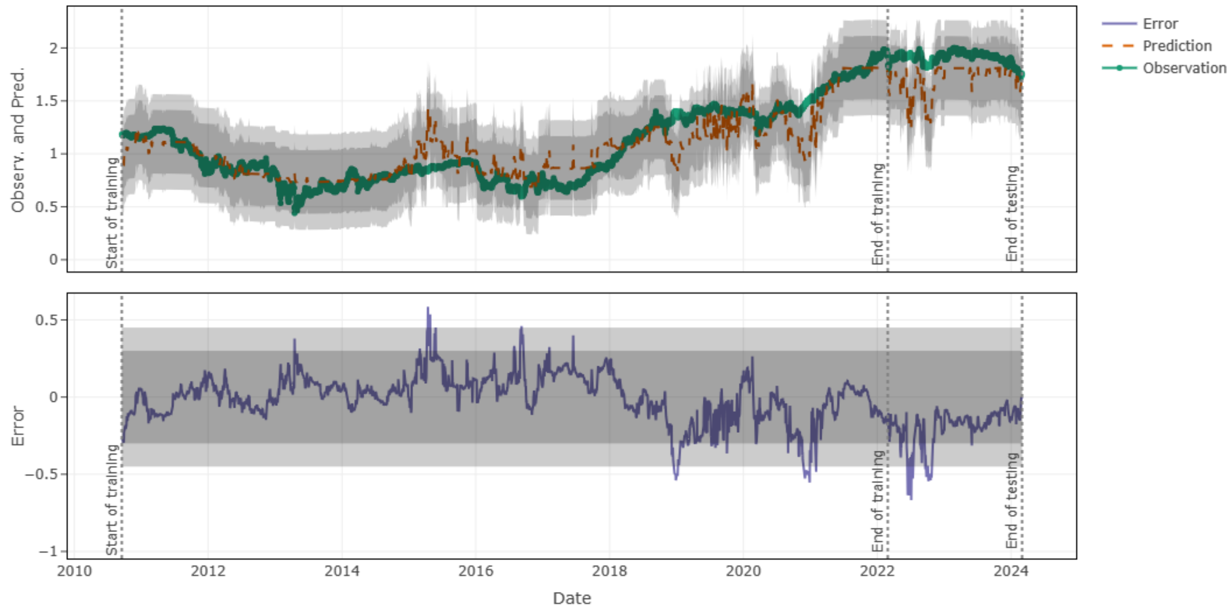


Fig.4. Forecasting and observations with Model 1 and using training parameters panel 1. Error and confidence intervals visualized.

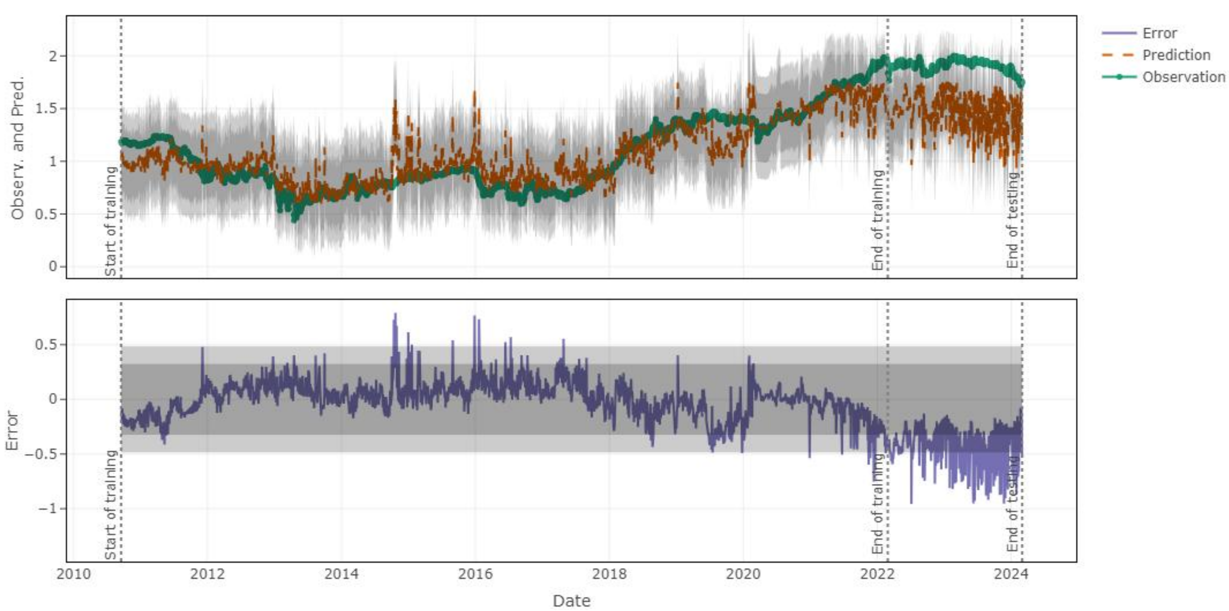


Fig.5. Forecasting and observations with Model 2 and using training parameters panel 1. Error and confidence intervals visualized.

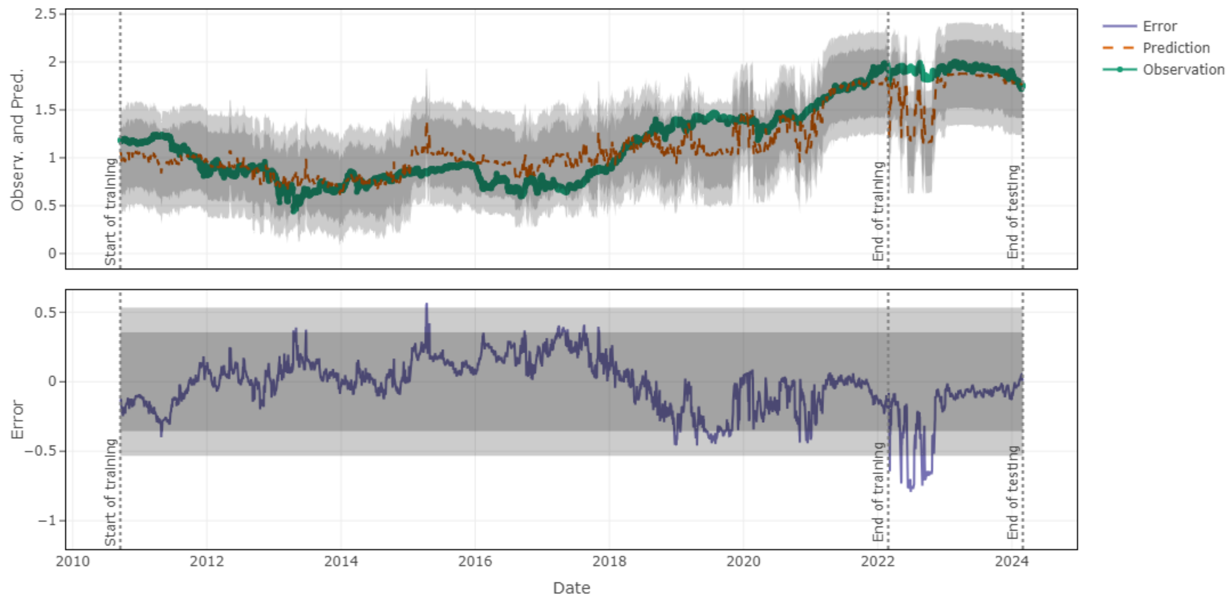


Fig.6. Forecasting and observations with Model 3 and using training parameters panel 1. Error and confidence intervals visualized.

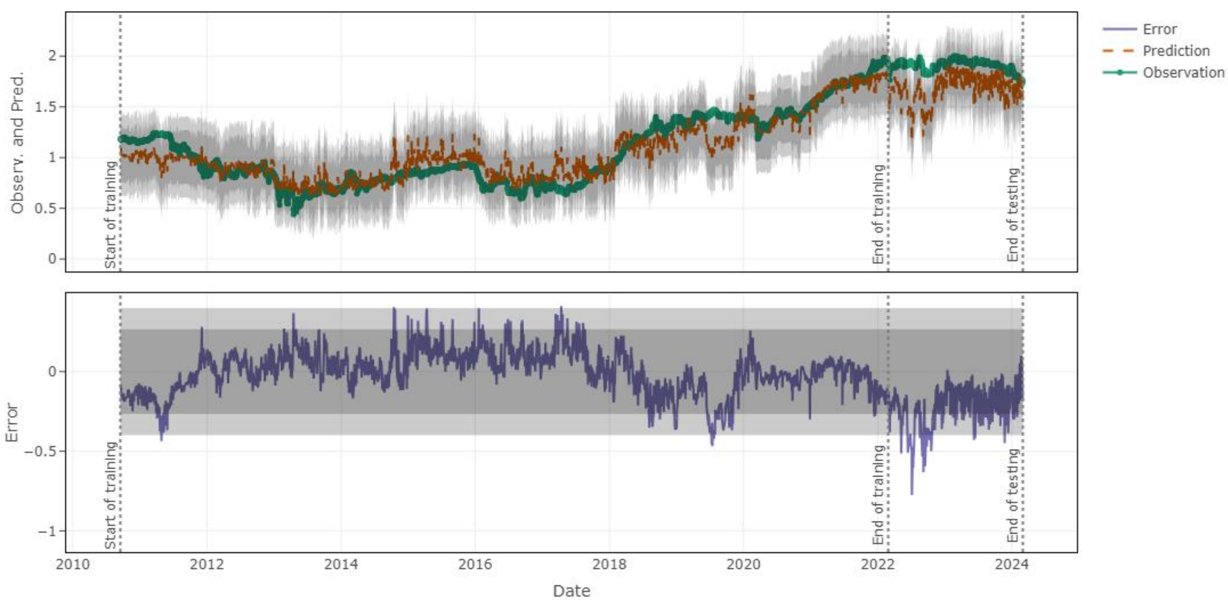


Fig.7. Forecasting and observations with Model 4 and using training parameters panel 1. Error and confidence intervals visualized.

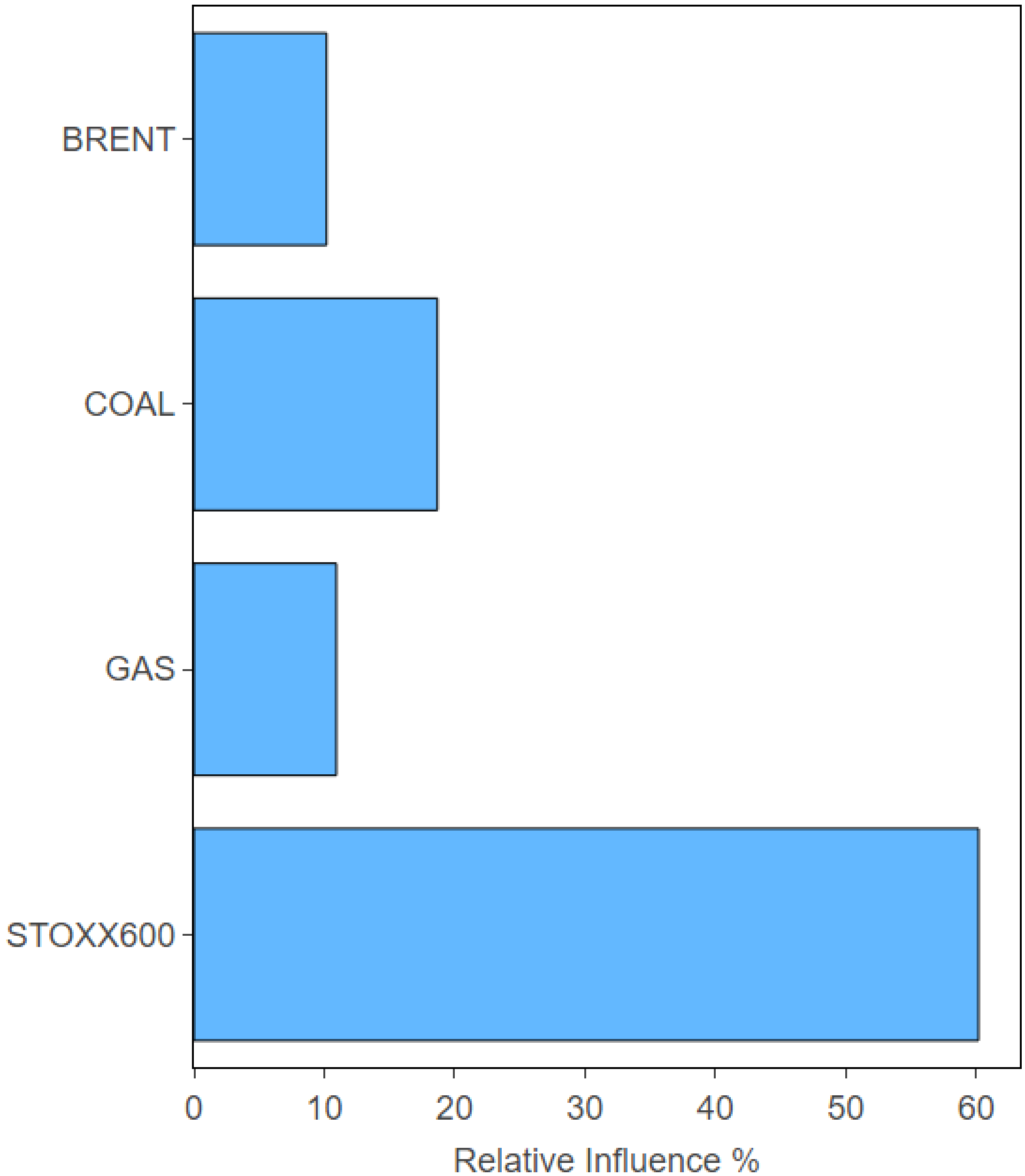
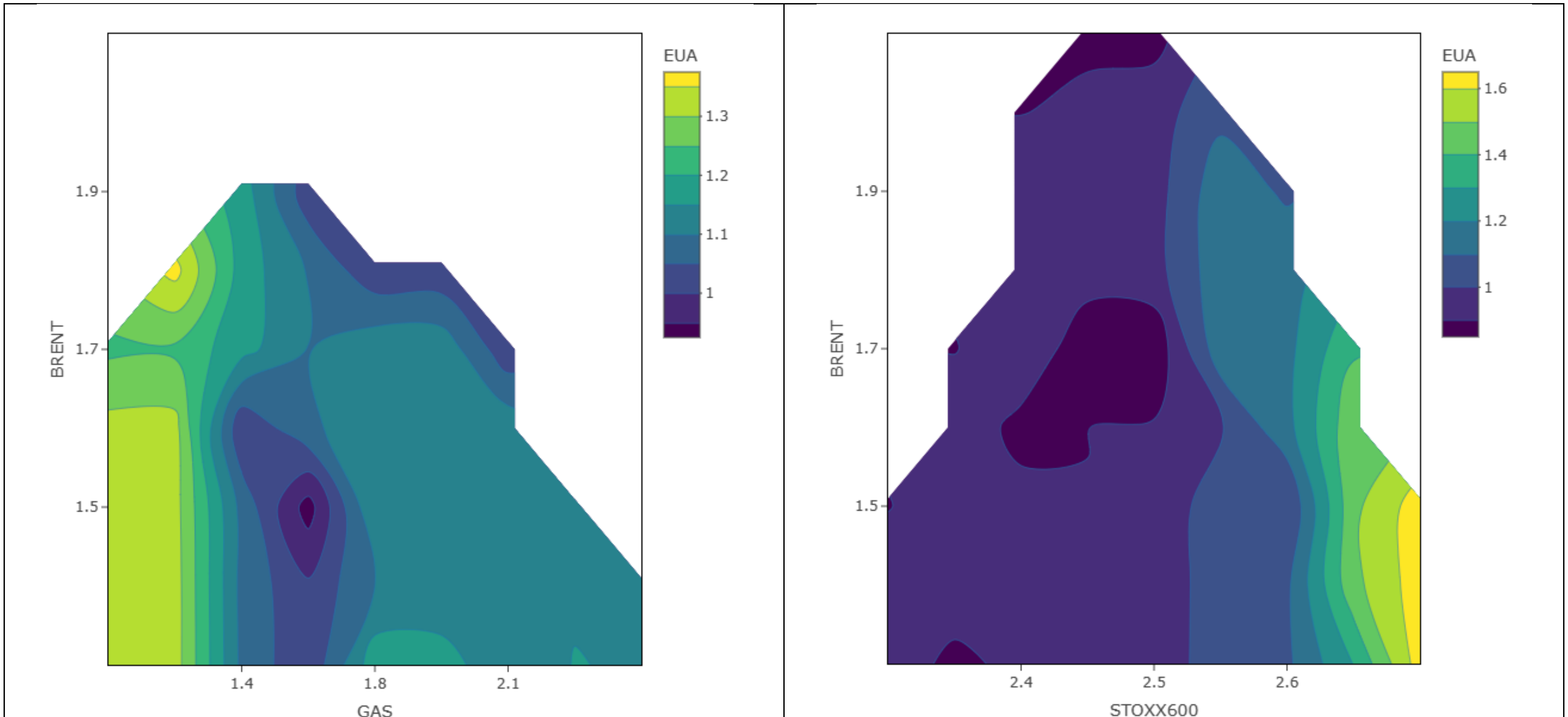
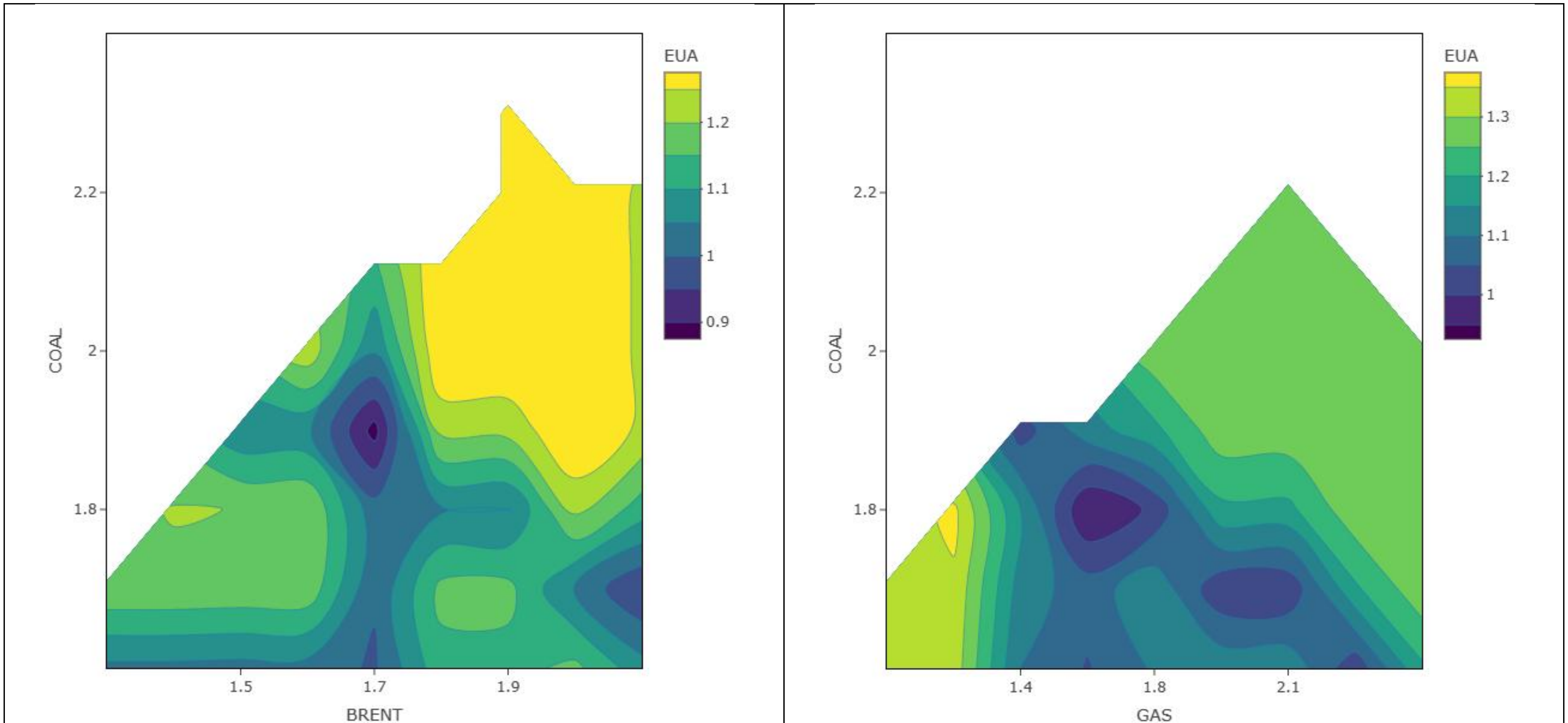


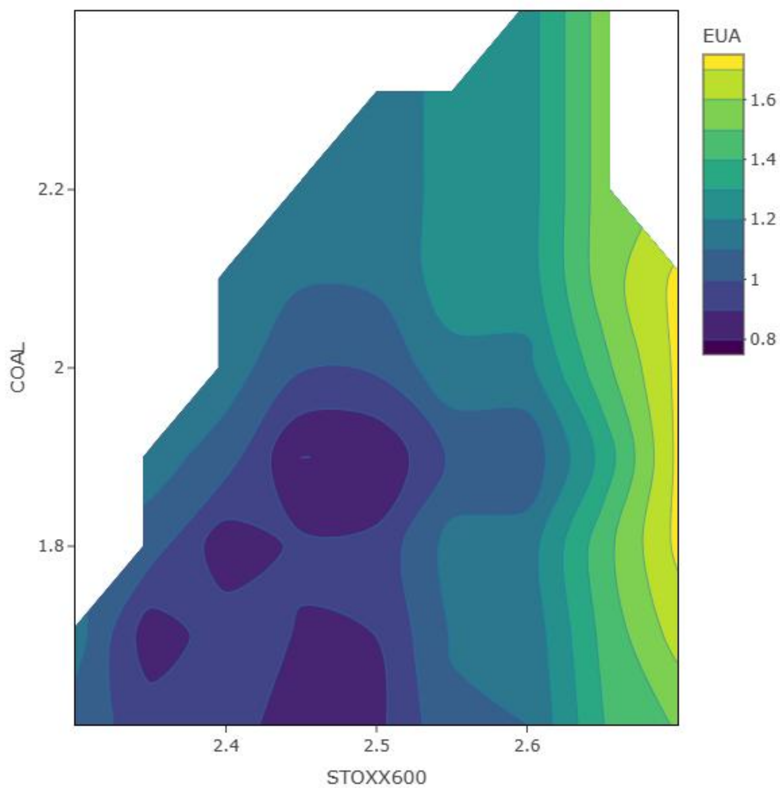
Fig.8. Assessing the relative importance of predictors in Model 1. This plot shows the relative influence of the predictors (BRENT, COAL, GAS, STOXX600) on EUA.


