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Enhancing Transparency of Climate Efforts: MITICA's Integrated Approach to Greenhouse Gas Mitigation

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Abstract: Under the Paris Agreement, countries must articulate their most ambitious mitigation targets in their Nationally Determined Contributions (NDCs) every five years and regularly submit interconnected information on greenhouse gas (GHG) aspects, including national GHG inventories, NDC progress tracking, mitigation policies and measures (PAMs), and GHG projections in various mitigation scenarios. Research highlights significant gaps in the definition of mitigation targets and the reporting on GHG-related elements, such as inconsistencies between national GHG inventories, projections, and mitigation targets, a disconnect between PAMs and mitigation scenarios, as well as varied methodological approaches across sectors. To address these challenges, the Mitigation-Inventory Tool for Integrated Climate Action (MITICA) provides a methodological framework that links national GHG inventories, PAMs and GHG projections, applying a hybrid decomposition approach that integrates machine learning regression techniques with classical forecasting methods for developing GHG emission projections. MITICA enables mitigation scenario generation until 2050, incorporating over 60 PAMs across Intergovernmental Panel on Climate Change (IPCC) sectors. It is the first modelling approach that ensures consistency between reporting elements, aligning NDC progress tracking and target setting with IPCC best practices while linking climate change with sustainable economic development. MITICA's results include projections that align with observed trends, validated through cross-validation against test data, and employ robust methods for evaluating PAMs, thereby establishing its reliability.

Keywords: Paris Agreement; climate change mitigation; sustainable development; National Determined Contributions; low carbon strategies; machine learning regression; mitigation scenarios; carbon modelling

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1. Introduction

The Paris Agreement [1] established the Enhanced Transparency Framework (ETF) with the aim to foster trust among Parties. Operationalised through the modalities, procedures, and guidelines (MPGs) [2], the ETF sets extensive reporting requirements, enabling effective tracking of progress toward the Agreement's objectives. Under the ETF, countries are required to submit biennial transparency reports (BTRs) every two years, with the first due by 31 December 2024. BTR content includes different information pieces related to greenhouse gases (GHG), including a national GHG inventory, GHG projections, information on mitigation policies and measures (PAMs), and information to track progress of the Nationally Determined Contribution (NDC). Parties are expected to report 'with measures' (WM) and may report 'with additional measures' (WAM) and 'without measures' (WOM) projections, allowing to assess impact of national PAMs into the future GHG emission profile [3].

In addition to BTRs, Parties are required to submit successive updated NDCs every five years, representing progression compared to the previous NDC and reflecting the highest possible ambition, especially in the form of mitigation targets. These submissions, initially due by 2020 and every five years thereafter, require information necessary for clarity, transparency, and understanding (ICTU), encompassing quantifiable details on reference points, time frames, scope, methodological approaches, and fairness of NDCs [4]. Despite synergies between reporting elements such as national GHG inventories, PAMs, projections, NDC updates, and NDC tracking, consistency issues and primary difficulties in periodically producing and reporting on these elements are anticipated. This is particularly attributed to data collection, lack of national expertise and weak institutional systems [5].

To further elaborate on the consistency issues and primary difficulties mentioned earlier, several key aspects need consideration. These include the inconsistency observed between national GHG inventories and projections, as highlighted by [6]. Additionally, a critical issue is the disconnection between PAMs and mitigation scenarios, as discussed by [7]. Furthermore, the utilisation of inconsistent methodological approaches across different sectors leads to a lack of clarity regarding aggregated emissions and mitigation targets, resulting in increased uncertainty — a concern emphasised by [8,9].

The literature also identifies a significant challenge related to the insufficient capacity in developing countries to employ complex modelling approaches for producing GHG projections in different mitigation scenarios, exacerbated by the absence of common guidelines to produce GHG emission projections [10–13].

To effectively address these challenges in developing mitigation scenarios for NDC design and tracking requires careful consideration of specific key elements. Firstly, there is a necessity for consistency between various GHG elements, namely national GHG inventories, PAMs, mitigation scenarios, and mitigation targets [13,14]. Ensuring alignment with the Intergovernmental Panel on Climate Change (IPCC) methodologies and nomenclatures [15,16] is crucial for maintaining standardised and comparable reporting practices, while adopting coherent and informed policy decisions.

Moreover, the adopted approaches should have the flexibility to accommodate limited data availability, recognising the resource constraints often faced by developing country Parties [17]. This adaptability is essential for enabling a broader spectrum of countries to effectively participate in both climate action and the ETF reporting process. Additionally, the utility of these approaches extends beyond mere reporting; they should facilitate the establishment of mitigation targets and streamline the tracking of mitigation efforts [18]. A robust framework that meets these requirements would not only enhance the transparency and comparability of reporting but also empower developing countries to actively contribute to the global efforts outlined in the Paris Agreement.

The current landscape of models and tools for developing mitigation scenarios falls short of meeting these criteria. Consequently, the proposed Mitigation-Inventory Tool for Integrated Climate Action (MITICA) aims to bridge these gaps by leveraging existing IPCC methodologies and expertise in developing national GHG inventories. MITICA's objective is to align national GHG inventories with GHG projections and PAMs, thereby facilitating NDC progress tracking, and harmonising mitigation planning. Through its innovative framework, MITICA endeavours to empower stakeholders with the tools and insights necessary to navigate the complexities of climate mitigation and contribute meaningfully to the objectives outlined in the Paris Agreement. This paper presents MITICA as a comprehensive solution to the identified challenges. It outlines the framework's structure, emphasising its role in reducing inconsistencies, enhancing transparency, and empowering countries to align their mitigation targets effectively. By integrating national GHG inventories, projections, and mitigation scenarios, MITICA provides a systematic and harmonised approach to mitigation planning that not only enhances the accuracy and reliability of reporting but also fosters a more coordinated and effective approach to climate action on a global scale.

The paper is organised in the following sections. Section 2 describes the material and methods of the study, before the results and discussion are presented in Section 3. Finally, in Section 4 the conclusions of the paper are discussed, delineating the main insights and avenues for future work.

2. Matherials and Methods

An extensive literature review in Appendix A discusses challenges in developing mitigation scenarios, approaches used by developed and developing countries for elaborating such scenarios, and relevant studies on GHG forecasting. From the assessment of developed Parties' submissions outlined therein, it is observed that most adopt sector-specific bottom-up models built from national GHG inventory methodologies and use them in conjunction with macro top-down models incorporating exogenous drivers that characterise their respective national economies. A notable drawback identified in this approach is the substantial resources, including time, personnel, and budget, required for generating distinct mitigation scenarios for each IPCC category and sector. This is attributed to the considerable human interventions necessary in model production. As a result of this observation, the objective of MITICA is to standardize a framework that enables any country, with a particular focus on developing nations, to formulate specific bottom-up mitigation scenarios specified at the IPCC category level by the country, combined with a top-down specification of their national economy. Additionally, MITICA draws inspiration from the main modelling alternatives utilised by developing countries, offering an extensive list of possibilities for PAMs, and developing sector-specific modelling approaches. Considering various alternatives discussed in the literature [19,20], the most suitable option to meet the study's requirements is statistical frameworks with the flexibility to accommodate diverse sector-specific models tailored to different circumstances and data availability, while maintaining overall consistency across sectors, scenarios, and time periods. Under these considerations, MITICA aims at establishing both a framework and a tool to create consistent mitigation scenarios that can be tracked against historical GHG emission trends and used as a benchmark to define and implement relevant interventions when needed. The following subsections describe MITICA's general framework, its forecasting approach, the accountability for PAMs, and the software characteristics.

2.1. General Framework

MITICA's conceptualization and development adhered to specific requirements. Aligned with its objectives, it followed IPCC nomenclatures, ETF definitions, and UNFCCC inventories as primary data inputs. The framework is designed to be universally applicable, offering a standardised methodology to overcome identified challenges effectively. It utilises national GHG inventories at the highest disaggregation level, mirroring their detailed structure to enhance model specification. MITICA employs a consistent modelling framework for all IPCC sectors to minimise inconsistencies, while still being emission source and country specific.

MITICA's goal is to address GHG emission sources and sinks comprehensively resulting from the implementation of various PAMs within user-defined macroeconomic and sectoral frameworks. The modelling approaches therefore consider the evolution of proxies, encompassing macroeconomic, demographic, and sectoral drivers across various scopes, influencing country-level GHG inventory methodologies. While MITICA's outcomes are not predictive, they serve to scientifically assess policy alternatives and derive potential mitigation targets. This aids both developed and developing countries in designing and tracking NDCs within the ETF of the Paris Agreement, as well as to assist in reporting to the UNFCCC.

Considering these requirements, MITICA develops mitigation scenarios starting with the estimation of a WOM scenario. This scenario represents projected national GHG emissions considering a set of projected proxies ceteris paribus; only the proxies change in the projected years, being the technology mix, consumer behaviour as well as the GHG accounting methodologies the same of the latest historical year; these elements will only change as a result of the implementation of PAMs. Indeed, MITICA uses the WOM as a benchmark for developing mitigation scenarios (WM and WAM, in line with ETF definitions). In these scenarios the only difference concerns the PAMs implemented and their impact on GHG emissions. Further information on the design of the forecasting approach selected for projecting WOM emissions in MITICA is provided in Section 2.2.

The input data required by MITICA for estimating the WOM scenario is the national GHG emission inventory and a set of projected proxies. MITICA's estimations are made at the highest disaggregation level available in the national GHG emission inventory. Inventory estimations can start from year 1990 and are provided on an annual basis. However, the flexibility provisions of the ETF allow developing Parties to develop and submit national GHG inventories with starting years other than 1990 [2]. Countries facing higher capacity constraints may only be able to develop and report limited time series, as can be observed in the biennial update reports (BURs) submitted until 2023 [21]. Despite shorter national GHG emission inventory time series, developing countries are required to develop and submit NDCs including mitigation targets, and also report on the tracking of progress of the NDC every two years. Furthermore, the completeness and the level of detail of national GHG emission inventories may vary due to the different methodological approaches that are allowed by the 2006 IPCC Guidelines. In this context, MITICA develops mitigation scenarios even with limited inventory time series and sectoral disaggregation. However, the quality of results is substantially improved with longer time series and higher sectoral granularity levels.

The proxies needed by MITICA to estimate the WOM scenario GHG emission consist of two layers: a first layer of national-level proxies needed to develop GHG projections, and a second layer of sector-specific proxies aimed at refining sectoral model specifications. Despite the forecasting approach is common for all sectors, different sectoral proxies enable MITICA to define national-specific sectoral models to project WOM emissions.

