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Greenhouse-gas emission trends and decarbonisation outlook for the Rabat-Salé-Kénitra Region (Morocco): An exploratory inventory and STIRPAT-machine learning assessment

Payâgda Misaël Tarpaga^{1†}, Ouadia Mouhat¹, Mounaim Halim El Jalil¹

¹Civil and Environmental Engineering Laboratory, High School of Technology, Mohammed V University of Rabat, Morocco

†Corresponding author: misael.tarpaga@research.emi.ac.ma

<https://orcid.org/0009-0008-4473-9356>;

<https://orcid.org/0000-0003-4456-0897>;

<https://orcid.org/0000-0002-8922-6932>.

Abstract

Regional greenhouse gas (GHG) data remain scarce in Morocco. This study reconstructs the Rabat-Salé-Kénitra inventory for 1989-2021 using the IPCC 2006 Tier-1 method and examines structural drivers and conditional decarbonisation pathways to 2050. Emissions increased from approximately 5.5 to 10.4 Mt CO₂e (+88%), while the energy sector's share rose from 61% to 75%. A circularity audit motivated a core STIRPAT-Ridge specification retaining GDP per capita and urbanised area. With no stable long-run relationship supported, the model was estimated in first differences. Nested expanding-window validation over 2006-2021 yielded $R^2 = 0.77$ and MAPE = 3.0%, but offered little improvement over a drift benchmark ($R^2 = 0.76$) and essentially no explanatory power in growth-rate space. Monte Carlo propagation of the large, asymmetric inventory uncertainty left no driver association distinguishable from zero. Under stated driver-growth assumptions, business-as-usual emissions reach approximately 18.4 Mt CO₂e in 2050; exogenous mitigation wedges of 20% and 40% yield 14.7 and 11.1 Mt CO₂e, respectively. These are conditional exploratory trajectories, not forecasts. Despite the short, partly reconstructed series ($n = 33$), the study provides a transferable protocol combining provenance and circularity audits, temporally ordered validation and uncertainty propagation for data-constrained regions.

Keywords

Rabat-Salé-Kénitra; Greenhouse-gas inventory; IPCC guidelines; STIRPAT; Ridge regression; Machine Learning; Decarbonisation scenarios

1. INTRODUCTION

Climate-change mitigation is increasingly shaped at the subnational scale, where urbanisation, economic growth, land-use change and infrastructure development directly govern emission trajectories. Human-induced warming is driven mainly by the accumulation of carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O): CO₂ dominates through fossil-fuel combustion, while CH₄ and N₂O are strongly linked to agriculture, waste and

energy systems (Fleming 1999, Cetin & Yucel 2018, Moumen et al. 2016, O et al. 2019, Rahman et al. 2023). Understanding emission dynamics at the regional scale has therefore become essential for designing targeted mitigation strategies.

Morocco is highly exposed to climate change, facing rising drought frequency, declining water availability and increasing temperatures (El Hafdaoui et al. 2024; Hssoune & Jaouhar 2025; Radmehr et al. 2024). In response, the country submitted its first Nationally Determined Contribution (NDC) in 2016 (United Nations Framework Convention on Climate Change (UNFCCC 2016)) and, in 2021, strengthened it while introducing a long-term low-carbon strategy to 2050 (El Hafdaoui et al. 2024; Kharbach & Chfadi 2022). The updated NDC targets a conditional reduction of 45.5% and an unconditional reduction of 18.3% by 2030 relative to a business-as-usual (BAU) baseline, together with a renewable share above 52% of installed power capacity by 2030 (MEME 2021). Translating such national ambitions into action requires robust territorial evidence, particularly in economically dynamic regions where emission pressures concentrate.

The RSK region is a relevant case study because of its economic, demographic and territorial significance. Organised around Rabat, Salé, Kénitra and Skhirate-Témara, it concentrates activity along the Kénitra-Rabat-Salé coastal corridor, generating high mobility and energy demand (Mazouz et al. 2025). As Morocco's second economic hub, it contributes about 15.8% of national GDP, dominated by services (65.9%) with significant agriculture and livestock (13%) and limited industry (7%) (Gauthier 2020; Mazouz et al. 2025). Yet no comprehensive long-term regional GHG inventory has previously been developed, limiting the capacity of policymakers to assess historical trends, identify drivers and evaluate decarbonisation pathways.

In parallel, machine learning (ML) techniques are increasingly used to explore GHG forecasting by capturing nonlinear relationships among socio-economic, demographic and energy variables (Adam et al. 2025; Bhatt et al. 2023; Emami Javanmard et al. 2023; Ene Yalçın 2024). However, most studies target national datasets or countries with mature statistical systems, while regional applications in developing contexts remain scarce. This creates a methodological gap for data-constrained settings where detailed inventories are unavailable but demand for forward-looking climate planning is rising. The present study addresses this gap through three contributions: (i) empirically, one of the first long-term (1989-2021) multi-sector regional GHG inventories for Morocco, together with a quantified audit of its provenance and uncertainty; (ii) methodologically, a transparent protocol that documents predictor-inventory circularity, tests for non-stationarity and spurious regression before interpreting coefficients, validates the model in temporally ordered fashion against benchmarks evaluated on identical years, and propagates inventory uncertainty into the driver analysis; and (iii) practically, conditional decarbonisation trajectories and policy-sensitivity scenarios discussed in the context of Morocco's national mitigation commitments, together with a region specific action plan.

The remainder of the paper is structured as follows: Section 2 provides a review of the primary approaches employed in GHG emission modelling and forecasting, paying particular attention to statistical models, machine learning methods, and STIRPAT based frameworks. Section 3 introduces the study area, the data sources used and the methodological framework adopted, which includes regionalisation, imputing missing data, constructing an IPCC Tier 1 inventory, assessing uncertainty, controlling for circularity and data provenance, STIRPAT-Ridge

modelling, the temporally ordered validation strategy, the scenario design and the time-series and uncertainty-propagation diagnostics. Section 4 reports on and discusses historical emission trends, inventory uncertainty, circularity and multicollinearity, the stationarity and specification diagnostics, model performance, driver associations, conditional trajectories and region-specific mitigation options. Finally, Section 5 summarises the study's main findings, methodological contributions, policy implications and limitations.

2. BACKGROUND RESEARCH

Forecasting GHG emissions supports climate policy design, long-term planning and mitigation assessment. Methodological approaches fall into three broad families: statistical models, ML techniques, and scenario-based hybrid frameworks. Statistical approaches remain popular for their interpretability and modest data needs: regression models have estimated CO₂ in Iran from demographic, economic and energy predictors (Hosseini et al. 2019), and ARIMA/SARIMA/Holt-Winters models capture temporal patterns where long series exist (Kumari & Singh 2023). These methods, however, struggle with nonlinear or structurally shifting relationships.

To overcome these limits, ML algorithms such as random forests, support vector regression, gradient boosting, neural networks and deep architectures have been widely applied (Ene Yalçın 2024; Faruque et al. 2022). Recent African evidence applied seven ML models to transport emissions across South Africa, Egypt, Nigeria and Algeria, underscoring transport and GDP drivers but remaining sector-specific (Adam et al. 2025). Studies also differ markedly in dataset design, from seven predictors (Rahman et al. 2023) to twenty-six (Sachin Kumar 2023) and thirty-eight including CH₄ and N₂O (Bhatt et al. 2023). Tree-based ensembles often outperform conventional regressions when emissions arise from complex interactions, but their flexibility is a liability on short annual series, where near-perfect in-sample fits reflect memorisation rather than skill.