EUA
1.3
1.2
1.1
1
1.9
1.7
1.5
BRENT
1.4
1.8
2.1
GAS
EUA
1.6
1.4
1.2
1
BRENT
2.4
2.5
2.6
STOXX600

(a) **(b)**


EUA
1.2
1.1
1
0.9
2.2
2
1.8
COAL
1.5
1.7
1.9
BRENT
EUA
1.3
1.2
1.1
1
2.2
2
1.8
COAL
1.4
1.8
2.1
GAS

(c) **(d)**


EUA
1.6
1.4
1.2
1
0.8
COAL
2.2
2
1.8
2.4
2.5
2.6
STOXX600
(e)

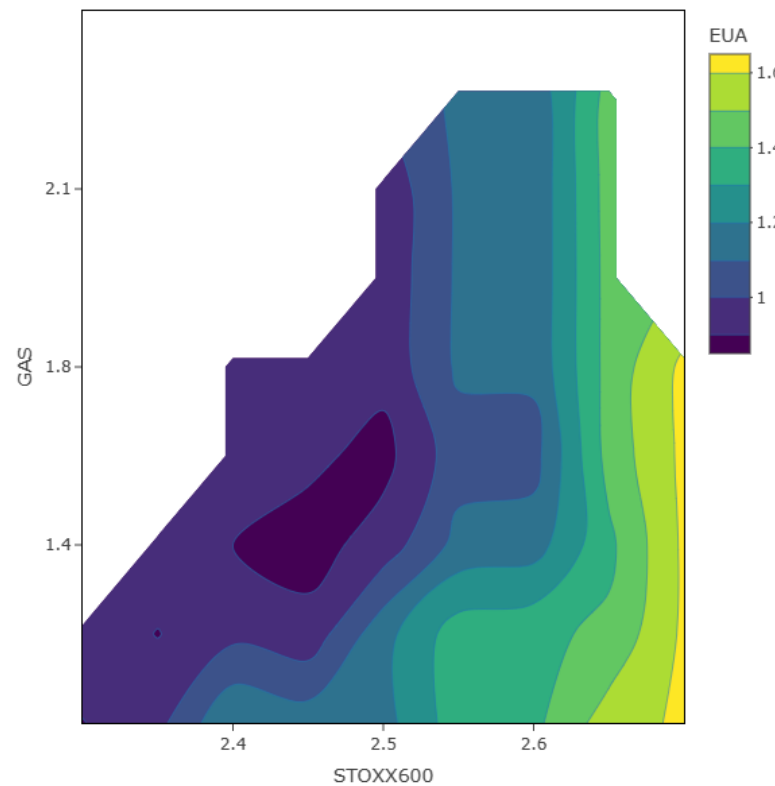

EUA
1.6
1.4
1.2
1
GAS
2.1
1.8
1.4
2.4
2.5
2.6
STOXX600
(f)

Fig.9. Partial dependance analysis with Model 1. The heatmaps illustrating the combined effect of the used predictors on EUA.

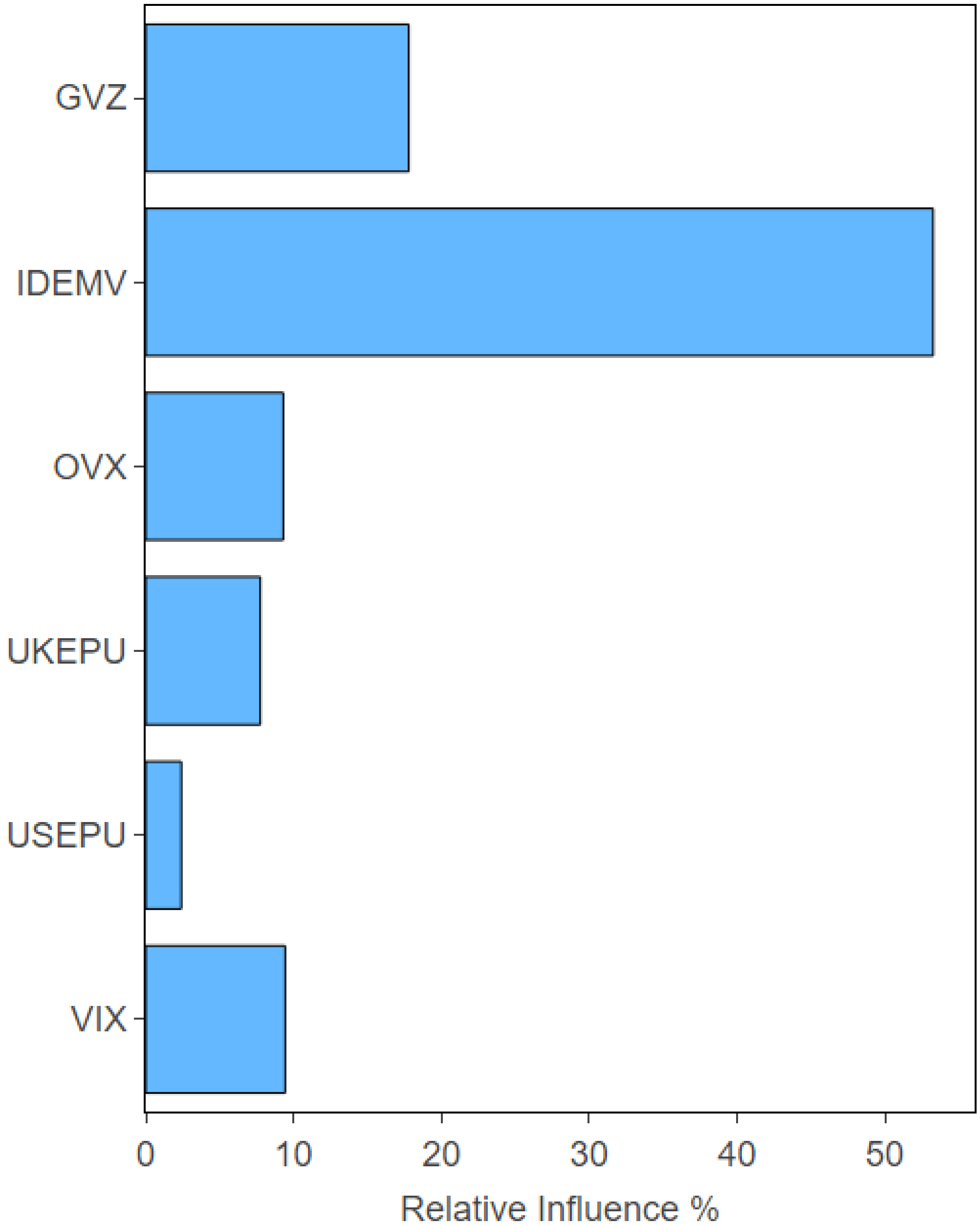
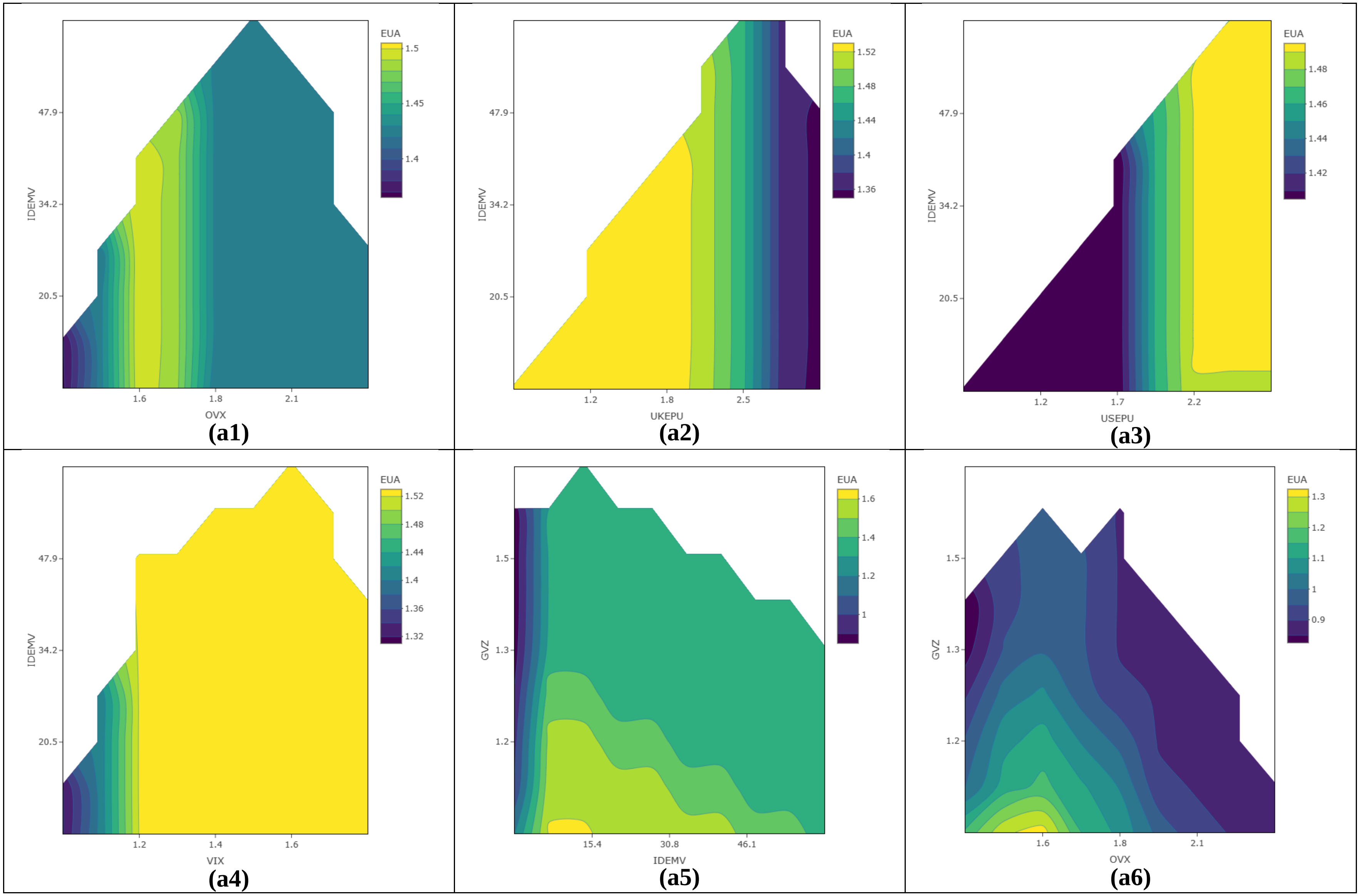
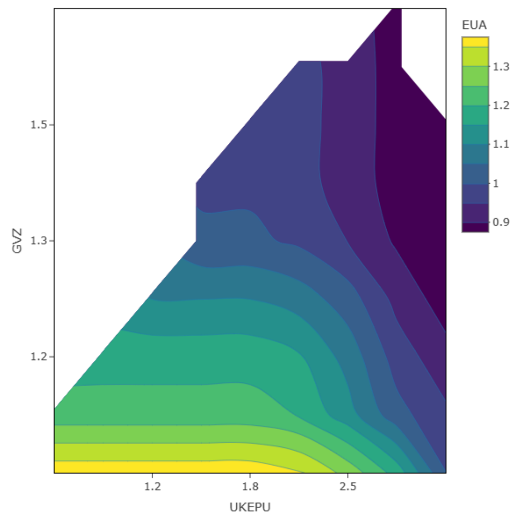
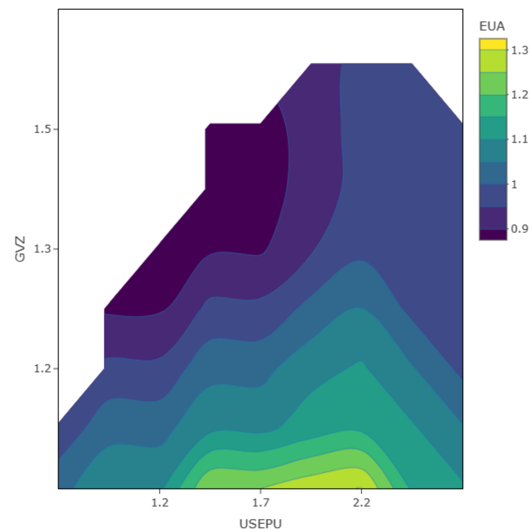


Fig.10. Assessing the relative importance of predictors in Model 2. This plot shows the relative influence of the predictors, i.e., global uncertainties (GVZ, IDEMV, OVX, UKEPU, USEPU, VIX) on EUA.

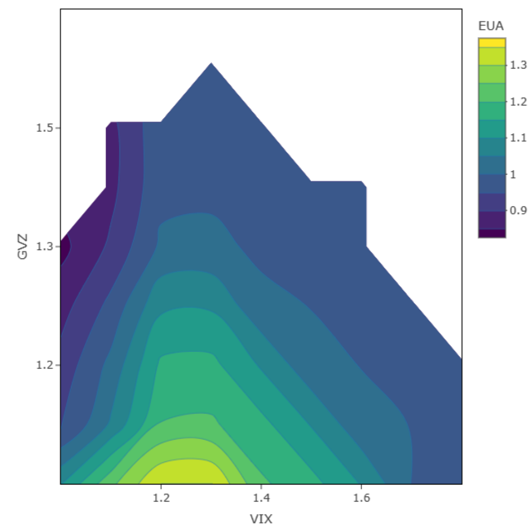

EUA
1.5
1.45
1.4
47.9
34.2
20.5
IDEMV
1.6
1.8
2.1
OVX
(a1)
EUA
1.52
1.48
1.44
1.4
1.36
47.9
34.2
20.5
IDEMV
1.2
1.8
2.5
UKEPU
(a2)
EUA
1.48
1.46
1.44
1.42
47.9
34.2
20.5
IDEMV
1.2
1.7
2.2
USEPU
(a3)
EUA
1.52
1.48
1.44
1.4
1.36
1.32
47.9
34.2
20.5
IDEMV
1.2
1.4
1.6
VIX
(a4)
EUA
1.6
1.4
1.2
1
1.5
1.3
1.2
GVZ
15.4
30.8
46.1
IDEMV
(a5)
EUA
1.3
1.2
1.1
1
0.9
1.5
1.3
1.2
GVZ
1.6
1.8
2.1
OVX
(a6)



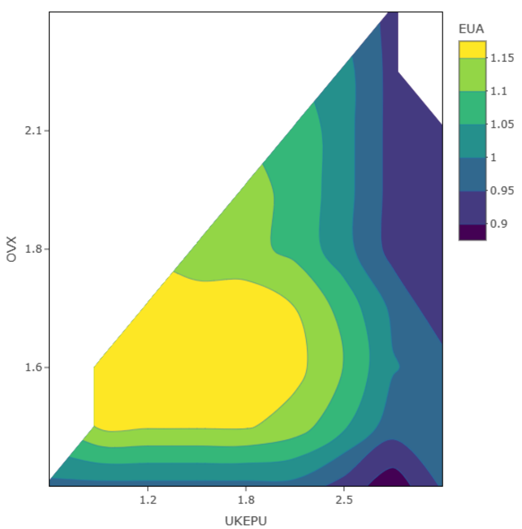
(a7)



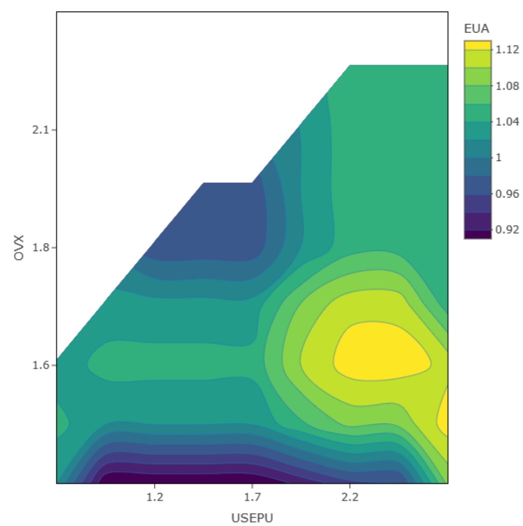
(a8)



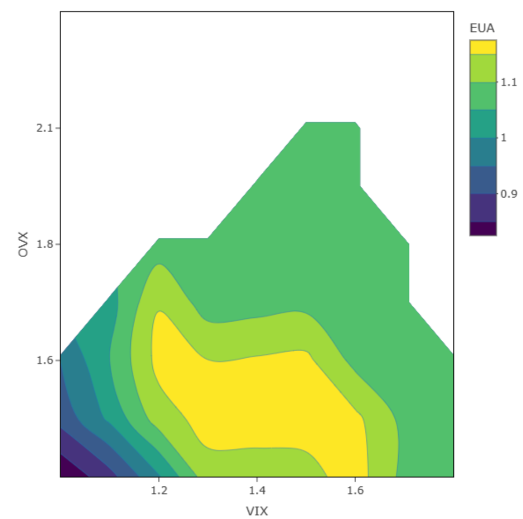
(a9)



(a10)



(a11)



(a12)

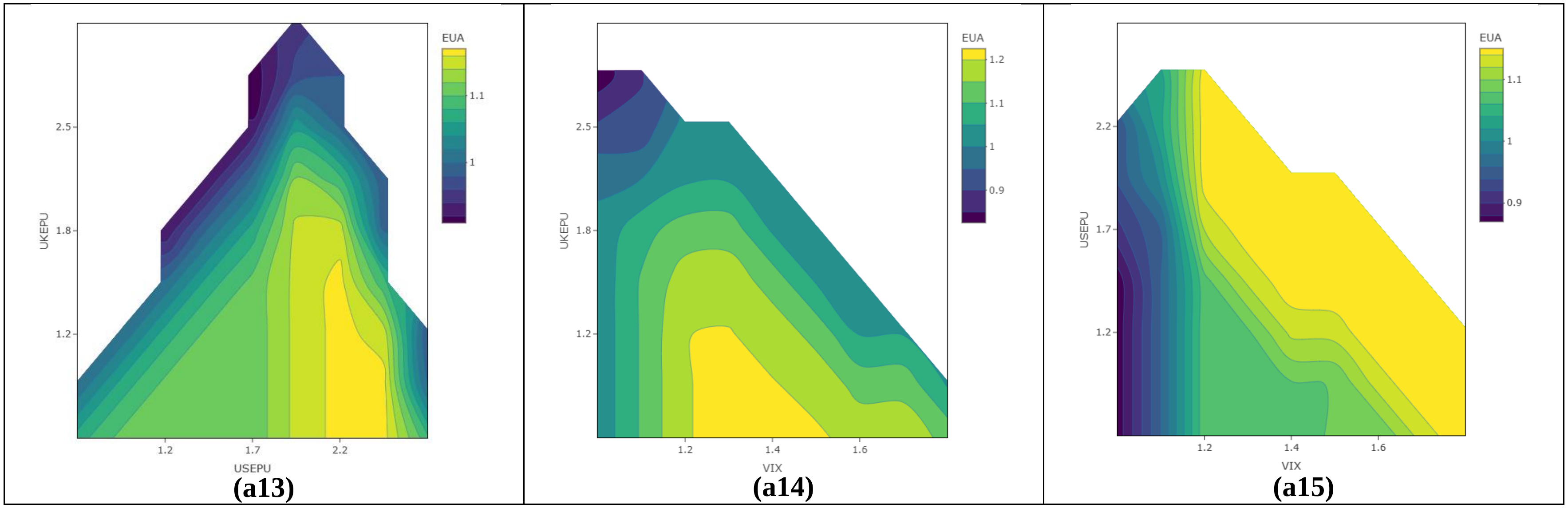


Fig.11. Partial dependance analysis with Model 2. The heatmaps illustrating the combined effect of the used predictors on EUA.

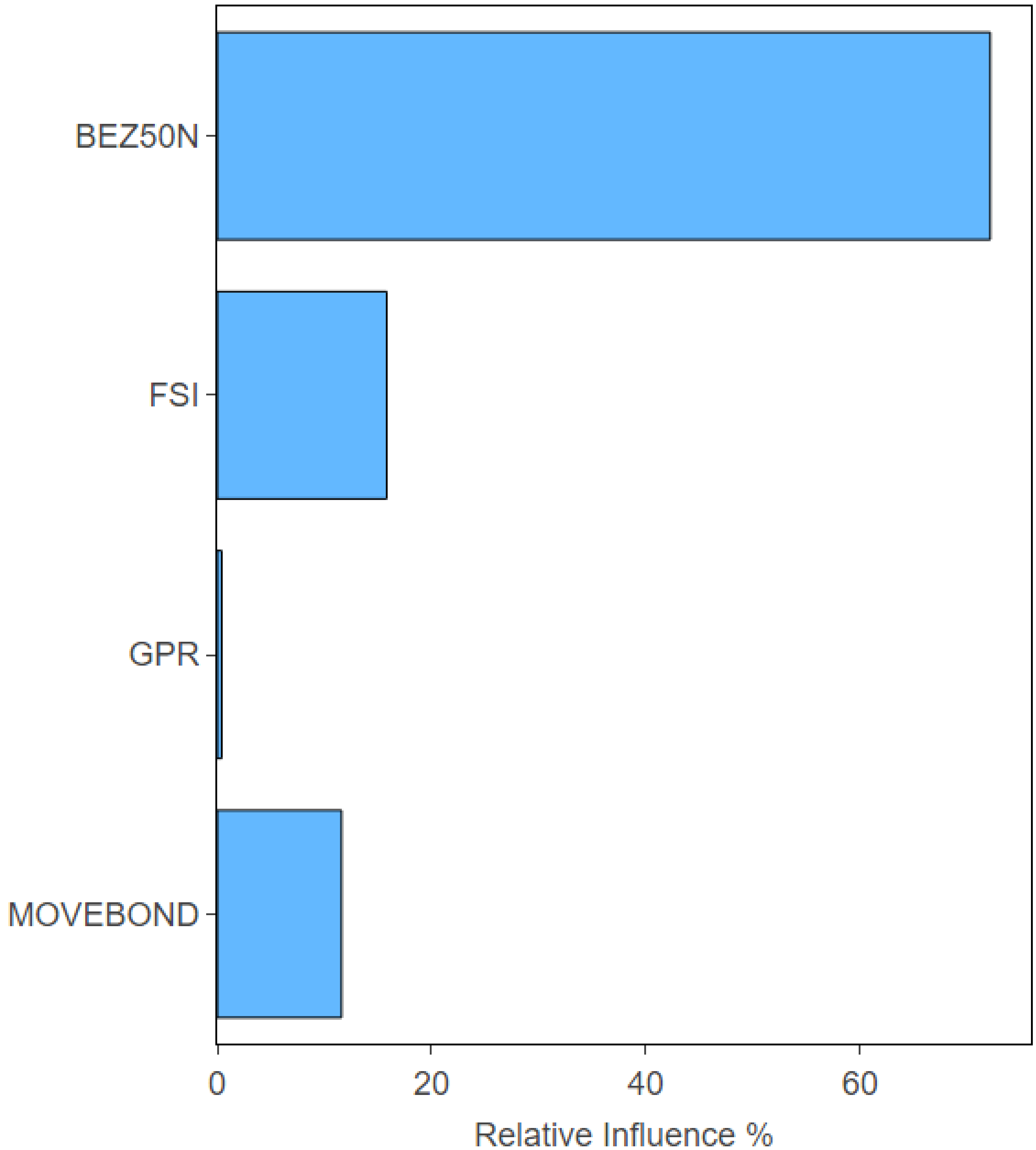


Fig.12. Assessing the relative importance of predictors in Model 3. This plot shows the relative influence of the predictors (MOVEBOND, GPR, FSI, BEZ50N) on EUA.

