From Data to Product

The Impact of Plastic Waste as a Currency

Arancha Ramirez 02122361
Zoe Hall 02269583

December 11, 2025

Table 1: Task distribution

	Arancha	**Zoe**
Ideation	50%	50%
Data sourcing	40%	60%
Data curation	50%	50%
Data product canvas	50%	50%
Conceptual and system design	60%	40%
Programming	50%	50%
Testing and validation	50%	50%
Archiving and documentation	50%	50%
Report writing	50%	50%

https://github.com/zoemhall/Data2Product

Disclaimer: GenAI was used to support this report; for more details, please see the Appendix Table 3.

1 Introduction

Plastic waste is a growing global challenge caused by rising consumption, poor waste-management systems and limited recycling capacity. While often viewed as a domestic issue, the international movement of plastic waste exposes deeper economic dependencies: high-income countries frequently export low-value plastics to lower-income nations, shifting environmental burdens onto regions with fewer protections. This unequal global waste trade has been further impacted by major policy shifts (most notably China's 2018 import ban [1] and recent amendments to the Basel Convention [2]), highlighting the urgent need for a more transparent, circular, and equitable system for managing plastic waste at the end of life.

2 Motivation

We were motivated by similarities between global waste flows and earlier manufacturing shifts, where low-cost markets evolved into specialised, high-capacity industries. We aimed to examine whether similar dynamics in plastic waste trade could support countries in strengthening their own circular economies. By revealing financial dependencies and processing roles, the data product clarifies responsibility for waste outcomes and provides insights to guide more sustainable and equitable investment in waste-management infrastructure.

2.1 Ideation

During the ideation phase we explored four possible narratives for modelling the value and movement of plastic waste:

- A base model estimating fair processing prices and trade margins assuming plastic exported would be processable [3]
- An infrastructure model forecasting how capacity growth shapes future dependencies
- A transport model comparing recycling costs with shipping distances
- An ethical-processing model linking trade patterns to environmental harm

Each concept was assessed for data availability and required assumptions, to evaluate feasibility and risk before selecting the most robust direction, summarised in Table 4.

Table 2: Comparison of Model Constraints and Rankings

	Amount of Assumptions	**Ranking / 5**
Base Model	Assumes strict recycling for all traded plastic and models energy costs as a fixed global rate per kg.	**4**
Ethical Processing	Relies on theoretical capacity limits to determine trade routes; shares speculative nature with Infrastructure.	**3**
Infrastructure	Requires speculative margins for future infrastructure investment prices.	**2.5**
Transport	Assumes fixed variable rates for maritime transport, ignoring fuel fluctuations and route specifics.	**2**

We selected the base model because it required the fewest assumptions while offering the richest analytical pathway for comparing countries.

2.2 Solution Description

Our solution integrates OECD waste and UN Comtrade data to show how countries process plastic waste domestically and for others. After processing the datasets, we estimate domestic and international processing and their relevant economic value, generating two indicators: self-sufficiency and local industry value.

The data product provides three analytical approaches: historical trends (descriptive), prescriptive metrics, and forecasting, allowing users to examine past behaviour, assess system performance, and explore potential plans for future growth. The aim is not to predict exact trade flows but to clarify global waste dependencies and the economic relationships behind them, consistent with our goal of treating plastic waste as a form of currency.

2.3 Audience

Our data product is designed for users who need to understand or plan around global plastic waste flows, including policymakers, environmental researchers, industry stakeholders, development agencies and NGOs. These groups rely on clear insights into waste dynamics, system performance and future capacity needs to inform regulation, investment and advocacy. This approach can help clarify global waste dependencies, support fairer, more sustainable policy decisions, and guide investment toward areas where additional processing capacity could make a real difference for the circular economy.

3 Methodology

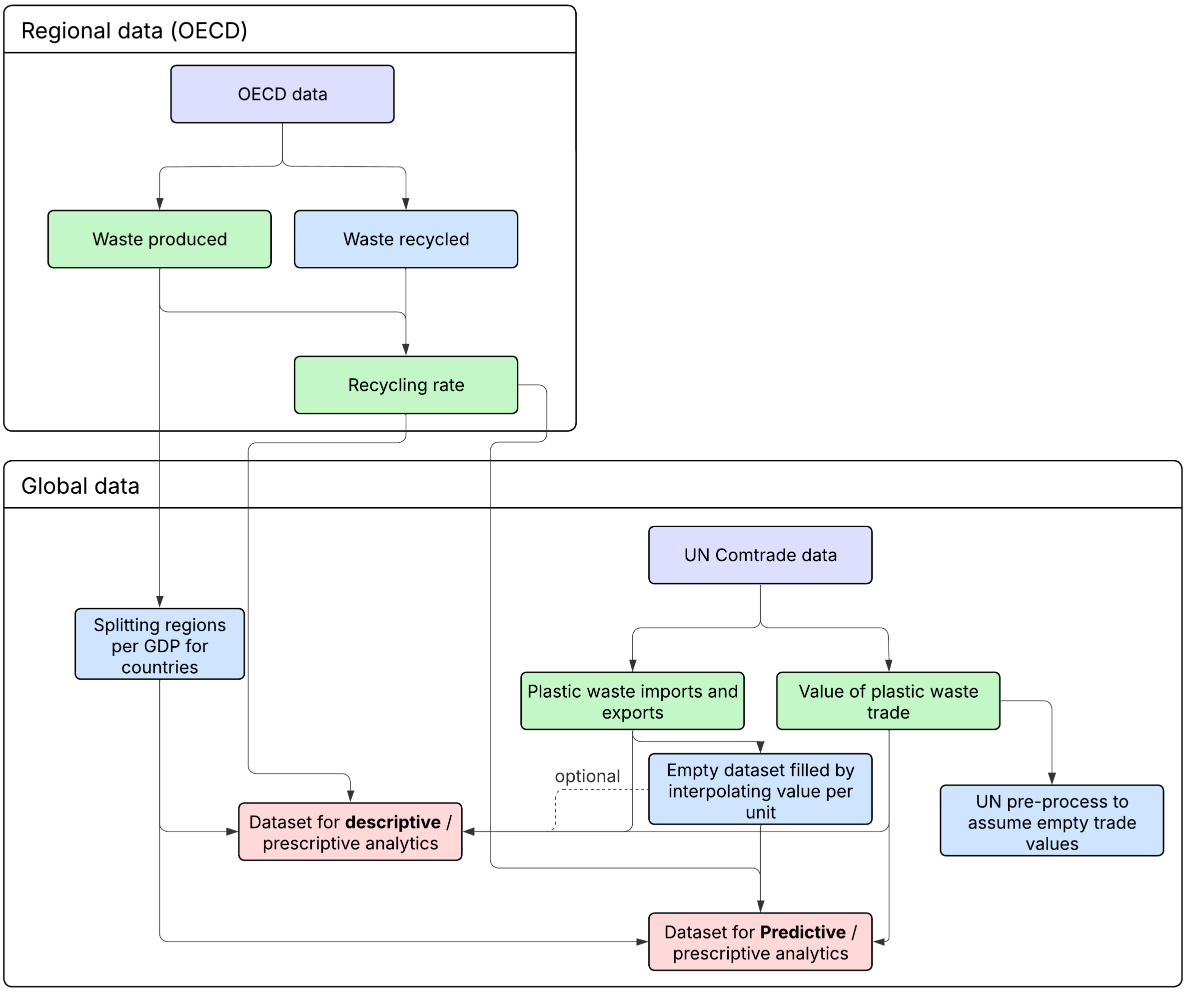


Figure 1: Flow map of data processing approach.