A complementary and theory-driven strand uses the STIRPAT framework (Stochastic Impacts by Regression on Population, Affluence and Technology), derived from the IPAT identity (Ehrlich & Holdren 1971; Dietz & Rosa 1994; York et al. 2003). Estimated in logarithms, STIRPAT provides interpretable elasticities linking emissions to demographic, economic and technological drivers. (Rosa Prado and Morales, 2026), using data for 143 countries from 1990 to 2022, showed that high goodness-of-fit values may coexist with severe multicollinearity, with variance-inflation factor (VIF) values above 100, making coefficient interpretation fragile. This is particularly relevant for regional studies based on short and highly trending annual series. Recent studies combine STIRPAT with regularisation, decoupling analysis and scenario modelling. He et al. 2025 modelled transport CO₂ emissions in Xuzhou using a STIRPAT-Ridge framework, Tapio decoupling and low-carbon scenarios, obtaining 10.66% and 13.00% reductions by 2030. Zhu et al. 2026 proposed a modified STIRPAT for Yunnan, integrating factor decomposition, Ridge regression, stepwise selection and scenario decoupling. Liu et al. 2025 applied a comparable logic to Jiangsu's energy-related CO₂ emissions through carbon accounting, Tapio decoupling and three scenarios. Tian et al. 2025 note a shift toward multivariable and hybrid forecasting models, while Chen et al. 2025 combine extended STIRPAT with GA-BiLSTM for provincial carbon-peak prediction. These contributions support STIRPAT as a transparent explanatory framework, provided that variable selection and validation remain rigorous.

Three gaps emerge. First, most studies operate at national scale, obscuring territorial heterogeneity in sectoral structure and drivers. Second, advanced modelling is concentrated in countries with continuous statistics, leaving data-constrained regions underserved. Third, many studies cover CO₂ only, whereas integrated mitigation requires multi-sector inventories spanning energy, agriculture and waste. Critically, several regional STIRPAT applications include activity or technology variables (e.g. energy structure, fuel turnover) that partly coincide with the inputs of the emission accounting, raising a circularity concern that is rarely made explicit. The present study addresses these gaps by coupling an IPCC-consistent multi-sector inventory with a circularity-controlled, regularised STIRPAT model and a rigorous small-sample validation protocol. Table summarises representative studies.

Table 1: Representative studies on GHG-emission modelling and forecasting.

References	Area	Scale	Output	Main inputs	Method	Limitation
(Hosseini et al. 2019)	Iran	National	CO ₂	GDP, population, energy	Regression	National only
(Kumari & Singh. 2023)	India	National	CO ₂	Time series	ARIMA, LSTM, RF	CO ₂ only
(Rahman et al. 2023)	Saudi Arabia	National	GHG	Socio-economic, energy	Ensemble trees	Low territorial detail
(Bhatt et al. 2023)	Multiple	Broad	GHG	Socio-economic, energy, CH ₄ , N ₂ O	ML	Limited regional focus
(Adam et al. 2025)	4 African countries	Sectoral	GHG	GDP, transport activity	CatBoost, RF, XGBoost	Sector only
(Rosa Prado & Morales 2026)	143 countries	National	CO ₂	Population, urbanisation, GDP/HDI	STIRPAT (OLS)	High VIF on aggregates
(He et al. 2025)	Xuzhou, China	Regional	CO ₂	8 vars incl. activity and transport drivers	STIRPAT-Ridge, Tapio	Sector-specific; circular predictors
(Zhu et al. 2026)	Yunnan, China	Regional / provincial	CO ₂	Multi-dimensional socio-economic and energy drivers	Modified STIRPAT-Ridge, scenario decoupling	Province scale; CO ₂ only
(Chen et al. 2025)	30 Chinese provinces	Provincial	CO ₂	Socio-economic, energy and	Extended STIRPAT, GA-BiLSTM	Data-intensive; China-specific

				technological indicators		
(Liu et al. 2025)	Jiangsu, China	Provincial	CO ₂	Energy consumption, economy, decoupling indicators	Carbon accounting, Tapio, extended STIR-PAT	Energy-related CO ₂ only
This study	RSK, Morocco	Regional	GHG	4 non-circular structural drivers (2 strict-core and 2 proxy-linked)	IPCC inventory, STIR-PAT-Ridge, uncertainty propagation	Short series (n = 33); exploratory

3. MATERIALS AND METHODS

3.1 Study area

The RSK region, shown in Fig. 1, is located in north-western Morocco. It covers an area of 18,194 km² and had a population of approximately 4.58 million in 2014, with an estimated average annual growth rate of 1.4% since 1989. The region was formed in 2015 through the merger of the former Rabat-Salé-Zemmour-Zaer and Gharb-Chrarda-Beni Hssen entities (MI 2015).

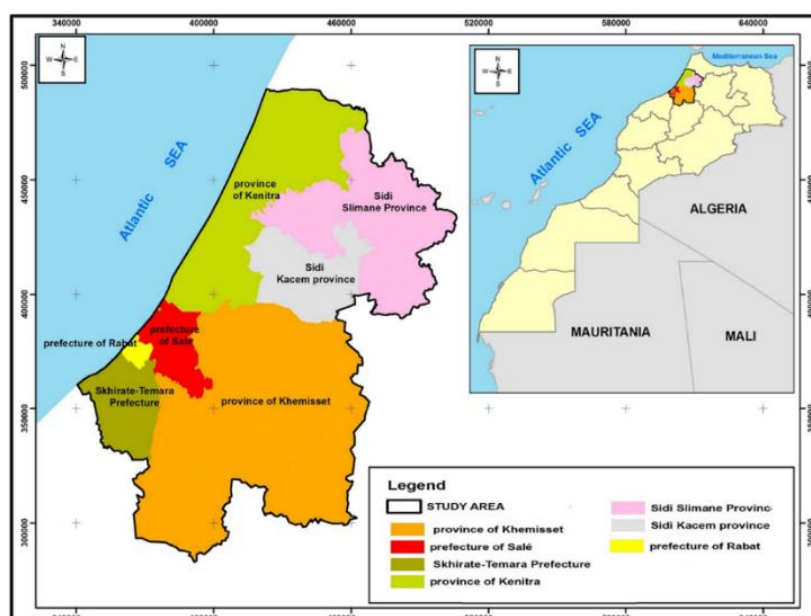


Fig. 1: Location and administrative composition of the Rabat-Salé-Kénitra study area.

Source: (Elmotawakkil & Enneya 2024)

3.2 Research framework

As shown in Fig. 2, the methodological workflow comprised six sequential stages: data collection; regionalisation of national activity data; imputation of missing values; IPCC Tier-1 inventory with Approach-1 uncertainty; non-circular driver selection and STIRPAT-Ridge modelling with ML comparison; and validation followed by decarbonisation scenarios to 2050.

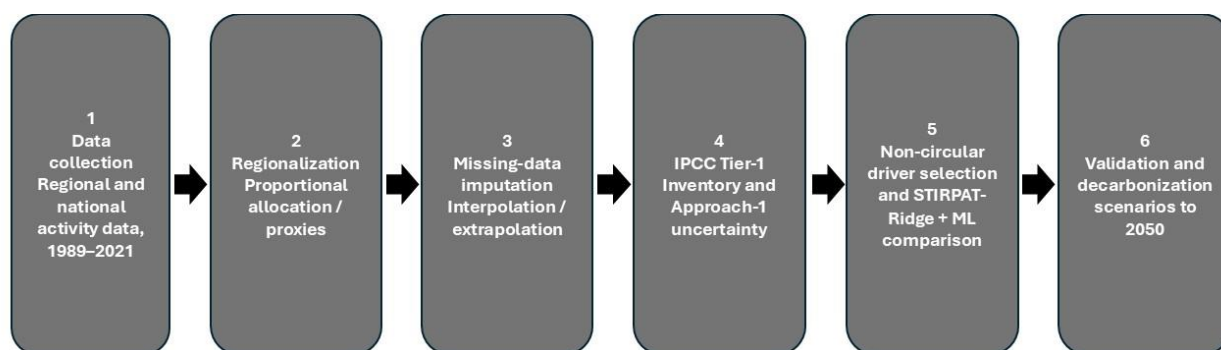


Fig. 2: Six-stage methodological framework of the study.