These proxies have been selected considering: (i) data availability, prioritising proxies with generally accessible and comprehensible data; and (ii) the theoretical relationship between sectoral emissions and the proxy, grounded in relevant research. Table 1 shows the main proxies considered, describing the theoretical relationship between variables building from [22,23].

Table 1. Sectoral proxies in MITICA.

Granularity 1	Proxy	Theoretical Relationship
All sectors	Gross Domestic Product (GDP)	GDP involves activity levels in the different inventory emission sources. Increasing GDP generally involves increasing emissions.
All sectors	Population	Increased population levels generally lead to increasing emissions.
Energy	Energy demand	Energy demand is directly related to increased fossil fuel emissions in the absence of technological changes.
Energy	Fuel prices	Increase in fuel prices generally result in a reduction in fuel consumption in the medium term.
Energy	Energy supply	The amount of energy supplied is directly correlated with sectoral emissions. An increase in energy supply contribute to higher emissions.
Transport	Fleet	A larger fleet, particularly if dominated by vehicles with higher emission profiles, tends to contribute to increased emissions.

Table 1. *Cont.*

Granularity 1	Proxy	Theoretical Relationship
Transport	Vehicle kilometre travelled	The total distance travelled by vehicles is positively associated with sectoral emissions. Higher vehicle kilometre travelled result in increased fuel consumption and emissions.
Fugitive emissions	Solid fuel production activity levels	The level of activity in solid fuel production is directly linked to emissions from the use of solid fuels.
Fugitive emissions	Oil production levels	Oil production levels have a direct impact on sectoral emissions.
Fugitive emissions	Natural gas production levels	The levels of natural gas production are positively associated with sectoral emissions.
Industrial Processes and Product Use—IPPU	Industrial activity index	Industrial activity levels lead to increased emissions in the absence of changes in technologies.
Industrial Processes and Product Use—IPPU	Income indicator	Income levels are correlated with consumption patterns, particularly on products use.
Agriculture	Crop activity index	An increase in crop activity levels lead to increased emissions from agriculture in the absence of changes in practices or technologies.
Agriculture	Livestock activity index	Increased livestock population produce increased emissions from agriculture.
Land Use, Land-Use Change and Forestry – LULUCF	Forest land cover growth	Increased forest land involves increased CO_2 removals, therefore reduced net GHG emissions.
Land Use, Land-Use Change and Forestry – LULUCF	Degree of conservation	Increased forest trends lead to enhanced biomass growth and subsequent CO_2 removals, therefore reduced net GHG emissions.
Other sectors	Service activity index	Increased service activity may contribute to higher energy consumption and emissions associated with the provision of services.
Other sectors	Households	Increasing households' size leads to increased household energy consumption and emissions.
Other sectoral proxies	-	-

Starting from an initial WOM projection, MITICA develops generic methodologies, building from [24], to estimate the impact of relevant PAMs on main emission sources and sinks. The approach and foundations of PAMs estimations are further elaborated in Section 2.3. WM and WAM scenarios are then constructed by considering the impact of user selected PAMs. By considering different sets of PAMs, policy makers can visualise the potential impact of implementing policies of interest into the national emission profile. This type of mitigation assessment can support in establishing informed mitigation targets and assessing their potential evolution under specified mitigation scenarios and a given macroeconomic framework. Figure 1 illustrates the generalised procedural steps of MITICA, which are subsequently elaborated upon below.

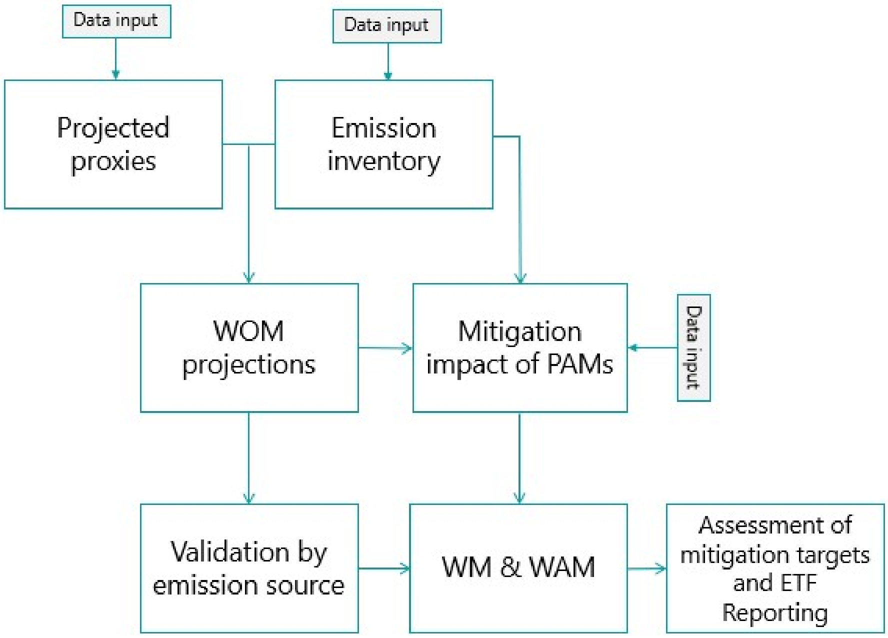

Figure 1. Generalised steps to obtain mitigation scenarios in MITICA.

A more detailed graphic workflow of MITICA is provided in Appendix C for further reference.

2.2. Methodology for Projecting GHG Emissions in the WOM Scenario

The methodology selection for projecting the WOM scenario within MITICA builds from the revision of the literature of time series forecasting. Table 2 shows the methods followed by a selection of studies of similar nature for time series forecasting.

Table 2. Selection of similar studies * for time series forecasting.

Study	Modelling Approach	Application
[25]	Autoregressive integrated moving average (ARIMA)	Energy consumption and GHG emissions from pig iron manufacturing in India.
[26]	Seasonal Autoregressive Integrated Moving average with Exogenous Factors (SARIMAX)	Forecast of short-term hourly electricity generation.
[27]	ARIMA & SARIMAX	Forecasting natural gas production and consumption in United States until 2025 on monthly basis.
[28]	Random Forest Regression model.	Forecasting CO_2 emissions at city level in China.
[29]	Random Forest Regression model.	Generation capacity forecasting of cascade hydropower stations
[30]	Random Forest Regression model with Slime Mould Algorithm.	Forecasting of CO_2 emissions from road transport.
[31]	Long-short Term Memory (LSTM) neural network compared with Least Squares Support Vector Machine and recurrent neural network.	Forecasting of NOx emissions from thermal power plant.
[32]	Three methods are applied, the ARIMA model, the SARIMAX model and the LSTM model.	Forecast of CO_2 emissions in India.

Table 2. *Cont.*

Study	Modelling Approach	Application
[33]	Least Squares Support Vector Machine	Projection of thermal comfort, CO_2 emission and economic growth.
[34]	Empirical mode decomposition and evolutionary least squares support vector regression.	Carbon price using EU ETS for years 2013–2016.
[35]	Least Squares Support Vector Machine.	CO_2 emissions of Hebei using a time series for years 1990–2016
[36]	6 different machine learning models, including GBR	Forecasts for solar radiation in daily and hourly timescales.
[37]	GBR tree and principal component regression models.	Forecast of electricity prices in Spain.
[38]	GBR combined with Random Forest Regression.	Prediction of net ecosystem carbon exchange using data from two sites for years 1997, 2010, 2012 and 2013.
[39]	Artificial Neural Network (ANN)	Forecast of the heating and cooling energy demands, energy consumptions and CO_2 emissions of office buildings in Chile using a dataset of 77,000 data points.
[40]	Artificial Neural Network	Annual forecasts of CO_2 emissions for 17 countries.
[41]	Comparison of several regression techniques, including Least Absolute Shrinkage and Selection Operator (LASSO).	Forecasting of long-route CO_2 emission from shipping using 40 data points.
[42]	LASSO-Deep Belief Networks (DBN)-Bootstrap Model.	Long term streamflow forecasting using monthly data for the period 1956–2015.
[43]	Three different models are used, including Grey Model GM(1,N), ANN and LASSO.	Short-term forecasting annual CO_2 emissions in Malaysia.
[44]	The LASSO model is compared to several shallow models.	China 2022–2027 forecasting of CO_2 emissions using a dataset from 2011 to 2021.

* In the table, studies of distinct nature are distinguished through the incorporation of ticker lines for easy reference.

When prioritising the key requirements for MITICA's methodology design, previous research was examined to assess the applicability and optimal performance of models. The primary criterion is the model's efficacy in projecting GHG emissions over extended time periods, ensuring its appropriateness for long-term forecasting. A secondary consideration involves the model's proficiency in managing small datasets, recognising the inherent limitations associated with restricted time series data. Additionally, the model's capacity to integrate external proxies assumes critical importance for capturing external factors that influence emissions. Lastly, the requirement for flexibility underscores the necessity for the model to be adaptable and tailored to the specific contexts of different countries.

In light of these criteria, Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) distinguishes itself for its ability to incorporate external regressors and manage limited data, while Least Absolute Shrinkage and Selection Operator (LASSO), Gradient Boosting Regression (LASSO), Gradient Boosting Regression (GBR) and Random Forest Regression have also proven advantageous for their aptitude in capturing intricate patterns and offering flexibility across diverse datasets and geographical contexts. Furthermore, the comparative performance of these methods has provided good results in previous studies [27,32,38]. In contrast, deep learning techniques such as the Long Short-Term Memory (LSTM) models may encounter challenges with small datasets and interpretability [44], while ARIMA and Least Squares Support Vector Machine may face difficulties in accommodating external proxies and adapting to the distinct contexts of different countries [45].

Based on this assessment, MITICA incorporates projection modelling approaches better suited for small data sets, long-term forecasting, and considering exogenous drivers. Consequently, a hybrid approach, named Artificial iNtelligeNce And cLassIcal STatistics (ANNALIST), is developed for projecting the WOM scenario. This hybrid model integrates LASSO, SARIMAX, and Random Forest Regression, leveraging the primary advantages of the forecasting methods investigated in GHG forecasting literature. MITICA also offers alternative but suitable methods, empowering users to select the preferred option based on the characteristics of the dataset and enabling the maximisation of available data utilisation while mitigating potential limitations associated with various modelling approaches. The model initiates by decomposing the trend and noise, a commonly employed practice in GBR [38]. The Exponentially Weighted Moving-Average (EWMA) algorithm is applied to derive the trend, similar to the approach taken by authors in [46]. Subsequently, the noise is obtained through subtraction. The selection of the trend-noise tuple is based on demonstrating stationarity noise, assessed using the Augmented Dickey Fuller test, and maximal standard deviation.