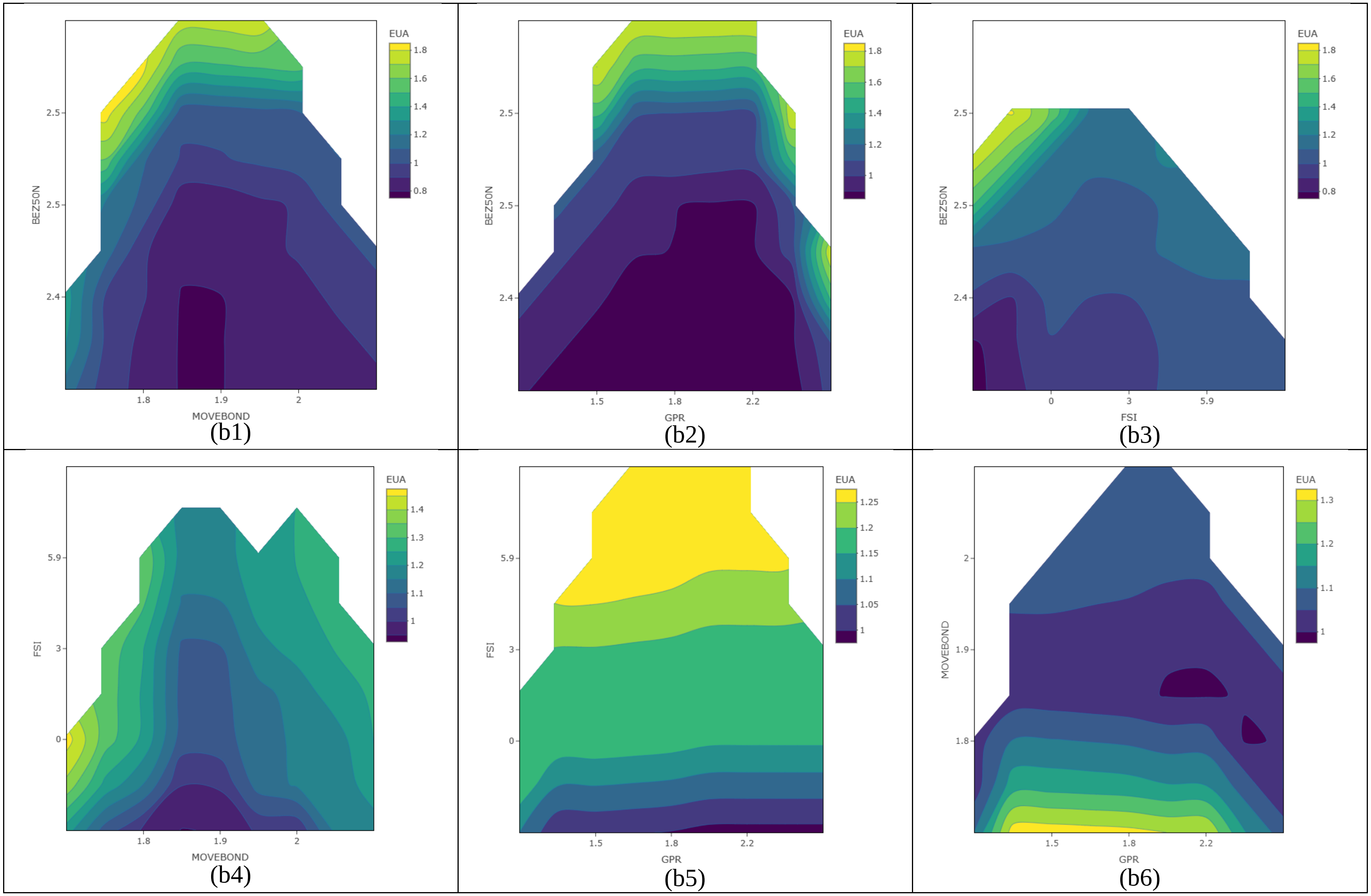


Fig.13. Partial dependance analysis with Model 3. The heatmaps illustrating the combined effect of the used predictors on EUA.

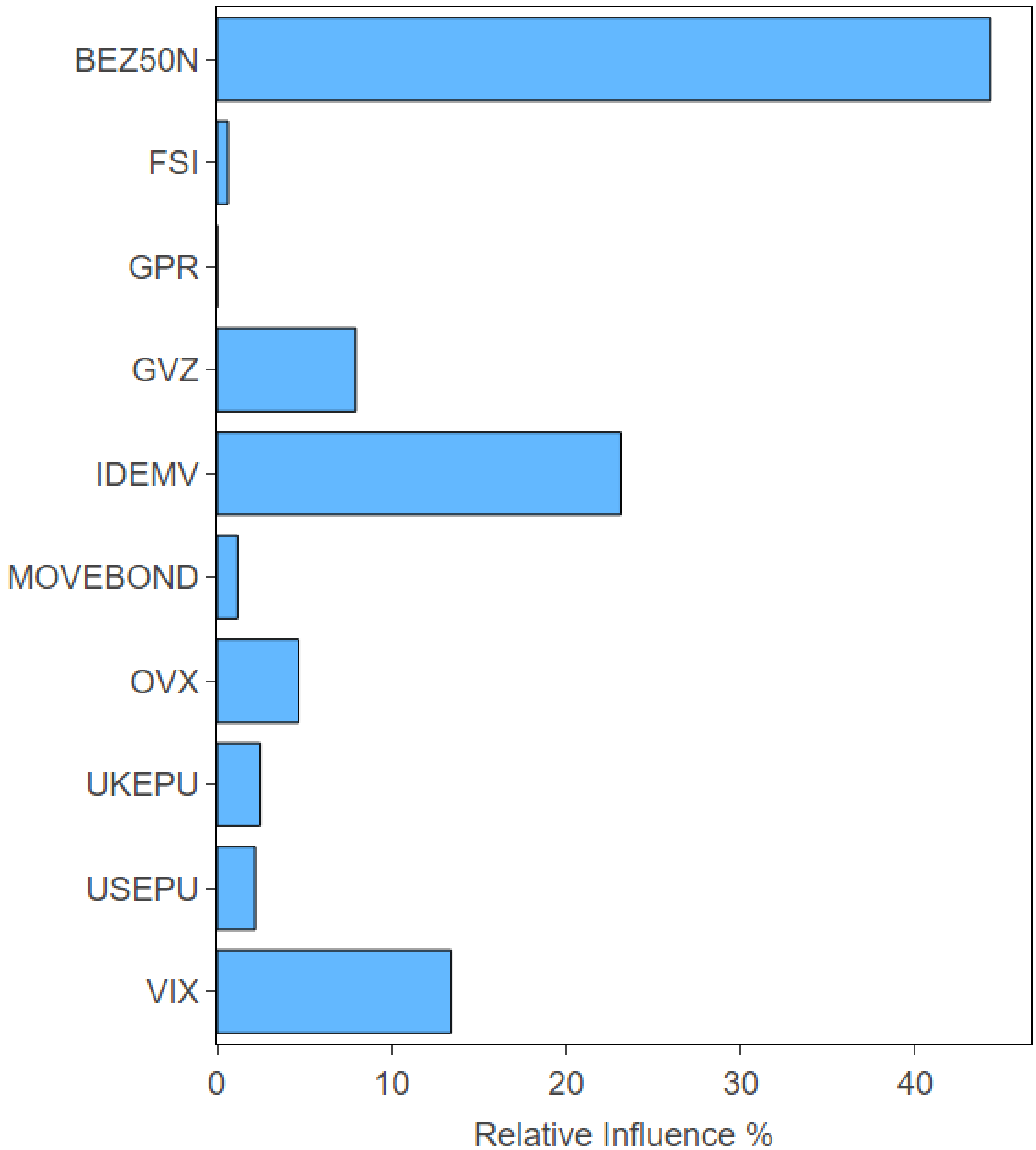
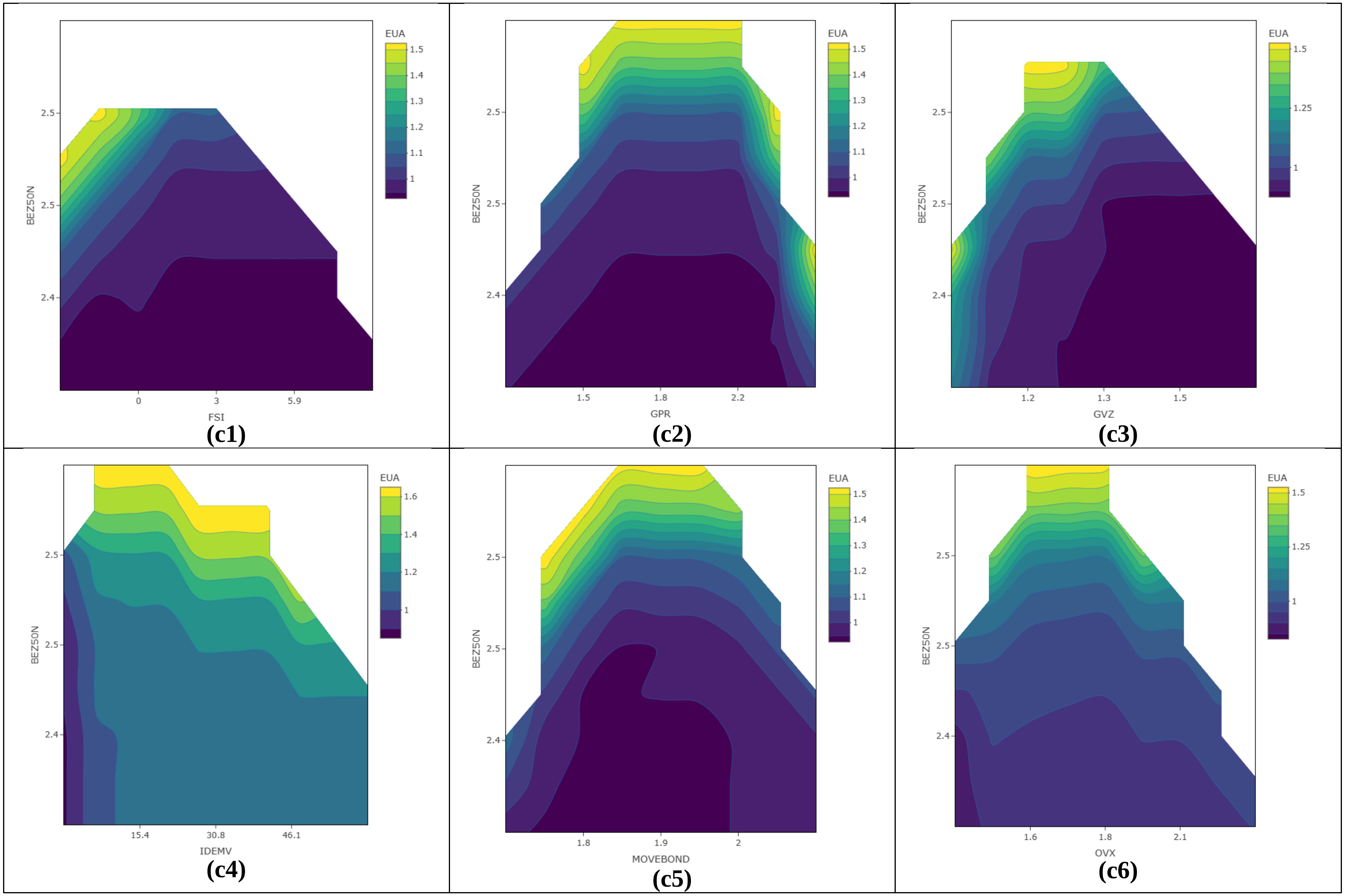
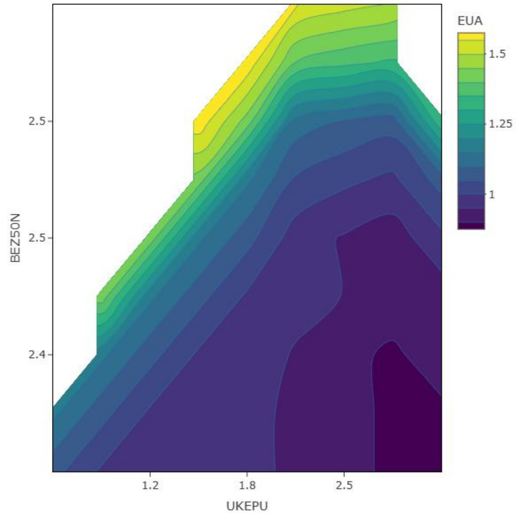
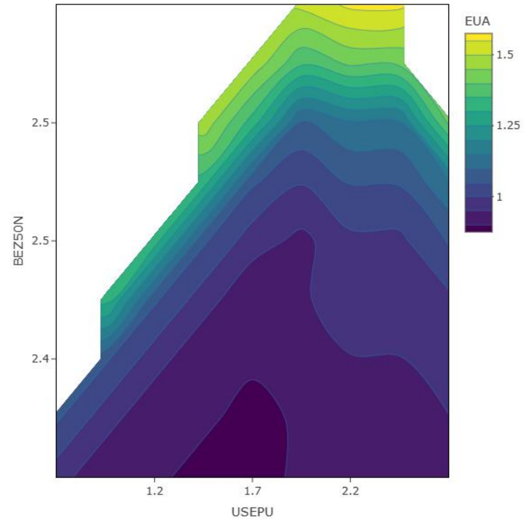


Fig.14. Assessing the relative importance of predictors in Model 4. This plot shows the relative influence of the predictors (financial and economic factors) on EUA.

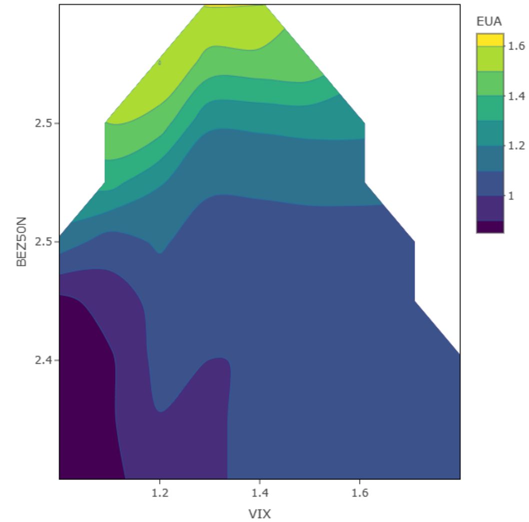

EUA
BEZ50N
FSI
(c1)
GPR
(c2)
GVZ
(c3)
IDEMV
(c4)
MOVEBOND
(c5)
OVX
(c6)



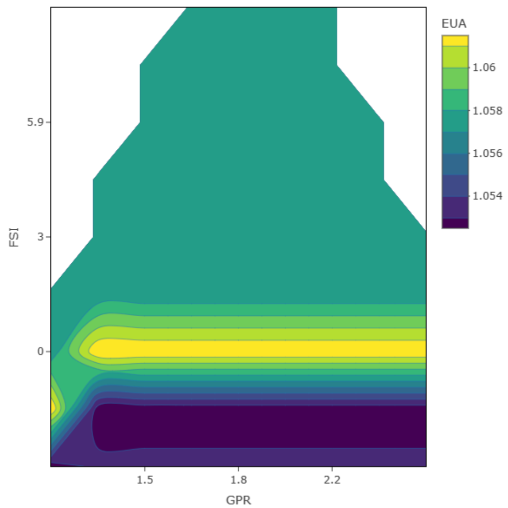
(c7)



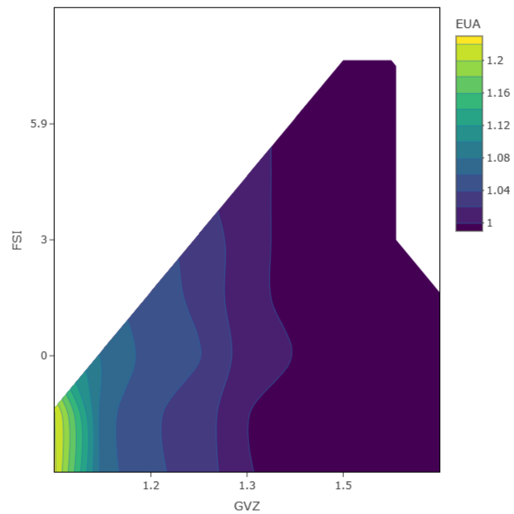
(c8)



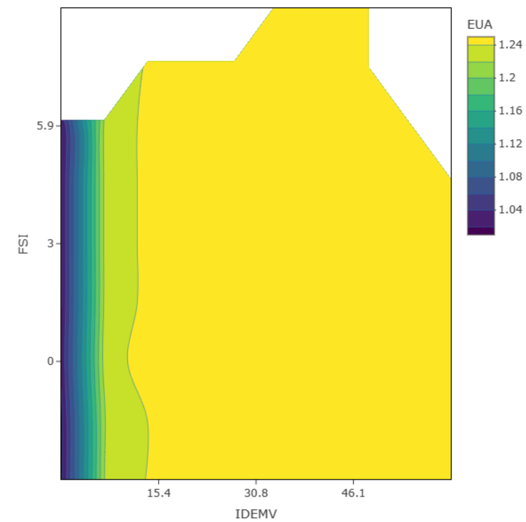
(c9)



(c10)



(c11)



(c12)

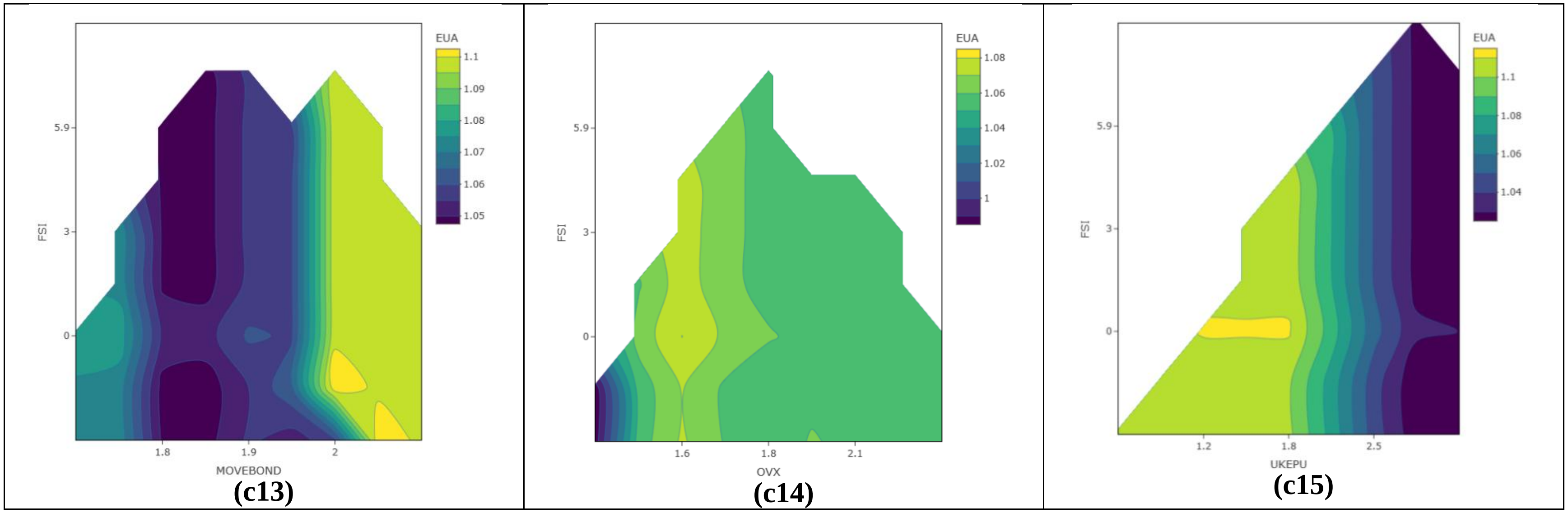
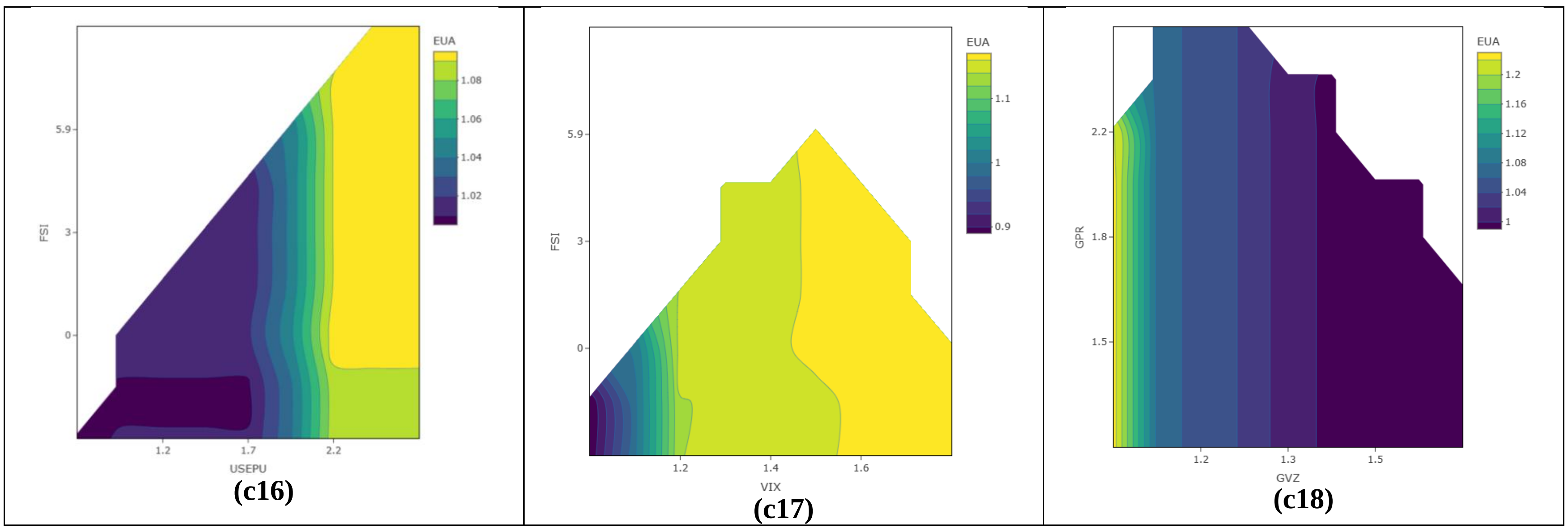
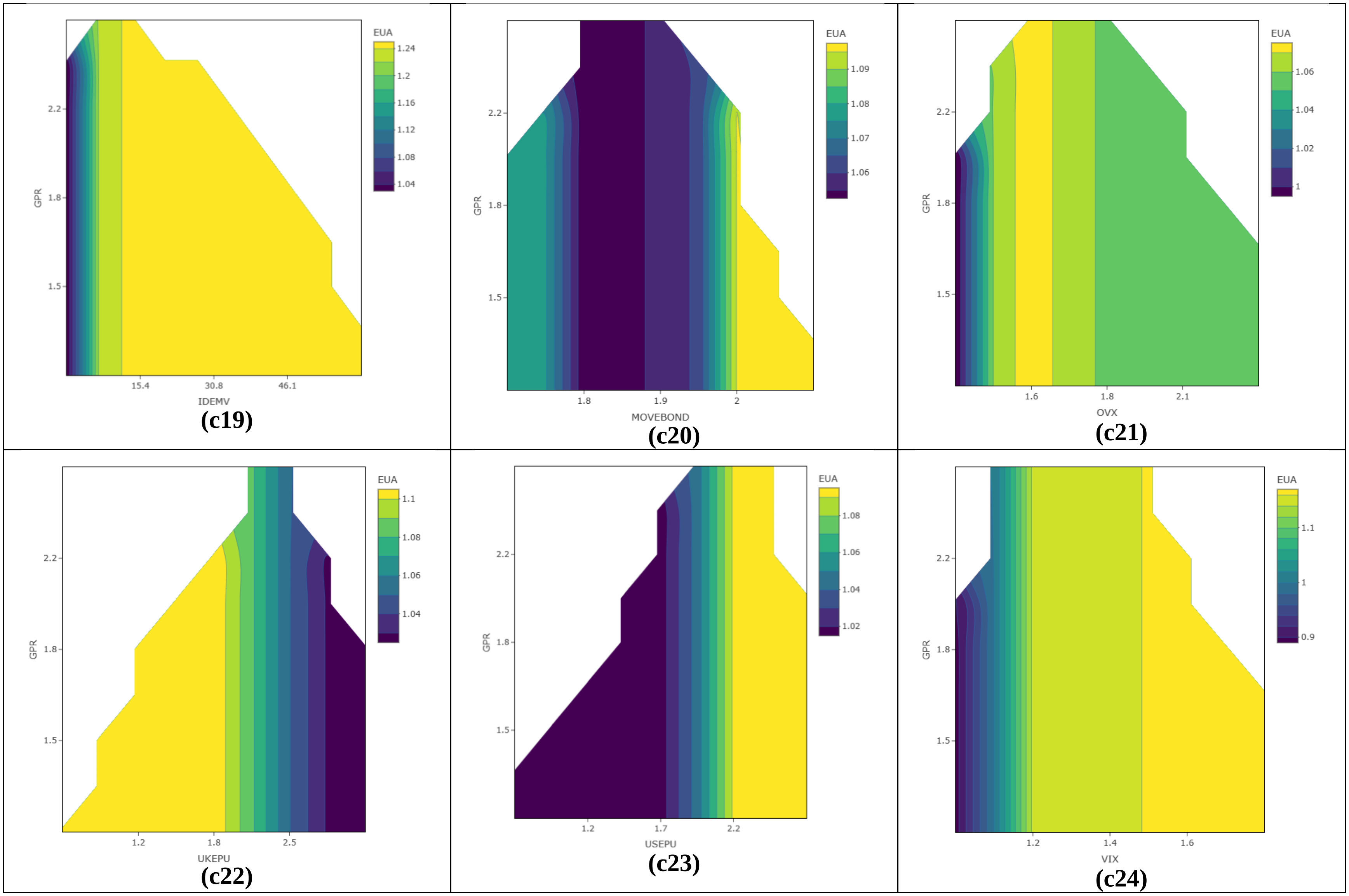
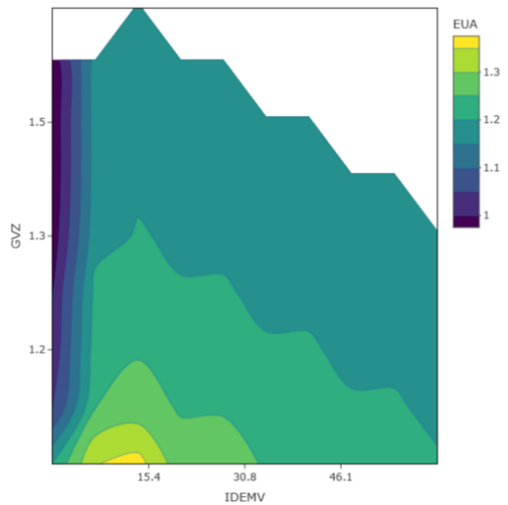


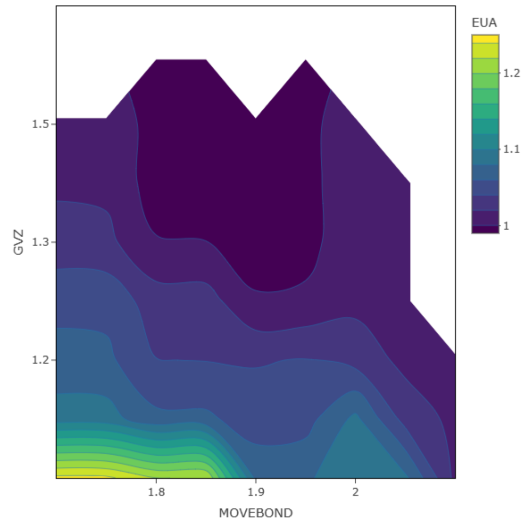
Fig.15. Partial dependance analysis with Model 4. The heatmaps illustrating the combined effect of the used predictors on EUA.