3.3 Data sources and processing

The analysis is based on official documents from the Moroccan government and statistical yearbooks, as well as scientific publications. Activity data relating to energy, agriculture and waste were collected for the period 1989–2021. Regional data were used where available, following verification of their consistency; where this was not the case, national data were regionalised using substitute indicators specific to each sector. In the absence of a pre-existing regional inventory, an inventory was compiled for the period under study, and any remaining gaps were filled by imputation.. As the region did not take on its current form until 2015, whilst the time series begins in 1989, an annual origin matrix was also drawn up, in which each observation is coded as follows: directly observed regional data (D), regionalised data (R), interpolated data (I), extrapolated data (E) or data derived from an indicator (P), with a primary code and a secondary code where an estimate combines several operations. All activity data, their sources and processing methods are presented in Tables S1 to S3 in the appendix. Fig 3 below shows the resulting source shares for the unweighted and emissions-weighted data.

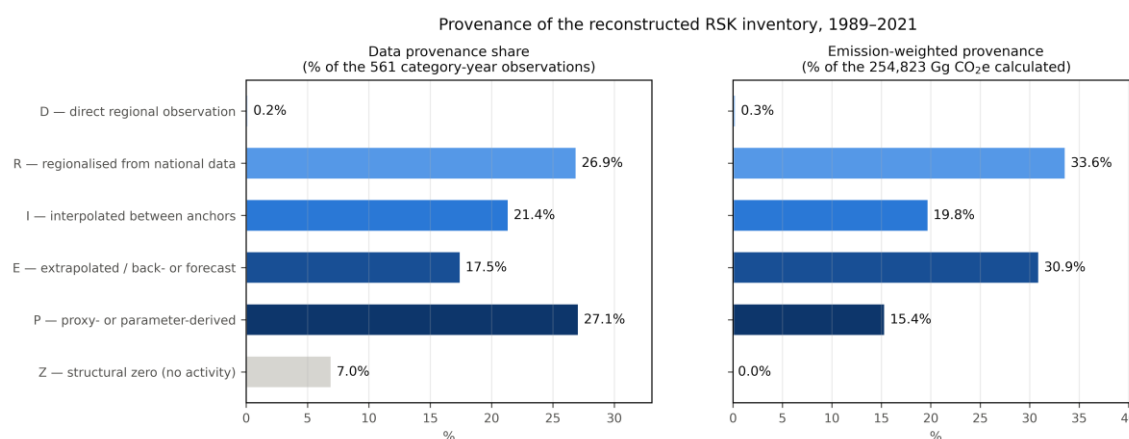


Fig 3 : Data provenance shares and emission weight

3.4 Regionalisation of activity data

A unified proportional allocation approach was applied to regionalise national activity data. For a given activity i and year t , the regional activity data were estimated using Equations (1) and (2):

$$AD_{r,i,t} = AD_{n,i,t} \times S_{p,t} \quad \dots(1)$$

$$S_{p,t} = \frac{P_{r,p,t}}{P_{n,p,t}} \quad \dots(2)$$

Where $AD_{r,i,t}$ is the regional activity data, $AD_{n,i,t}$ is the corresponding national activity data, and $S_{p,t}$ is the regional share of the allocation proxy p . $P_{r,p,t}$ and $P_{n,p,t}$ represent the regional and national values of the selected proxy, respectively (Sedgwick 2012). The choice of proxy was based on the physical or socio-economic driver of each emission source. When several drivers were relevant, a composite allocation key was applied using Equation (3):

$$S_{i,t} = \sum_{k=1}^n w_k S_{k,t} \quad \dots(3)$$

where w_k is the weight assigned to proxy k , with $\sum w_k = 1$. This ensured methodological consistency across sectors while preserving the specific emission logic of each activity (Droesbeke et al. 2005).

3.5 Imputation of missing data

Missing values were treated using a harmonised decision framework. Internal gaps between two observed years were filled by linear interpolation using Equation (4):

$$AD_t = AD_{t_1} + \frac{AD_{t_2} - AD_{t_1}}{t_2 - t_1} (t - t_1) \quad \dots(4)$$

where t_1 and t_2 are the nearest observed years surrounding the missing value. For variables with smooth demographic or structural growth, log-linear interpolation was preferred. Missing values at the beginning or end of a series were estimated using a cautious extrapolation based on the compound annual growth rate using Equation (5):

$$AD_t = AD_{t_0} (1 + r)^{(t - t_0)} \quad \dots(5)$$

where r is the annual growth rate derived from the closest reliable observations. Extrapolated rates were capped to avoid unrealistic trends (Wahab 2017). When the relationship with a driving variable was more robust than the time trend, ratio-based imputation was applied using Equation (6):

$$AD_t = AD_{t_0} \times \frac{X_t}{X_{t_0}} \quad \dots(6)$$

where X_t represents a relevant driver. Activities or technologies that were clearly absent during specific periods were treated as structural zeros rather than missing values. For parameters with insufficient evidence of annual variation, values were held constant between anchor years or adjusted only when supported by documented changes.

3.6 GHG inventory and uncertainty (IPCC Tier 1, Approach 1)

GHG emissions were calculated using Tier 1 methods from the 2006 IPCC Guidelines, with updates from the 2019 refinement where applicable (IPCC 2019). For each source category, annual emissions were estimated by using Equation (7):

$$E_{g,i,t} = AD_{i,t} \times EF_{g,i} \quad \dots(7)$$

where $E_{g,i,t}$ represents emissions of gas g from source i in year t , $AD_{i,t}$ is the activity data, and $EF_{g,i}$ is the emission factor. Emissions were then converted into carbon dioxide equivalent using global warming potentials in Equation (8):

$$E_{CO_2e,t} = \sum_g E_{g,t} \times GWP_g \quad \dots(8)$$

Uncertainty followed IPCC Approach 1 (error propagation). Within a category, activity data and emission factor uncertainties combine in quadrature; categories combine to the total with the weighted rule using Equations (9) and (10):

$$U_E = \sqrt{U_{AD}^2 + U_{EF}^2} \quad \dots(9)$$

$$U_{total} = \frac{\sqrt{\sum_i (E_i U_i)^2}}{\sum_i E_i} \quad \dots(10)$$

Observed regional data were assigned lower uncertainty, whereas interpolated, extrapolated, regionalised or proxy-based data received higher uncertainty. Because the resulting uncertainty is large and markedly asymmetric, Approach 1 alone does not describe the distribution of the inventory. A Monte Carlo propagation of the sectoral ranges is therefore added, and Approach 1 is retained as a QA/QC control on it. The detailed sectoral formulations (energy, agriculture, waste) are provided in the Supplementary Material, and the per-sector uncertainty tables in Table S4.