Assuming a time series $Y_t = T_t + R_t$ where Y_t represents the value at time t, T_t denotes the trend, and R_t the noise, the variance is formulated as:

$$VAR(Y_t) = VAR(T_t + R_t) \quad (1)$$

Under the assumption of independent noise and trend, it is posited that:

$$VAR(Y_t) = VAR(T_t) + VAR(R_t) \quad (2)$$

Further assuming that $VAR(Y_t) = C$ due to its constancy, and $VAR(R_t) = nVAR(T_t)$:

$$C = VAR(T_t)(1 - n) \rightarrow VAR(T_t) = \frac{C}{(1 + n)} \quad (3)$$

This reveals that as n increases, reflecting a larger $VAR(R_t)$, $VAR(T_t)$ decreases. This drives the rationale for selecting noise with a higher standard deviation. SARIMAX is employed to capture intricate patterns, functioning optimally in the presence of stationary values. In such cases, SARIMAX predicts the noise seamlessly, and simultaneously, the trend remains simplified, thus enhancing predictive accuracy. In instances where noise does not meet these criteria, zero noise is considered, treating the entire dataset as the trend. Utilising regression techniques on a pool of potential variables for model development often results in overfitting, characterised by an excessive inclusion of variables in the final model and an overestimation of its performance [47]. To tackle this issue in trend prediction, the LASSO model is employed [48]. LASSO determines the best fit model specification by IPCC category, considering the proxies inputted by the user. As a default setting, in order to offer a priori information for various models by sector, ANNALIST includes a prioritisation weight for the proxies. This weight assigns greater importance to the parameters of sectoral drivers that have demonstrated better performance within their respective sectors, as outlined by [23].

For noise treatment and assembling, ANNALIST applies a first difference in the presence of non-stationarity by applying the Augmented Dickey Fuller test. Once stationarity is ensured, the following SARIMAX specification is applied: $(p, 0, q)(0, 0, 0, 0)$.

Following the addition of trend and noise predictions, a series of automated corrections employing machine learning is applied throughout the process. The initial step involves outlier filtering using the Isolation Forest model [49], a machine learning tool designed for outlier detection. Subsequently, a Random Forest Regressor model [38] is employed to train on historical data and update predictions. A comprehensive hyperparameter optimisation is then conducted using Grid Search CV [50], a machine learning technique seeking the optimal parameter combination to enhance model accuracy. This optimisation is reinforced with time series cross-validation, ensuring the model's robustness and generalisability across different temporal datasets. Thus, a reliable model is obtained, maximising the strengths of SARIMAX while simplifying the trend in the most robust manner. Subsequently, the model undergoes various machine learning analyses to ensure the maximum likelihood of the outcome. The graphic workflow of ANNALIST is provided in Appendix B.

To enable the application of MITICA across various input datasets and time series, alternative approaches to ANNALIST for projecting the WOM scenario are integrated. This includes a GBR model without decomposition and the SARIMAX method. GBR has proven particularly useful for very short time series (from 2 observation years), making it valuable for countries with limited time series data. SARIMAX yielded results similar to ANNALIST, except for linear trend functions characterised by the consolidation of all noise variation predominantly at the upper end of the series. Therefore, it is incorporated for cross-comparison purposes. MITICA requires users to validate the forecasts produced for the WOM scenario by IPCC category, incorporating the possibility to modify the model specified by ANNALIST by changing the type of modelling approach from ANNALIST to GBR or SARIMAX.

Regarding the software aspect, MITICA has been deployed in a desktop application using Phyton as the main programming language. By adopting Python, MITICA ensures compatibility with various operating systems, including Windows, macOS, and Linux, making it accessible to a broader user base. This cross-platform compatibility enhances the usability and accessibility of MITICA, allowing users from different backgrounds to leverage MITICA's features for GHG forecasting and mitigation analysis. Furthermore, MITICA's deployment as a desktop application offers several practical benefits. For instance, users can run MITICA locally on their computers, ensuring data privacy and security. Moreover, being a standalone application, MITICA does not require an internet connection to function, providing users with uninterrupted access to its features and functionalities, regardless of their location or internet connectivity.

2.3. Mitigation Impact of PAMs and Definition of WM and WAM Scenarios

The PAMs accounting approach of MITICA extends the methodological framework described in [24] to encompass all IPCC sectors and main mitigation alternatives, aligning with the principles and requirements described in Section 2.1. The methodological framework outlined in [24] has already undergone testing and its estimates have been included in the National Energy and Climate Plan of Greece [51], proving its applicability in the context of the study. The basic estimation approach is depicted as:

$$ME_{t_i-t_f} = R \cdot M_{t_i-t_f}[REF_t - MEF_t] \quad (4)$$

where $ME_{t_i-t_f}$ represents the mitigation effect of the PAM for the entire projected period, $M_{t_i-t_f}$ is the magnitude of the PAM representing the affected activity levels, R represents the reduction factor in magnitude from PAM implementation, REF_t stands for the reference emission factor in the absence of the PAM at time t, and MEF_t is the mitigation emission factor post implementation of the PAM at time t. Based on this generalisation, PAM methodologies are specified case-by-case, inked to the reference national GHG inventory through the REF, and associated with the WOM scenario through $M_{t_i-t_f}$.

Building from this conceptual framework, an extensive list of PAMs (Appendix D) is available within MITICA, providing default factors and specific methodologies covering all emission sources and sinks defined by the IPCC Guidelines [15,16]. In the final tool, users are required to define the magnitude of the desired PAM and adjust, if necessary, any of the methodological parameters. Once the list of PAMs is defined, MITICA aggregates the individual impact assessment of PAMs to produce the WM and WAM scenarios, thereby allowing to define scenarios based on national circumstances and stakeholder agreements.

Figure 2 shows MITICA´s rationale to account for the impact of PAMs from the estimation of the WOM scenario.

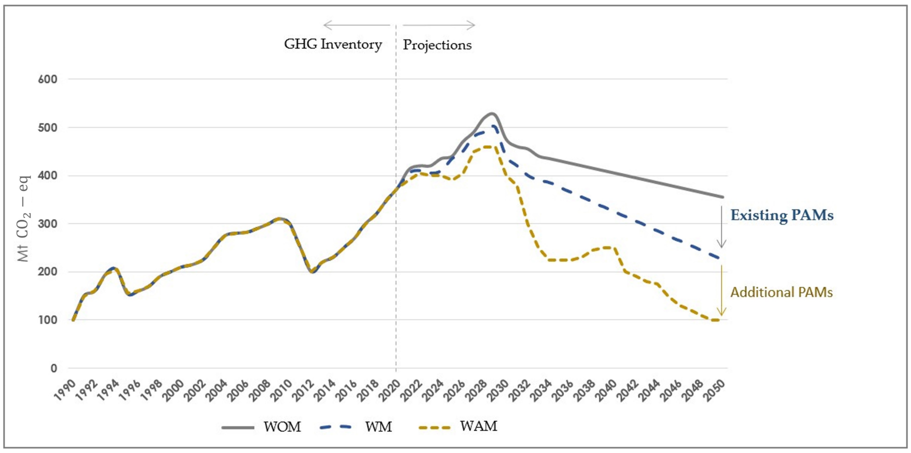

Figure 2. Illustrative example of scenario design from the WOM scenario.

3. Results and Discussion

The projection of the WOM scenario constitutes a critical step in developing mitigation scenarios, as it creates the benchmark against which the impact of PAMs is evaluated. The robustness f the results provided by MITICA for the WOM are analysed by applying different projection methods on historical datasets to ascertain the modelling approach providing best results compared to real data. Yearly datasets spanning a typical historical data length (approximately 30 years since UNFCCC data collection starts in 1990) plus the maximum prediction range (year 2050) are selected for analysis. Three datasets from the World Bank database are used: total energy use [52], goods export data [53] and use of alternative and nuclear energy [54]. The time period from 1960 to 2022 is categorised into historical (1960–1990) and projection (1991–2022) periods. The forecasting process considers GDP [55] and population [56] as proxies. These datasets serve as plausible representative examples of the data that MITICA will process, and the results can be compared to observed values. The selection of countries for the analysis is driven by data availability, and includes Australia, Finland, France, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom, and the United States. Figure 3 shows an extract of the results obtained for four countries.

The brown line depicts the actual observed data, juxtaposed with alternative forecasting methodologies within the MITICA framework, namely ANNALIST, GBR, and SARIMAX. Additionally, two methods are included for comparative analysis: a linear regression forecast and a linear extrapolation utilising the annual growth rate of the latest time series value (AG Forecast). AG Forecast serves as a metric for evaluating the performance of these methods, observing that the annual growth deviates further from the actual values. The examination of the figures reveals that, in general, ANNALIST and SARIMAX exhibit results closest to the real data, effectively capturing observed trends. The deviation of each model's results from actual data is quantified in Table 3, serving as a metric for assessing the performance of each modelling approach.

The average deviation, considering results across all countries, further indicates that ANNALIST, with its modelling approach, yields outcomes closest to the actual data. This underscores the proficiency of MITICA in generating scenario projections. The validation of PAMs has been analysed broadly in several studies [57–59], offering supporting evidence for the reliability of MITICA's outcomes in developing WM and WAM scenarios based on WOM results.

In addition to the earlier evaluations, the beta release of MITICA underwent testing with a variety of input datasets. These datasets encompassed the Tajikistan national GHG inventory sourced from [60], confidential information provided by Uruguay regarding its inventory, and a set of simulated databases from the IPCC software [61]. The testing primarily focused on assessing the functionality of the software and identifying any potential bugs.

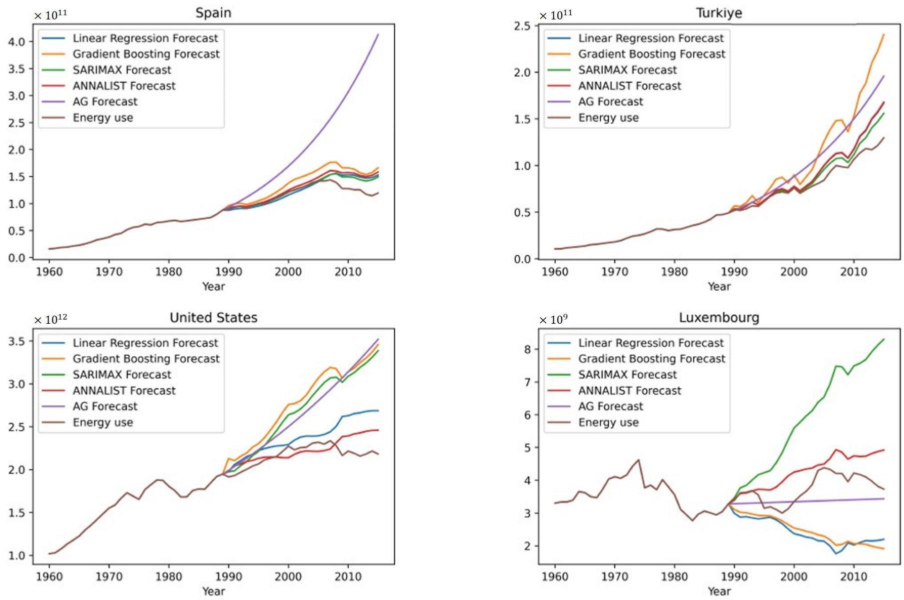

Figure 3. Robustness of MITICA's results, exemplified by the analysis of energy use data for Spain, Turkey, the USA, and Luxembourg.