3.1 Data Sourcing and Curation

All datasets used, with appropriate file names and directory paths, are listed in the Appendix.

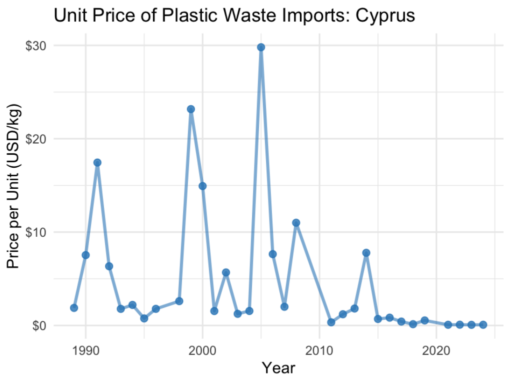
We sourced two initial datasets from Our World in Data [4], which summarise plastic imports and exports in tons. These are based on UN Comtrade **UN comtrade** records, with basic standardisation applied. Because this dataset had already been processed, we went directly to the UN Comtrade database to retrieve the raw trade quantities and values. This allowed us to work with the original records and simplify later calculations by using the reported trade value divided by quantity to estimate a local unit price. Using the initial Our World in Data dataset, we obtained the raw data via the OECD Data Explorer [5]. The dataset was archived, with the same public version excluding data between 1990-2000 [6]. For this reason, we decided to continue with the archived dataset.

3.2 Data Imputation

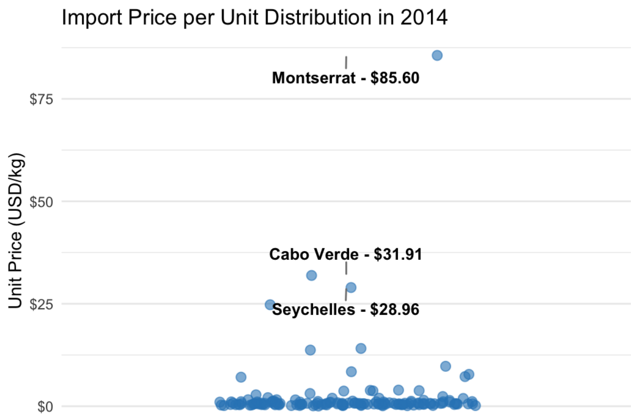
The UN Comtrade dataset contained trade values reported without corresponding quantities, requiring us to estimate missing weights to build a usable time series for forecasting. We addressed this by deriving country-specific unit prices and applying temporal smoothing, using global medians when no local history existed. These imputed values are reserved solely for forecasting (toggle to view in descriptive), ensuring continuous model-ready data while keeping descriptive analytics based only on reported figures.

3.2.1 Calculating Unit Values

First, we checked if we could use a standard global price for plastic waste to fill in the gaps. We plotted the Quantity vs. Value for imports in 2024 to see if there was a consistent pattern Figure 8.



(a) Unit Price of Plastic Waste Imports for Cyprus over time



(b) Unit price for imports globally in 2014

Figure 2: Comparing variation in unit values for plastic waste (USD/Kg).

As the chart shows, there is a considerable variation in prices. The cost of plastic waste varies across regions, likely due to differences in quality or labour costs. Because of this, we couldn't use one global average. Instead, we calculated a per-kg price for each country. The imputation process first derives a time series of Unit Value for each country, filling gaps using temporal smoothing (linear interpolation and forward/backward filling) to maintain year-over-year market continuity.

Only when no country-specific history was available did the process use the global median unit price for that trade flow. For any year t and country i, we calculated the local average price:

$$UnitValue_{i,t} = \frac{\text{Total Trade Value (USD)}}{\text{Total Net Weight (kg)}} \tag{1}$$

If a record had the price but was missing the weight, we used that country's specific unit value to fill it in:

$$EstimatedWeight_{i,t} = \frac{\text{Reported Price (USD)}}{UnitValue_{i,t}} \tag{2}$$

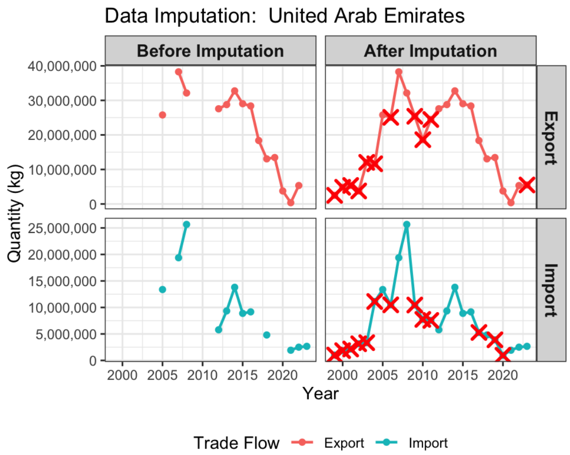
3.2.2 How We Use These Estimates

We wanted to be careful about where we used the filled-in data:

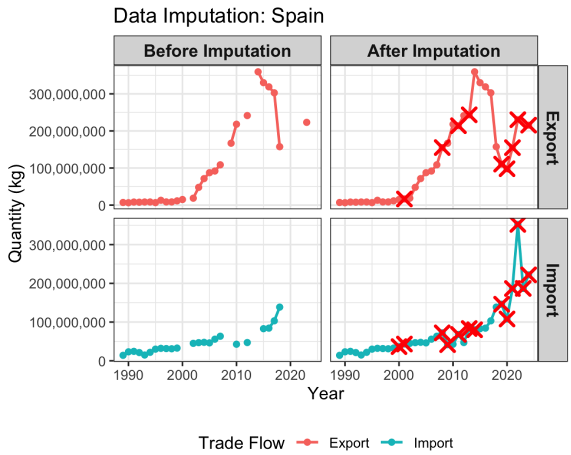
- **Descriptive analysis (History):** We do **not** show these estimates on the map. The map only shows the actual, reported data to avoid misleading the user, but an additional tab will be included for users who want to view the estimated values.
- **Predictive Analysis (Future):** We **do** use these estimates for the forecasting models. This fills the gaps in the timeline, allowing the code to run.

3.2.3 Results of Data Imputation

The necessity of this imputation is demonstrated by comparing the raw versus imputed Comtrade data for key countries, such as the United Arab Emirates or Spain.



(a) Data Imputation results for UAE



(b) Data Imputation results for Spain

Figure 3: Comparing before and after Data Imputation process.

Before correction, records for specific years, such as the United Arab Emirates imports and exports from 2000 to 2012, reported a quantity of zero kilograms despite showing substantial trade values. This significant data mismatch would have rendered the subsequent forecasts for the data product inaccurate. By successfully imputing country-specific quantities, the process transformed incomplete data into continuous, usable time series as shown in Figure 3.

3.3 Prescriptive metrics

3.3.1 Local Industry Value

Local Industry Value measures the economic benefit a country derives from processing plastic waste, combining both domestic material and imports. We calculate it by multiplying the total quantity of waste processed with a country-specific, smoothed unit price derived from UN Comtrade data. This metric helps reveal where waste processing already functions as an economic asset and where future investment may create value, though it remains sensitive to price volatility.