3.7 Variable selection and circularity control

A predictor is circular if it enters the emission calculation. Such variables cannot be independent explanators of the very emissions they define; feeding them into a regressor merely reproduces the accounting identity and inflates the fit spuriously. Diagnostic correlations confirm the risk: electricity consumption ($r = 0.98$) and municipal solid waste ($r = 0.97$) correlate almost perfectly with the target, while livestock heads ($r = 0.02$) and thermal generation ($r = -0.44$) do not, yet all four are inventory inputs and were excluded. Cropland is activity-linked and kept descriptive only; the three gas columns are emission outputs. Direct inclusion in the emissions equation is, however, not the only way in which a predictor may depend on the inventory. Following an analysis of the dependence between each candidate predictor and each activity data point, allocation key and proxy used in the reconstruction, it appears that population is partly the key to regionalising certain activity data from the energy and waste sectors. The regional share of the national vehicle fleet, on the other hand, is the regionalisation key for the energy sector. Thus, the relevant source categories account on average for 11.6% and 29.2%, respectively, of total regional emissions. Population and vehicle fleet are consequently classified as proxy-linked rather than as strictly exogenous. Two specifications are presented and compared throughout the study: a strict baseline specification, which retains GDP per capita and urbanised area, and for which no link with the allocation key is identified; and an extended sensitivity specification, which adds the two variables linked by proxy variables, as shown in Table . This explicit control distinguishes the present work from regional STIRPAT studies that include activity variables amongst the set of predictors.

Table 1: Variable roles and circularity decision (correlation with total GHG)

Variable	Role	In inventory	Corr	Specification
Population	structural	regionalisation	0.94	extended sensitivity
GDP per capita	structural	No link	0.98	strict core
Urbanised area (km ²)	structural	No link	0.96	strict core
Vehicle fleet	structural	regionalisation	0.96	extended sensitivity
Cropland (Mha)	activity-linked	partly	-0.38	descriptive only
Electricity consumption	activity	enters	0.98	exclude
Thermal generation	activity	enters	-0.44	exclude
Municipal solid waste	activity	enters	0.97	exclude
Livestock heads	activity	enters	0.02	exclude
CO ₂ , CH ₄ , N ₂ O	emission output	yes	-	target components

3.8 STIRPAT-Ridge model and machine-learning comparison

The extended STIRPAT model relates emissions to structural drivers in logarithmic form, such that the coefficients are elasticities as defined in Equation (11):

$$\ln E = a + b \times \ln(Pop) + C \times \ln(GDPpc) + d \times \ln(Urb) + e \times \ln(Veh) + \varepsilon \quad \dots(11)$$

In logarithmic levels the structural drivers are jointly trending and multicollinearity is severe, which destabilises ordinary least squares. Ridge (L2) regression is therefore used as the estimator, consistent with (He et al. 2025) and (Zhu et al. 2026). The form of the specification is dictated by the time-series diagnostics. Because the logged series are integrated of order one and no stable long-run relationship is supported, the model is estimated in first differences, where the collinearity largely disappears (variance-inflation factors of 1.01 - 1.02 for the strict core and 1.15 - 1.33 for the extended set) and the coefficients are interpreted as regularised statistical associations rather than long-run elasticities; the logarithmic-level specification is retained as a comparison. Regularisation therefore addresses collinearity, while differencing addresses non-stationarity, the two being distinct problems. Comparison learners were also examined: Elastic-Net, Random Forest, Gradient Boosting and ordinary least squares, together with a naive persistence baseline and a drift baseline. Tree ensembles were treated as robustness checks only: on $n=33$ a near-perfect in-sample fit signals memorisation rather than skill. Deep-learning models (LSTM/BiLSTM) were excluded because their parameters greatly exceed the available observations and cannot be credibly validated on a single short annual series. Hyper-parameters are not tuned on the full sample and, the penalty is re-selected at every forecasting origin using only observations that precede the year being predicted.

3.9 Temporally ordered validation strategy

Validation uses a nested expanding-window procedure rather than a random split. Starting with 1989-2005, the training window expands annually to generate sixteen one-year-ahead predictions for 2006-2021. At each origin, Ridge tuning uses TimeSeriesSplit and negative MSE on the logarithmic scale, with standardisation fitted within the training pipeline to prevent information leakage. Performance is assessed using R^2 , RMSE, MAE and MAPE on the natural scale (Gg CO₂e). The first-difference model is also evaluated in growth-rate space to

assess information added beyond the previous year's level. Naive persistence and drift benchmarks are evaluated on identical test years, with drift estimated exclusively from each training window. Leave-one-out cross-validation and a hold-out trained on 1989-2011 and tested on 2012-2021 serve only as supplementary diagnostics, since their tuning does not preserve temporal ordering. Driver-association uncertainty is assessed using moving-block and stationary bootstraps applied to joint annual vectors, with 2,000 replications, a fixed seed and block-length sensitivity from two to five years to account for serial dependence.

3.10 Conditional trajectory and decarbonisation scenario design

BAU trajectories are generated by applying the retained first-difference STIRPAT-Ridge model to exogenous driver-growth paths. Central assumptions follow the 1989-2021 compound annual growth rates: population, 1.2%; GDP per capita, 4.3%; urbanised area, 3.1%; and vehicle fleet, 4.5%. Low and high cases use the 10th and 90th percentiles of ten-year rolling growth rates. These assumptions remain provisional pending official regional projections. The Increased Ambition (IA) and Green Development (GD) scenarios impose reductions of 20% and 40% relative to BAU, phased in linearly by 2050. These are exogenous policy-sensitivity assumptions, not model-estimated effects of sectoral measures. Table 6 and Table 7 distinguish driver assumptions, mitigation assumptions and model outputs. Morocco's updated NDC (MEME 2021) provides policy context rather than a quantitative benchmark because baseline, target year, coverage and geographical scale differ. No external sectoral data are introduced. Since long-horizon predictive skill has not been established, all outputs are conditional exploratory trajectories rather than forecasts.

3.11 Time-series diagnostics and inventory-uncertainty propagation

Because every series is strongly trending, the logarithms of total emissions and of each candidate driver are tested for unit roots with the Augmented Dickey-Fuller test in levels and in first differences, with and without a deterministic trend and with the lag order selected by the Akaike criterion, and complemented by the KPSS test of the null of stationarity (Mushtaq 2011). Where the variables share an order of integration, the existence of a long-run relationship is examined with the Engle-Granger residual-based procedure, which is parsimonious enough for $n = 33$ (Gregory & Hansen 1996); a Johansen-VECM system is not used, its parameter count being disproportionate to the sample. Residual dependence is examined through the autocorrelation and partial autocorrelation functions, the Durbin-Watson statistic (Ali 1987) and the Ljung-Box test (Burns 2002). The specification and the interpretive vocabulary follow these results rather than preceding them. Inventory uncertainty is then propagated into the modelling. A full IPCC Approach 2 propagation at input level requires the activity-data, emission-factor and parameter probability distributions and their correlation groups, which are not available at the regional scale for the whole period; what is reported is therefore a sector-level approximation, explicitly labelled as such. Each sectoral estimate is sampled from a median-preserving two-piece lognormal distribution whose 2.5th and 97.5th percentiles coincide with the asymmetric bounds of Table S4, which respects both the asymmetry and non-negativity. Because emission factors are shared across years, 80% of the variance within each sector is assigned to a year-invariant systematic component and 20% to a year-specific component, with a sensitivity over that split and over a positive cross-sector correlation. Ten thousand realisations are generated

with a fixed seed, convergence of the median and of the 2.5th and 97.5th percentiles is verified, and the retained model is refitted on each realisation with the penalty held at its central temporally selected value.

4. RESULTS AND DISCUSSION

4.1 Historical GHG inventory (1989-2021)

Total GHG emissions in the RSK region rose steadily between 1989 and 2021, increasing from approximately 5.5 Mt CO₂e to 10.4 Mt CO₂e. This trend corresponds to an overall increase of approximately 88% over the study period, representing a compound annual growth rate of nearly 2% per year, as illustrated in **Error! Reference source not found.** The general trend remains upward overall, despite some occasional year-to-year decreases.