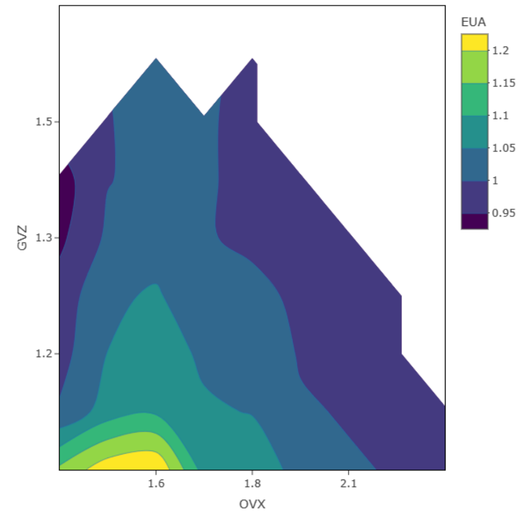

EUA
GPR
IDEMV
15.4
30.8
46.1
1.24
1.2
1.16
1.12
1.08
1.04
(c19)
MOVEBOND
1.8
1.9
2
1.09
1.08
1.07
1.06
(c20)
OVX
1.6
1.8
2.1
1.06
1.04
1.02
1
(c21)
UKEPU
1.2
1.8
2.5
1.1
1.08
1.06
1.04
(c22)
USEPU
1.2
1.7
2.2
1.08
1.06
1.04
1.02
(c23)
VIX
1.2
1.4
1.6
1.1
1
0.9
(c24)
2.2
1.8
1.5



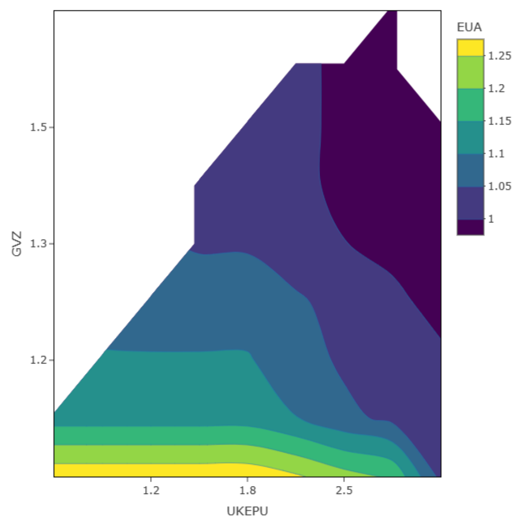
(c25)



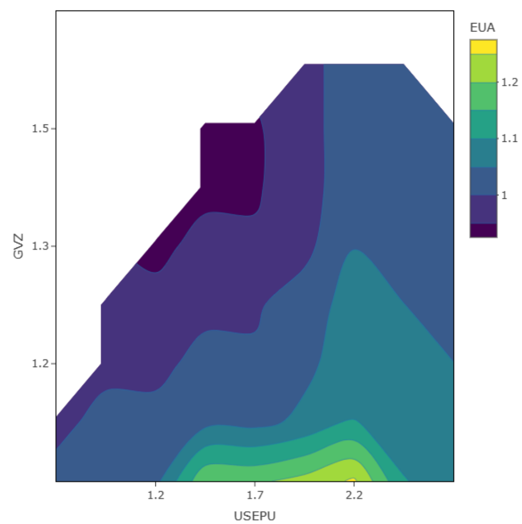
(c26)



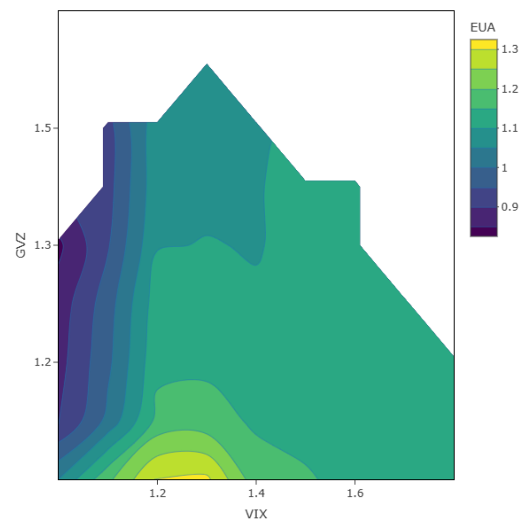
(c27)



(c28)

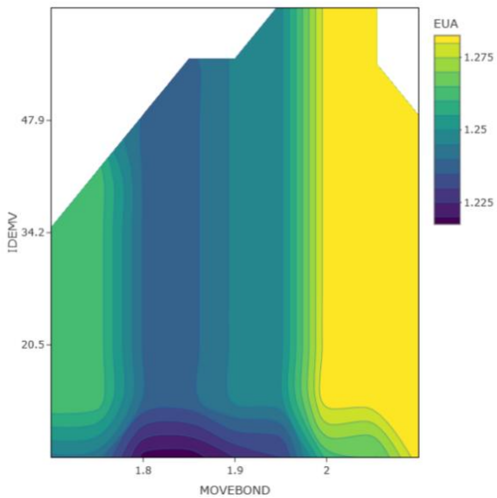


(c29)

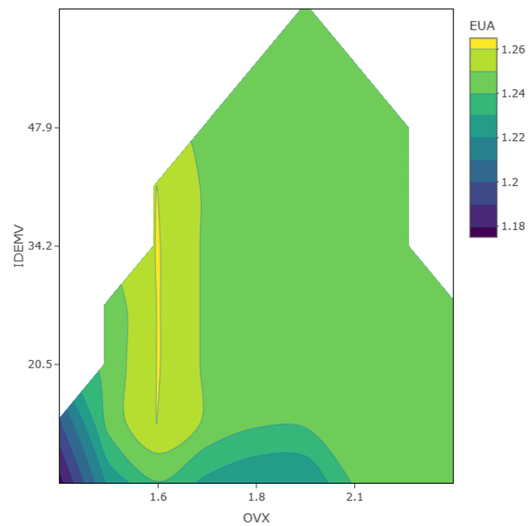


(c30)

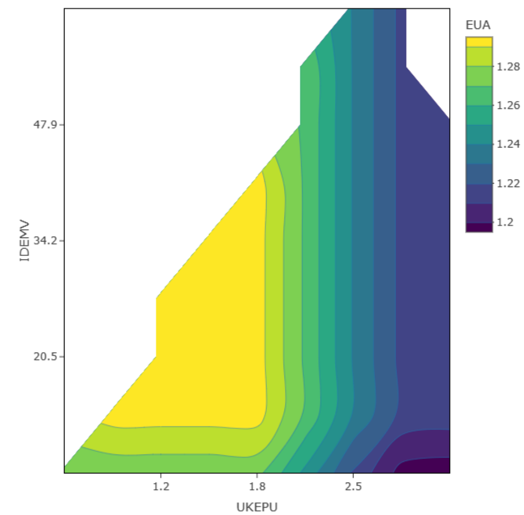
Fig.15. Continued,



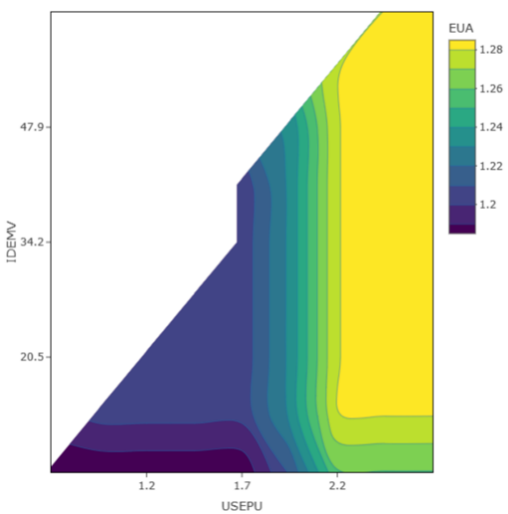
(c31)



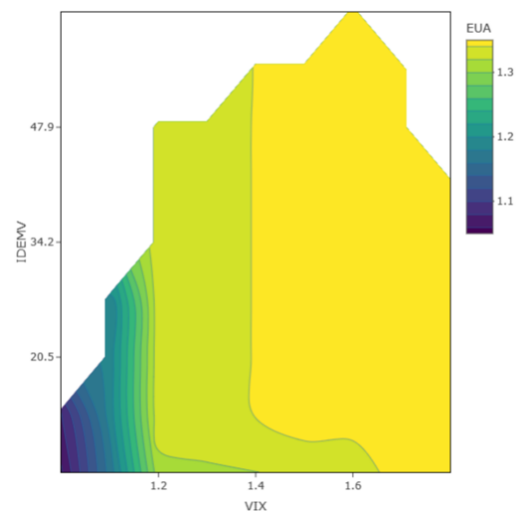
(c32)



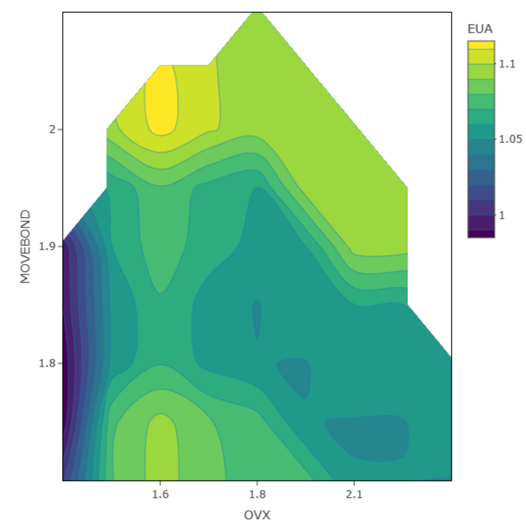
(c33)



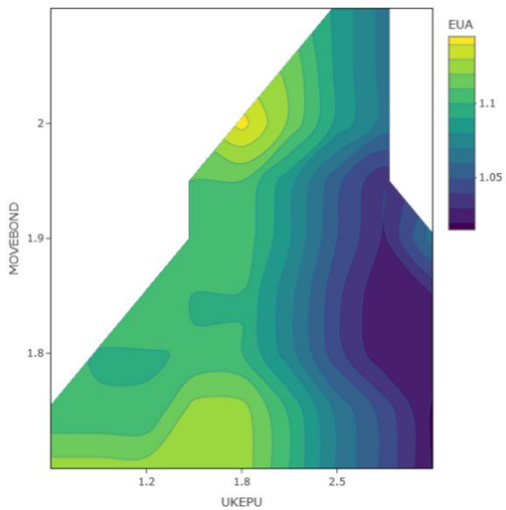
(c34)



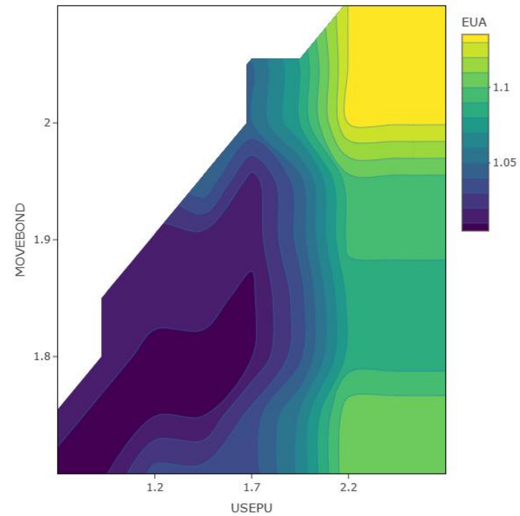
(c35)



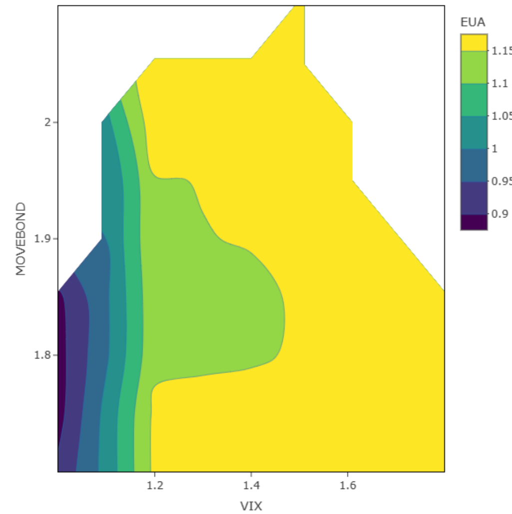
(c36)



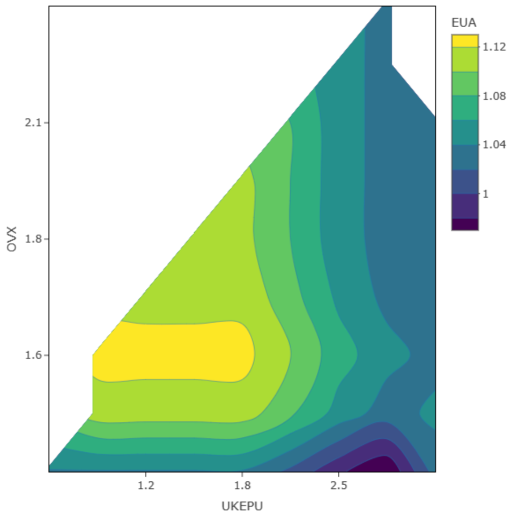
(c37)



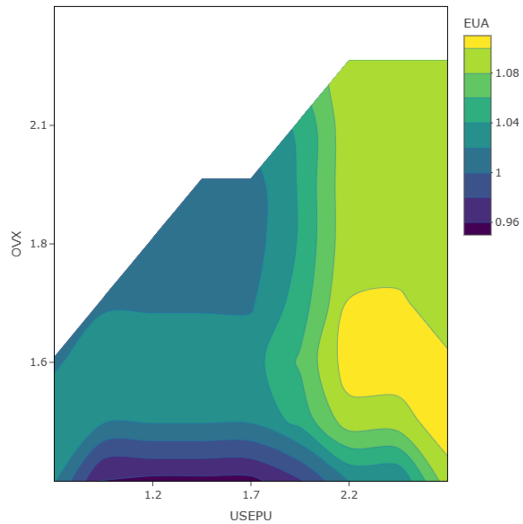
(c38)



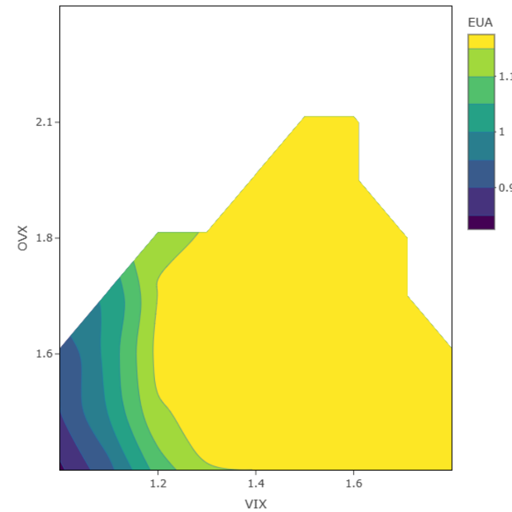
(c39)



(c40)



(c41)



(c42)

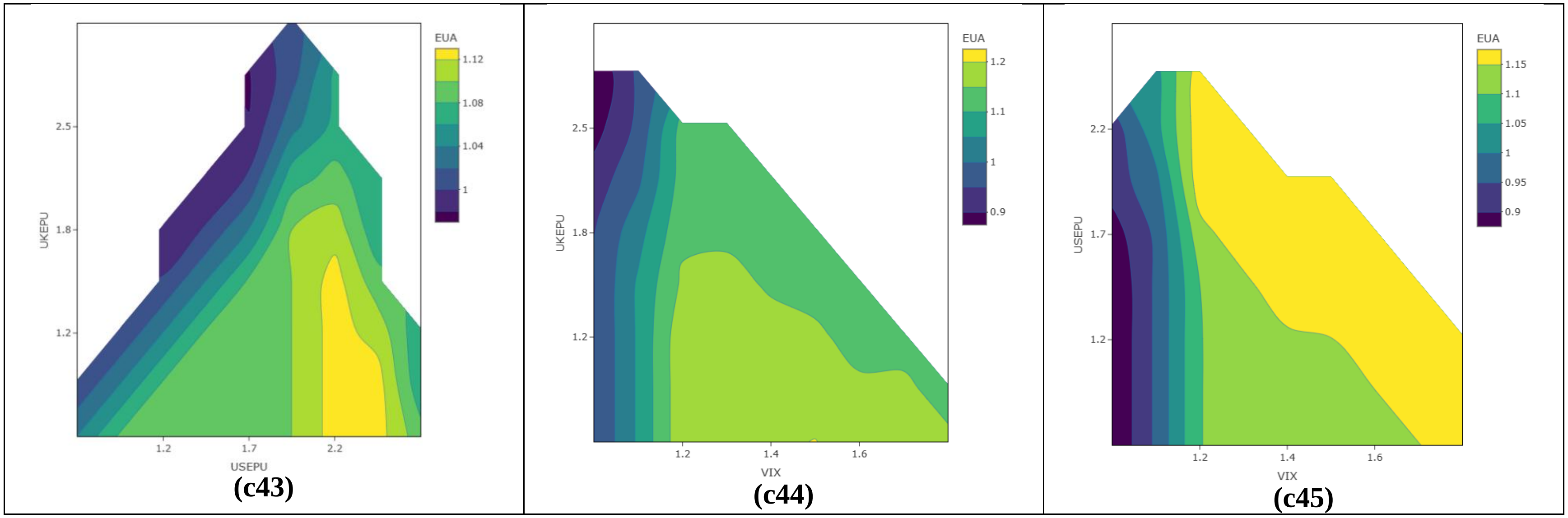


Fig.15. Continued, Partial dependance analysis with Model 4.

Appendix A.

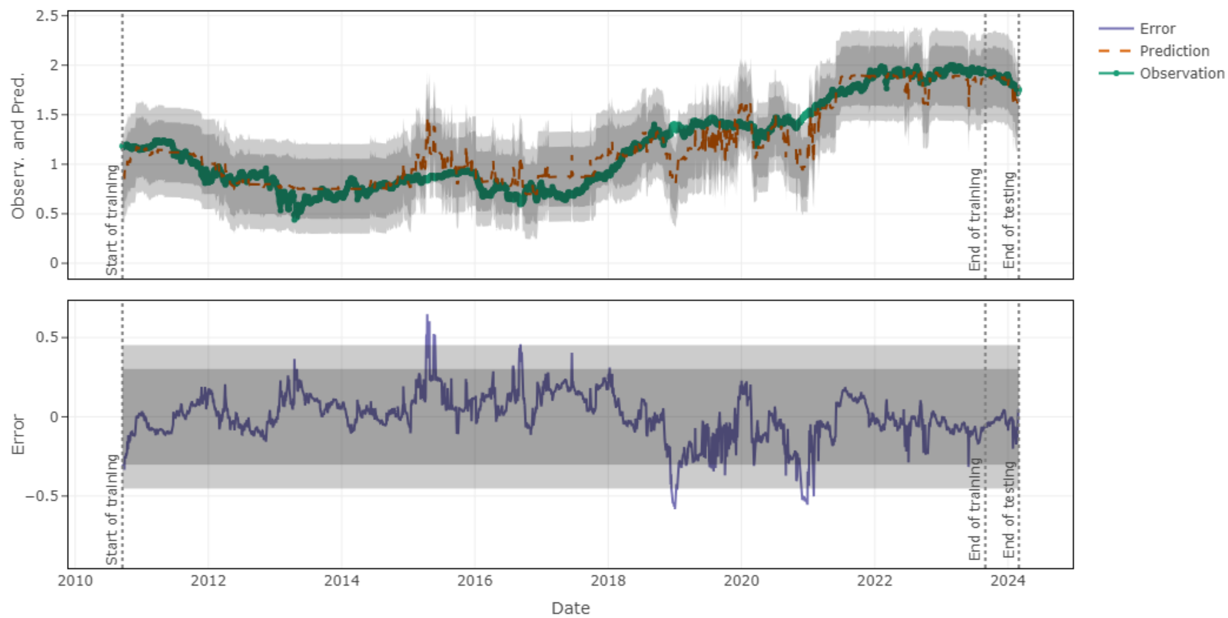


Fig.A1. Forecasting and observations with model 1 and using training parameters panel 2. Error and confidence intervals visualized.

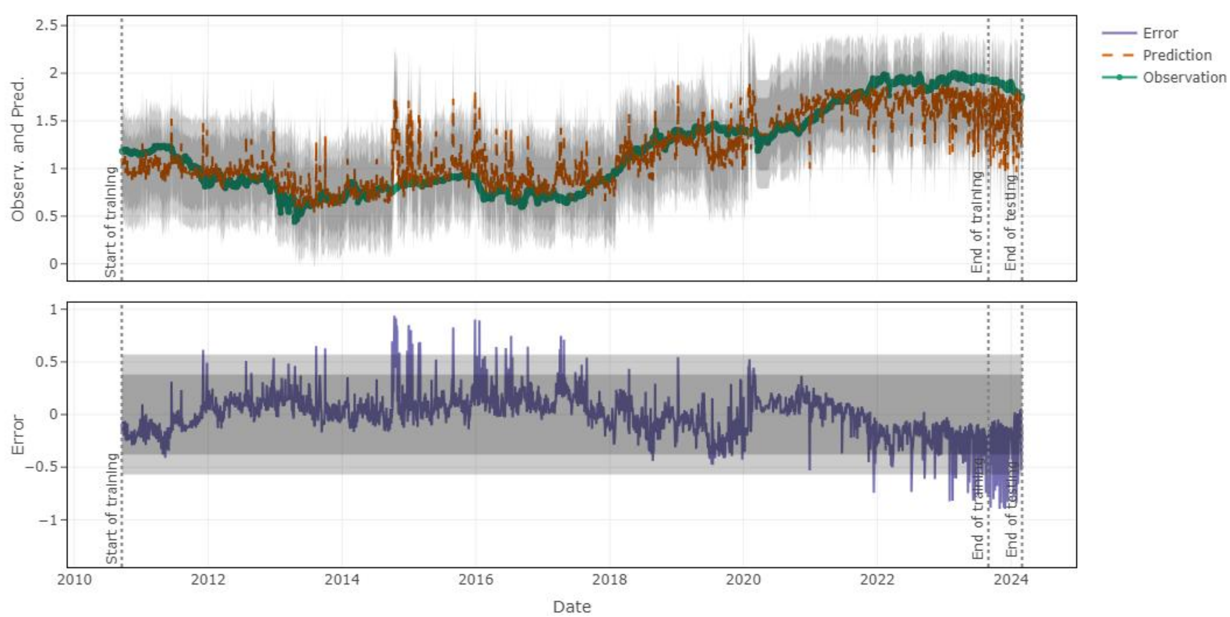


Fig.A2 Forecasting and observations with model 2 and using training parameters panel 2. Error and confidence intervals visualized.