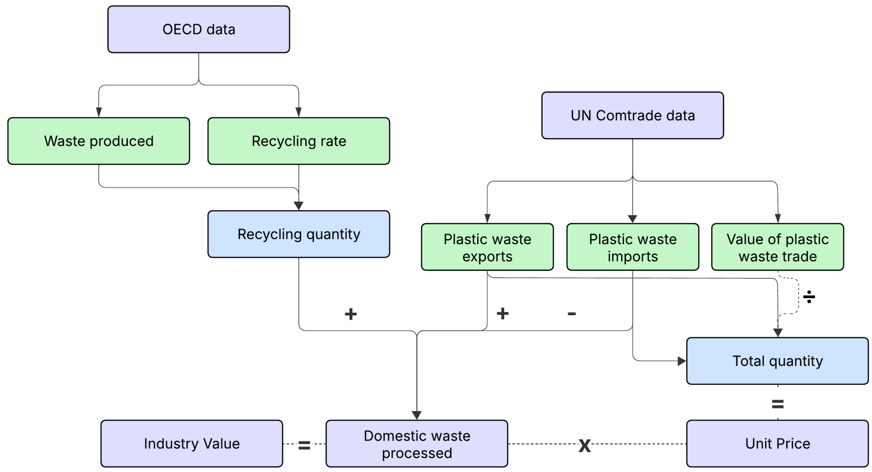


Figure 4: Local industry value derivation.

3.3.2 Self-sufficiency

Self-sufficiency captures the extent to which a country can process its own plastic waste rather than relying on others. It is computed as the share of waste produced that is recycled domestically, using OECD production and recycling data combined with trade flows from UN Comtrade. This metric highlights structural dependencies in the global waste system and identifies countries that may be emerging or declining as core processors.

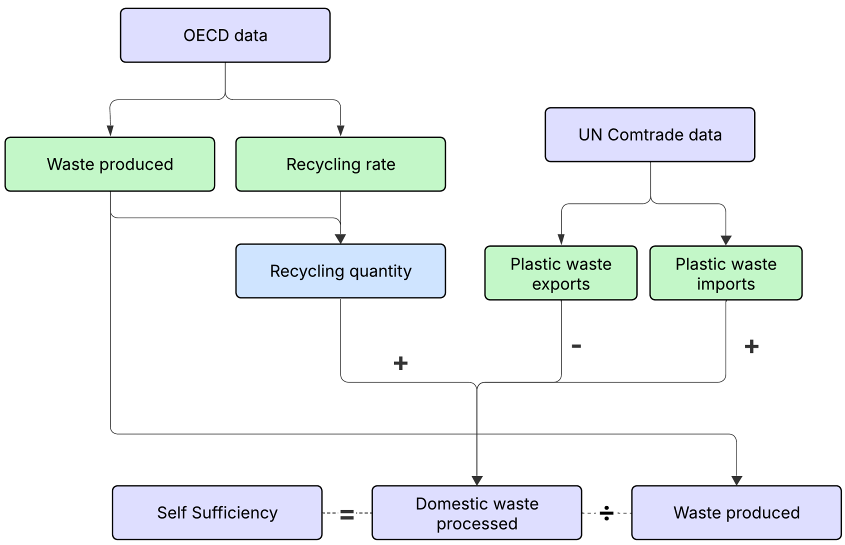


Figure 5: Self-sufficiency derivation.

3.4 Testing assumptions

Value to process waste is different per country. While we initially planned on using local energy prices with a fixed rate of energy needed to process a unit of plastic, the UN Comtrade data includes the value of plastic sold and the quantity. To test our assumption, we plotted the value (USD) against the quantity to confirm there wasn't a consistent unit price.

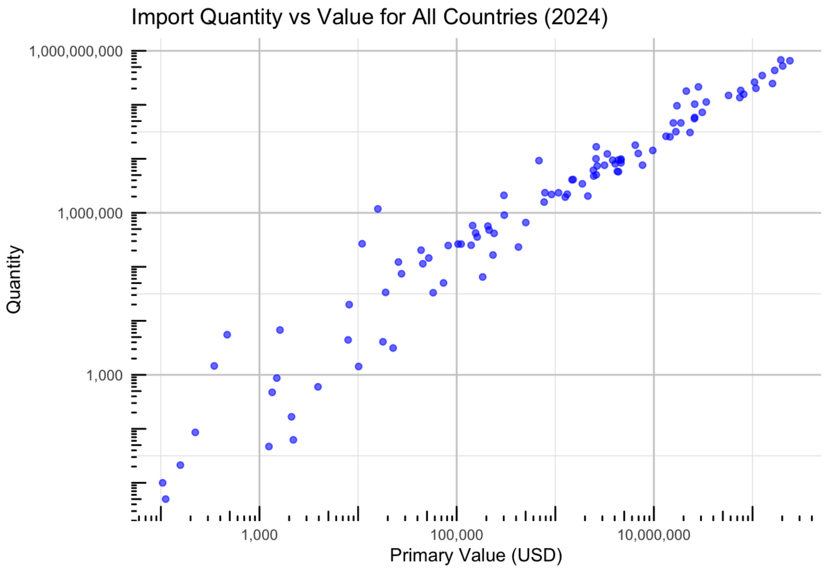
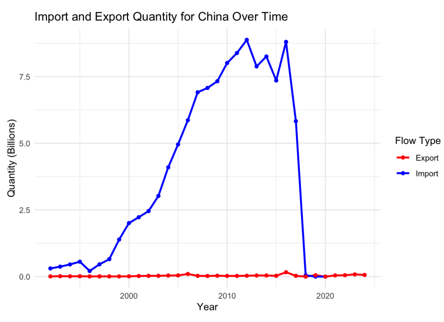


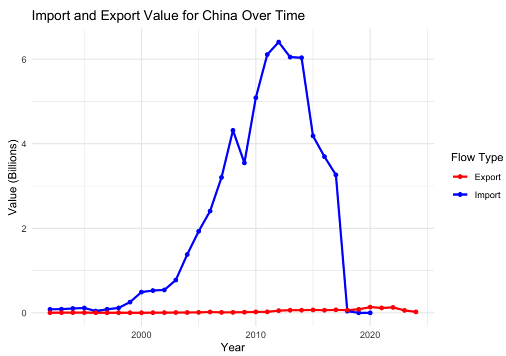
Figure 6: Import Quantity vs. Value (2024). The wide spread shows that prices vary too much to use a single global average.

Figure 8 shows that there is no linear relationship for unit prices globally. This confirms that unit prices vary because of differences in plastic type, labour cost, and contamination. This directly justifies country-specific price interpolation rather than a global constant.

Reliability of our dataset compared to real-world events: To validate the reliability of our dataset, we compared it against known trade events. Although sourcing raw data directly from the UN provides a strong baseline, we also checked alignment with major historical shifts, most notably China's 2018 ban on plastic waste imports [1].



(a) Import and Export quantity for China over time



(b) Import and Export value for China over time

Figure 7: Comparing China's plastic waste trade history against historical markers.

This shows the sudden dip in plastic waste trade in 2018, with a slight dip in 2017 as they started introducing the ban, validating that our dataset matches this historical marker. We can also see the impact of this trade ban by looking at the global response to this ban.

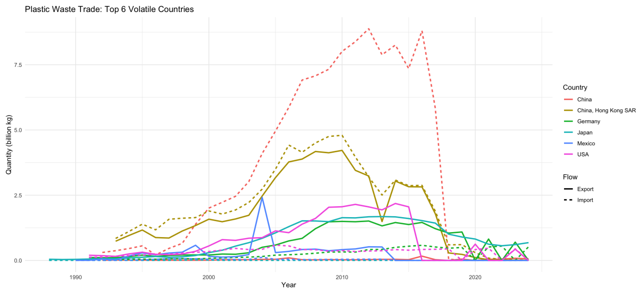


Figure 8: 6 most volatile countries by variation in import and export quantities.

By looking at the behaviour of the most volatile countries in terms of variation for import and export data, we can see the impact of this ban on other countries.

Price per kg fluctuates and responds to market events: As we're assuming the behaviour of value per kg is a volatile, dynamic factor influenced by policy, contamination, or local conditions, we treat it as a country-specific signal that must be smoothed and capped rather than modelled as a fixed global rate.