Table 3. Deviation between the actual mean and the predicted mean of different models in the tested datasets.

	Linear Regression	Annual Growth	GBR	SARIMAX	ANNALIST
Goods export data	29%	127%	22%	28%	19%
Total energy use	19%	52%	25%	18%	16%
Use of alternative and nuclear energy	52%	-	56%	57%	44%
Mean	33%	-	34%	34%	26%
Average computing time (s)	0.038	0.013	0.05	52	0.97

4. Conclusions

Previous research has highlighted gaps and challenges in generating mitigation scenarios and ensuring consistent reporting under the ETF across various facets of GHG emissions. This encompasses areas such as national GHG emission inventories, the impact assessment of PAMs' impact, GHG emission projections, and NDC design and tracking, particularly for developing parties within the Paris Agreement.

An evaluation of existing models and approaches revealed several insights: (i) developed countries commonly employ a combination of sectoral models for each IPCC sector coupled with a top-down macroeconomic framework; (ii) alternatives used by developing countries exhibit strengths in assessing individual PAMs and developing sectoral models but show limitations in integrating all IPCC sectors and assessing PAMs within mitigation scenarios; (iii) diverse time-series innovative forecasting methods, applied in prior studies, offer applicability to address the study's challenges.

Building upon this foundation and introducing an innovative approach utilising machine learning regression techniques for GHG forecasting, MITICA successfully addresses identified goals. It establishes an integrated methodological framework for mitigation scenario production, ensuring consistency between national GHG emission inventories, PAMs, and projections. This allows for the transparent generation of mitigation scenarios, thereby facilitating NDC design and tracking, as well reporting under the ETF.

The MITICA approach has been subjected to comprehensive testing in three distinct phases. Initially, projections were computed utilising data spanning from 1960 to 1990 as a baseline, forecasting variables such as total energy use, goods exports, and the utilisation of alternative and nuclear energy for the period spanning 1991 to 2022. The exogenous variables GDP and population were incorporated into the analysis, computed for Australia, Finland, France, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Turkey, the United Kingdom, and the United States. A comparison of the MITICA projections against observed values from 1991 to 2022 reveals a cumulative deviation throughout the projected time series below 20 percent for total energy use and goods exports (16 and 19 percent, respectively). This alignment effectively captures the observed trends within the respective time series data, thereby affirming the robustness of the approach's results. Secondly, MITICA's methodology for evaluating PAMs has been tested in several published studies, providing additional evidence supporting the reliability of MITICA's outcomes. Finally, the beta release of MITICA underwent comprehensive testing using a diverse range of input datasets. This testing phase was crucial for assessing the functionality of the software and refining any operational bugs.

Several limitations are discerned in the development of MITICA. Aligned with its objectives, MITICA formulates projections based on the assumption that GHG emissions are solely influenced by a set of proxies, holding other factors constant. This assumption dictates that changes in technology mix and consumer behaviour solely occur due to the implementation of PAMs. While essential for the study's objectives, this assumption presents a significant limitation by overlooking the inherent evolution of emission profiles even in the absence of public intervention. Technology mixes and resource consumption are subject to modification based on different consumer preferences, which are not adequately captured by the current model. Although MITICA incorporates various PAMs allowing interventions at different levels (industries, consumers, or sectors), it fails to account for the natural evolution of emission sources and sinks without public intervention. Future enhancements could address this limitation by incorporating varying levels of change in further endogenous parameters into the WOM design to capture the evolution of emissions in the absence of public intervention.

The conducted robustness analysis indicates that the reliability of the forecast diminishes significantly in very long time frames. To enhance the reliability of mitigation scenarios beyond 2035, alternative methodological approaches such as back casting methods could be considered in conjunction with MITICA's existing approach. Moreover, the incorporation of back casting approaches into MITICA's framework could allow for a more holistic, long-term analysis without the necessity to define and calculate all PAMs individually. By adopting a forward-looking perspective, MITICA could provide a more comprehensive assessment of GHG emission scenarios.

Moreover, MITICA has not undergone empirical testing against alternative modelling frameworks. The use of sectoral methods instead of integrated sectors and the challenges in achieving consistency impede the identification of equivalent approaches to MITICA. Future research could address this limitation by conducting comprehensive empirical comparisons with alternative modelling frameworks, or sectoral modelling frameworks.

Further work in MITICA is identified in several key areas. Firstly, there is a need for extensive testing and fine-tuning, a process informed by rigorous testing outcomes. This iterative phase is crucial to enhance the reliability and precision of MITICA.

Additionally, MITICA should consider the incorporation of costs associated with PAMs and the generated scenarios. This enhancement would enable the model not only to estimate GHG emission reductions but also to provide insights into the potential costs associated with these mitigation measures. Such an inclusive approach would offer a more nuanced understanding of the economic implications of implementing various PAMs.

A further dimension for exploration involves assessing the impact of PAMs and GHG emission reductions on key economic variables such as GDP and population. Integrating the MITICA framework into a general equilibrium model would facilitate a comprehensive analysis, shedding light on the interconnected dynamics between environmental and economic factors.

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Appendix A

Appendix A.1. Challenges to Develop Mitigation Scenarios for NDC Design and Tracking

The identification of a disconnection between historical GHG trends and projections presents a notable challenge in assessing the evolution of mitigation efforts and global ambition [6,12,62]. When projecting unaudited or unofficial GHG emissions, the results become challenging to interpret in comparison to the actual historical GHG profile. This can result in biased assessments and the formulation of unrealistic NDC targets. Overcoming this issue could be achieved by using national GHG inventories estimated following IPCC Guidelines [15,16] as a basis for modelling GHG projections. In this context, authors of [12] determined that, particularly for economy wide NDCs encompassing GHG emissions and removals from all IPCC sectors, the consideration of national GHG inventories remains the most critical element for enabling tracking NDC progress. The study emphasised that adhering to the same IPCC methodological guidance for national GHG inventories and mitigation scenarios would significantly enhance the transparency and comparability of NDC progress tracking across all Parties under the Paris Agreement.

Another significant drawback identified in the literature pertains to the misalignment between PAMs and mitigation scenarios, which impacts the interpretability of results and increases uncertainty. Authors in [7] evaluated mitigation scenarios within submitted NDCs, revealing critical implications arising from the ambiguity of NDC assumptions for scenario development, lack of clarity on policy incorporation in mitigation scenarios, and the absence of robust tracking systems of GHG emissions, PAMs and NDC targets. This issue is also affected by inconsistencies between the PAMs considered in mitigation scenarios, due to the use of heterogeneous methodologies for PAMs of similar nature even within the same mitigation scenario, as identified by [63].

Exploring sectoral modelling approaches and their integration into mitigation scenarios reveals insights from several studies [8,9] suggesting that inconsistent sectoral methodological approaches result in unclear and uncertain aggregated emissions and targets. Such inconsistencies significantly affect the transparency of both national and global efforts, generating uncertainty when translating scenario results into specific policy actions. These varied sectoral modelling approaches adopted by Parties also considerably increase the challenge to assess and compare progress made towards achieving their NDCs as they often deviate from IPCC guidance or national GHG inventory standards.

The lack of consistency between GHG-related components is further emphasised by [13], stressing the need for an internally consistent package of information to effectively track NDC progress. Addressing linkages between different GHG-related elements becomes crucial for enhancing transparency, ensuring consistency across methodologies and data used in different communication and reporting tools, and facilitating timely communication or reporting.

The challenges enumerated could result in NDC targets that are unrealistic, detached from GHG emissions of each country, and fail to consider actual and future policy alternatives to reduce or avoid emissions [64,65]. Beyond technical aspects related to mitigation scenario development, the literature identifies significant drawbacks related to institutional and technical capacity in developing countries as overarching issues. Refs. [5,66] assert that developing countries urgently need to establish robust reporting systems and enhance national capacity to facilitate their transition to the ETF. In line with this, authors of [11] highlight the need for technical capacity on mitigation scenarios to alleviate reporting pressure on developing parties under the Paris Agreement. These considerations contribute to the design criteria for MITICA, emphasising the importance of a framework that does not introduce markedly different concepts compared to the existing baseline knowledge on GHG emissions and the latest IPCC Guidelines, currently [15,16].

Appendix A.2. Existent Models and Approaches to Produce Mitigation Scenarios

A diverse array of models and approaches for developing mitigation scenarios have been identified [19], offering potential solutions to the challenges described in the Appendix A.1 of the literature review. To evaluate the current state of the art, an initial analysis is conducted focusing on developed Parties' submissions on GHG emission projections and GHG emission targets to the United Nations Framework Convention on Climate Change (UNFCCC). These Parties have been engaged in generating estimates and national reports since the 1990s, in line with the requirements of the UNFCCC and the Kyoto Protocol, particularly for monitoring progress towards national mitigation targets [67].

Detailed insights into the models and approaches employed by the analysed developed countries are presented in Table A1, drawing on information reported in their last submissions to the UNFCCC available, namely the eighth National Communication (NC) and Fifth Biennial Report (BR) under the UNFCCC. The utilisation of sectoral models for each IPCC sector, in line with national GHG inventory methodologies, combined with a top-down macroeconomic framework is a common practice. Notably, national modelling systems often prioritise two IPCC sectors: the Energy sector, including transportation, and the Land Use, Land-Use Change, and Forestry (LULUCF) sector. Energy planning optimisation models, such as TIMES-Markal [68], are observed in 10 out of 32 developed countries analysed. Similarly, various countries employ national-specific carbon models for LULUCF, as documented in [69–72]. The energy and LULUCF sectors often encompass areas with higher mitigation potential, either for the reduction of emissions or the enhancement of sinks. Therefore, this is identified as the main reason for prioritising improvements in the modelling approach for these two sectors. Conversely, the Waste and Industrial Process and Product Use (IPPU) sectors are frequently approached as an extension of the national GHG inventory methodology, estimating projections using ad hoc nationally customised models.