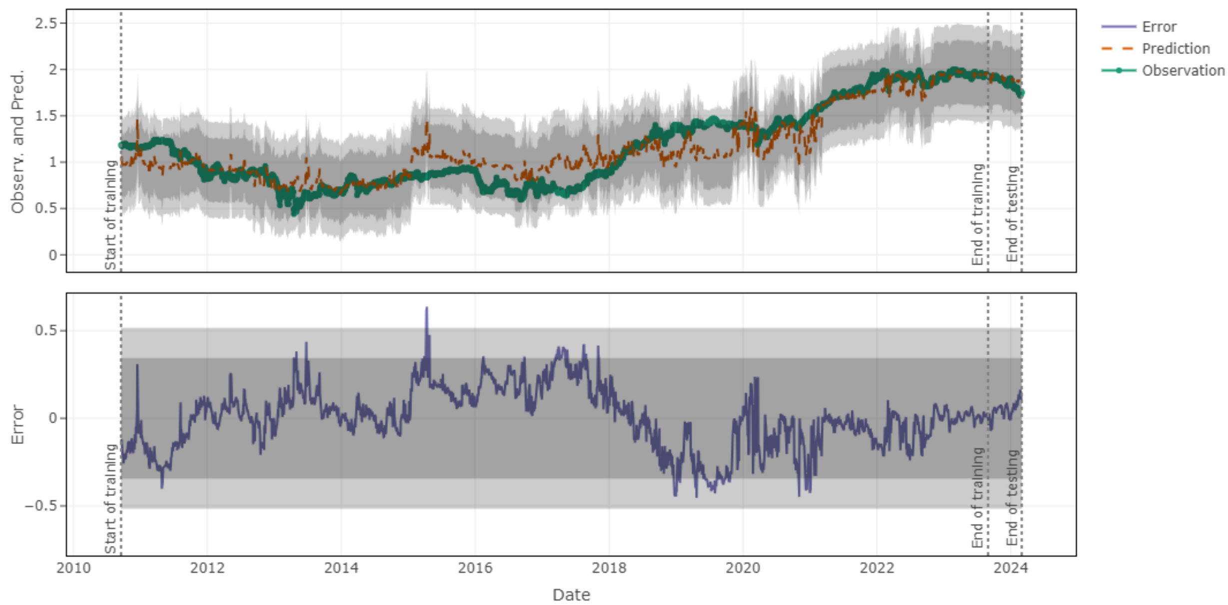


Fig.A3 Forecasting and observations with model 3 and using training parameters panel 2. Error and confidence intervals visualized.

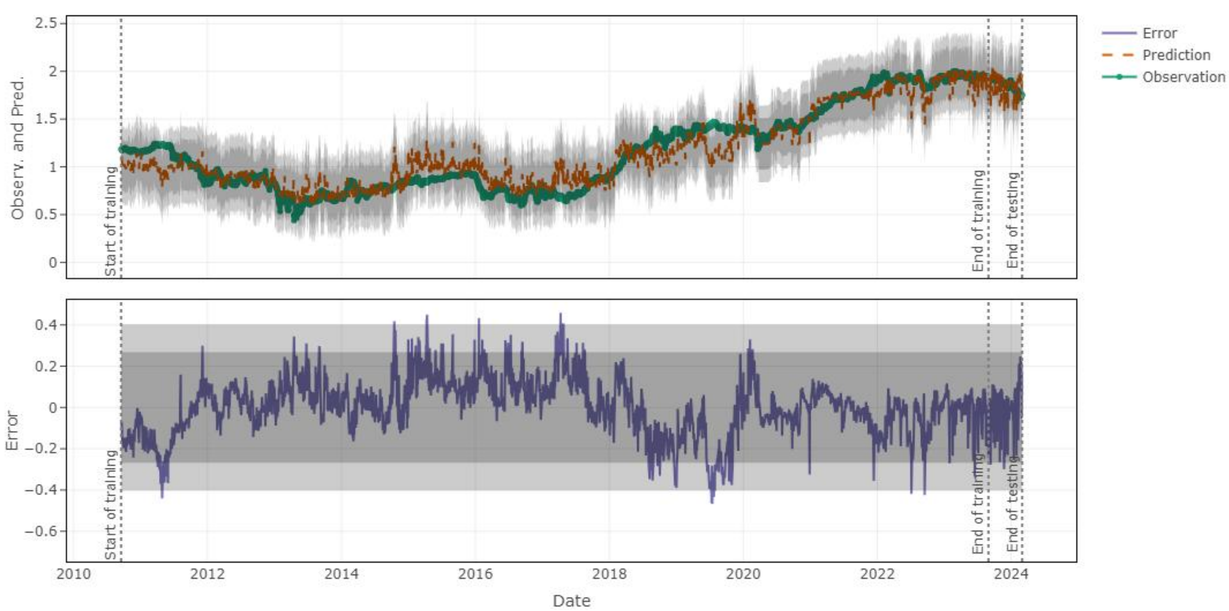
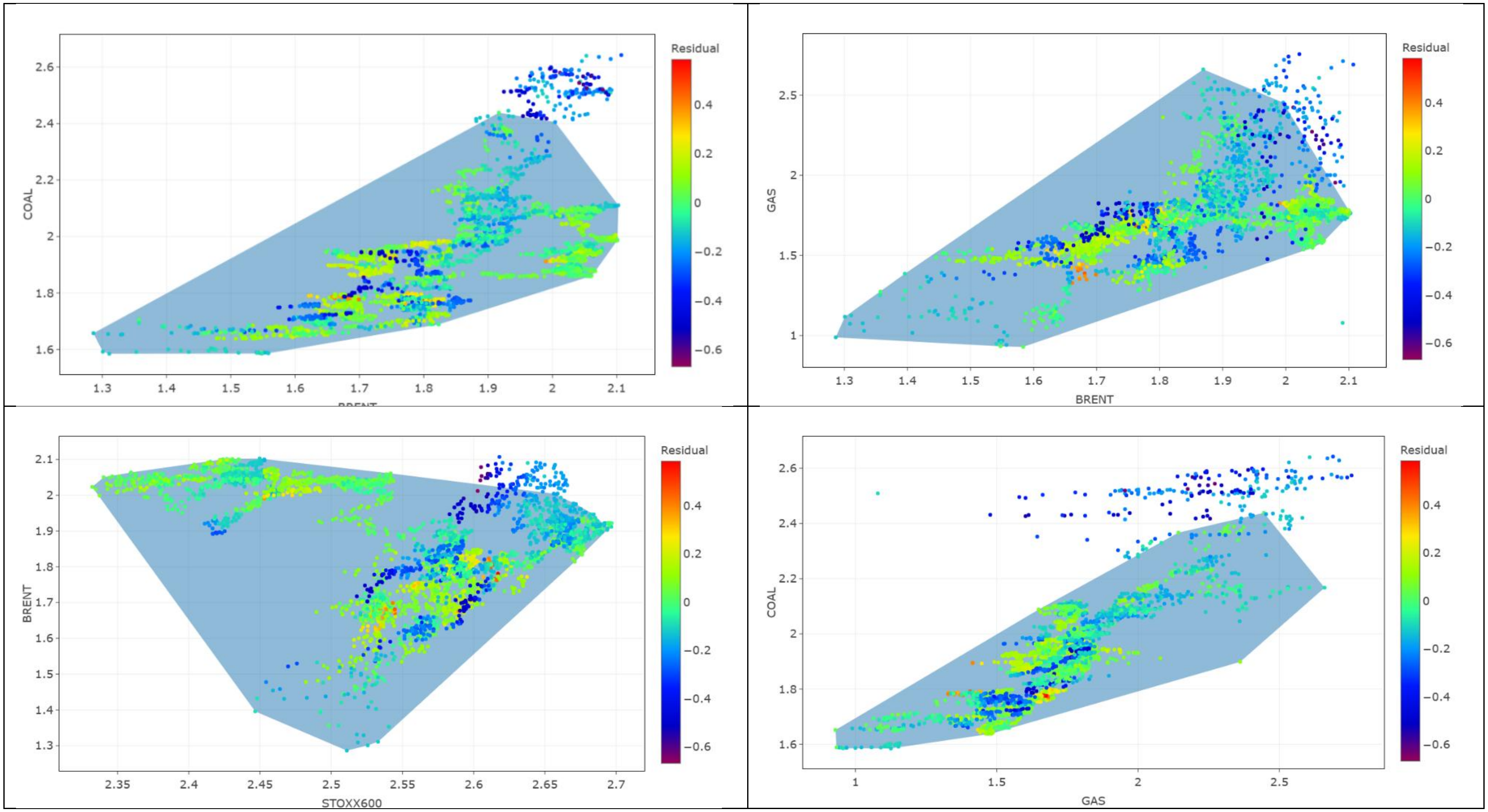


Fig.A4 Forecasting and observations with model 4 and using training parameters panel 2. Error and confidence intervals visualized.


COAL
BRENT
Residual
GAS
BRENT
Residual
BRENT
STOXX600
Residual
COAL
GAS
Residual

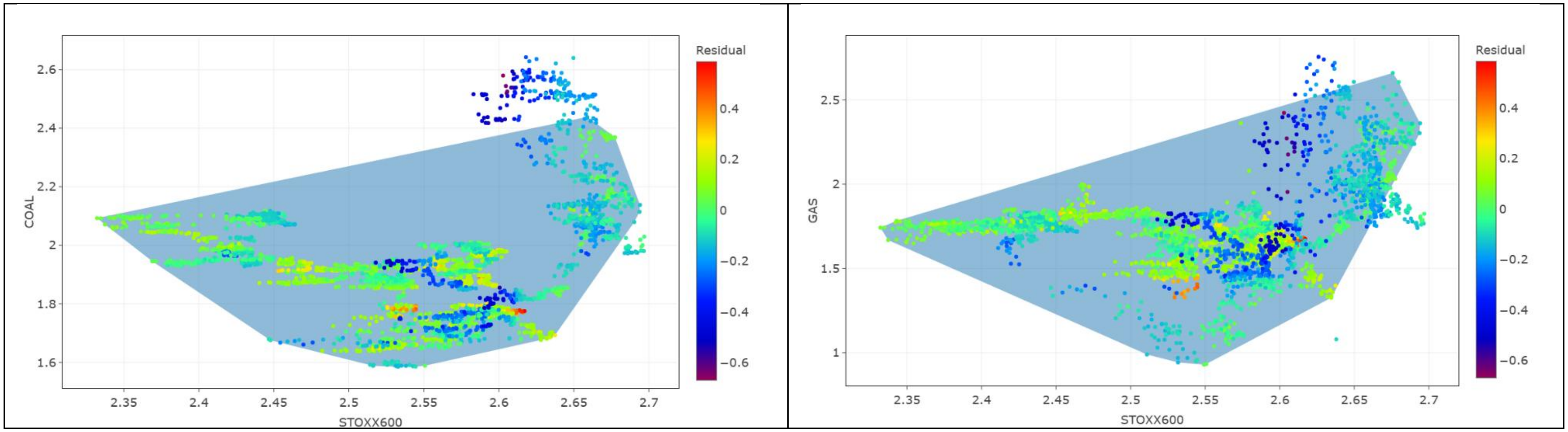
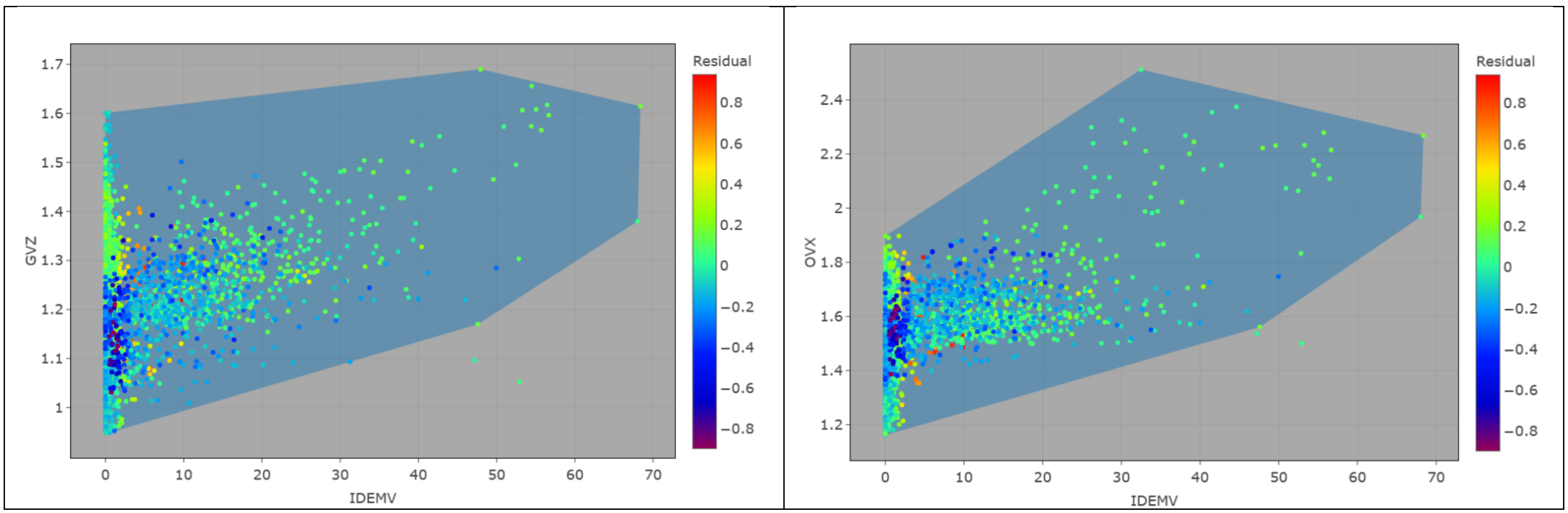


Fig.A5 Residual scatterplot with convex hull (the range of values containing the training set) based on Model 1.



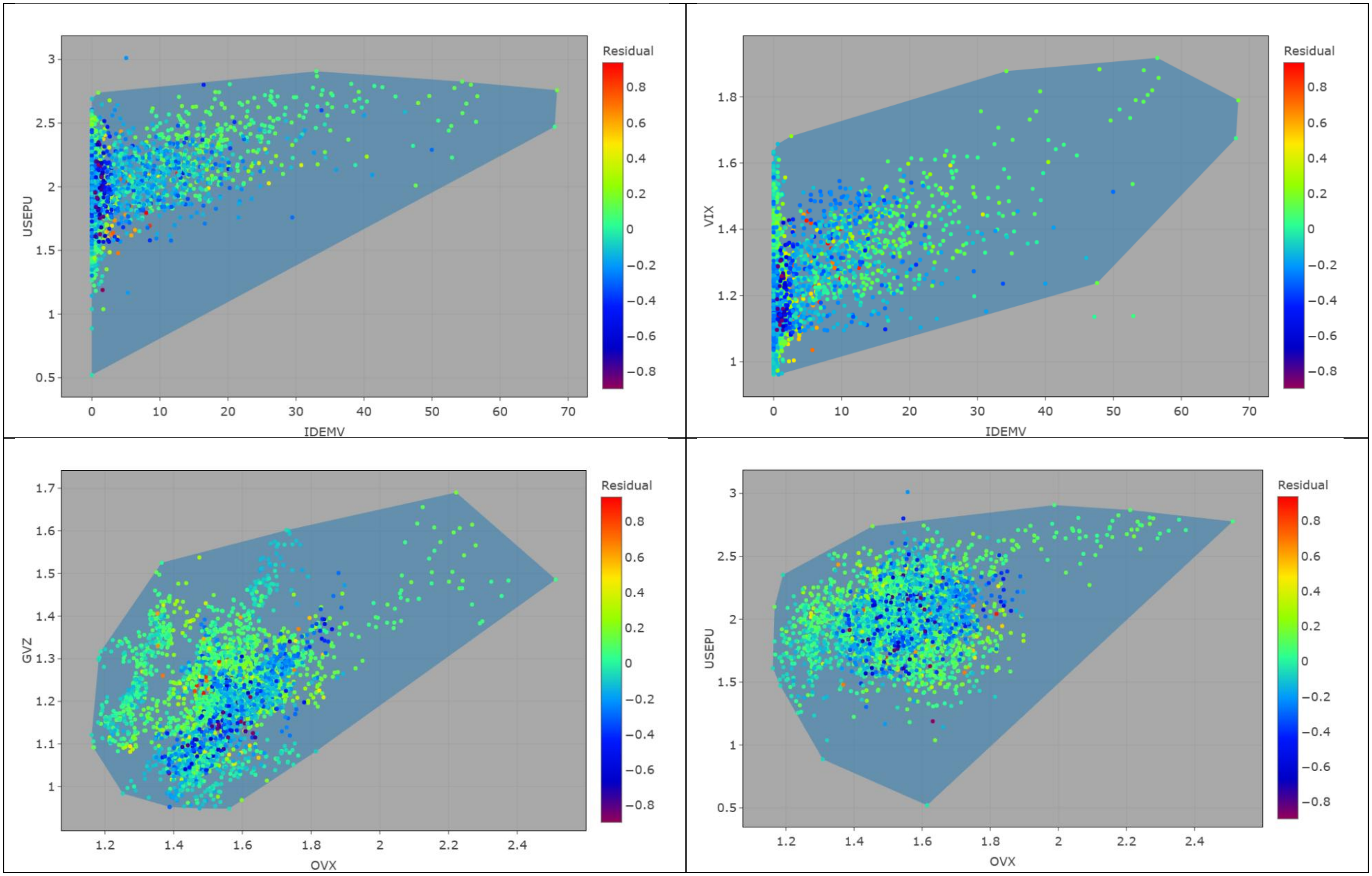
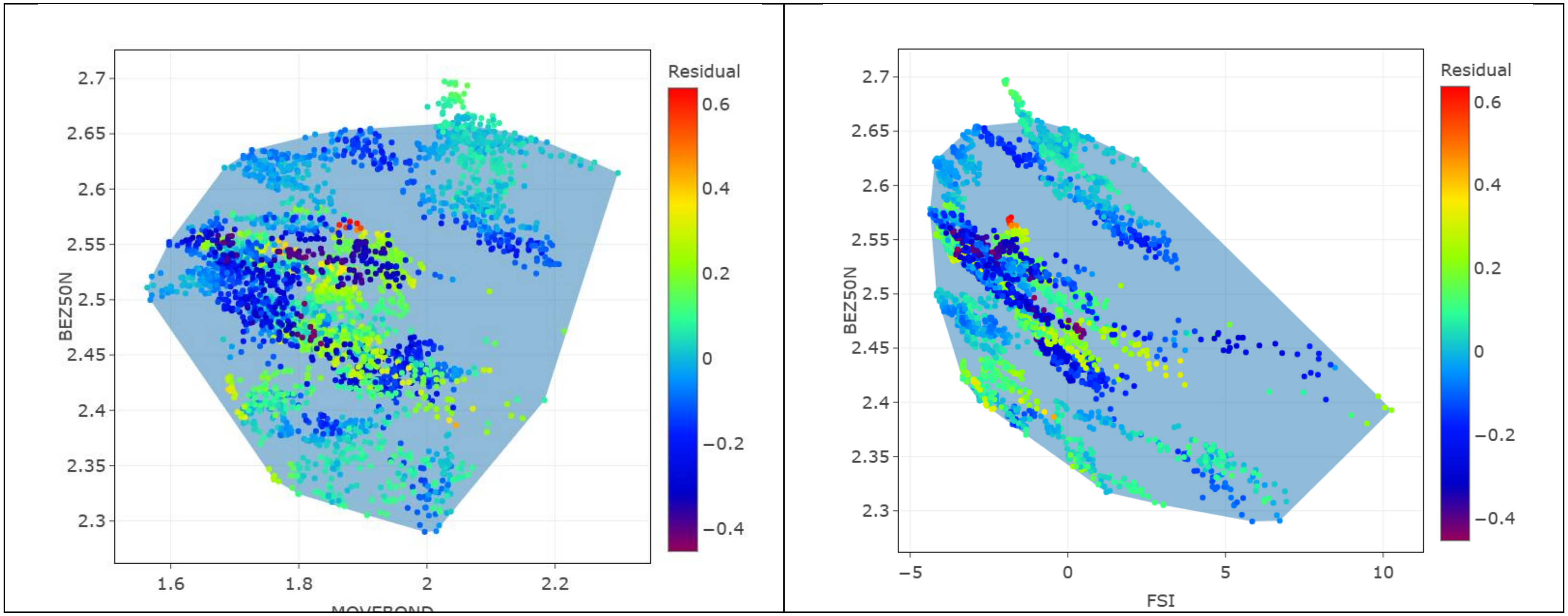
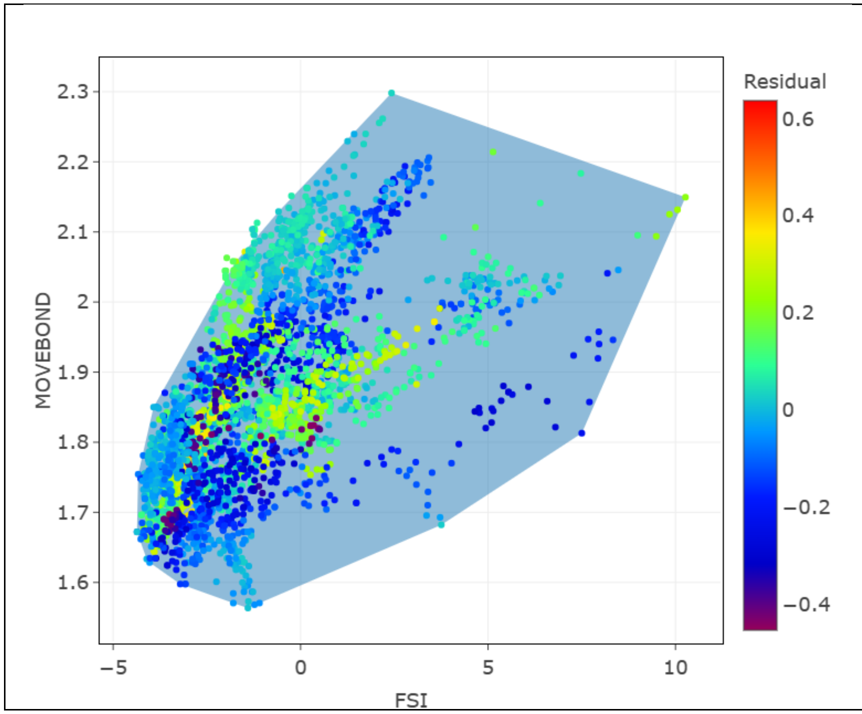
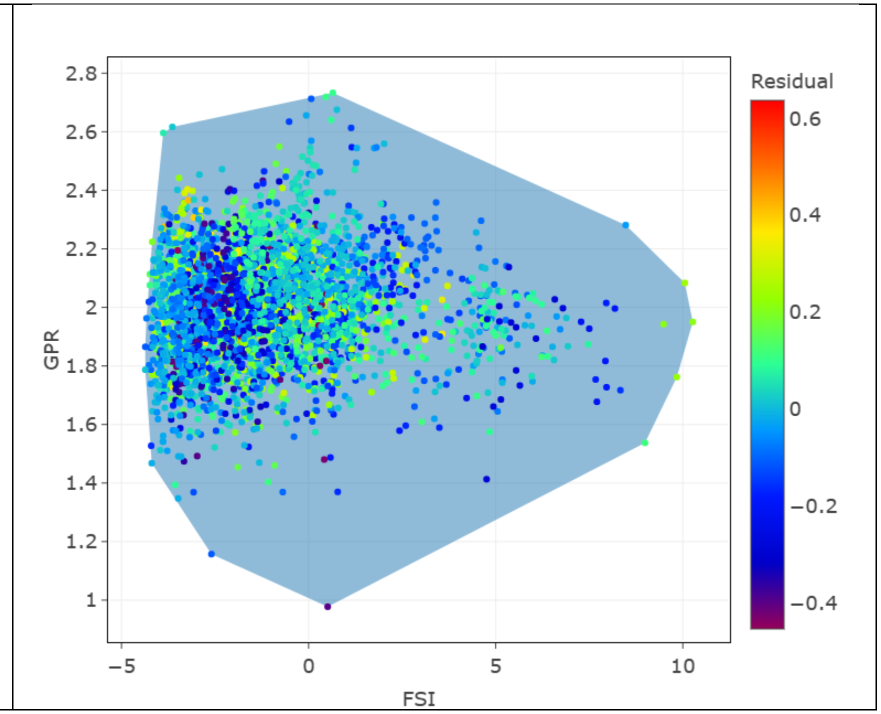


Fig.A6 Residual scatterplot with convex hull (the range of values containing the training set) based on Model 2.