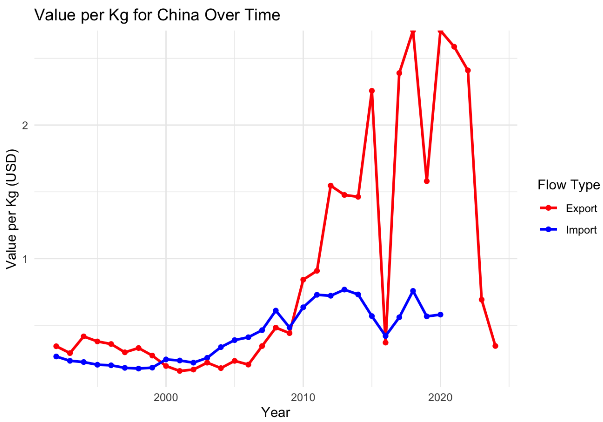
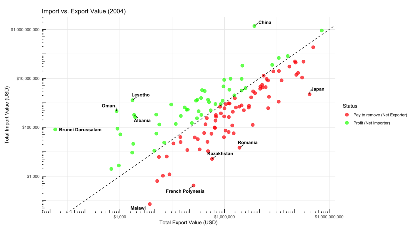


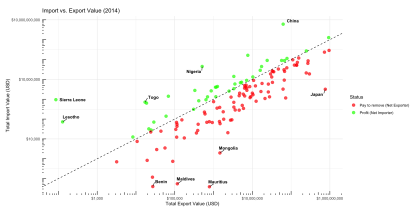
Figure 9: Value per kg for China over time.

Figure 9 shows sharp upward jumps following tightening contamination standards. This demonstrates that price signals respond to market behaviour and should not be smoothed into a static input.

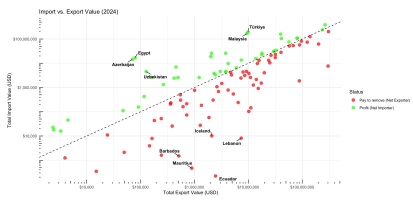
Import and export behaviour is structurally different: Assuming that countries behave differently as importers vs exporters as exporters tend to trade lower-value material. This will impact our interpolation for unit prices when computing the prescriptive analysis later.



(a)2004



(b) 2014



(c) 2024

Figure 10: Import vs Export value behaviour.

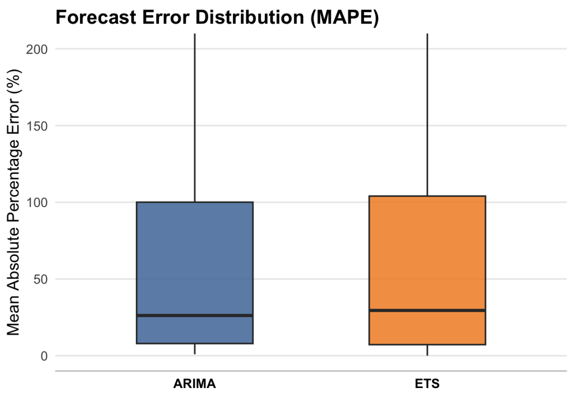
The Export vs Import Value per kg plots show systematic asymmetry: exporters cluster at lower values, while importers often pay more per kg. This supports the model's decision to treat import and export flows separately instead of assuming symmetric behaviour. The equal distribution either sides of the division line shows that there's a balanced behaviour between net importers and exporters of plastic waste.

3.5 Comparing different forecasting approaches

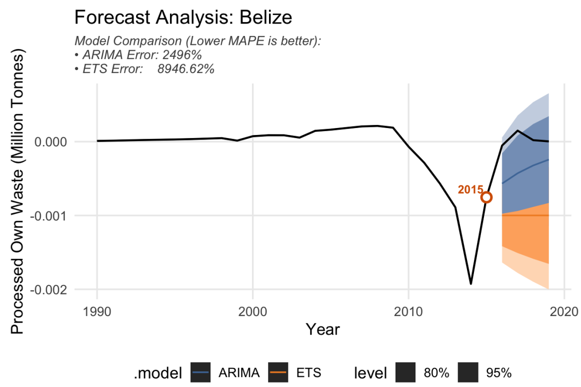
We tested two standard statistical models: ETS (Exponential Smoothing) and ARIMA (AutoRegressive Integrated Moving Average).

To determine which model was most effective, we split the data into a training set (1990–2015) and a test set (2016–2019). The models were asked to predict the last four years, which were then compared with the observed values and MAPE (Mean Absolute Percentage Error) was compared.

3.5.1 Forecasting prescriptive data (Direct forecast)



(a) Direct forecast errors for global data.



(b) Direct forecast example for Belize.

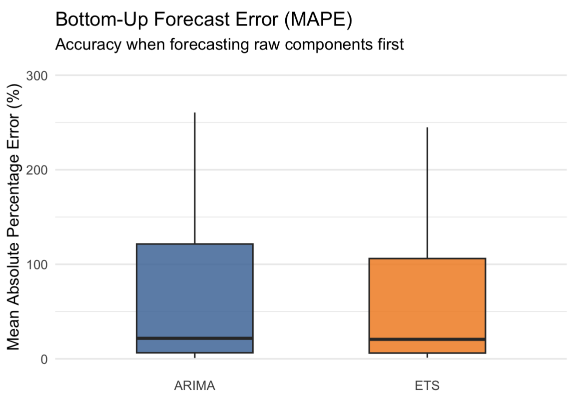
Figure 11: Comparing ETS and ARIMA for the direct forecast of prescriptive metrics.

We tested both models on all countries in the dataset. As shown in Figure 11a, the ARIMA model generally performed better than ETS. To understand where they disagreed, we examined Belize (Figure 11b); sudden drops in its trade history caused both models to struggle.

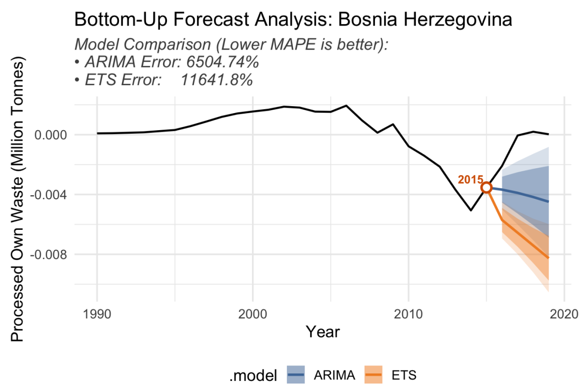
Because global plastic trade is volatile and prone to shocks, ARIMA is the better choice for the direct approach, as it handles irregular patterns more robustly than ETS.

3.5.2 Forecasting raw data, then applying prescriptive analytics (Bottom–up forecasting)

In the bottom–up approach, we first forecast the raw quantities (imports, exports, production and recycling) and then compute the prescriptive metrics from those forecasts.



(a) Bottom–up forecast errors for global data.