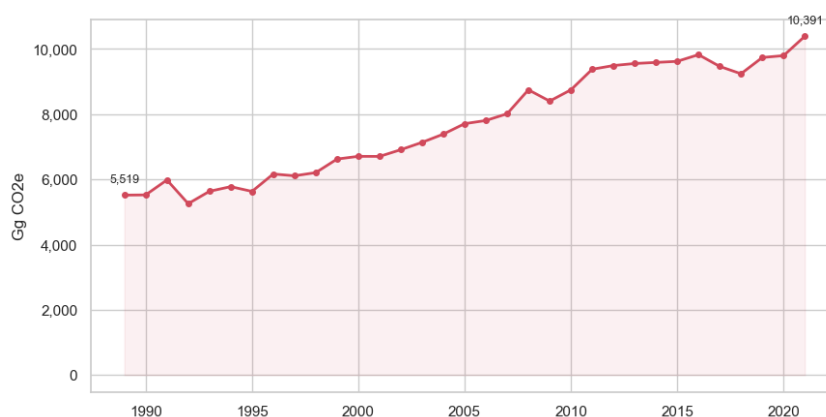


Fig. 3: Total GHG emissions of the RSK region, 1989-2021 (Gg CO₂e).

As shown in **Error! Reference source not found.**, CO₂ is the dominant gas and the main driver of emissions growth, rising from approximately 3.3 Mt CO₂e in 1989 to 7.8 Mt CO₂e in 2021. Emissions of CH₄ and N₂O remain lower but are still significant, particularly due to their link to agricultural activities and waste management. Expressed in CO₂ equivalent, the CO₂ share of the total rises from 60.3% to 74.8%, while the CH₄ and N₂O contributions fall from 26.3% to 19.0% and from 13.5% to 6.2% respectively. The sectoral analysis presented in **Error! Reference source not found.** highlights the consistent dominance of the energy sector, whose contribution rose from approximately 61% in 1989 to nearly 75% in 2021. The increase in the waste sector's contribution beginning in 2007 coincided with the commissioning of the Oum Azza controlled landfill, which led to better accounting for emissions associated with waste disposal (Bouaouda et al. 2023). At the same time, the adoption of the National Energy Strategy in 2008, which focused in particular on the development of renewable energy, coincided with the stabilisation of the energy sector's share of regional emissions (Alhamwi et al. 2015). This strategy was accompanied by several national and regional policies aimed at improving energy efficiency and reducing energy consumption, particularly in the building sector (Hafdaoui et al. 2023). The enactment in 2011 of Law No. 47-09 on energy efficiency reinforced this approach by requiring, notably in Article 3, that energy performance requirements be incorporated into urban planning and building codes (Merini et al. 2020). These measures coincided with the observed stabilisation of emissions from the energy sector and may be consistent with a policy effect; the design of the present study contains no identification strategy and cannot

establish causality. Finally, the COVID-19 pandemic caused a temporary decline in economic activity and mobility, simultaneously affecting emissions from both the energy and waste sectors (Khazraji et al. 2022).

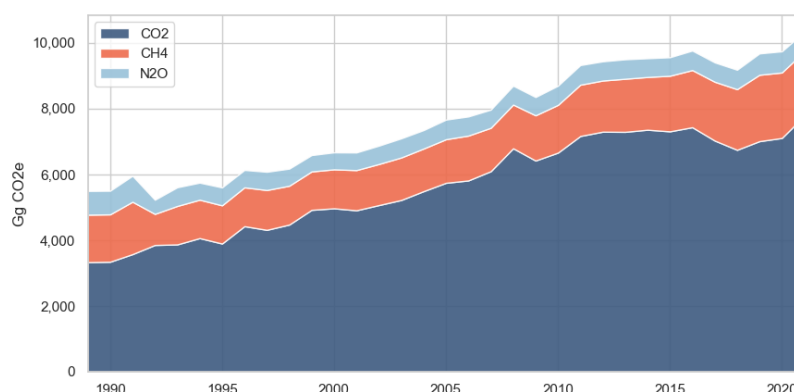


Fig. 4: Contribution by gas, in Gg CO₂e, 1989-2021.

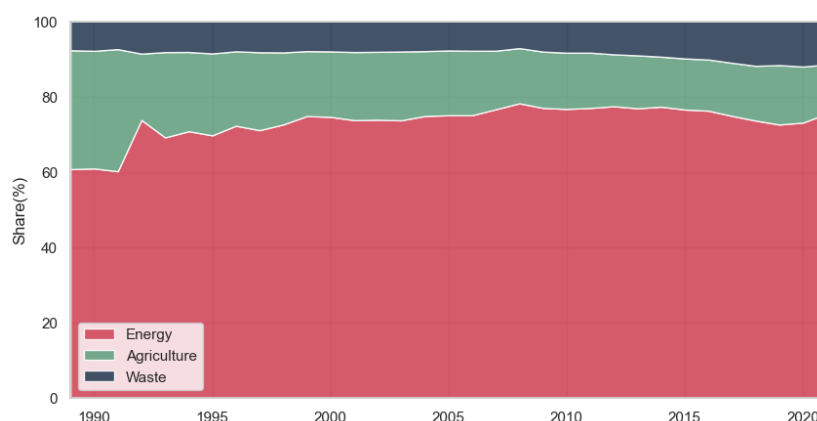


Fig. 5: Sectoral contribution to total emissions (%), 1989-2021.

4.2 Inventory uncertainty

Two independent checks were applied to the total inventory uncertainty. Recalculation of IPCC Approach 1 from the sectoral entries closely reproduces the reported lower bound, with reported-to-recomputed ratios of 0.97–0.99, but not the upper bound, which is 1.75–2.93 times higher than the recomputed value. As shown in Fig. X, the sector-level Monte Carlo median closely follows the inventory point estimate throughout 1989–2021, while the shaded 95% interval widens as emissions increase. In 2021, the propagated uncertainty ranges from approximately –33.8% to +39.5% around the point estimate. The upper bound remains between +34.9% and +39.7% under the correlation-sensitivity analysis. These results confirm that the lower bound in Table S4 is internally consistent with its sectoral components, whereas the aggregated upper bound is not. This discrepancy is retained as an open QA/QC issue, and subsequent analyses use the internally consistent sectoral ranges.