BEZ50N
2.7
2.65
2.6
2.55
2.5
2.45
2.4
2.35
2.3
1.6
1.8
2
2.2
Residual
0.6
0.4
0.2
0
−0.2
−0.4
BEZ50N
2.7
2.65
2.6
2.55
2.5
2.45
2.4
2.35
2.3
−5
0
5
10
FSI
Residual
0.6
0.4
0.2
0
−0.2
−0.4



Residual
0.6
0.4
0.2
0
−0.2
−0.4
MOVEBOND
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
−5
0
5
10
FSI



Residual
0.6
0.4
0.2
0
−0.2
−0.4
GPR
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
−5
0
5
10
FSI

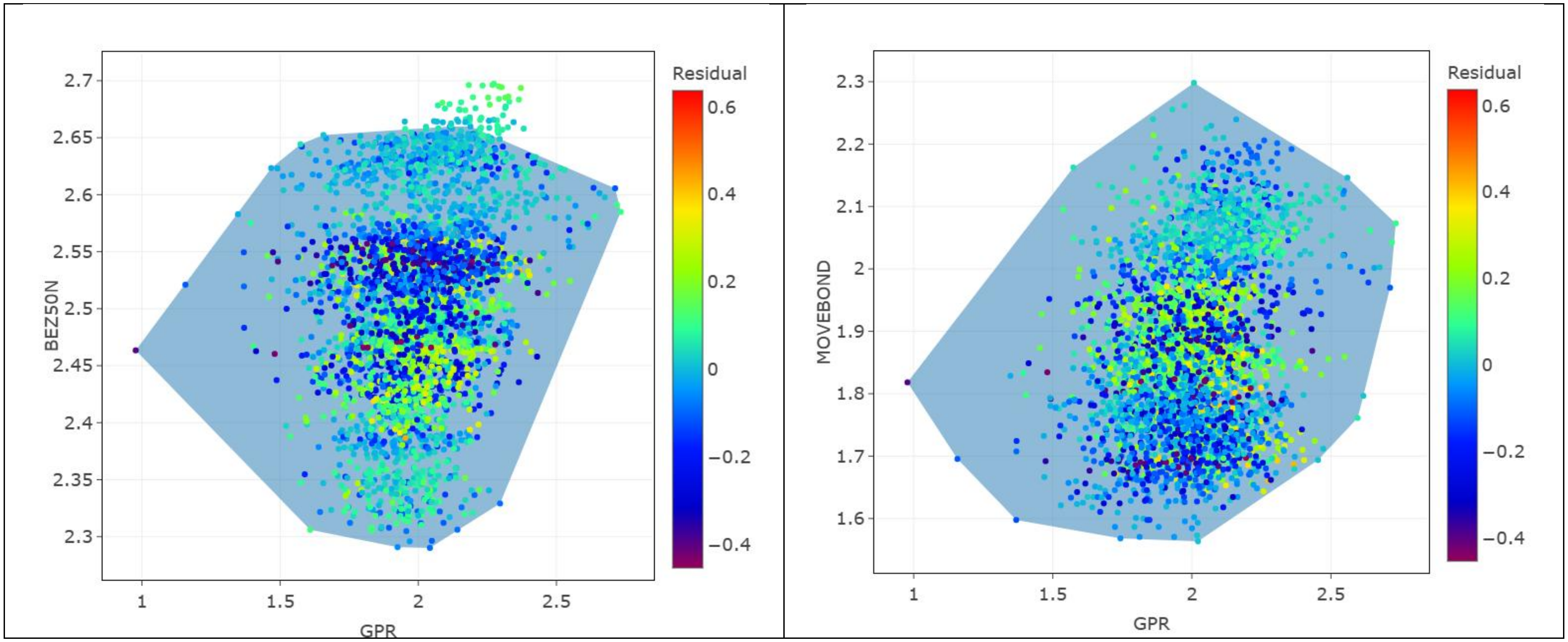
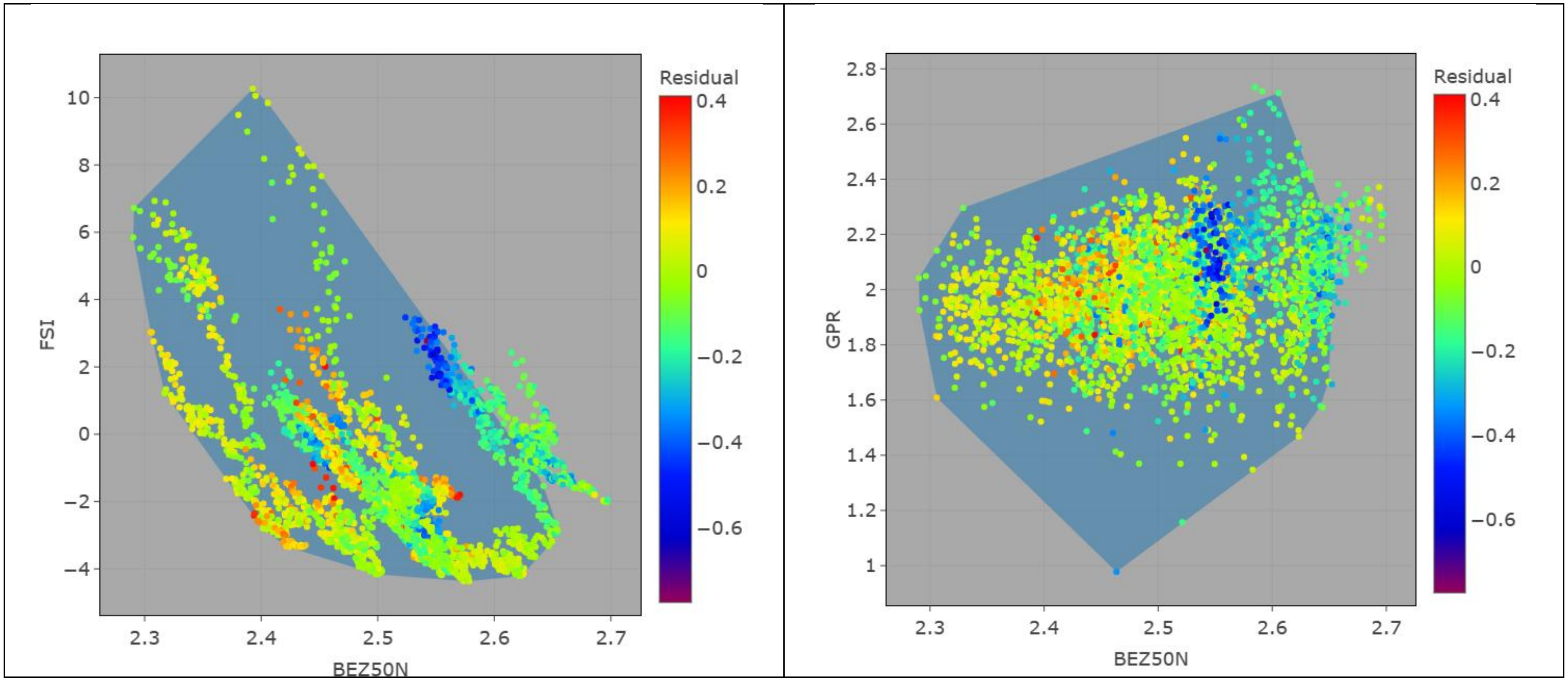
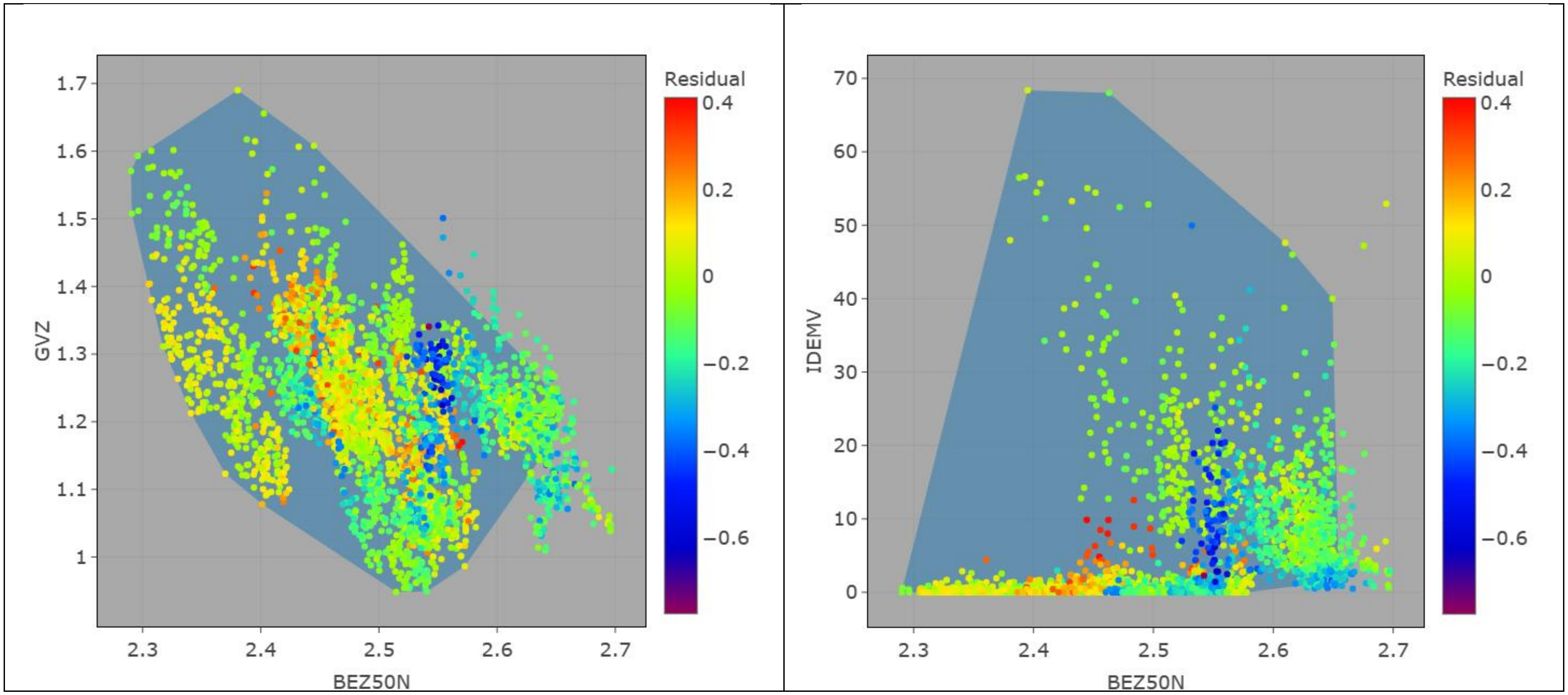
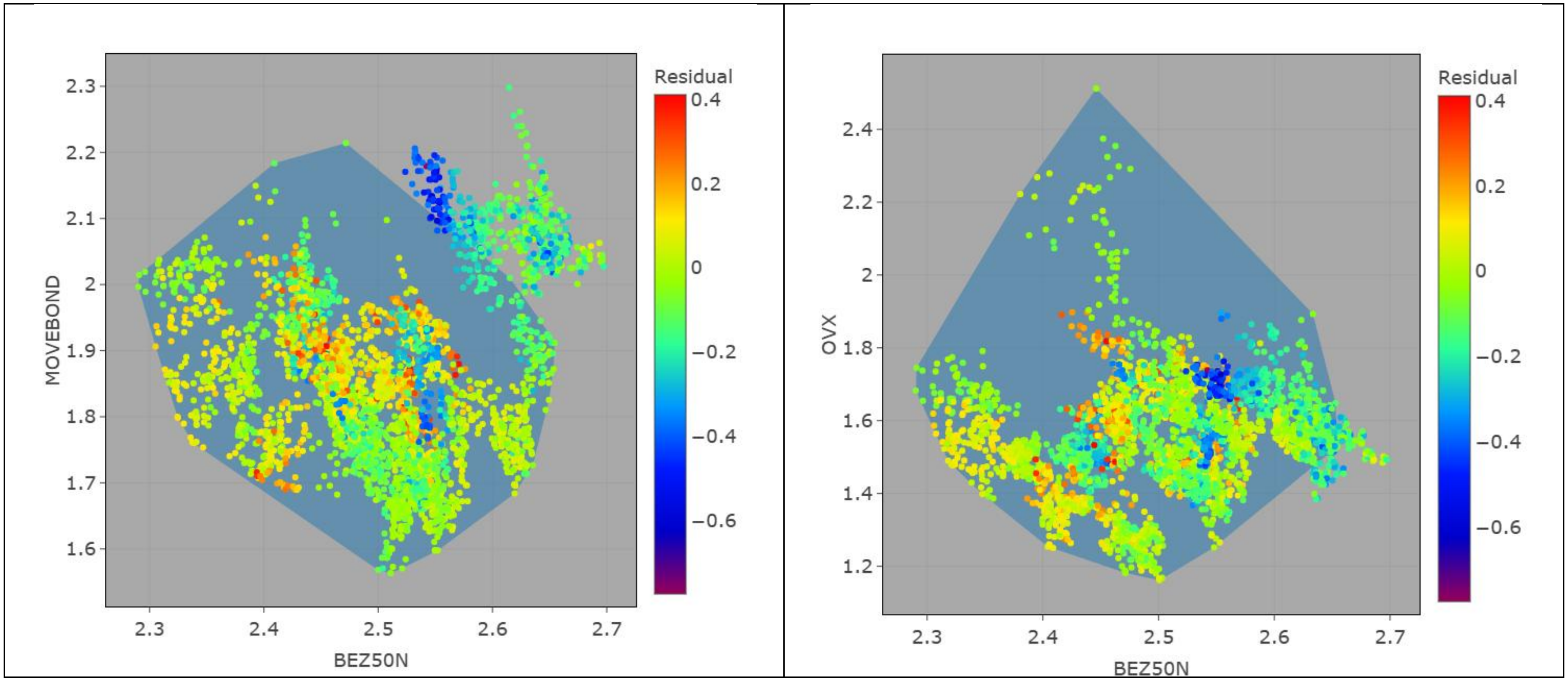
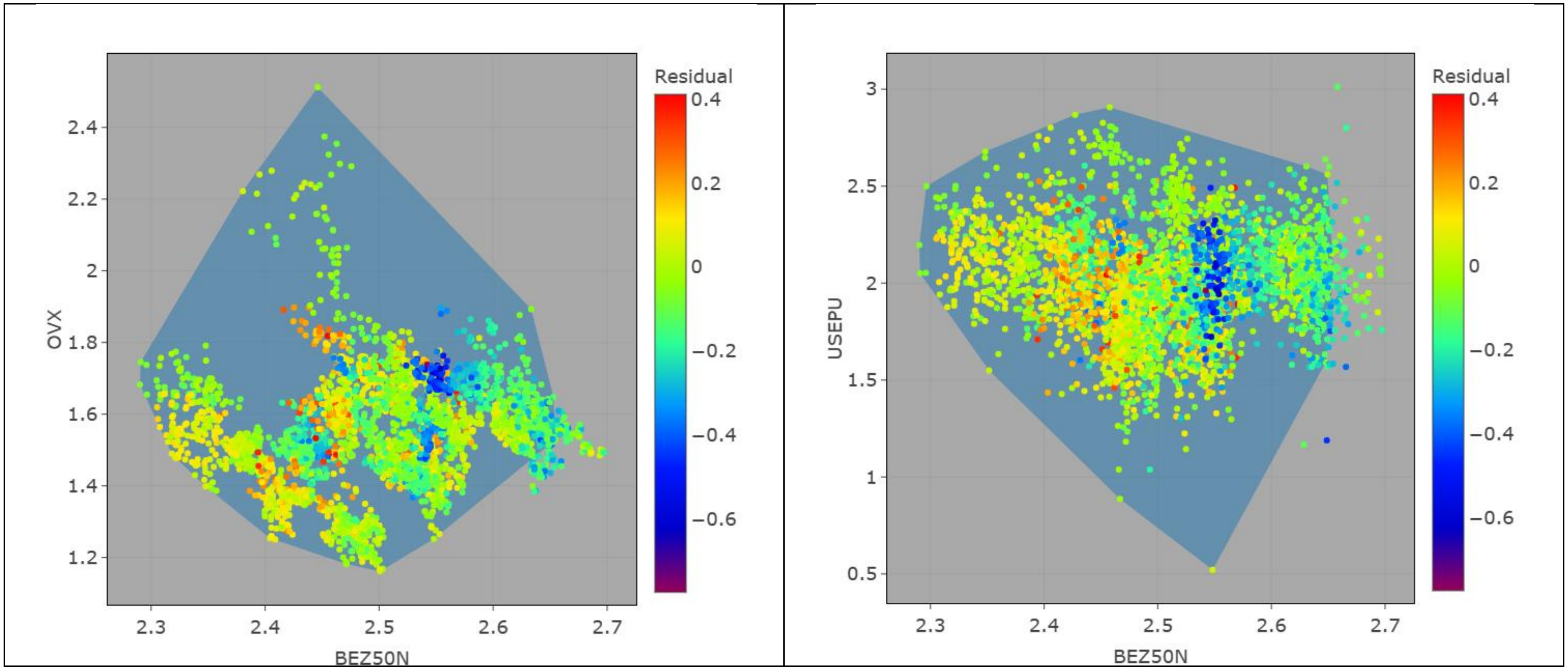


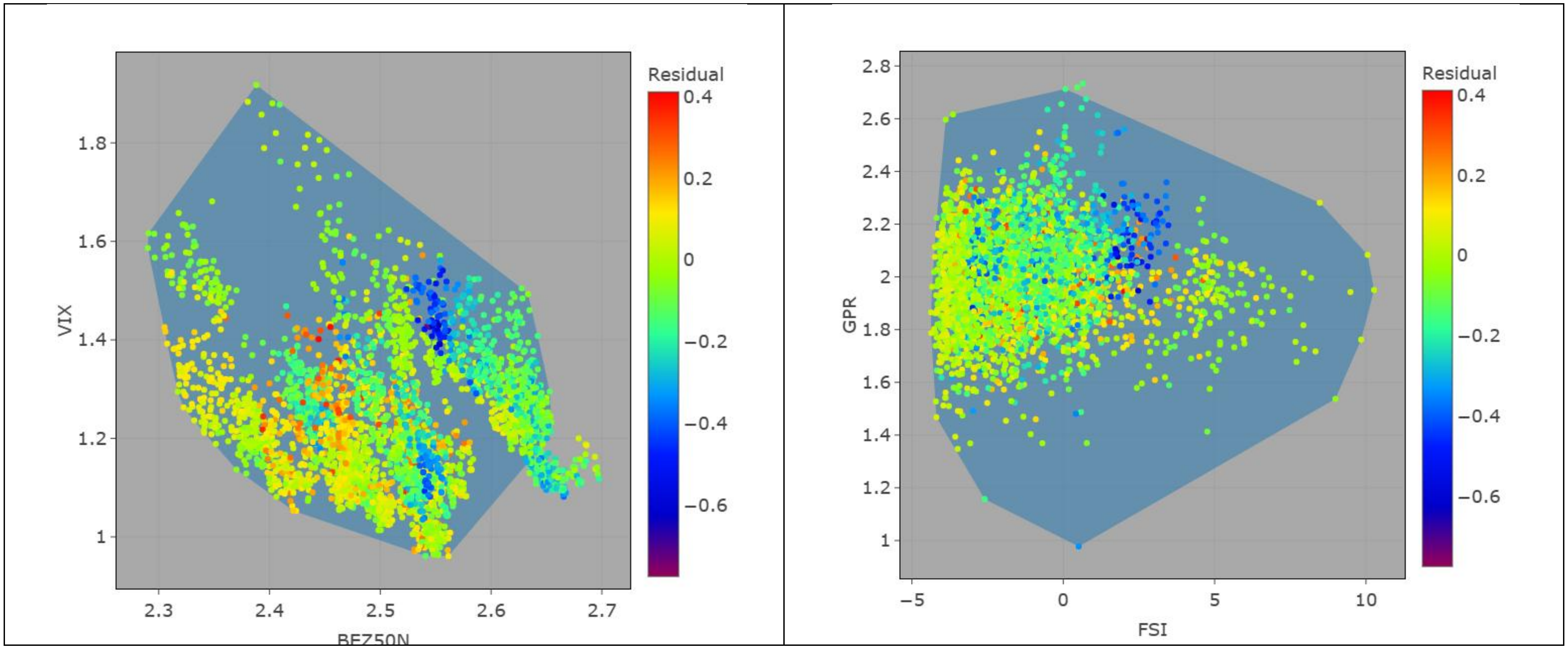
Fig.A7 Residual scatterplot with convex hull (the range of values containing the training set) based on Model 3.