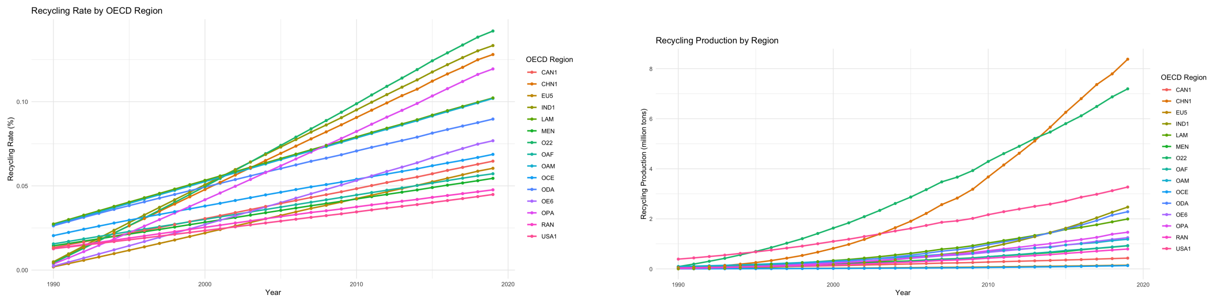


(b) Bottom–up forecast example.

Figure 12: Bottom–up forecasting of raw components before computing prescriptive metrics.

This approach slightly improves accuracy relative to the direct method, because errors are introduced at the level of underlying quantities rather than directly in the transformed indicators.

Exception: Forecasting recycling rates over production quantities. When comparing prescriptive metrics, using recycling rates rather than raw recycling quantities yielded higher forecasting accuracy.



(a) Recycling rate for plastic waste by OECD region.

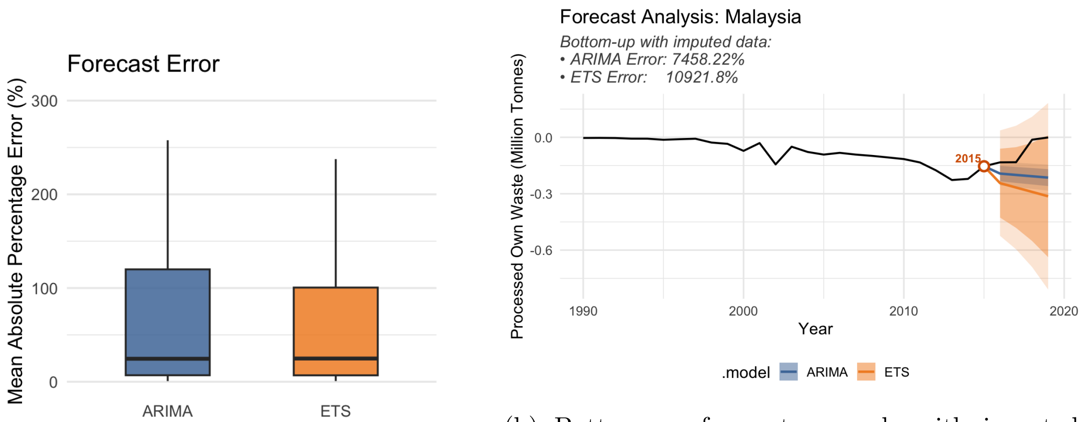
(b) Recycling production quantities by OECD region.

Figure 13: Comparing recycling metrics used for forecasting.

We tested whether forecasting recycling quantities or recycling rates would produce more reliable downstream results. Figure 13 shows that recycling rates produce smoother series, lower error and avoid scaling OECD quantities to global levels, so the rate metric was preferred.

3.5.3 Forecasting raw, fully imputed data, then applying prescriptive analytics

Finally, we tested a bottom–up approach using the fully imputed dataset to ensure continuity for countries with missing values.



(a) Forecast errors using imputed data.

(b) Bottom–up forecast example with imputed data.

Figure 14: Performance of forecasting on fully imputed data.

Although this produces continuous time series, it introduces additional uncertainty from the imputation step and leads to higher MAPE than using only reported data. Imputed data is therefore used only to keep the forecasting engine running for all countries, not as a way to increase accuracy.

3.5.4 Comparison

Overall, ARIMA consistently outperforms ETS across direct and bottom–up approaches. The best performance is achieved by the bottom–up ARIMA model using raw data, while forecasts based on imputed data are clearly less reliable Table 7.

3.6 Conceptual and System Design

This involves the system description, i.e., how the frontend should look like (and related coding requirements), choice of visualisations, what functions and blocks of code will be necessary on the back-end side

3.7 Plan for the UI

The UI was structured into three tabs to reflect the product's analytical stages and support clear navigation:

- Raw Data Visualisation for exploring historical production and trade patterns
- Prescriptive Analytics for evaluating system performance through derived metrics
- Forecasting for generating country-level projections under user-controlled modelling choices

Its design aligns with user needs by enabling rapid country comparison, visibility of historical patterns and intuitive exploration of global waste dependencies.A world heat map was chosen as the primary visualisation to provide an immediate, spatially coherent view of system behaviour, offering clearer contextual insights than tables or static plots.

A summary of the interface plan is provided in Table 6, with the initial Figma prototype shown in Figure 15.

Figure 15: Initial design prototyped in Figma

4 Development process and outcomes

4.1 Descriptive analytics

The descriptive analytics stage turns the cleaned historical data into indicators that can be explored at the country level. The system combines UN Comtrade and OECD records into yearly totals for imports, exports and waste-system quantities, while handling missing or zero-weight entries carefully so they do not distort the results.

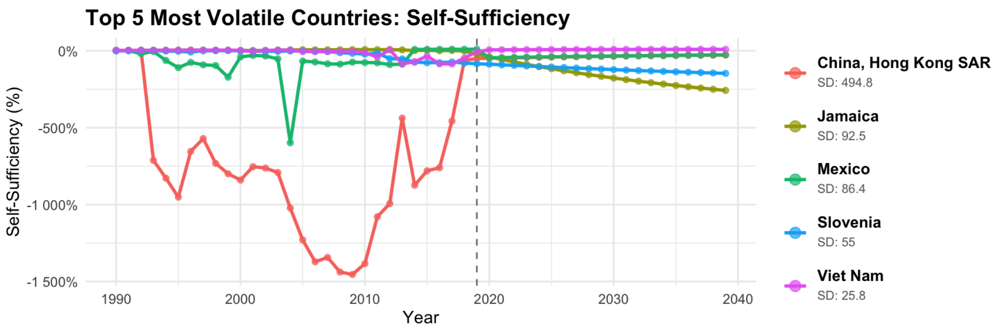
For the descriptive tab, the main challenge was updating global indicators quickly when users changed the year or metric. We solved this by organising the data into year-indexed summaries that could be filtered without recalculating everything. When a country was selected, the system aggregated its production, processing, and trade data into a single time series. This required cleaning and aligning country identifiers so the datasets matched correctly before plotting.

4.2 Forecasting Methods for Prescriptive Analytics

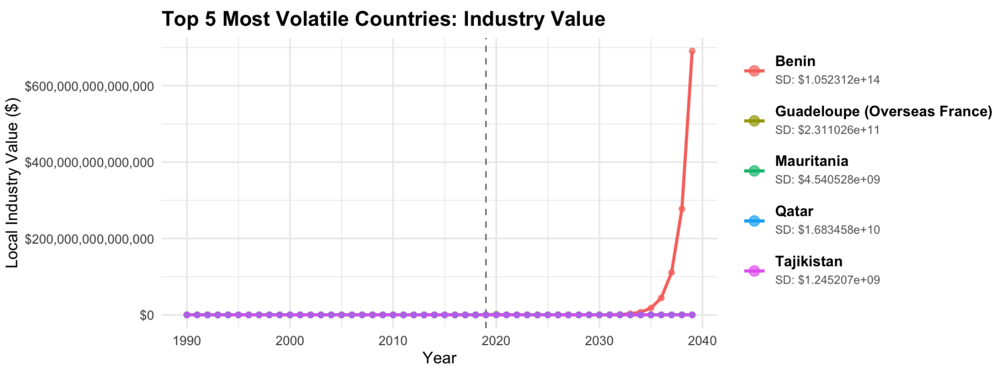
Forecasting global plastic waste flows introduces several challenges. The historical data contains gaps, abrupt policy-driven shocks, and large differences in volatility between countries. These features make the forecasting task sensitive to model choice and preprocessing. To ensure the prescriptive results were meaningful, we tested each forecasting method on the most volatile countries. This surfaced weaknesses early and helped refine the forecasting engine.