Table A1. Assessment of models and tools used by Annex I Parties to the Kyoto Protocol to create GHG emission scenarios. Eight National Communication and Fifth Biennial Reports submitted to the UNFCCC.

Country	Models and Tools Used	Assessment of Consistency	Source
Australia	"Purpose-built, bottom-up models estimating emissions by sector" for the Stationary energy, transport, fugitive emissions, IPPU, LULUCF, Agriculture and Waste sectors. For electricity, Australia uses the model PLEXOS [73], a linear programming optimisation model.	The Department of Climate Change, Energy, the Environment and Water applies consistent assumptions across all sectors of these projections. Data used: Inventory data and Emission factors and Commodity forecasts from different public agencies.	[74]
Austria	An economic top-down model (DYNK model; [75]) combined with sectoral specific models, as follows. Energy sector. Domestic heating and domestic hot water supply model (INVERT/EE-Lab model; [76]), Public electrical power and district heating supply (TIMES Austria model; [77]) and Energy demand and emissions of transport (NEMO & GEORG model; [78]). IPPU and Waste sectors. Expert judgement based on national reports. Agriculture sector. Austrian agricultural model (PASMA model; [70]). LULUCF models. For forest growth two models were used, one on individual-tree based forest growth model (CALDIS model; [69]), and one for organic soil carbon YASSO 07 (YASSO 07 model, [79]). For cropland and grassland, PASMA model [70]. For harvested wood products, a forest sector simulation model (FOHOW2 model, [80]).	The same methodologies as for the national GHG inventory are applied, as reported in Austria's National Inventory Reports. The projections are consistent with the historical emission data of the Austrian Emission Inventory.	[81]
Belgium	Belgium uses different models by region and sector, as follows: The Flemish energy and greenhouse gas simulation model, a bottom-up model for all sectors except LULUCF (no reference available). FASTRACE [82], a traffic emission model that uses a detailed break-down of the vehicle fleet to simulate the flow of traffic. TIMES Wallonia [83] for the energy sector emissions and customised excel tools for the remaining sectors.	The lack of documentation available impedes the assessment of consistency. For Wallonia, the study mentions that "Wallonia is in a transition period. Ultimately, the idea is to perform all the scenarios using the same tool(s), while linking the different models used in the most effective possible way", pointing out to potential consistency issues resulting from the use of different models.	[84]
Bulgaria	Bulgaria uses only one tool, focused on the energy sector: the (B)EST Energy System Tool, which projects the energy demand, supply and energy prices using macroeconomic and demographic proxies provided by different Ministries. (B)EST Energy System Tool is an optimisation tool developed in the General Algebraic Modelling System (GAMS; [85]), aimed at minimising the cost by finding the equilibrium with the price-elastic behaviours of demanders for energy. Projections for IPPU, Agriculture, LULUCF and Waste sectors are projected ad hoc based on the inventory methodology and the outputs from the energy modelling.	The same macroeconomic and demographic framework is used for projecting all sectors. Inventory data is used as a reference for projecting all sectors.	[86]
Canada	Canada applies the Environment Canada's Energy, Emissions and Economy Model for Canada (E3MC model), which incorporates a Keynesian economic model that provides long-term economic forecasts, with an optimisation energy model that balances energy supply and demand.	Canadas approach considers the interaction between policies. However, no information is provided in the study on how non-energy sector emissions are modelled, pointing out to a potential source of non-consistency.	[87]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Cyprus	Cyprus makes use of two models for the energy sector, an optimisation model for energy planning (OSeMOSYS; [88]) and Final energy demand projection model (no further information available). Waste sector projections were developed through the 2006 IPCC waste model, while the projections of Agriculture and LULUCF are based on trends in the activity data used in the emission inventory calculation. No information is provided on the projections developed for IPPU.	The report described that three elements ensure the alignment of projections with the national inventory: data sources (the same sources for inventory and projections), methodology (the latest methodology from the national inventory), and experts (the experts involved in the preparation of the inventory are the same as the experts involved in the preparation of the projections).	[89]
Czechia	Czechia reported the use of models for the energy (a data-driven model structure applying expert judgement), LULUCF (a carbon budget model of the Canadian forest sector; [71]) and IPPU sector (a bottom-up model for F-gases; [90]), while projections for agriculture and waste are described to be linked to inventory calculations.	Czechia reported issues in the model previously used for energy, the MESSAGE model, due to due to laborious data entry and incompatibility with models from neighbouring countries. Information reported suggest consistency between approaches followed in the GHG inventory and projections.	[91]
Denmark	The methodologies followed for projections are linked to [92], that provides an overview of the models and tools used. Models are based on a list of assumptions by sector which pass a public consultation process. Sectoral models used include a simulation model for electricity (RAMSES model; [93]), a model that integrates a general equilibrium model with an energy system model (IntERACT model; [94]) and a transport model (FREM model, no reference available).	The authors in [95] describe that projections are a collection of a number of different projections from the Danish Energy Agency and the Danish Centre for Environment and Energy, which the Danish Energy Agency combined with statistical data to produce an overall projection for Denmark.	[95]
Estonia	Estonia used different models by sector and subsector consistent with 2006 Guidelines and EMEP/EEA manuals. For electricity generation, Estonia used a cost optimisation model (The Balmorel model; [96]). A tool for estimating the stock of vehicles was used for the GHG projections in the road transport sector (Sybil baseline model; [97]). The model is compatible with COPERT, the approach used in the national GHG inventory. In the IPPU sector, Estonia uses activity level projections from companies and expert judgement. In the Agriculture sector, Estonia uses a dynamic econometric model based on proxies (Agriculture Projections Model; no external references), developed in 2021 by Agricultural Research Centre. For LULUCF, projections are developed based on expert judgment and assumption by category level. For Waste, projections are estimated with the 2006 IPCC Waste Model.	Estonia uses activity data from the inventory in all cases. No further information is provided on the consistency of the different GHG components.	[98]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Finland	Finland describes a common projection framework with common assumptions and a common economic model (FINAGE model; [99]), which is connected to sectoral sectors as follows. An optimisation energy system model (TIMES-VTT energy system; [100]). A model exercise for the energy consumption of the building stock (VTT model; no further reference available). A model to estimate future vehicle fleet, energy and fuel consumption and GHG emissions (the LIPASTO model; [101]). A model on off road vehicles, which is used for the inventory calculations, and also for projections (TYKO machinery; no further reference available). A dynamic regional sector model of Finnish agriculture (Dremfia model; [102]), together a nitrogen application model, and a computation approach in excel file. A carbon accounting model for soil carbon (MELA model, based on the YASSO model—[72,79]) for the LULUCF sector.	Finland applies sector-specific modelling that is coordinated and manually interlinked across sectors.	[103]
France	France describes the use of a large variety of sectoral techno-economic models, whose energy consumptions and GHG emissions are aggregated in accordance with GHG inventory methodologies. This modelling approach allows for a fine description of sectoral transformations associated with the scenarios. Some of the models used include a model for energy (GEStime tool; no further reference available), transport (Modev model; no further reference), for the buildings sector (Menfis model on energy efficiency; [104]), and one bottom-up model for the agriculture and forestry sector.	On the consistency between models, the report stated that "Its main weakness, compared to the use of a single top-down model, is that extra attention needs to be given to the potential interactions between sectors, and that it takes a long time to proceed to all the modelling (one full run may take up to 6 months)."	[105]
Germany	Germany employs sector-specific models integrated through the EnUSEM integration model, ensuring a cohesive amalgamation of approaches (no further reference found in English language). The sectoral models encompass the transport sector, which utilises Öko-Institut's TEMPS model (no further reference available). For the buildings sector, both residential and non-residential, the INVERT/EELab model is employed (INVERT/EE-Lab model; [76]). Electricity is modelled using FORECAST, and partially IPPU. FORECAST is a bottom-up simulation model focused on the energy sector and the development of long-term scenarios [106]. AFOLU employs an ad hoc bottom-up model developed by the Thünen Institute (no further reference available). Waste emissions are calculated internally within the inventory.	The report specify that the scenario calculations rely extensively on the National Greenhouse Gas Inventory. Sectors are integrated with support from an additional model, the EnUSEM integration model. However, no information is provided on how the integration is performed.	[107]
Greece	Greece employs distinct approaches for the energy and non-energy sectors. In the energy sector, the country utilises the Integrated TIMES-MARKAL model along with a probabilistic production simulation model (ProPSim). On the other hand, GHG emissions in the non-energy sectors are computed using spreadsheet models. These models determine emissions through the analysis of activity data, emission factors, and sector-specific assumptions.	The same exogenous forecasts are used in all sectors, based on most recent data available at country level. The study specifies that models are fully consistent with the inventory	[108]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Hungary	The Integrated MARKAL-EFOM System and the Green Economy Model (GEM) originated from a computer simulation approach tailored to streamline policy planning over the medium to long term.	The interaction between GEM and TIMES occurs through two mechanisms. In the first, GEM operates its energy modules. Alternatively, in the second approach, GEM utilises inputs from TIMES, bypassing its own energy demand calculation. This approach enables the integration of the strengths of both models, capitalising on the dynamic and comprehensive nature of GEM alongside the higher level of detail for the energy sector offered by TIMES.	[109]
Ireland	Ireland described its projections of energy demand by the use of a general equilibrium model (I3E model; [110]), which is used to assess impact of PAMs withing policy scenarios and is used in conjunction with other modelling tools (the following tools are mentioned: Plexos Integrated Energy Model, SEAI National Energy Modelling Framework, SEAI BioHeat Model).	Sectoral interlinkages are approached within the I3E model. No further information is provided.	[111]
Italy	TIMES-MARKAL combined with customised bottom-up models by sector consistent with TIMES-MARKAL outputs and inventory methodologies, for the agriculture, LULUCF, waste F-gases and Industrial process sectors.	Common assumptions and general economic parameters are described to be used in all sectors to ensure consistency. Inventory methodology is considered as a main reference for all sectors (with the exception of the use of the reference approach for energy sector emissions, based on TIMES-MARKAL outputs).	[112]
Japan	Japan described the use of a main model for fuel combustion emissions (IPCC category 1A), using an energy supply and demand model, which is composed by several sub-models, namely a macroeconomic model, an energy price model, and an optimum generation planning model. The projections in sectors other than fuel combustion are conducted by bottom-up models created using spreadsheets following the calculation methods of the national GHG inventory, extended to projected years.	The report emphasises the importance of preventing overlaps in emission reduction efforts between PAMs related to energy consumption and measures pertaining to the energy supply. The efficacy of the energy supply and demand model lies in its capability to comprehensively address various factors influencing both energy consumption and CO_2 emissions within a single model. Nevertheless, there is a lack of information regarding the methodological consistency across sectors and components.	[113]
Latvia	Two main models are used, one for energy (TIMES-Markal) and another one for LULUCF (AGM using data from the national forest inventory; [114]). The remaining sectors are projected using Excel or R-based estimations of activity data, maintaining methodologies from the latest inventory.	The report specifies that the modelling approach followed ensures the comparability of calculations with those of the inventory as well as the calculation consistency. However, the potential for human errors in the calculations as well as the simplicity of the calculations are highlighted as main weaknesses.	[115]
Lithuania	Lithuania has built nine bottom up models representing all relevant emission sources and sinks. In all cases, the models are built from inventory methodologies, using common proxies and parameters, consistent with EU recommended parameters. No further references available on the models used.	The Information provided did not allow an assessment of consistency between components. The report describes that the main weaknesses of the models/approaches is that it does not take into consider overlap or synergies that may exist between different PAMs.	[116]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Malta	PAMs are reported to be estimated using a Marginal Abatement Cost Curve (MACC) tool plus eleven bottom up models for sectors and subsectors as follows: Electricity dispatch model, Industry Fuel Consumption model (non-transport), Energy Demand Model, Road transport Biofuels S/O Model, PV model, Road Transport Model, IPPU sector, Inland Navigation Fuel Consumption Model, Agriculture Model, LULUCF model, Waste generation and treatment model (Waste sector).	Models are interlinked among each other. However, the information reported did not allow to fully assess the consistency of reporting components.	[117]
Netherlands	The National Energy Outlook Modelling System (NEOMS) is a comprehensive suite encompassing various simulation models for different sectors. SAVE-Productie calculates energy demand for industry, agriculture, and CHP based on economic growth and measures taken. SAVE-Services projects future gas and electricity demand in the services sector using economic subsector growth and interventions. SAWEC evaluates household energy use, while EVA modelling national electricity consumption of household appliances. The transport model incorporates diverse sector-specific transport models into NEOMS databases. COMPETES guides decisions on centralised EU electricity production investments and operations. SERUM optimises the Dutch oil refining sector, calculating crude intake and refining configuration. RESolve-E focuses on renewable energy production, and the gas/oil production model determines natural gas and crude oil supply. NEOMS results are supplemented with non-CO_2 and non-energy-related CO_2 emissions modelling using sectoral models and spreadsheet tools. This suite provides a holistic view of the national energy landscape, integrating diverse sectors and anticipating future energy demands while considering economic and policy factors.	Within the energy sector, the consistency is made by integrating submodels within NEOMs. The consistency between sectors, within PAMs and between projections and the inventory are not further detailed.	[118]
New Zealand	Projections of greenhouse gas emissions are estimated across various sectors using different methodologies. In the energy and transport sectors, a bottom-up approach is used, relying on economic data, energy sector information, and inventory models to project future emissions. IPPU projections utilise a top-down methodology, considering historical emissions, industry forecasts, and F-gas import regulations. Agriculture projections adopt a bottom-up approach, integrating economic and agricultural data along with inventory models. LULUCF projections involve a bottom-up modelling approach, leveraging historical and projected activity data to assess the impact of PAMs on emissions. Waste projections utilise bottom-up methodologies with inventory models following IPCC guidelines. International transport projections employ a top-down approach based on historical emission data. These sector-specific methodologies contribute to comprehensive and accurate projections of future greenhouse gas emissions.	The report specifies that the consistency among sectors is achieved using key underlying assumptions that are consistent across sectors, while the modelling approaches used are tailored to the particular characteristics of each sector	[119]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Norway	Norway's emission projections employ diverse sources and methods. Energy-related emissions projections primarily use simulations with the macroeconomic model SNOW (no further references available), supplemented by micro studies within a computable general equilibrium model. Emission projections from LULUCF sector are derived from the Norwegian Institute of Bioeconomy Research (NIBIO) using the Yasso07 decomposition model. Other sectors use an Excel spreadsheet model based on inventory methodologies for estimation.	The Information reported did not allow to fully assess the consistency of reporting components. However, the use of common parameters as well as the consistency with the national inventory were described in the report.	[120]
Poland	The STEAM-PL and MESSAGE models were used to prepare a forecast of the national energy demand and its results were then used to estimate the greenhouse gas emissions from the energy sector. STEAM-PL is an "end-use" consumption model dedicated to the national fuel and energy system, reflecting in detail the technical aspects related to energy use in the particular sectors of the economy. It is an integrated hybrid model which makes it possible at the same time to determine the future energy demand for useful energy (using the classical "bottom-up" approach) and the ways of meeting the demand (using the "top-down" approach). On the basis of the identified electricity and district heat demand, in the next step, the optimum structure of the generation sector and the demand-driven production by individual generation units in the MESSAGE-PL model was determine	The Information reported did not allow to fully assess the consistency of reporting components. However, the use of common parameters as well as the consistency with the national inventory were described in the report.	[113]
Portugal	Energy system: GHG emissions were estimated based on the TIMES_PT. Agriculture, forests and other land uses: GHG emissions were estimated based on different assumptions aligned with the narratives of the socioeconomic scenarios, from which the respective evolutionary trends of the crop and animal sector, and their emissions, were established. Waste and wastewater: GHG emissions were estimated based on projections of the volume of municipal waste and domestic wastewater generated each year, considering the resident population, and the impact of the policies already adopted. This sector includes emissions from the Fluorinated gases: GHG emissions were estimated based on the implications of implementation of the Kigali Agreement and the European Regulations that foresee the phasing out of some of these gases over coming decades.	In all sectors, GHG emissions estimation follows the methodologies presented in the national emissions inventories, which comply with the emissions calculation guidelines of the 2006 Intergovernmental Panel on Climate Change and relevant UNFCCC decisions for calculation of emissions and reporting emissions projections	[121]
Slovakia	The report described that projections in Slovakia are based on the MS Excel platform and the calculation includes various policies and measures defined according to the WM and WAM scenarios. The projections of emissions and removals in the Forest category used outputs from the national FCarbon model to project LULUCF emissions (no further reference available).	The report justified the use of the national Fcarbon model based on the requirements for consistency with the reporting of GHG emissions and removals in national emission inventories and also the inclusion of forest dynamics through characteristics related to the age structure of the forest. The information available did not allow further analysis of consistency between components.	[122]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
Slovenia	Several models were used to produce projections in Slovenia, including a technology simulation bottom-up model for energy (the Reference Energy Ecological Model for Slovenia; no further reference in English), a transport model for Freight and passenger transport (Integralni prometni model Slovenije; no further reference in English available), and a model for LULUCF emissions (the CBM-CFS3 model; [123]).	A relational model is used to compile GHG projections integrating all sectoral estimates (the BILANCA TGP NH3 NOX model; no further reference available in English).	[124]
Sweden	Sweden's approach to projecting GHG emissions involves comprehensive methodologies for various sectors. Projections for the whole energy system are made using the national version of TIMES-Markal [68], which includes its relationship with neighbouring countries (Times-Nordic; no further reference available). Industry sector projections rely on an Excel-based model linking energy use with economic relations and energy prices. Transport sector emissions projections are based on energy use forecasts. Industrial process emissions are determined through Excel-based trend analysis. Waste sector landfill emissions use a modified IPCC model. Agricultural sector projections rely on the Swedish Agricultural Sector model (SASM model; no further reference available) and economic equilibrium assumptions. Forest land net removals projections mainly use the Heureka Regwise modelling tool, simulating future forest development.	The report does not address specifically how consistency between components is addressed.	[125]
Switzerland	Switzerland describes the modelling approach followed for all sectors. In the energy sector, a network of various energy system models is utilised, and the resulting energy demand is integrated into the EMIS national air pollution database to calculate GHG emissions. For Industrial Processes and Product Use and Agriculture sectors, bottom-up estimates align with the 2006 IPCC guidelines for national GHG inventories. LULUCF projections utilise the Massimo model, a stochastic empirical single tree forest management scenario model for CO_2 emissions, incorporating simple assumptions for CH_4 and N_2O.	The report describes that the modelling scenarios are tailored to the particular characteristics of each sector, always ensuring consistency with actual data of the greenhouse gas inventory.	[126]
Türkiye	The report only mentions that the "TIMES-MACRO model has been used for energy related modelling and industrial processes and product use, while for non-energy emissions different national models and studies have been used"	The Information reported did not allow to fully assess the consistency of reporting components.	[127]