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
FSI
BEZ50N
GPR
BEZ50N


GVZ
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
2.3
2.4
2.5
2.6
2.7
BEZ50N
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
IDEMV
70
60
50
40
30
20
10
0
2.3
2.4
2.5
2.6
2.7
BEZ50N
Residual
0.4
0.2
0
−0.2
−0.4
−0.6


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
MOVEBOND
BEZ50N
OVX
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
2.4
1.4
1.2
2.5
2.6
2.7


OVX
BEZ50N
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
USEPU
BEZ50N
Residual
0.4
0.2
0
−0.2
−0.4
−0.6



Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
2.3
2.4
2.5
2.6
2.7
BEZ50N
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
GPR
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
−5
0
5
10
FSI

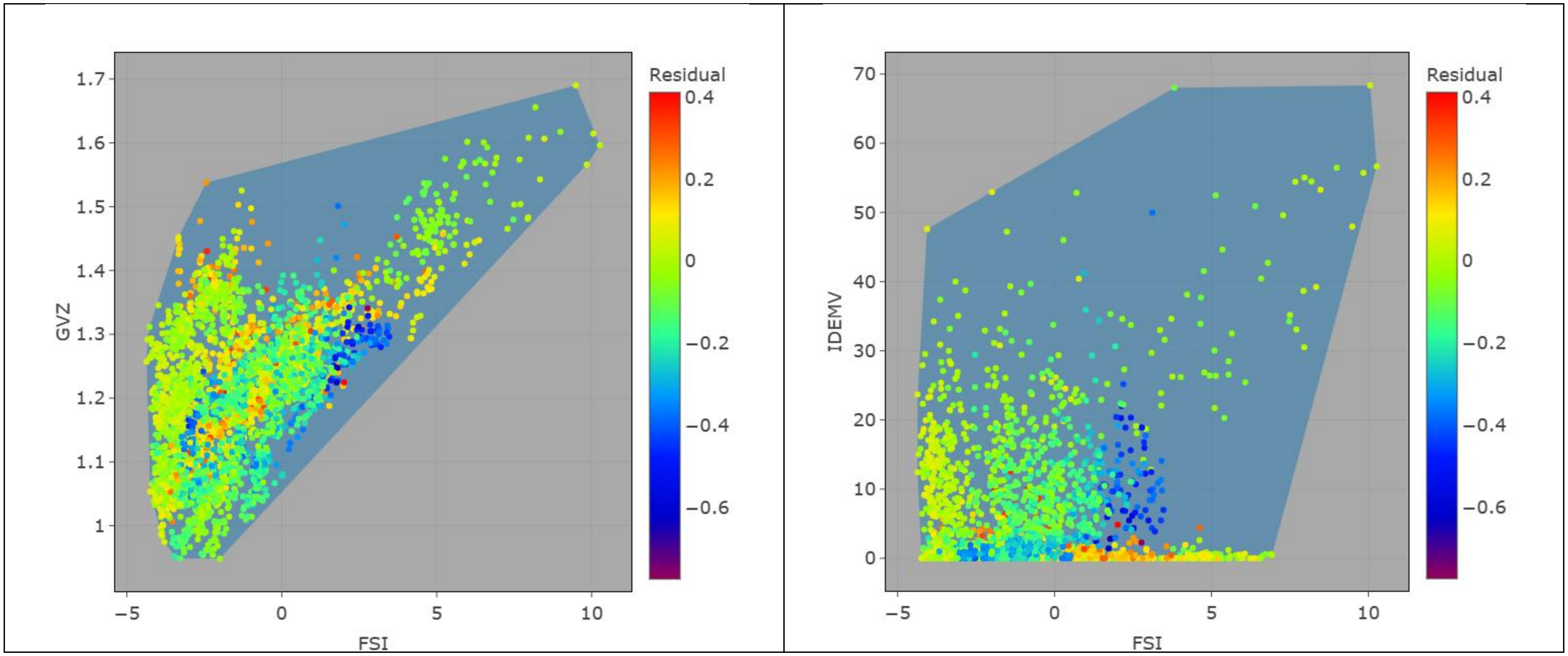
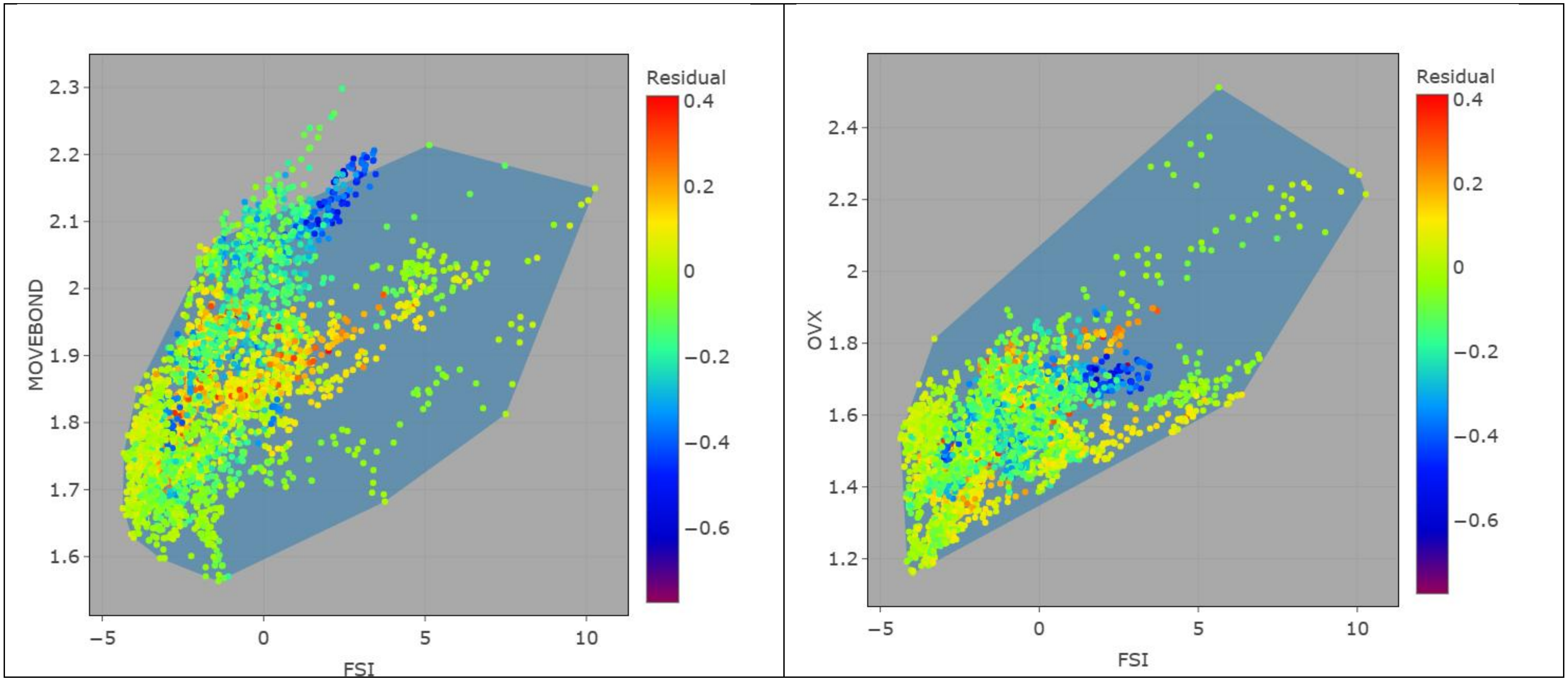
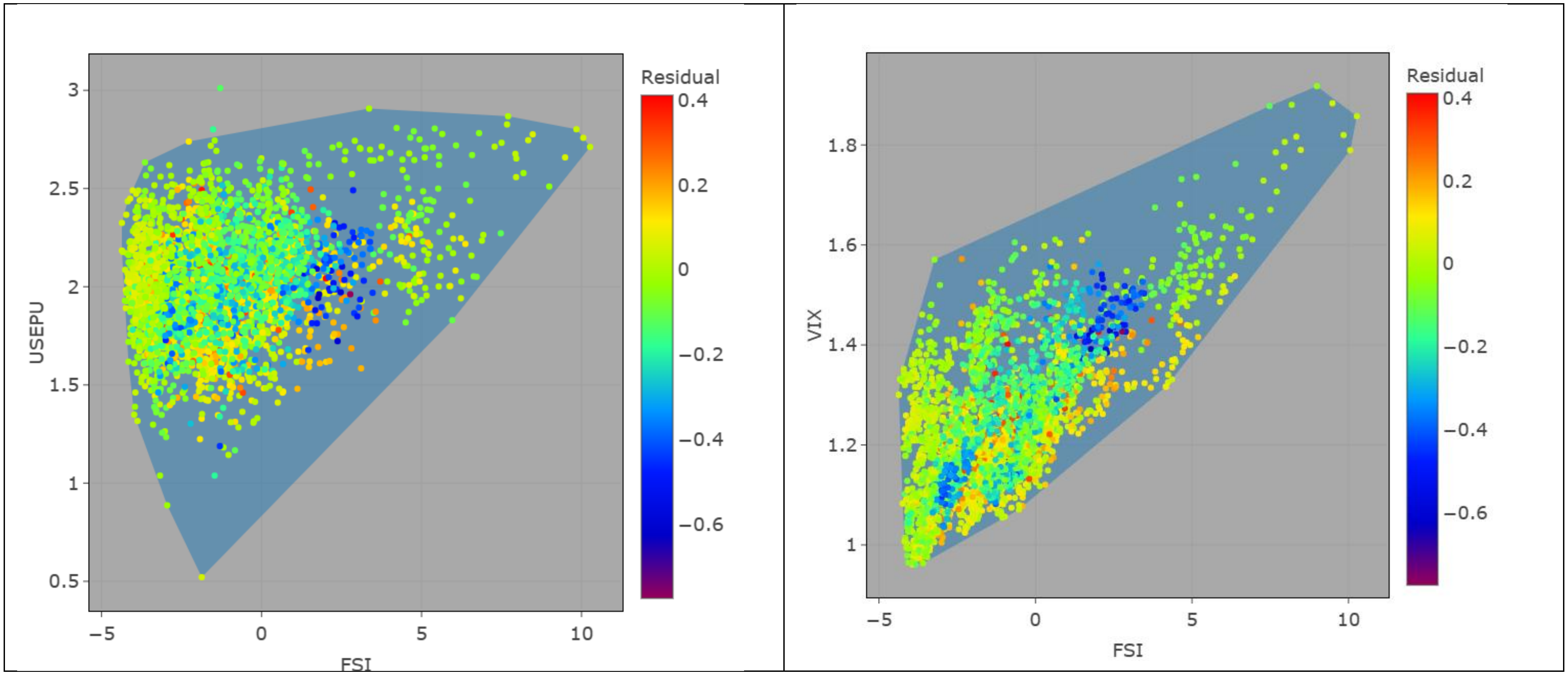
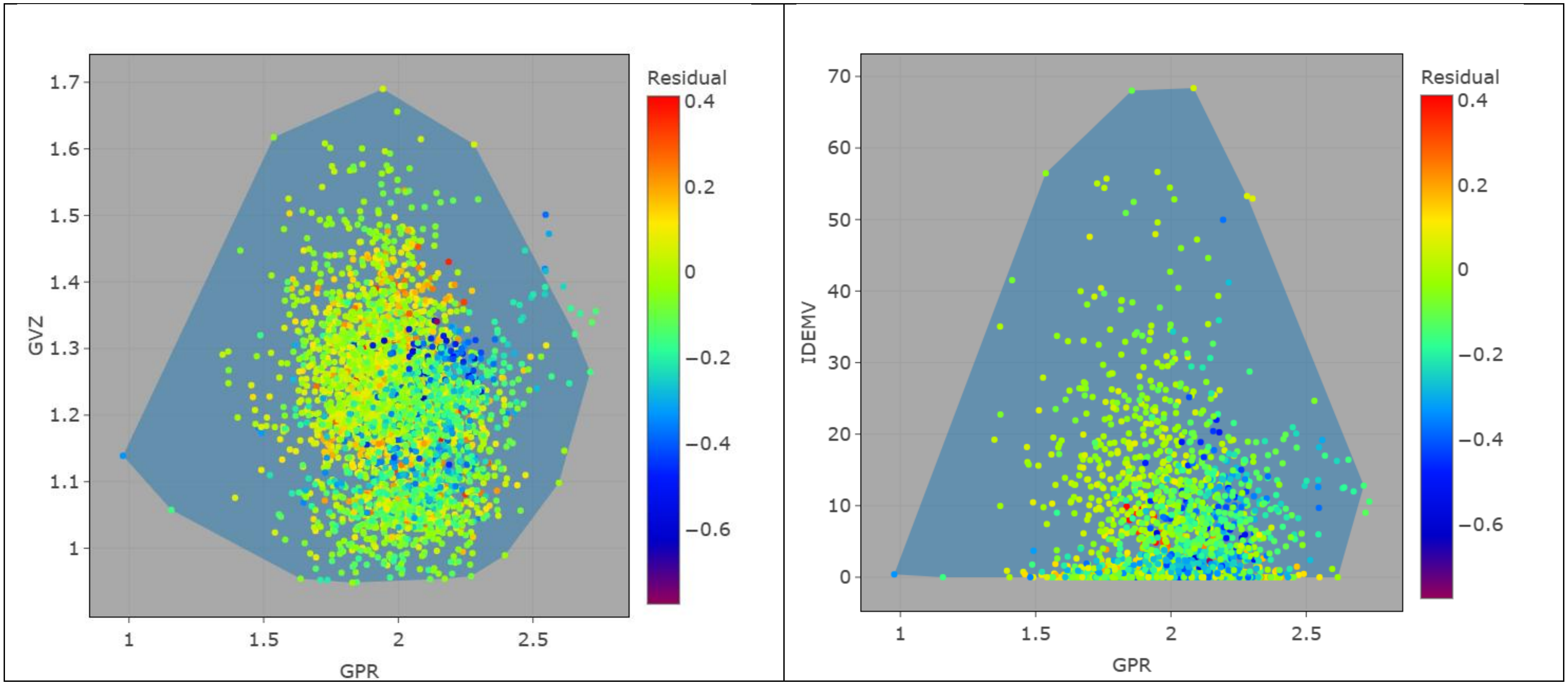


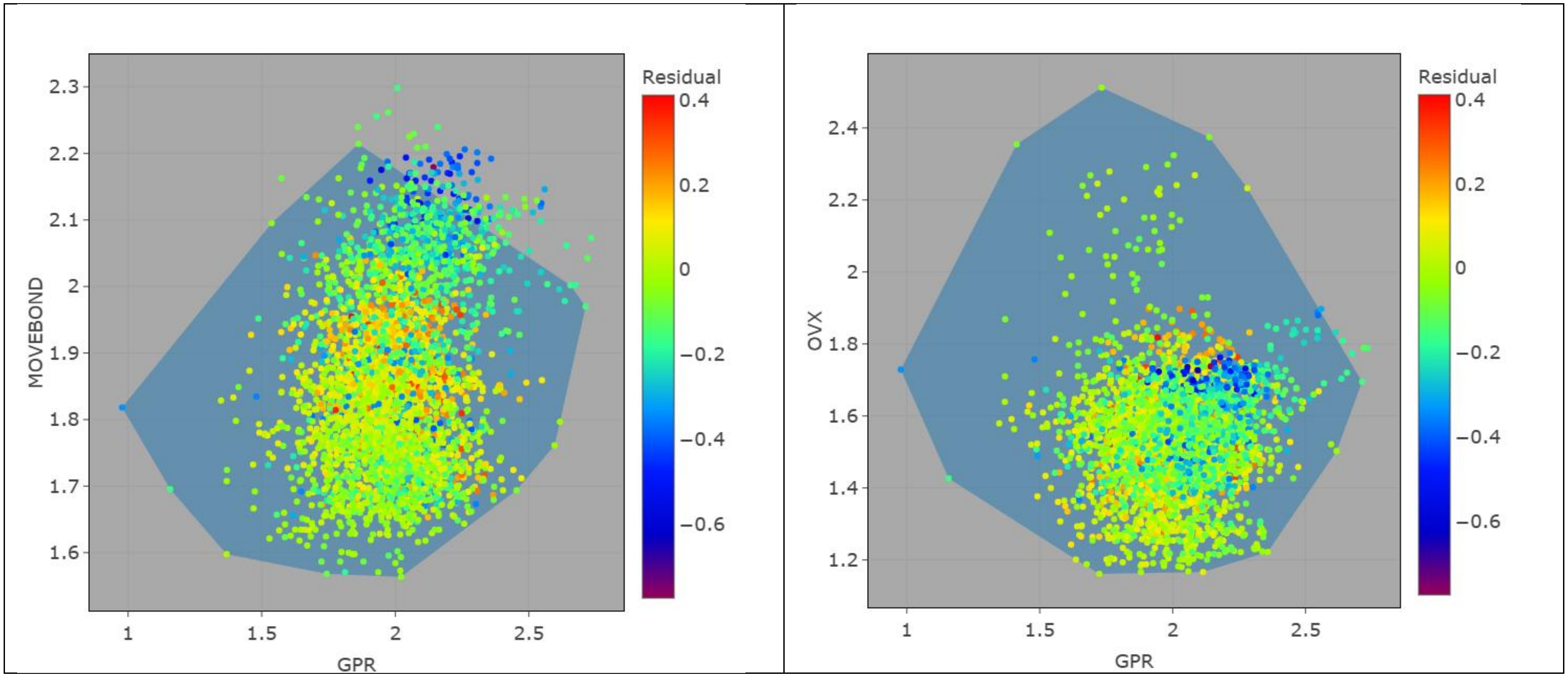
Fig.A8 Residual scatterplot with convex hull (the range of values containing the training set) based on Model 4.

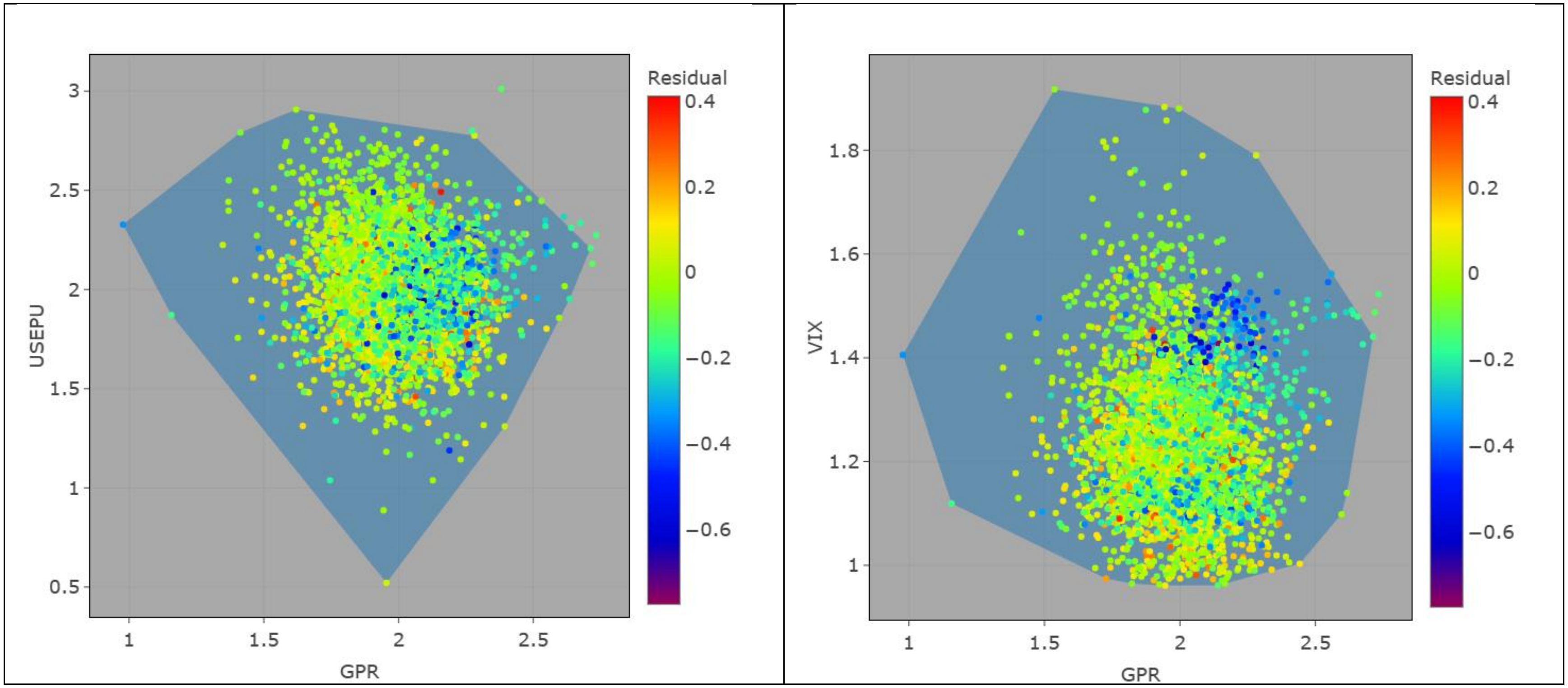


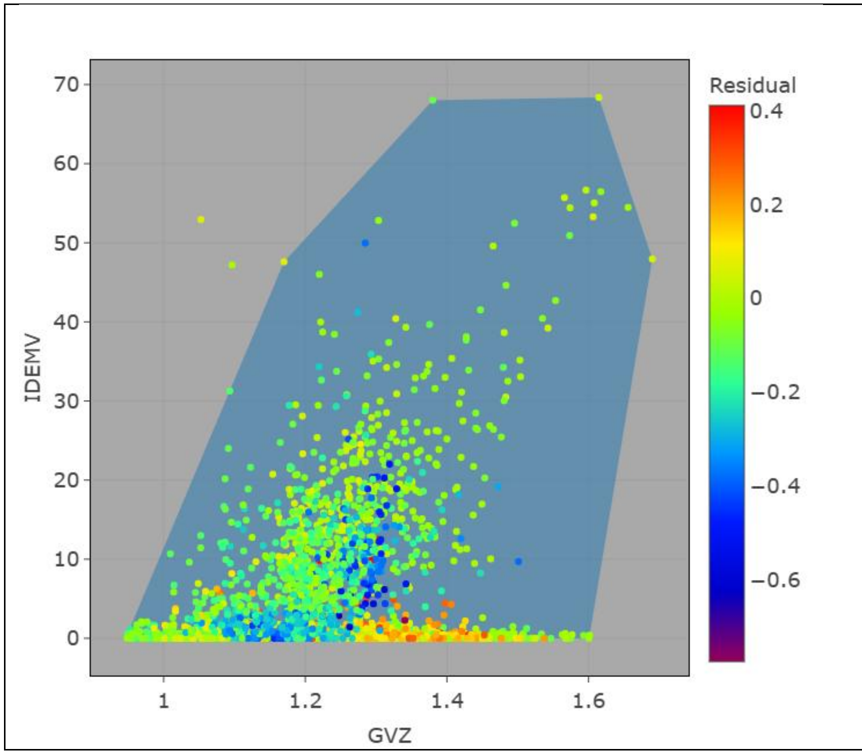
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
MOVEBOND
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
−5
0
5
10
FSI
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
OVX
2.4
2.2
2
1.8
1.6
1.4
1.2
−5
0
5
10
FSI


USEPU
3
2.5
2
1.5
1
0.5
−5
0
5
10
FSI
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
−5
0
5
10
FSI
Residual
0.4
0.2
0
−0.2
−0.4
−0.6


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
GVZ
GPR
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
1.5
2
2.5
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
IDEMV
GPR
70
60
50
40
30
20
10
0
1
1.5
2
2.5


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
MOVEBOND
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
1
1.5
2
2.5
GPR
OVX
2.4
2.2
2
1.8
1.6
1.4
1.2


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
USEPU
3
2.5
2
1.5
1
0.5
1
1.5
2
2.5
GPR
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
1
1.5
2
2.5
GPR