Initially, we planned to present prescriptive analytics using a fixed ARIMA model projecting 20 years ahead. As constraints and errors accumulated, we evaluated the model by forecasting the five most volatile countries, those with the most significant historical variance. This made issues in the system immediately visible.

4.2.1 Simple ARIMA forecasting model



(a) Self-sufficiency results



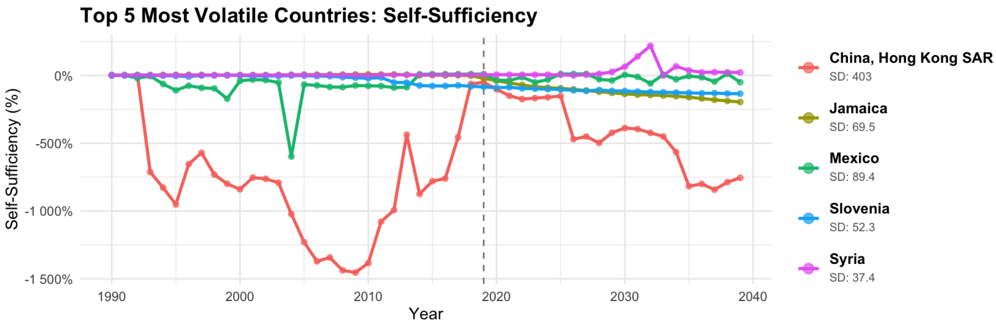
(b) Local industry value results

Figure 16: Initial forecasting outputs demonstrating volatility issues

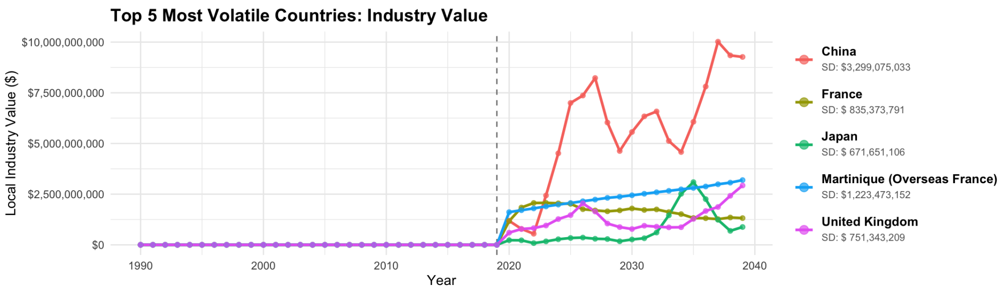
Self-sufficiency is a ratio (processed domestic waste / waste produced), so it's susceptible to noise, especially when the denominator is small. Even modest fluctuations in the forecasted components can produce large swings in the percentage.

Industry value combines several transformed variables, forecasted flows, smoothed prices, and caps, so any drift is amplified. This creates unstable behaviour in some countries Figure 16, even when underlying quantities remain reasonable.

4.2.2 Adding error through bootstrap sampling



(a) Self-sufficiency results with bootstrap error



(b) Local industry value results with bootstrap error

Figure 17: Forecasts using ARIMA with bootstrap-resampled errors

In this model, all forecasted variables were generated using a standard ARIMA model with bootstrap sampling. Bootstrap sampling adds realistic uncertainty by reusing past forecast errors, creating future values that reflect historical variation.

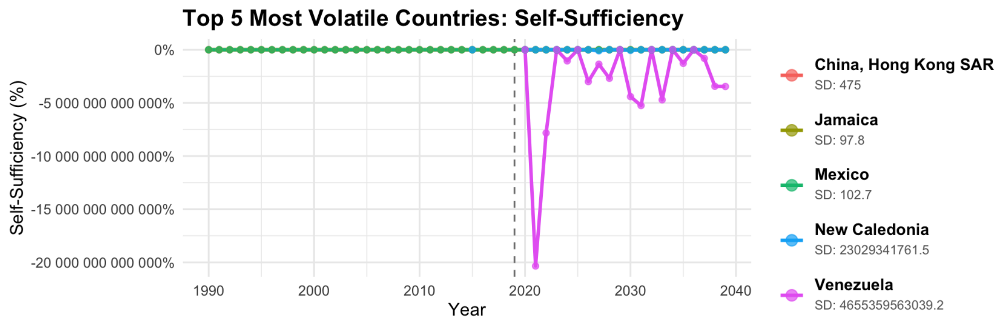
While this model works for the self-sufficiency model, it fails at being realistic for forecasting industry value. This is because industry value is computed after multiple non-linear transformations, so variance accumulates. Bootstrap sampling only works well when the original data has enough variability to produce meaningful residuals.

4.2.3 Adding controlled noise and price smoothing

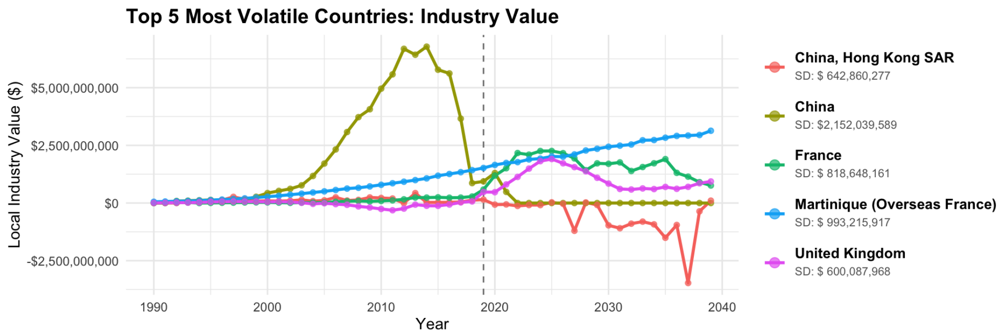
To address the previous model's limitations, we added controlled noise, which introduces only a small amount of variation based on each country's historical volatility. This preserves meaningful uncertainty without letting randomness dominate the forecast.

We also stabilised the unit price by interpolating missing values, applying a strict upper cap, and smoothing the result with a rolling mean. This prevents isolated price spikes from distorting industry value.

Together, these adjustments produce more realistic long-term industry value trajectories, as shown in Figure 18b, while avoiding the instability observed in earlier models.



(a) Self-sufficiency forecast using a more complex model



(b) Improved industry value forecast

Figure 18: Comparison of alternative forecasting methods for each system

4.2.4 Final forecasting method

To compute self-sufficiency, we forecast the underlying quantities (production, recycling, imports, and exports) using an ARIMA model with bootstrap errors, and then compute the ratio of processed domestic waste to total waste produced. Forecasting components rather than ratios avoids instability from small denominators and yields smoother, more interpretable results.

Local Industry Value behaves more like an economic time series, so we use an enhanced ARIMA model with controlled noise and smoothed, capped unit prices to prevent unrealistic spikes. This generates credible long-term trends with moderate fluctuations.

Overall, the bottom-up ARIMA approach is most appropriate for self-sufficiency. At the same time, the enhanced ARIMA + noise + price smoothing model is better suited to Local Industry Value, reflecting the differing mathematical behaviour of the two metrics.

4.3 Development of UI

The UI was developed to display the analytical outputs in a consistent, interactive environment, ensuring that the system remained interpretable and consistent.