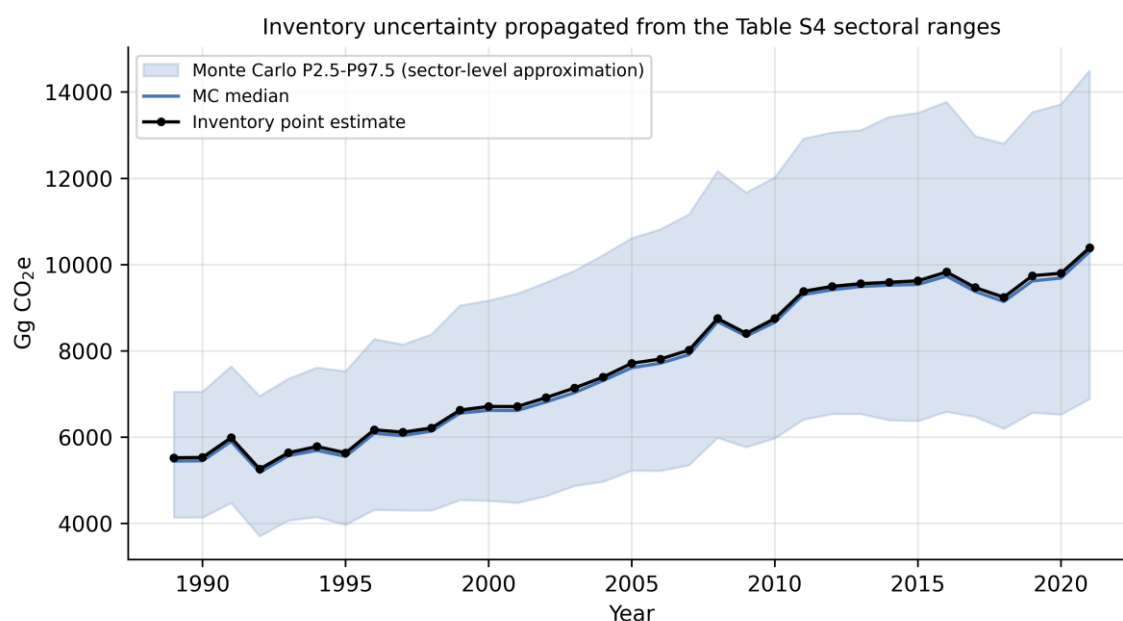


Fig. 6: Inventory point estimate and Monte Carlo P2.5-P97.5 envelope propagated from the sectoral ranges.

4.3 Circularity diagnosis and multicollinearity

As shown in Table 2, the circularity analysis confirms that the activity variables used in the previous models are mechanically linked to the inventory. Electricity consumption and municipal solid waste show a correlation with the objective of approximately $r = 0.97$ - 0.98 . Limiting the set of predictors to structural factors eliminates this direct artefact, but not the indirect artefact. The dependency analysis, meanwhile, shows that two of the four structural variables are themselves used as regionalisation keys inside the inventory, and that the source categories to which they are assigned account on average for 29.2% of total emissions for the vehicle fleet and 11.6% for the population. These two variables are therefore treated as proxy-linked and confined to the extended sensitivity, while the strict core retains GDP per capita and urbanised area. The provenance audit quantifies how far the reconstructed series stands from direct regional measurement. As shown in Fig 3, of the 561 category-year observations, one is based on a directly observed regional activity level used as is, representing 0.2% of the observations and 0.3% of the calculated emissions; 26.9% of the observations and 33.6% of the emissions derive from national activity data regionalised using an allocation key but observed during the year in question; 21.4 %and 19.8 %are based on an interpolated year, 17.5% and 30.9% on an extrapolated year, and 27.1% and 15.4% on an activity level itself derived from parameters. The remaining 7.0% of observations are structural zeros and do not include any emissions. Half of the calculated emissions are therefore based on a year that has been interpolated or extrapolated. The distribution varies significantly from one sector to another: the energy sector is dominated by regionalisation (45.5% of its emissions), agriculture by interpolation (68.7%) and the waste sector by extrapolation (84.4 per cent), with the entire time series for municipal solid waste being based on a single regional observation for 2015. It also varies from one period to another, with the proportion of emissions derived by extrapolation rising from 13.4% over the 1989 - 2004 period to 42.2% over the 2005 - 2021 period. These shares are, by their very nature, conservative; according to a modal rule, the share derived from direct observations amounts to 11.8% of the observations and 12.6% of emissions, and limiting the

classification to the spatial dimension alone yields 33.4% of emissions of regional origin. Nevertheless, strong multicollinearity persists between the factors themselves, with variance inflation factors (VIFs) of 34 (population), 88 (GDP/capita), 163 (urbanised area) and 505 (vehicle fleet). These values are all well above the threshold of 10 (Kim 2019). This trend is consistent with the findings of Rosa Prado & Morales 2026, who report VIFs exceeding 100 on trend aggregates. This justifies the use of Ridge regularisation rather than ordinary least squares. However, multicollinearity is a manifestation of the common temporal trend rather than a structural property of the factors: in first differences, these same variables yield variance inflation factors ranging from 1.15 to 1.33, and 1.01 for the strict kernel. Differentiation, which unit-root diagnostics require in any case, therefore also resolves the multicollinearity, and regularisation is retained for the purposes of dimensionality reduction rather than to justify the specification.

4.4 Stationarity, long-run relationship and specification

In logarithmic levels with a constant, the Augmented Dickey-Fuller test does not reject the unit root for any series ($p = 0.32$ for population, 0.41 for urbanised area, 0.89 for total emissions, 0.95 for GDP per capita and 0.99 for the vehicle fleet), while KPSS rejects stationarity for all five at the 1% level. In first differences the unit root is rejected for every series ($p < 0.001$) and KPSS no longer rejects stationarity, except marginally for the vehicle fleet ($p = 0.03$). All five logged series are therefore treated as integrated of order one, with the caveat that these tests have limited power on 33 observations. Because the variables share an order of integration, the Engle-Granger procedure is applied to both specifications. It does not support a long-run relationship in either case: the test statistic is -2.39 against a 5% critical value of -4.02 for the strict core ($p = 0.54$) and -2.58 against -4.87 for the extended specification ($p = 0.79$), and no pairwise combination of total emissions with an individual driver is significant either. The residual diagnostics point the same way for the strict core, whose logarithmic-level residuals have a Durbin-Watson statistic of 1.04, a first-order autocorrelation of 0.45 and Ljung-Box p -values below 0.01 at every lag examined, the classic signature of a spurious level regression; the extended specification, with four regressors on 33 observations, has less autocorrelated residuals (Durbin-Watson 1.45, Ljung-Box $p = 0.53$ at lag 4) but does not pass the cointegration test either. Two consequences follow and are applied throughout. The logarithmic-level coefficients are not interpreted as long-run elasticities but as regularised statistical associations, and the retained specification is estimated in first differences, which are stationary and free of the severe collinearity of the levels.

4.5 Model training, tuning and temporal validation

The Ridge penalties selected inside each historical training window are reported in Table 3, and the resulting performance in Table 4. Over the sixteen test years 2006-2021 the logarithmic-level specification reaches $R^2 = 0.592$ for the extended predictor set and $R^2 = 0.649$ for the strict core, with MAPE of 3.84% and 3.58%. The first-difference specification performs better, with $R^2 = 0.782$ (extended) and $R^2 = 0.766$ (strict core, retained) and MAPE of 2.84% and 2.97%; Fig. 7 shows the corresponding year-by-year predictions. These values must be read against benchmarks evaluated on exactly the same years: naive persistence gives $R^2 = 0.722$ and MAPE = 3.08%, and the drift benchmark gives $R^2 = 0.764$ and MAPE = 2.94%. The margin of the retained model over benchmarks that use no driver information at all is therefore very small, and the logarithmic-level

specification is outperformed by both. The decisive diagnostic is the growth-rate space, in which the drivers must add information beyond the previous year's level: there the coefficient of determination is -0.047 for the retained strict-core model and 0.033 for the extended one, in other words indistinguishable from zero. The high R^2 values obtained in level space are produced by the persistence anchor rather than by the socio-economic drivers, and the model is accordingly not presented as having demonstrated forecasting skill. Two complementary diagnostics complete the picture and are labelled as non-temporal. Leave-one-out cross-validation, which does not preserve temporal ordering, gives $R^2 = 0.965$ with $RMSE = 304 \text{ Gg CO}_2\text{e}$ and $MAPE = 3.44\%$; the contrast with the temporally ordered result measures how much apparent performance is gained when later observations are allowed to inform earlier predictions, and illustrates why such schemes cannot support claims about future generalisation on strongly trending series. Tree ensembles reach an in-sample R^2 of 0.99 on $n = 33$, a sign of memorisation, and are therefore retained only as robustness checks. STIRPAT-Ridge in first differences is adopted as the primary model for its interpretability, its parsimony and its stationarity, and not on the basis of a performance advantage. A second substantive finding concerns temporal stability. A single hold-out trained on 1989-2011 and tested on 2012-2021 gives $R^2 = -3.68$, which shows that a relationship fitted on the earlier period extrapolates poorly to the following decade. Regional emissions plateaued at around $10 \text{ Mt CO}_2\text{e}$, whilst GDP per capita and the size of the vehicle fleet continued to increase. Consequently, a relationship fitted using the 1989-2011 data overestimates the recent plateau. This pattern is compatible with a post-2011 structural change, although a single failed extrapolation cannot by itself separate structural change from model misspecification, sampling variability and the smoothing introduced by reconstruction. Comparable phased decoupling has been documented in Xuzhou (He et al. 2025), and it mirrors China's stabilisation between 2011 and 2015 under its 12th Five-Year Plan, despite the presence of factors driving growth (Rosa Prado & Morales 2026). This finding calls for caution in long-range extrapolation and reinforces the exploratory approach.