Table A1. *Cont.*

Country	Models and Tools Used	Assessment of Consistency	Source
United Kingdom	The UK employs a comprehensive modelling approach for emission projections, primarily using the national Energy and Emissions Projections modelling suite for annual publications and internal analyses. The suite encompasses a top-down econometric model of energy demand and combustion-related GHG emissions, complemented by a bottom-up supply side Dynamic Dispatch Model. Energy demand projections undergo adjustments for policy impacts modelled separately using detailed sectoral models. The Transport sector utilises a road transport model integrated into the Energy Demand Model, calibrated against the National Transport Model. For IPPU, CO_2 emissions projections rely on Manufacturing subsector Gross Value Added or energy demand projections. LULUCF emissions are modelled by the Centre for Ecology and Hydrology and Forest Research. Waste projections use the national MELMod model, based on IPCC's first-order decay methodology. Agriculture projections employ the Food and Agricultural Policy Research Institute methodology for activity projections up to 2030, with later years held constant.	The modelling estimates the mitigation impacts of policies using a common cross Government methodology.	[128]
United States of America	The United States reports using a differentiated approach for modelling energy CO_2 emissions and non-energy CO_2 and non-CO_2 GHG projections. In the first case, the National Energy Modelling System (NEMS) is employed. NEMS is organised and implemented as a modular system, with modules representing fuel supply markets, conversion sectors, and end-use consumption sectors of the energy system. Additionally, NEMS includes macroeconomic and international modules. It utilises information from the most recent greenhouse gas inventory as the starting point for emissions and underlying activities. The Environmental Protection Agency (EPA) projects changes in activity data and emission factors from that base year, incorporating macroeconomic drivers such as population, gross domestic product, and energy use, as well as source-specific activity data. Official sources are consulted where possible, and future changes in emissions factors are determined by past trends and expected policy implementations.	PAMs are integrated in the modelling approach for projecting CO_2 emissions from the energy sector. Furthermore, non-CO_2, and non-energy emissions are estimated building from inventory methodologies.	[129]

In summary, it is observed that most developed Parties adopt sector-specific bottom-up models built from national GHG inventory methodologies and use them in conjunction with macro top-down models incorporating exogenous drivers that characterise their respective national economies. A notable drawback identified in this approach is the substantial resources, including time, personnel, and budget, required for generating distinct mitigation scenarios for each IPCC category and sector. This is attributed to the considerable human interventions necessary in model production.