4.3.1 Descriptive Interface

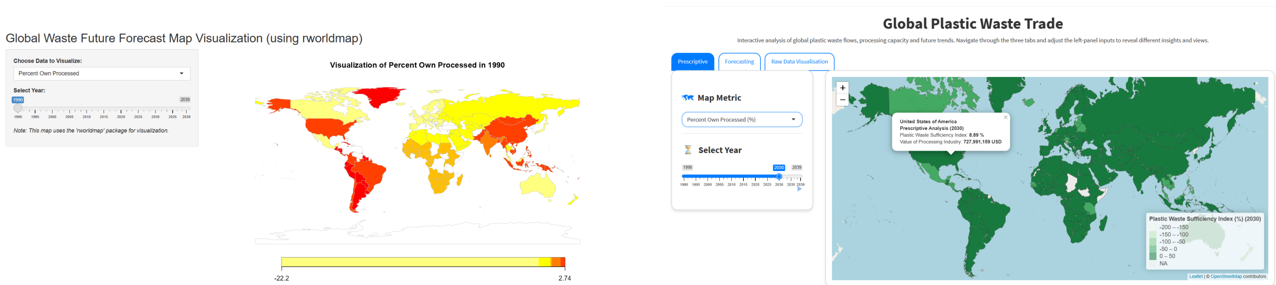
The descriptive interface centres on a global heatmap that updates with user inputs and allows country selection to reveal detailed waste-system data and a "waste history" graph. This structure enables users to identify meaningful trends, such as shifts in processing behaviour, and validate the dataset against known events. The interface underwent several iterations to improve usability, ultimately adopting a single-page layout that avoids scrolling and placing the country details and history graph above the map with simple open/close controls to keep the display clean while ensuring deeper insights remain accessible, as shown in Figure 19.

Iteration 1 Iteration 6 Iteration 11

Figure 19: Descriptive UI iterations

4.3.2 Prescriptive Interface

The prescriptive interface imitates the descriptive layout but displays model-derived indicators, so users can interpret system performance within a familiar visual structure. Because these metrics depend on multiple transformed variables, the interface recalculates only the required components when users adjust the selected metric, showing only the final values to preserve clarity. Using a global heatmap highlights spatial differences in processing capacity and economic value, while country-specific pop-ups offer contextual summaries. This interface also evolved through several iterations to balance interpretability and simplicity, as illustrated in Figure 20.

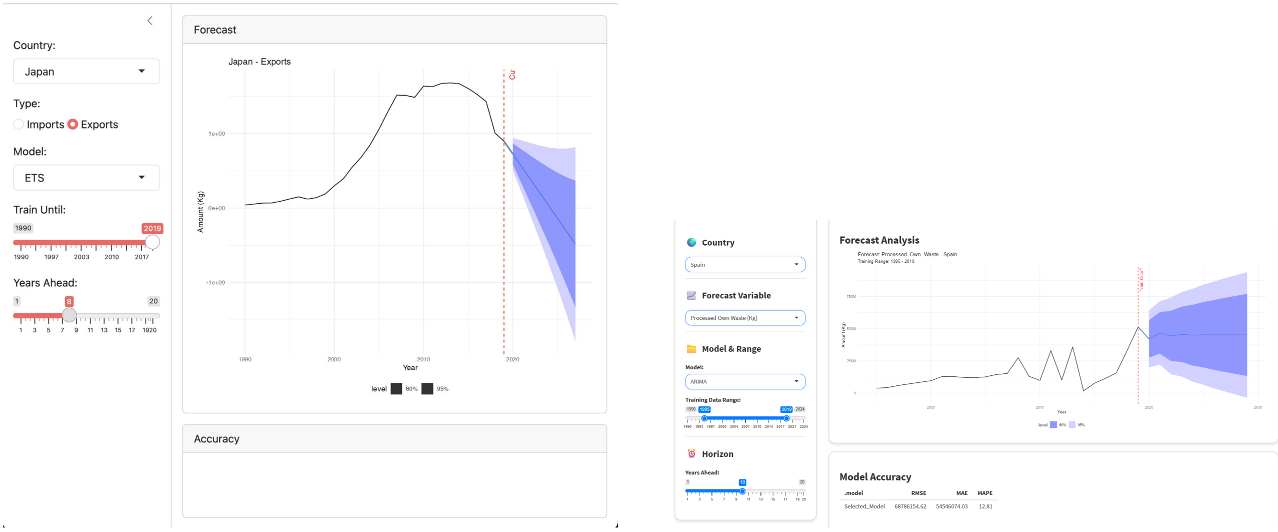


(a) Iteration 1 (b) Iteration 6

Figure 20: Prescriptive UI iterations

4.3.3 Forecasting Interface

The forecasting interface enables users to generate country-level projections by selecting modelling parameters with each change triggering a reactive rebuild of the forecast. The main panel overlays projections with historical data to illustrate continuity and uncertainty, complemented by confidence intervals that communicate volatility in the forecasted series. To keep the visual output clear despite complex backend transformations, only the relevant forecasted quantities or prescriptive metrics are displayed, while an accuracy table summarises model performance for the chosen configuration. This interface, like the others, underwent multiple iterations to refine clarity and usability, as shown in Figure 21.



(a) Iteration 1 (b) Iteration 6

Figure 21: Forecasting UI iterations

4.3.4 Design Standardisation and Usability

Across all tabs, the interface uses a consistent structure: a sidebar with inputs and a central output panel, supported by a unified visual theme to keep navigation intuitive and the layout clear. This standardisation allows users to move seamlessly between descriptive, prescriptive, and forecasting views without adapting to new interaction patterns, thereby maintaining the coherence of the overall product Figure 22.

Raw Data UI Prescriptive UI Forecasting UI

Figure 22: Data product final 3 main UI displays

5 Discussion

The development of this data product successfully demonstrated how fragmented global plastic waste records can be transformed into a coherent analytical system that supports descriptive, prescriptive and predictive insights. We achieved our objective of clarifying global waste dependencies and revealing how financial and material flows shape national processing roles. The descriptive interface revealed clear structural patterns and aligned closely with real-world events, validating both the dataset and the chosen visual approach. The prescriptive analytics provided an accessible way to interpret system performance, though the sensitivity of self-sufficiency to small denominators and the volatility of industry value highlighted inherent limitations in ratio-based indicators. The forecasting engine further extended the product's usefulness by allowing users to explore potential future scenarios. However, this component remains constrained by shocks, sparse histories, and the unpredictability of policy changes.

Several trade-offs shaped the final design. Separating raw, prescriptive and forecasted outputs into distinct tabs simplified navigation. Similarly, restricting descriptive outputs to reported data avoided misleading users but introduced discontinuities that had to be resolved for forecasting. These decisions reflect a broader tension between transparency, accuracy and usability, which is central to any real-world data product. The user interface reached a standardised form through iterations, but further refinements could improve how uncertainty is communicated, particularly for countries with minimal historical data.

5.1 Reflections and Next Steps

In retrospect, the product could be strengthened by incorporating datasets that capture policy changes, to contextualise historical patterns better and distinguish behavioural trends from policy-driven shocks. This would improve the interpretability of forecasts and clarify sources of uncertainty. From a UI perspective, features such as country comparisons could further enhance its value for decision-makers.

5.2 Conclusion

Overall, the data product helps users make sense of global waste flows by turning fragmented records into a clear picture of who processes what, for whom, and at what economic value. By bringing together historical trends, system performance metrics and simple forecasting, it enables users to visualise how waste-processing roles might evolve in ways similar to earlier manufacturing growth. This perspective highlights where countries could strengthen their infrastructure and how fair compensation for processing could support more balanced global relationships. While the product can be expanded further, the current version already provides a practical foundation for exploring how plastic waste functions within broader economic and capacity-building dynamics.