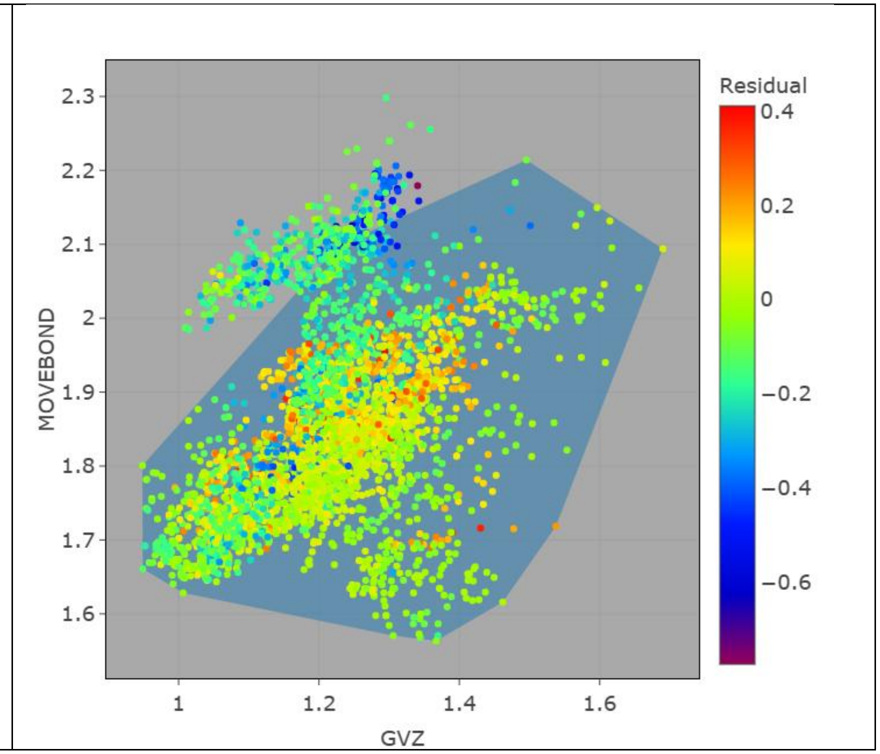
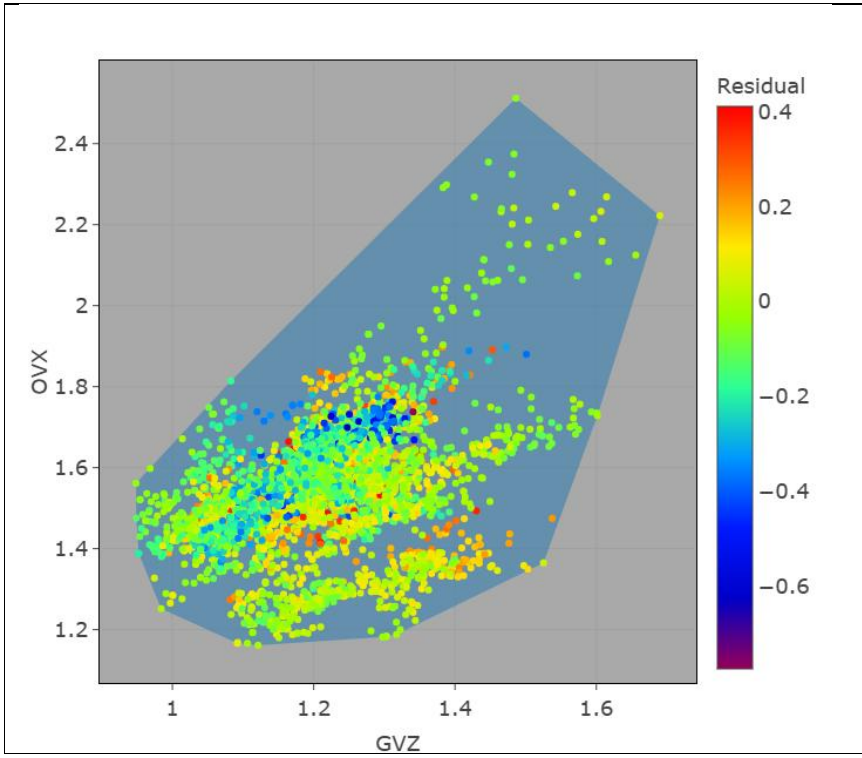
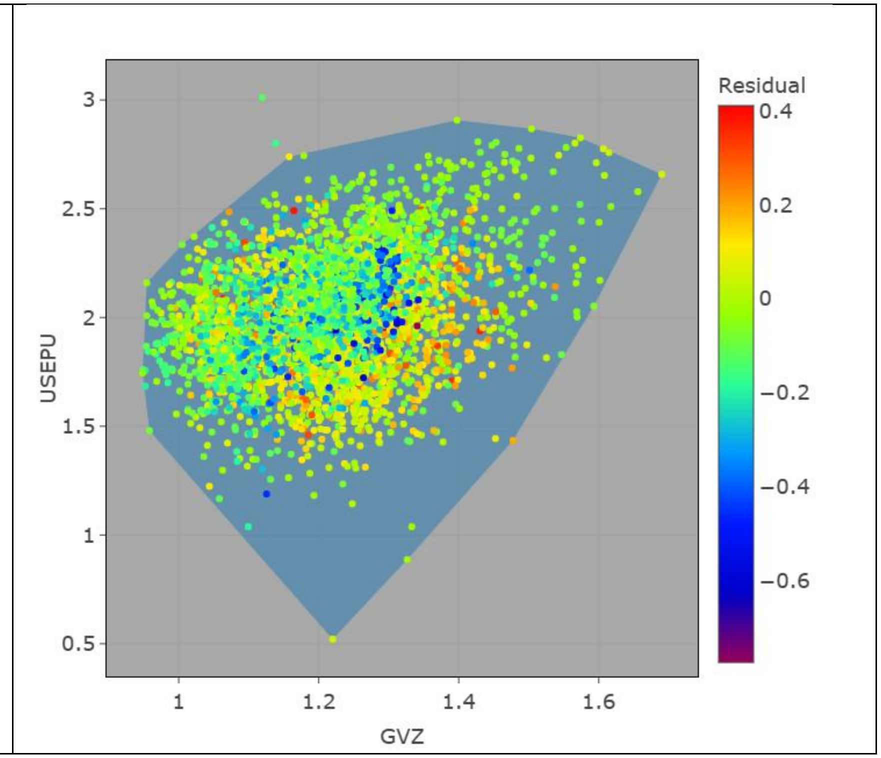


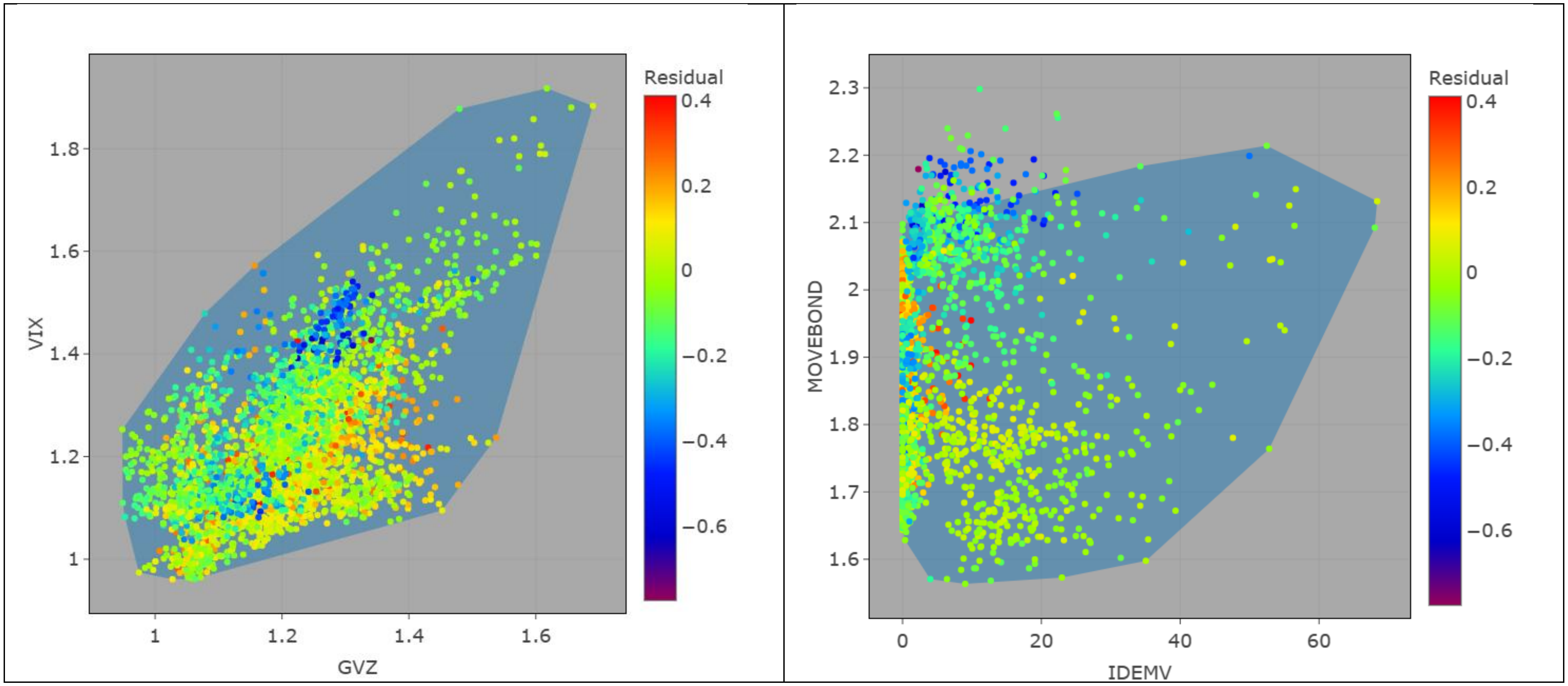
Fig.A8 Continued.

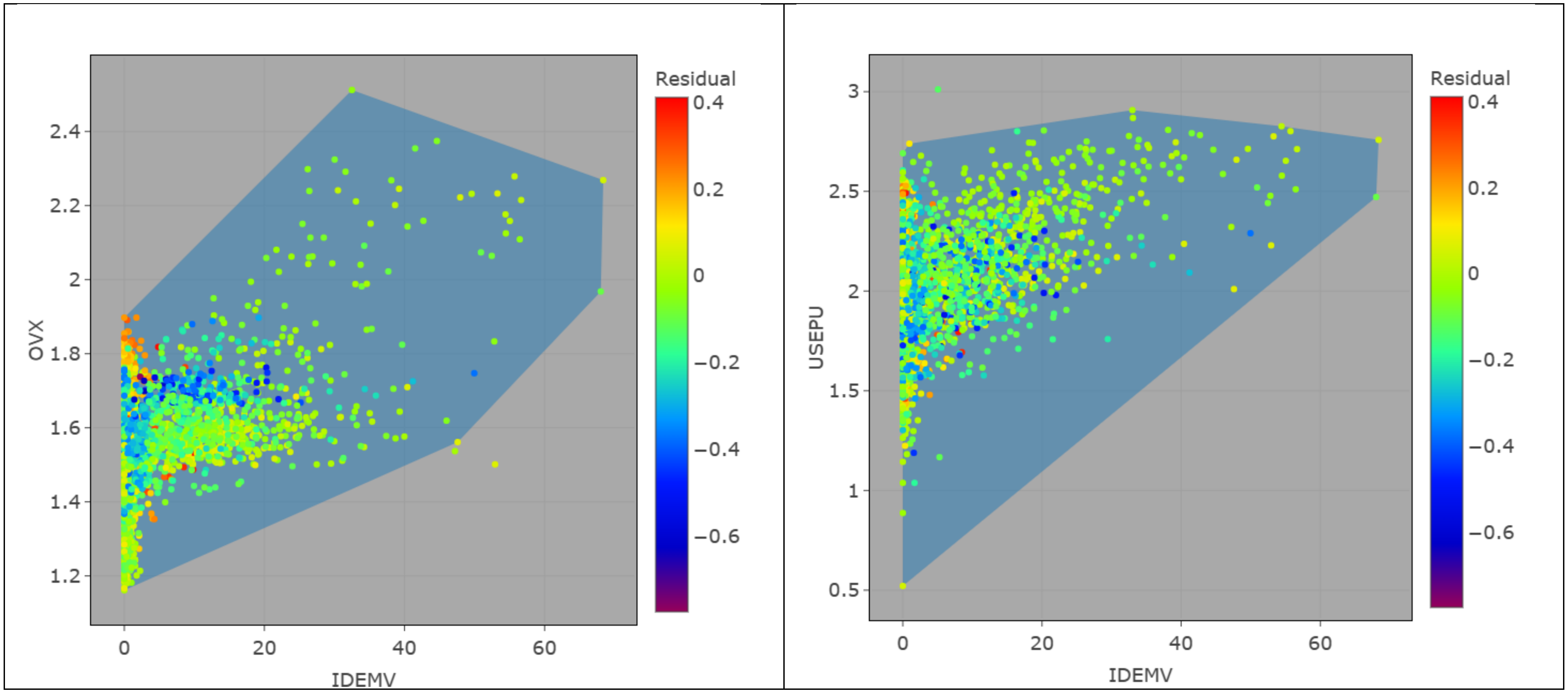


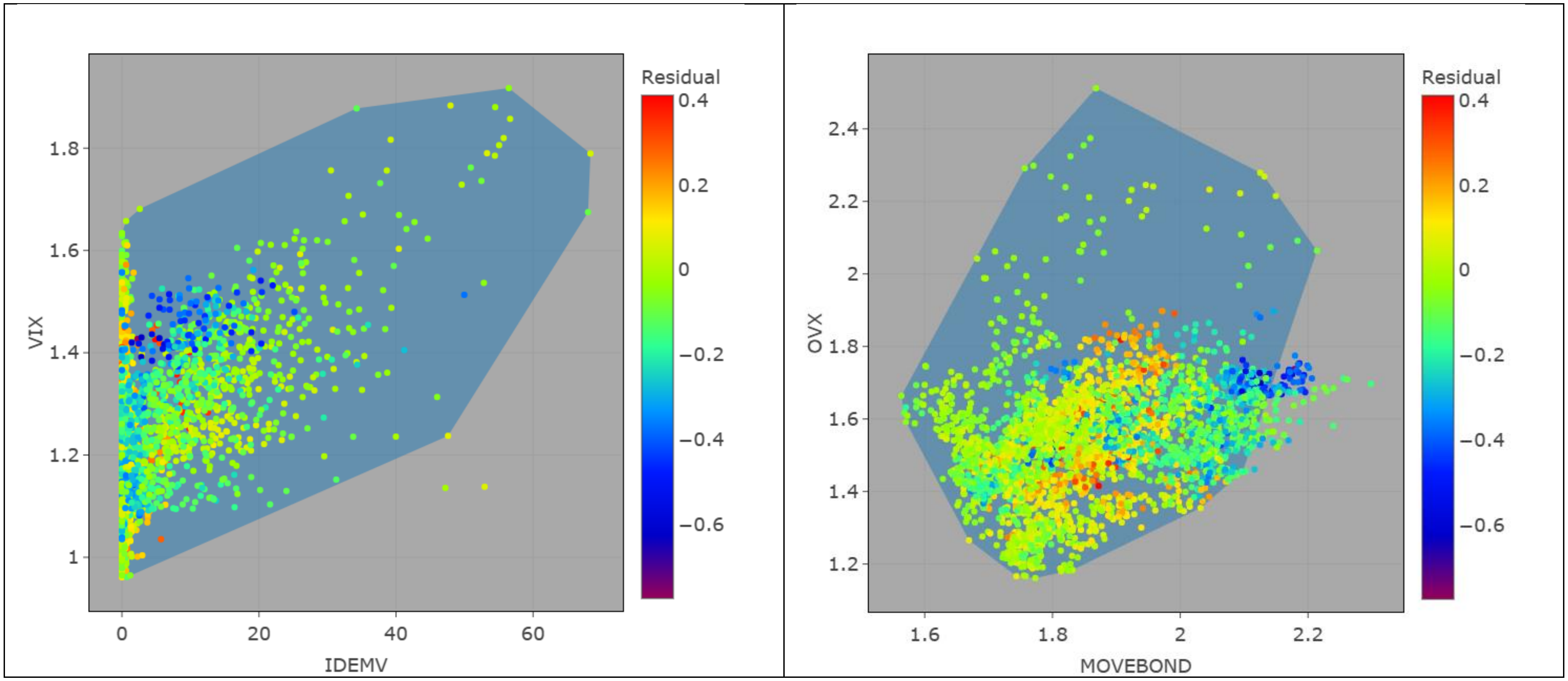
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
OVX
2.4
2.2
2
1.8
1.6
1.4
1.2
1
1.2
1.4
1.6
GVZ

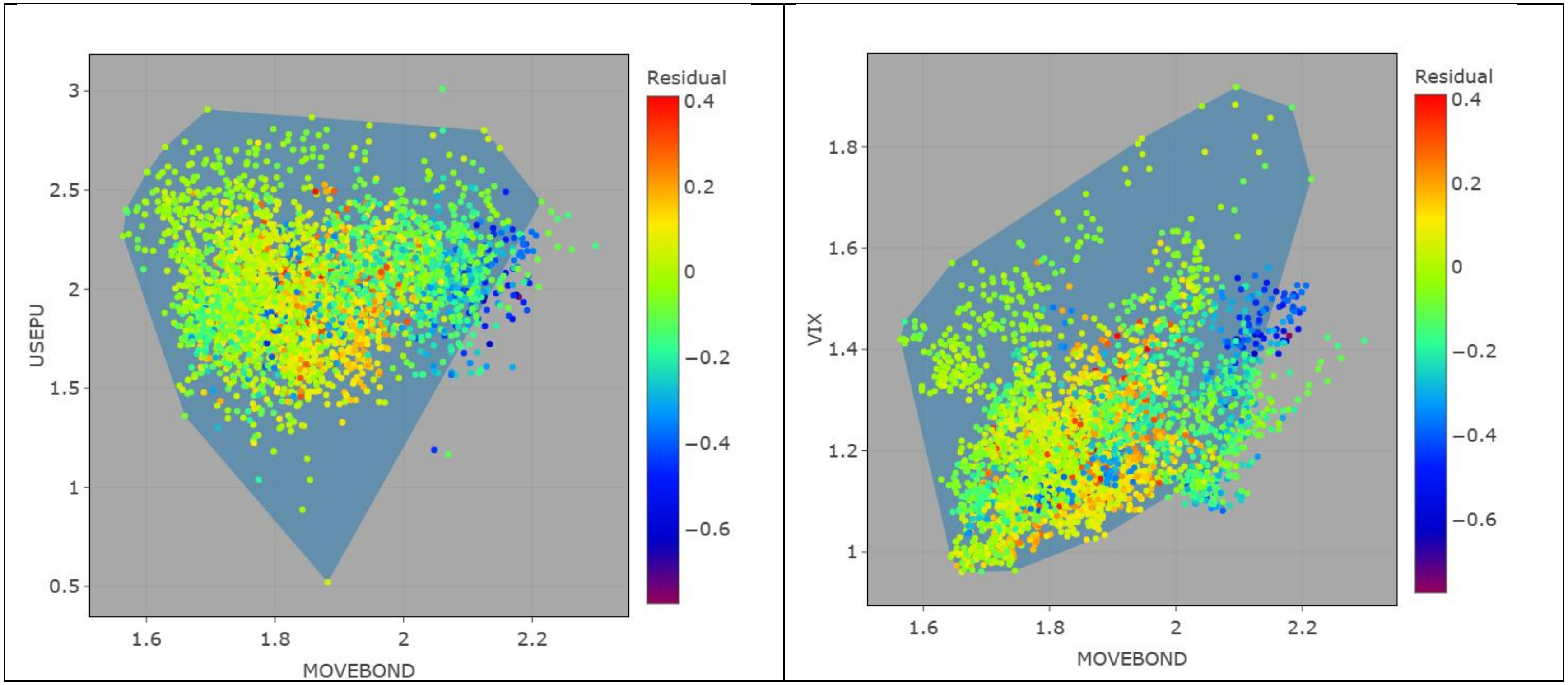


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
USEPU
3
2.5
2
1.5
1
0.5
1
1.2
1.4
1.6
GVZ

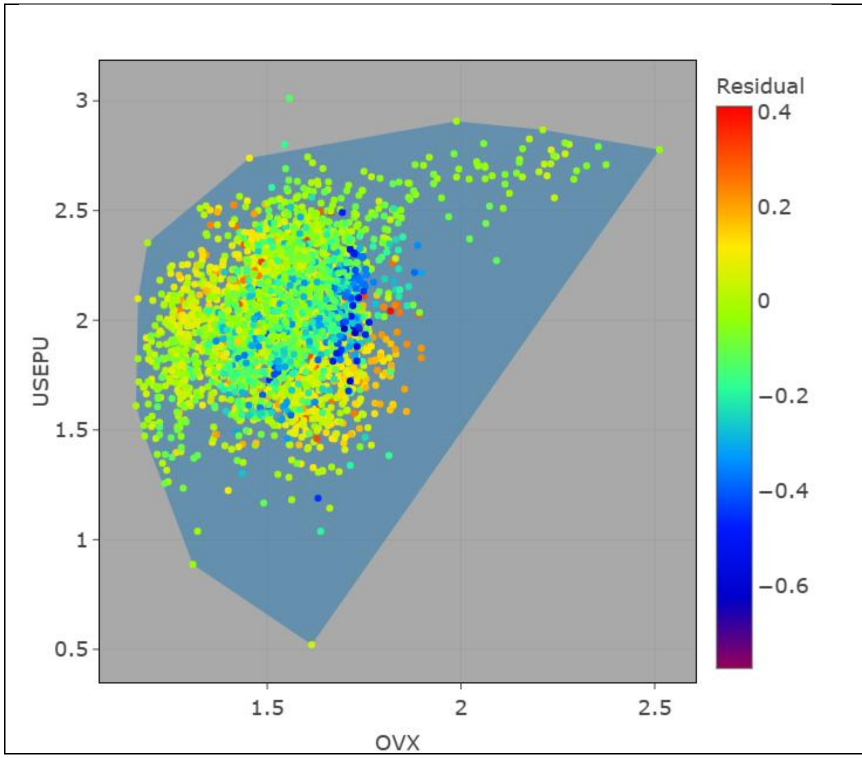

Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
GVZ
1
1.2
1.4
1.6
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
MOVEBOND
2.3
2.2
2.1
2
1.9
1.8
1.7
1.6
IDEMV
0
20
40
60


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
OVX
2.4
2.2
2
1.8
1.6
1.4
1.2
0
20
40
60
IDEMV
USEPU
3
2.5
2
1.5
1
0.5


Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
0
20
40
60
IDEMV
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
OVX
2.4
2.2
2
1.8
1.6
1.4
1.2
1.6
1.8
2
2.2
MOVEBOND



Residual
0.4
0.2
0
−0.2
−0.4
−0.6
USEPU
3
2.5
2
1.5
1
0.5
1.6
1.8
2
2.2
MOVEBOND
Residual
0.4
0.2
0
−0.2
−0.4
−0.6
VIX
1.8
1.6
1.4
1.2
1
1.6
1.8
2
2.2
MOVEBOND



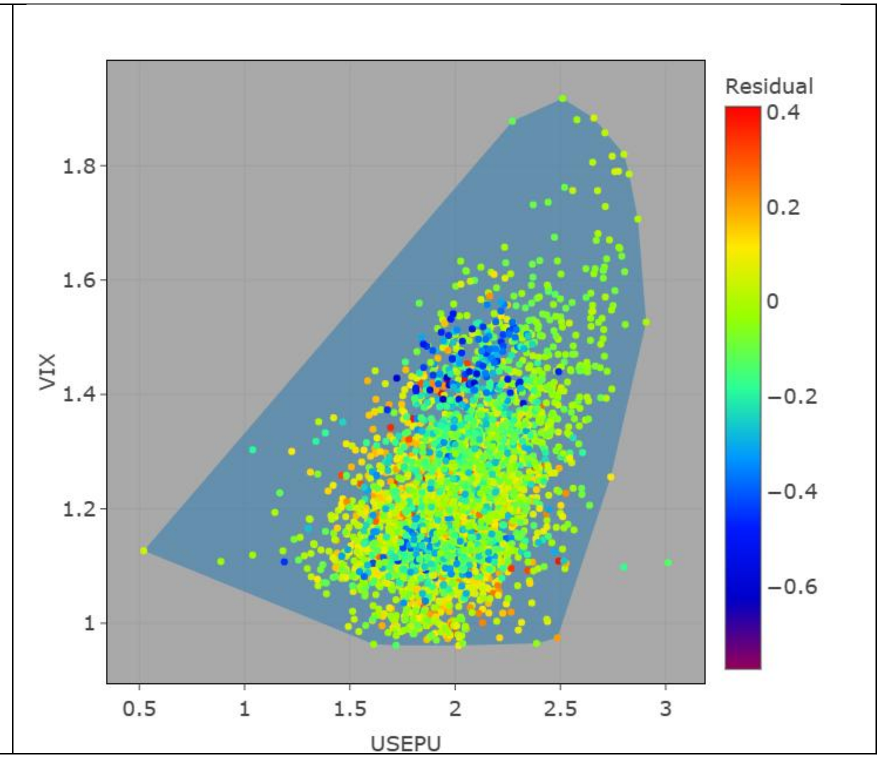


Fig.A8 Continued.