Apart from analysing approaches employed by developed countries, the paper also delves into the modelling approaches currently applied by developing countries for the development of mitigation scenarios within submitted NDCs. This provides insights into the starting situation that MITICA should build upon. Since [20] have already outlined the main alternatives for developing countries, this paper does not offer an exhaustive review on the subject. Several models and tools are broadly recommended for adoption in developing countries, including LEAP, GACMO and NEXT, among others.

The Long-range Energy Alternative Planning (LEAP) system is applied by numerous countries to produce mitigation scenarios within the energy sector [130]. LEAP is defined as a framework that could be used to accommodate different modelling approaches [131]. The main drawbacks found in countries using LEAP is the challenge to clearly incorporate and assess the impact of PAMs, considering historical GHG emission trends, as well as the uncertainty associated with ad-hoc modelling assumptions beyond the scope of energy planning. As such, the use of LEAP may impede the accurate reporting of the impacts of individual PAMs, as well as the comprehensive modelling of all sectors within the national GHG inventory.

The Greenhouse gas Abatement Cost Model (GACMO) is a GHG projections tool developed by the United Nations Environment Programme (UNEP) [132]. GACMO operates by inputting the national energy balance and utilises growth rates for various sectors to create GHG emission projections. It offers methodologies for estimating the mitigation impact and cost of various policy alternatives, aligning with internationally recognised methodologies. Despite its strengths in addressing PAMs, GACMO does have limitations. These include the simplistic approach to projecting GHG emissions, the limited consideration of the national GHG inventory, and the inability to directly create WM and WAM scenarios.

The Nationally Determined Contribution Expert Tool (NEXT) is a GHG accounting tool to support annual environmental impact assessment (EIA) for the Agriculture, Forestry and Other Land Use (AFOLU) sector [133]. The NEXT tool adheres to ETF definitions and IPCC good practices, and therefore is considered as a robust alternative to produce mitigation scenarios in the AFOLU sector. However, the incorporation of the energy, waste, and IPPU sectors remains a challenge for this tool.

The Paris Agreement requires that developing countries adhere to reporting requirements equivalent to those of developed countries, although flexibility provisions are provided [67], but which are not considered in this study. As such, it's implied that comparable approaches to those of developed parties should be adopted by developing countries. Additionally, MITICA draws inspiration from the main modelling alternatives utilised by developing countries, offering an extensive list of possibilities for PAMs, and developing sector-specific modelling approaches. Considering various alternatives discussed in the literature [19,20], the most suitable option to meet the study's requirements appears to be statistical frameworks with the flexibility to accommodate diverse sector-specific models tailored to different circumstances and data availability, while maintaining overall consistency across sectors, scenarios, and time periods. In this vein, Appendix A.3 delves into the key insights from the literature review on time series forecasting approaches, commonly employed in projecting GHG emissions.

Appendix A.3. Time Series Forecasting

The widely applied autoregressive integrated moving average (ARIMA) models offer several advantages in the context of time series forecasting for GHG emissions. One notable advantage lies in their ability to capture and model the temporal dependencies within the data. Furthermore, ARIMA models have the capacity to autonomously determine the appropriate order of differencing, autoregressive, and moving average components, thereby alleviating the need for manual intervention in selecting these parameters. The estimation of parameters in ARIMA is based on rigorous statistical methods, enabling robust inference and hypothesis testing [134].

The authors of [25,135] provide relevant examples of the use of ARIMA models for projecting time series data. In [25], the authors employed ARIMA models for forecasting energy consumption and GHG emissions from pig iron manufacturing in India. Their findings highlight the need to properly define the ARIMA model specification to obtain accurate results. Similarly, the authors in [135] applied ARIMA models to project CO_2 emissions in South Africa for the years 2015–2027, highlighting the relevance of the approach for framing feasible environmental policies. Despite their strengths and applicability in projecting greenhouse gas (GHG) emissions, ARIMA models have certain limitations that require consideration in the context of time series forecasting for GHG emissions. One notable drawback is the limitations associated with dealing with the complex and nonlinear dynamics of GHG emissions [136]. Additionally, ARIMA may face challenges in adequately addressing long-term trends or cycles, as its forecasting horizon is inherently limited [137]. These limitations may impede the model's utility when projecting GHG emissions over extended timeframes. Consequently, ARIMA models were discarded for MITICA, as they fail to meet its conceptualisation requirements.

A refinement of ARIMA models that mitigates most of its challenges is found in the Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) framework. Notably, one significant improvement offered by SARIMAX is its ability to incorporate exogenous factors alongside the autoregressive, integrated, and moving average components. This feature proves particularly advantageous in the context of GHG emissions, where various environmental, economic, or other determinants may drive emissions trends. SARIMAX is better equipped to handle nonlinearity in the data and provides a longer forecasting horizon compared to traditional ARIMA models [138]. As such, by leveraging the seasonal components and incorporating exogenous variables, SARIMAX can produce more accurate and reliable forecasts over an extended period, addressing one of the limitations of ARIMA that restricts its forecasting capabilities beyond a short timeframe.

Authors of [26] applied SARIMAX to forecast hourly electricity generation for the year 2015, utilising data from 2012 to 2014 for calibration. The study found that the SARIMAX model incorporating exogenous proxies provides the best fit to the actual data. Similarly, the authors in [27] compared the ARIMA and the SARIMAX methods in forecasting natural gas production and consumption in the United States from 2013 to 2025. Their findings revealed an improved forecast accuracy for SARIMAX, measured by the results of the root mean square error (RMSE) and mean absolute percentage error (MAPE) as indicators.

In addition to ARIMA and SARIMAX methods, state-of-the-art prediction approaches for time series data include different methods based on artificial intelligence and machine learning techniques. These approaches use computation to improve the model efficiency and prediction accuracy. Among the main innovative methods, four stand out for their applicability and widespread use: Support Vector Regression (SVR), Artificial Neural Network (ANN), Random Forest Regression, and Gradient Boosting Regression (GBR).

By using observed data to estimate a function, the SVR approach trains a Support Vector Machine (SVM). SVM is widely used to accurately forecast time series data, particularly in situations where the underlying system processes are nonlinear, non-stationary, and lack a predetermined framework [45]. The main weaknesses of SVR for time series forecasting include sensitivity to hyperparameter estimation, and challenges in handling noisy or high-dimensional time series data. Furthermore, SVR frequently needs data normalisation, added to an observed propensity for the overestimation of the influence of exogenous factors in model specification [139].

ANNs constitute a class of machine learning models inspired by the structure and functioning of the human brain. Comprising interconnected nodes, or neurons, organised into layers, ANNs are proficient in learning complex relationships from data. In the area of time series forecasting, ANNs exhibit prowess in non-linear modelling, enabling them to capture complex temporal patterns and depict dynamic relationships in sequential data. However, an important drawback of ANNs is their tendency to overfit, particularly in the presence of noise or outliers in the training data, leading to suboptimal generalisation to new data. Additionally, the training process of ANNs often requires substantial amounts of data, and they may struggle with performance when faced with limited datasets.

Random Forest Regression, an adaptable ensemble technique, displays considerable potential in time series forecasting, outperforming in the analysis of high-dimensional data and discerning complex non-linear patterns. Its ability to mitigate overfitting, achieved through ensemble averaging of individual tree predictions, contributes to the creation of more robust and comprehensive models [140,141].

GBR stands out as a robust machine learning technique known for its effectiveness in time series forecasting. As an ensemble learning technique, GBR combines the strengths of several weak learners—typically decision trees—to gradually construct a predictive model. The key of GBR is its capacity to improve its forecast accuracy incrementally by iteratively rectifying errors made by earlier models. Particularly adept at identifying complex temporal patterns, trends, and dependencies in data when it comes to time series forecasting, GBR outperforms in managing nonlinear interactions, rendering it well-suited for situations characterised by complex and non-stationary temporal processes. Several studies have compared the applicability and performance of the main methods for time series forecasting. For instance, in their study on forecasting the net ecosystem carbon exchange between biological organisms and the atmosphere, the authors of [38] demonstrated that GBR outperformed SVM, Stochastic Gradient Descent, and Bayesian Ridge techniques. GBR shows higher R-squared values, as well as lower mean absolute error and root mean squared error values. These results confirmed the finding from [36,37], which showed the advantages of GBR, notably its low prediction errors and increased stability.

Furthermore, authors in [32] projected the CO_2 emissions from India up to 2030 using a dataset from 1980 to 2019. They employed various methods, including ARIMA, SARIMAX, the Holt-Winters model, random forest model and a deep learning-based long short-term memory (LSTM) model. Their study concluded that SARIMAX and the LSTM showed the most accurate prediction results.

Based on the previous studies, we concluded that SARIMAX, GBR and the Random Forest Regression model align best with the requirements of MITICA for projecting the WOM. These methods demonstrate good modelling results with limited time series data and offer the capability to specify category-specific models by emission source. Conversely, deep learning methods, ANN and SVR were discarded due to their dependency on big datasets and their tendency to overfitting.

Finally, various studies underscore the applicability of LASSO (Least Absolute Shrinkage and Selection Operator), a novel regression model that integrates shrinkage and variable selection methods to improve prediction accuracy. LASSO has demonstrated superior performance in forecasting time series with limited samples, as demonstrated by [42,44]. Hence, it is emphasised in this literature review for its applicability under the requirements of this study.