References

[1] *China's waste import ban*, 2025. [Online]. Available: https://en.wikipedia.org/wiki/China%27s_waste_import_ban.

[2] U. Nations, *Basel convention on the control of transboundary movements of hazardous wastes and their disposal*, 2025. [Online]. Available: https://www.basel.int/Implementation/Plasticwaste/Overview/tabid/8347/Default.aspx#:~:text=In%202019%2C%20the%20Conference%20of%20the%20Parties%20adopted%20the%20Plastic,for%20exports%2C%20transit%20and%20imports..

[3] *New EU rules restrict export of plastic waste — Food Packaging Forum*, en-US, Jan. 2021. Accessed: Dec. 9, 2025. [Online]. Available: https://foodpackagingforum.org/news/new-eu-rules-restrict-export-of-plastic-waste.

[4] *Plastic Waste and Pollution Data Explorer*, en. Accessed: Dec. 10, 2025. [Online]. Available: https://ourworldindata.org/explorers/plastic-pollution?tab=table&time=earliest..2019&hideControls=false&Metric=Plastic+waste+generation&Per+capita=false&Share+of+world+total=false&Source=OECD&country=USA~CHN~IND~GBR~MYS~DEU.

[5] *OECD Data Explorer - Archive • Plastic waste by region and end-of-life fate*. Accessed: Dec. 10, 2025. [Online]. Available: https://data-explorer.oecd.org/vis?tenant=archive&df%5Bds%5D=DisseminateArchiveDMZ&df%5Bid%5D=DF_PLASTIC_WASTE_5&df%5Bag%5D=OECD&dq=.&lom=LASTNPERIODS&lo=5&to%5BTIME_PERIOD%5D=false.

[6] R. Geyer, J. R. Jambeck, and K. L. Law, "Production, use, and fate of all plastics ever made," en, *Science Advances*, vol. 3, no. 7, e1700782, Jul. 2017, ISSN: 2375-2548. DOI: 10.1126/sciadv.1700782. Accessed: Dec. 10, 2025. [Online]. Available: https://www.science.org/doi/10.1126/sciadv.1700782.

6 Appendices

Table 3: Use of genAI throughout the project

	Sources	Description
Ideation	N/A	No AI was used for Ideation, Data Sourcing or Curation.
Coding	Copilot	Use of Copilot within RStudio for formatting and debugging.
Report writing	Gemini	AI was used to assist with rephrasing and formatting in overleaf.

Table 4: Model Datasets, Assumptions, and Risk Assessment

Label	Datasets	Assumptions	Risk
Base model	Local waste production data, recycling rate. Local energy costs	Imported/exported plastic is only to be recycled. Energy costs assumed to be a fixed rate per kg of plastic	2
Infrastructure	Global data, energy needed to process 1 ton of plastic, global energy costs, investment in waste infrastructure, amount of waste produced locally.	We would need to assume a margin of price to be invested into infrastructure in the future	3.5
Transport	Global data, nautical miles between countries, energy needed to process 1 ton of plastic, global energy costs.	Assuming all boat transport at a fixed variable rate.	4
Ethical Processing	Europe data, plastic % in the ocean, amount of waste produced locally.	Similar assumptions around infrastructure and defining a capacity to determine trade routes	3

Table 5: Dataset Sourcing - pre-processing

Dataset	Sources	Data range	Processing	Directory name
Plastic Imports	Our World in Data	1988 - 2024	Low	Imports.csv
Plastic Exports	Our World in Data	1988 - 2024	Low	Exports.csv
Plastic waste recycling	OECD	1990 - 2019	None	Recycling.csv

Table 6: Summary of User Interface Components for the Data Product

UI Component	Description	Left Panel	Main Panel / Extra Features
Descriptive Analytics	Uses a world heat map to display historical production, recycling, imports, and exports.	Year selection; trade direction; metric controls.	Interactive world map; country click shows metrics and historical graphs.
Prescriptive Analytics	Visualises model-derived indicators (self-sufficiency, industry value).	Selection of prescriptive metric and year.	Heat map coloured by selected indicator; country summary pop-up.
Forecasting	Allows users to generate customised country-level forecasts.	Country selector; variable; model type; training range; forecast horizon.	Forecast plots with confidence intervals; historical comparison; accuracy table (MAE, RMSE, MAPE).

Table 7: Comparison of forecasting models (MAPE).

Approach	Model	MAPE
Direct Forecast	ARIMA	7.164360
Direct Forecast	ETS	7.379748
Direct Forecast	Mean	63.312254
Bottom–Up (Raw)	ARIMA	6.982194
Bottom–Up (Raw)	ETS	7.299045
Bottom–Up (Raw)	Mean	68.169698
Bottom–Up (Imputed)	ARIMA	17.260236
Bottom–Up (Imputed)	ETS	17.347871
Bottom–Up (Imputed)	Mean	37.015205

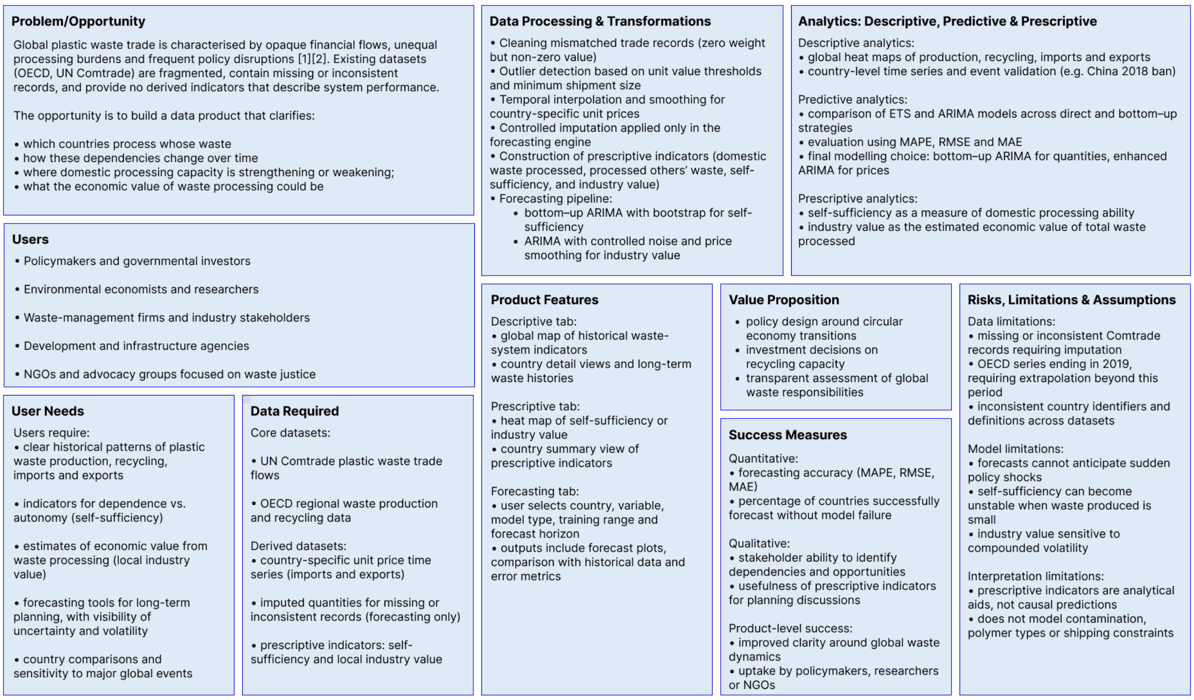


Figure 23: Project model canvas