Table 3: Ridge penalties selected within each historical training window using nested expanding-window (EW) evaluation across 16 forecasting origins from 2006 to 2021

STIRPAT-Ridge specification	Median α	Range
Log differences : strict core (retained)	76.1	14.8 - 1000
Log differences : extended sensitivity	47.6	18.7 - 1000
Log levels : strict core	1.42	1.12 - 2.87
Log levels : extended	1.42	0.010 - 3.63

Table 4: Temporal validation on identical test years 2006-2021 (natural scale, Gg CO₂e), with the non-temporal diagnostics and the effect of inventory-uncertainty propagation.

Model / specification	Validation scheme	R ²	RMSE	MAE	MAPE%
STIRPAT-Ridge, log differences, extended	EW*, 2006-2021	0.782	319	263	2.84
STIRPAT-Ridge, log differences, strict core (retained)	EW, 2006-2021	0.766	331	274	2.97
Drift Y(t-1)	benchmark	0.764	332	272	2.94
Naïve persistence Y(t-1)	benchmark	0.722	360	284	3.08
STIRPAT-Ridge, log levels, strict core	EW, 2006-2021	0.649	405	327	3.58
STIRPAT-Ridge, log levels, extended	EW, 2006-2021	0.592	437	350	3.84
STIRPAT-Ridge, log levels, extended	LOOCV	0.965	304	256	3.44
STIRPAT-Ridge, log levels, extended	Hold-out	-3.684	629	522	5.41
Retained specification, inventory uncertainty propagated	median	-0.270	1098	874	9.87

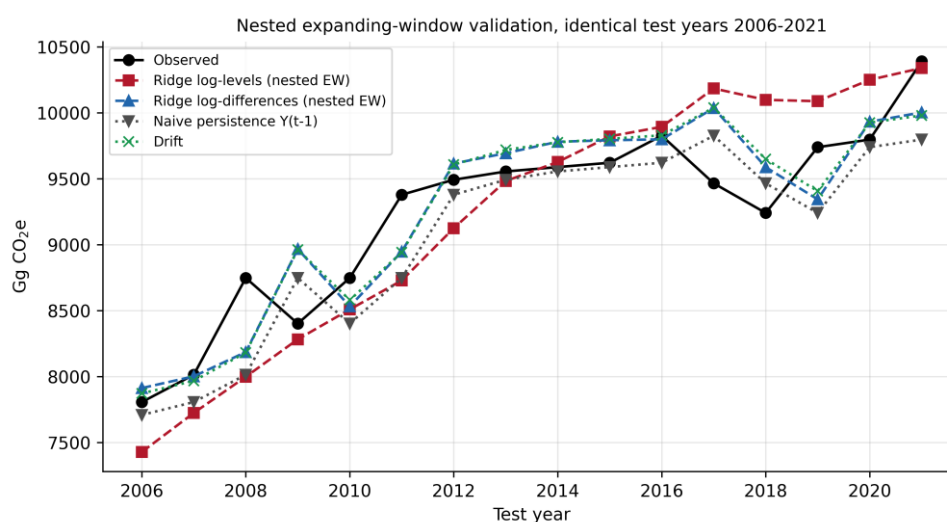


Fig 7: Nested expanding-window validation over the identical test years 2006-2021: observed emissions, STIRPAT-Ridge in logarithmic levels, STIRPAT-Ridge in logarithmic first differences (retained), and the naive persistence and drift benchmarks.

4.6 Associations between structural drivers and regional GHG emissions

Table 5 reports regularised statistical associations from the retained first-difference model. The moving-block bootstrap indicates a positive association between GDP per capita and GHG emissions (0.106; 95% CI: 0.017–0.167), whereas the association with urbanised area is positive but uncertain (0.097; 95% CI: –0.125–0.287).

After propagating inventory uncertainty, both confidence intervals include zero, indicating that neither association remains statistically distinguishable from zero. These results suggest that affluence is the dominant structural correlate of emissions, consistent with (Rosa Prado & Morales 2026), but the estimates should be interpreted cautiously given the short sample and inventory uncertainty.

Table 5: Regularised statistical associations of the retained first-difference specification, moving-block bootstrap (block length four years, 2,000 replications, seed 42), before and after propagation of inventory uncertainty.

Driver	Method	Association ($\Delta \ln \text{GHG} / \Delta \ln \text{driver}$)	CI : 2.5% - 97.5%
GDP per capita	Moving-block bootstrap	0.106	0.017 to 0.167
Urbanised area	Moving-block bootstrap	0.097	- 0.125 to 0.287
GDP per capita	Uncertainty propagation	0.126	- 0.155 to 0.405
Urbanised area	Uncertainty propagation	0.059	- 0.372 to 0.476

4.7 Conditional decarbonisation trajectories to 2050

The trajectories are summarised in Fig. 8 and Table 6 and Table 7, which separates exogenous driver assumptions, exogenous policy assumptions and model outputs. Under a BAU pathway with central driver growth and no mitigation wedge, continued growth in the structural drivers would lift emissions to approximately 12.4 Mt CO₂e in 2030, 15.1 Mt in 2040 and 18.4 Mt in 2050, roughly 1.8 times the level of 2021. Substituting the low and high driver-growth cases moves the 2050 level to 17.3 and 19.7 Mt respectively, so the sensitivity to the growth assumption is of the order of $\pm 6\%$, appreciably narrower than the uncertainty of the historical inventory itself. The IA and GD pathways reduce 2050 emissions by 20% and 40% relative to BAU, reaching approximately 14.7 and 11.1 Mt CO₂e; by 2030, with the linear phase-in, these reductions are 6% and 12% below BAU, a range comparable to the 10.7-13.0% obtained for Xuzhou's transport sector under low-carbon scenarios (He et al. 2025). Three qualifications must accompany these figures. First, the 20% and 40% reductions are exogenous policy-sensitivity assumptions imposed for the purposes of the study; the model does not generate them and cannot attribute them to specific sectoral levers. Second, Morocco's updated NDC ambition of a 45.5% reduction by 2030 at the national, economy-wide level (MEME 2021) is cited as policy context and not as a quantitative benchmark for these regional pathways, since the reference baseline, target year, gas and sectoral coverage and the national-to-regional transposition rule differ. Third, and most importantly, the temporal validation does not establish forecasting skill at this horizon, and the relationship is not temporally stable across the study period. These scenarios are not forecasts of what will occur, but conditional illustrations of what would occur under the stated socioeconomic and mitigation assumptions.