Appendix B. Modelling Steps in ANNALIST

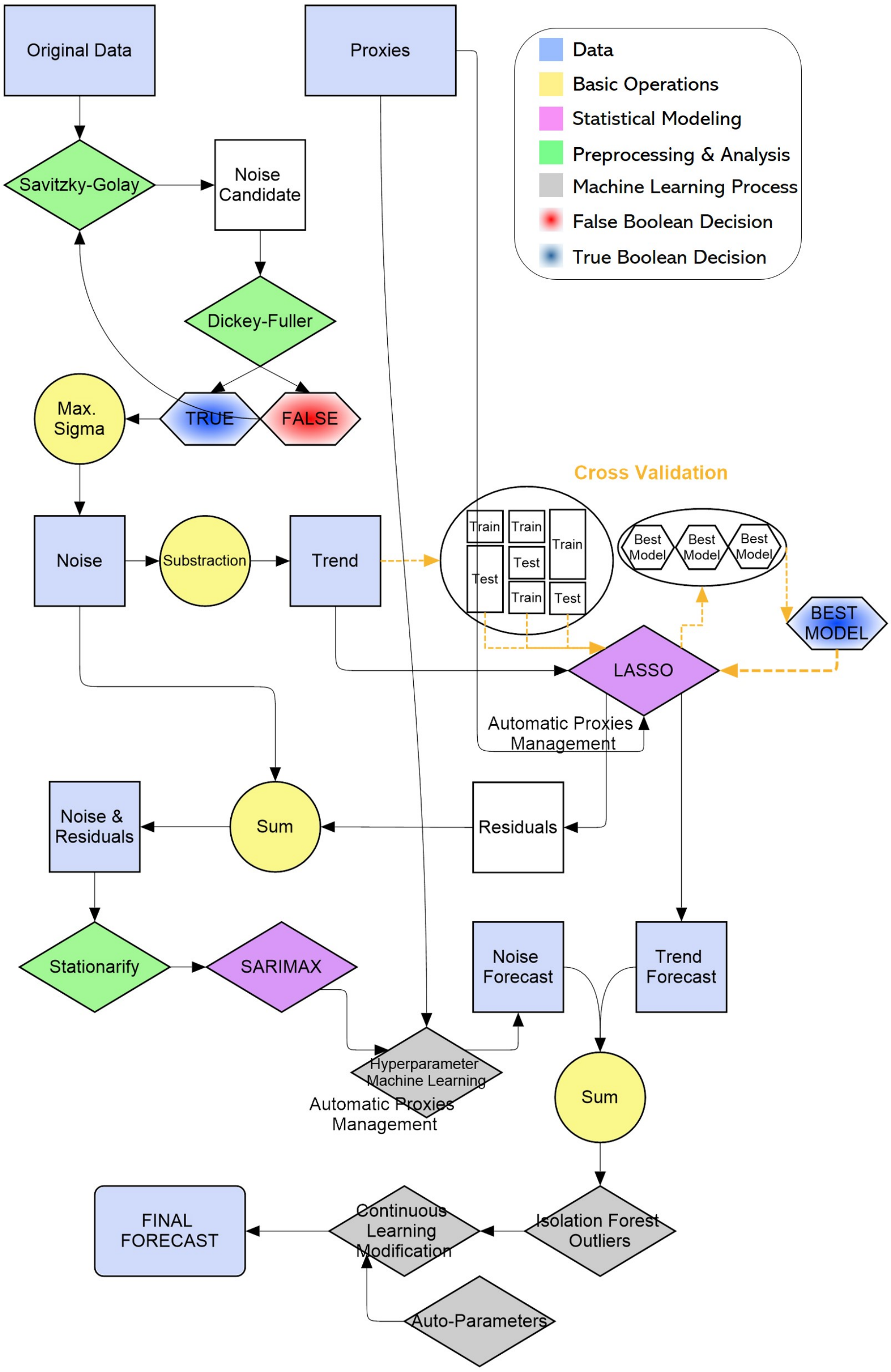

Figure A1. Modelling steps in ANNALIST.

Appendix C. MITICA Workflow

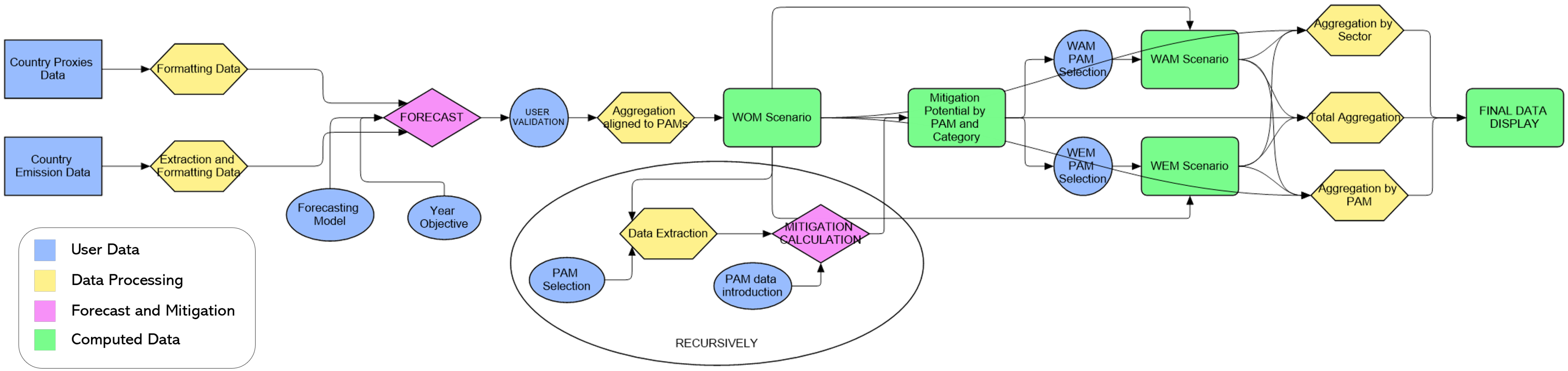

Figure A2. MITICA Workflow.

Appendix D. List of PAMs Incorporated in MITICA

Table A2. List of PAMs incorporated in MITICA.

IPCC Sector	Mitigation Sector	Name of the Policy	Associated IPCC Category
Energy	Power sector	Use of RES for power production	1A1a
Energy	Power sector	Commissioning of new efficient plants and/or fuel switch to less carbon intensive fuels	1A1a
Energy	Power sector	Production of electricity from biomass residues	1A1a
Energy	Power sector	Improvement of the energy efficiency of the electricity grid	1A1a
Energy	Power sector	Development of advanced metering infrastructure in the electricity grid	1A1a
Energy	Industry	Fuel switch from coal to natural gas	1A2
Energy	Industry	Fuel switch from coal to biomass	1A2
Energy	Industry	Fuel switch from Heavy Fuel Oil (HF) to Natural Gas (NG)	1A2
Energy	Industry	Replacement of clinker with other physical raw materials	2A1
Energy	Industry	Combined Heat and Power (CHP) in industry	1A2
Energy	Transport	Renewal of diesel vehicles	1A3b
Energy	Transport	Renewal of gasoline vehicles	1A3b
Energy	Transport	Fuel switch from fossil diesel to biodiesel	1A3b
Energy	Transport	Fuel switch from fossil gasoline to bio-gasoline	1A3b
Energy	Transport	Electric cars	1A3b
Energy	Transport	Electric mopeds	1A3b
Energy	Transport	Battery Electric Buses	1A3b
Energy	Transport	Promotion of public means or transport and more energetic ways of transport	1A3b
Energy	Other sectors (Commercial, Residential and Agriculture)	Fuel switch from diesel to NG	1A4a 1A4b
Energy	Other sectors (Commercial, Residential and Agriculture)	Fuel switch from diesel to biomass efficient boilers	1A4a 1A4b 1A4c
Energy	Other sectors (Commercial, Residential and Agriculture)	Fuel switch from diesel to biomass high efficiency stoves	1A4a 1A4b
Energy	Other sectors (Commercial, Residential and Agriculture)	Retrofitting of buildings towards improving energy efficiency	1A4a 1A4b
Energy	Other sectors (Commercial, Residential and Agriculture)	Switching to efficient residential air conditioners	1A4a 1A4b
Energy	Other sectors (Commercial, Residential and Agriculture)	Switching to efficient residential refrigerators	1A4a 1A4b
Energy	Other sectors (Commercial, Residential and Agriculture)	Switching to efficient domestic lighting with light-emitting diode (LEDs)	1A4a 1A4b

Table A2. *Cont.*

IPCC Sector	Mitigation Sector	Name of the Policy	Associated IPCC Category
Energy	Fugitives	Reduction of coal mining in surface mines	1B1aii
Energy	Fugitives	Reduction of coal mining in underground mines	1B1ai
IPPU	Industrial processes	Replacement of clinker with other physical raw materials with hydraulic properties	2A1
IPPU	Industrial processes	N_2O abatement from nitric acid production	2B2
IPPU	Product use	Substitution of high GWP F-gases with low GWP ones	2F1
AFOLU	Livestock and Manure Management	Improved feeding practices	3A1
AFOLU	Livestock and Manure Management	Feed additives for ruminant diets	3A1
AFOLU	Livestock and Manure Management	Optimisation of feeding strategies for livestock	3A2
AFOLU	Livestock and Manure Management	Longer-term management changes and animal breeding	3A1
AFOLU	Livestock and Manure Management	Improving animal health through better monitoring	3A1 3A2
AFOLU	Forestry	Afforestation and reforestation	3B1
AFOLU	Forestry	Restoration of degraded forests	3B1
AFOLU	Forestry	Reducing deforestation	3B1
AFOLU	Croplands and Grasslands	Reduced and Zero Tillage	3B2
AFOLU	Croplands and Grasslands	Agronomic practices: Residue management	3B2
AFOLU	Croplands and Grasslands	Agronomic practices: cease of field burning of vegetation and agricultural waste	3B2
AFOLU	Croplands and Grasslands	Agronomic practices: temporary vegetative cover	3B2
AFOLU	Croplands and Grasslands	Soil and nutrient management plan	3C4 3C5
AFOLU	Croplands and Grasslands	Biological N fixation in rotations and in forages	3C4
AFOLU	Croplands and Grasslands	Water management	3B2 3B3
AFOLU	Croplands and Grasslands	Development of new fruit orchards	3B2
AFOLU	Croplands and Grasslands	Rice management	3C7
AFOLU	Croplands and Grasslands	Agroforestry	3B2 3B3
AFOLU	Croplands and Grasslands	Grazing land management and pasture improvement	3B3
AFOLU	Croplands and Grasslands	Land cover (use) change: Conversion of arable land to grassland	3B2 3B3
AFOLU	Croplands and Grasslands	Land cover (use) change: Wetland conservation / restoration (drained croplands back to wetlands)	3B2 3B4
AFOLU	Croplands and Grasslands	Management of organic/peaty soils	3B4

Table A2. *Cont.*

IPCC Sector	Mitigation Sector	Name of the Policy	Associated IPCC Category
AFOLU	Croplands and Grasslands	Nitrification inhibitors (which slow the microbial processes leading to N_2O formation)	3C4 3C5
Waste	Solid waste	Methane recovery in Solid Waste Disposal Sites (SWDS)	4A
Waste	Solid waste	Reduction of biodegradable material that is disposed in SWDS	4A
Waste	Solid waste	Reduction of waste production per capita	4A
Waste	Solid waste	Composting of organic municipal waste	4A 4B
Waste	Solid waste	Diversion of solid waste from unmanaged disposal sites to aerobic landfills	4A
Waste	Wastewater	Improvement of the wastewater treatment infrastructure	4D1
Waste	Wastewater	Improvement of the wastewater treatment infrastructure	4D1

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