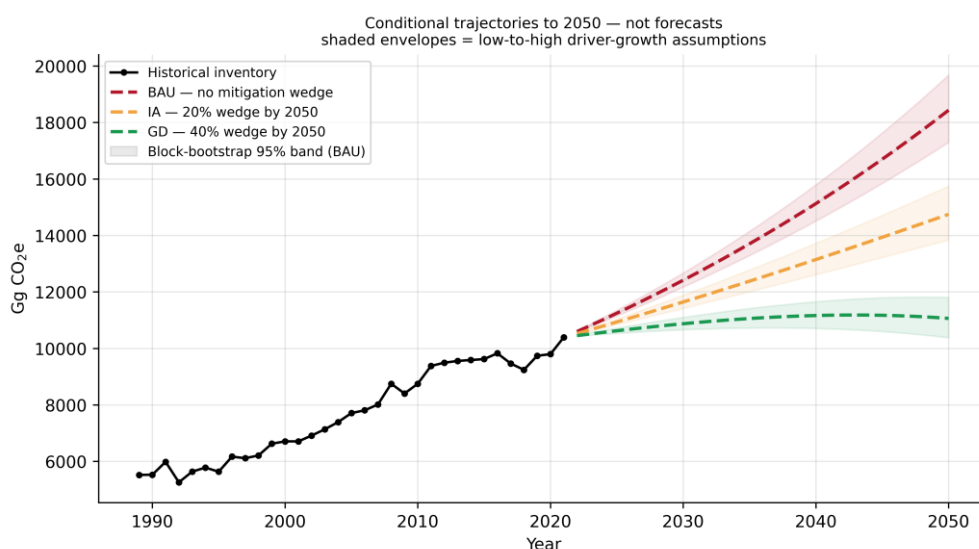


Fig. 8: Historical emissions and conditional BAU/IA/GD trajectories to 2050 under central driver growth, with the low-to-high driver-growth envelope and the block-bootstrap. These are conditional trajectories, not forecasts.

Table 6: Conditional trajectories (Mt CO₂e) and reduction relative to BAU, with the underlying exogenous assumptions. Model outputs and assumptions are labelled separately.

Year/case	BAU	IA	GD	IA vs BAU	GD vs BAU
2030	12.414	11.644	10.873	−6%	−12%
2040	15.128	13.146	11.164	−13%	−26%
2050 (central driver growth)	18.436	14.749	11.062	−20%	−40%
2050 (low driver growth)	17.296	13.837	10.378	−20%	−40%
2050 (high driver growth)	19.678	15.743	11.807	−20%	−40%

Table 7 : Exogenous driver-growth assumptions

Driver	Central growth	Low growth	high growth
Population	1.22%	0.53%	1.82%
GDP per capita	4.25%	3.03%	5.57%
Urbanised area	3.07%	1.96%	4.10%

4.8 Comparison with other regions

A comparison of emissions from the RSK region with those of other regions in the Kingdom, presented in Table 8, shows that the region accounts for a significant share of the national total, with approximately 15% of the country's total emissions. This finding confirms its role as Morocco's second-largest economic hub. However, when compared to emissions from certain Mediterranean regions and elsewhere, emissions from the RSK region remain relatively moderate.

Table 8: Comparison of regional GHG emissions.

Country	Region	GHG (Mt CO ₂)	Per capita (t CO ₂)	Year	Source
Morocco	Rabat	9.8	2.1	2016	This study
Morocco	Tangier	7.58*	2.1*	2016	(MEME-DE 2020)
Morocco	Souss-Massa	4.15*	1.15*	2013	(Climate chance 2019)
Tunisia	Tunis	12.5*	11.4*	2016	(Tarpaga et al. 2025)
Spain	Andalusia	50*	6*	2016	(Climate chance 2019)
France	Marseille	23*	12.5*	2016	(MAMP 2020)
China	Xiamen	19.85*	8.17*	2007	(Yang et al. 2015)

*Including industrial-sector emissions.

4.9 Policy recommendations

Although projections do not indicate explosive growth, sustained mitigation remains essential. The energy sector, the backbone of a service-dominated regional economy, is the priority. Renewable deployment is central, but previous studies caution that more renewable consumption does not automatically lower CO₂ without parallel efficiency gains (Altın 2024 ; Wang et al. 2022 ; Rehman et al. 2022). Efficiency improvements, by contrast, are consistently associated with reductions. Because most of the region's energy-related emissions are ultimately tied to grid electricity, greening the national electricity mix is a decisive lever, as shown for a Moroccan electricity operator whose scope 2 footprint dominates its balance (Majaty et al. 2024); circular-economy practices along the supply chain further act on indirect emissions. Because a full fossil phase-out is constrained in the short term by intermittency and system inertia, policymakers should combine efficiency measures with targeted renewable investment, prioritising the tertiary sector. Concrete levers include rooftop photovoltaics on public buildings, fiscal incentives for efficient technologies, public–private partnerships for waste valorisation, and a gradual increase in the economic cost of fossil-fuel use. Table 9 lists region-specific actions toward 2050.

Table 9: Region-specific decarbonisation action plan toward 2050.

Sector	Category	Proposed actions
Energy	Electricity	Combined-cycle plant; new grid-connected solar PV for tertiary (MV) and residential (LV); promotion of low-energy lamps and high efficiency appliances.
Energy	Stationary combustion	Generalisation of solar water heaters in tertiary and residential buildings to cut electricity, butane and propane use.
Energy	Mobile combustion	Public-transport fleet renewal; gradual renewal of taxis; eco-driving training; clean-vehicle standards and incentives; alignment with stricter EU emission norms.
Agriculture	Soils	Solar pumping for irrigation as a substitute for butane.
Waste	Solid waste	Bio-mechanical treatment with co-incineration (sorting, grinding, aerobic drying).
Waste	Wastewater	Biogas recovery from wastewater-treatment plants for electricity.

Other options include carbon capture and storage (which is limited in the short term), reforestation (which is subject to hydrological and water footprint constraints, as discussed by (Rehman et al. 2022)), and emissions trading. To achieve carbon neutrality by 2050, a gradual, adaptive approach combining technological progress, an evolving energy mix and carbon offset mechanisms will be required.

5. CONCLUSIONS

This study combines a reconstructed IPCC Tier 1 inventory with a STIRPAT-Ridge analysis of the Rabat-Salé-Kénitra region from 1989 to 2021. Estimated emissions increased from approximately 5.5 to 10.4 Mt CO₂e (+88%), with the energy sector accounting for an increasing proportion (61% to 75%). However, the first-difference model provides little improvement over simple benchmarks and has essentially no explanatory power in growth-rate space. A separate hold-out diagnostic covering 2012–2021 indicates poor temporal transferability. Once inventory uncertainty is propagated, no driver association can be distinguished from zero.

Conditional emissions in 2050 reach approximately 18.4 Mt CO₂e under a business-as-usual scenario, compared to 14.7 and 11.1 Mt CO₂e under the Increased-Ambition and Green-Development scenarios, respectively. These alternatives apply mitigation wedges of 20% and 40% respectively; they are illustrations, not forecasts or estimated policy effects. Regional priorities include improving the energy efficiency of buildings, installing solar photovoltaics, developing public transport systems, and recovering resources from municipal waste and wastewater.

The principal contribution is a transparent, transferable framework for evaluating the limited regional data available. The framework's limitations include short series ($n = 33$), extensive reconstruction and downscaling, and propagation of sector-level uncertainty rather than a full input-level IPCC Approach 2 analysis. Only 0.3% of the calculated emissions are based on directly observed regional activity data, and no causal attribution of the stabilisation after 2011 to specific policies is claimed. Future work should prioritise direct regional observations,

input-level uncertainty distributions and correlations, longer time series and assessments of mitigation costs, feasibility and social impacts.

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