Supplementary Information

Carbon Emission Quantification via Explainable Deep Learning Demand Forecasting in Retail Supply Chains

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Table 1: **Supplementary Table S1. GHG Protocol Scope 3 category mapping.** Each emission component in the carbon quantification framework is mapped to the corresponding GHG Protocol category and data source.

Component	GHG Scope 3 Category	Data Source
Product emission ($w_i \times \mathrm{EF}_i$)	Cat. 1: Purchased Goods	Ecoinvent 3.9 category-avg EF
Warehousing emission (WEF)	Cat. 8: Upstream Leased Assets	Industry-avg warehouse energy
Overstock waste	Cat. 5: Waste Generated	Forecast residual $\times$ safety stock
Avoided emission	Counterfactual	Scenario comparison vs. baseline

Table 2: **Supplementary Table S2. Model configuration details.** Hyperparameters for the CGAN, multi-channel encoder, and ensemble components.

Component	Parameter	Value
CGAN	Generator layers	3$\times$ TransConv1D (128$\rightarrow$64$\rightarrow$32)
	Discriminator layers	4$\times$ Conv1D + Spectral Norm
	Noise dim / Embedding dims	100 / 50+50+20
	λ_{GP} / Training epochs	10 / 200
	Batch size / Learning rate	128 / 2×10^{-4} (Adam)
Encoder	CNN filters	[64, 128], kernel 3, MaxPool
	BiLSTM hidden / BiGRU hidden	128 per dir / 64 per dir
	Deep LSTM	2 layers, 256 units, dropout 0.1
	Attention	Bahdanau (learnable $\mathbf{v}, \mathbf{W}_a$)
	Encoder epochs / Batch size	100 / 256
Ensemble	Ridge α / KNN k	1.0 / 5
	Random Forest	100 trees, max depth 8
	λ (carbon reg.)	0.01 (tuned via Optuna)

Table 3: **Supplementary Table S3. Emission factor sensitivity analysis.** Relative model rankings are preserved across all emission factor variation scenarios, supporting the framework's utility for comparative assessment despite uncertainty in absolute values.

EF Variation	Carbon Change	Ranking	Interpretation
$\pm$10%	$\pm$10.2%	Preserved	Low sensitivity
$\pm$30%	$\pm$30.8%	Preserved	Moderate; regional databases recommended
Product-level LCA	Varies	Preserved	Absolute values change; % reduction stable

Table 4: **Supplementary Table S4. CGAN generation quality metrics on M5 dataset.** Discriminative score near 0.5 indicates the discriminator cannot distinguish real from synthetic data. Sparse SKUs show slightly lower fidelity but still exceed the quality threshold.

Metric	All SKUs	Dense SKUs	Sparse SKUs
Discriminative score ($\rightarrow$ 0.5)	0.527	0.512	0.543
Predictive score (RMSE $\downarrow$)	2.134	1.987	2.412
MMD ($\downarrow$)	0.023	0.018	0.031

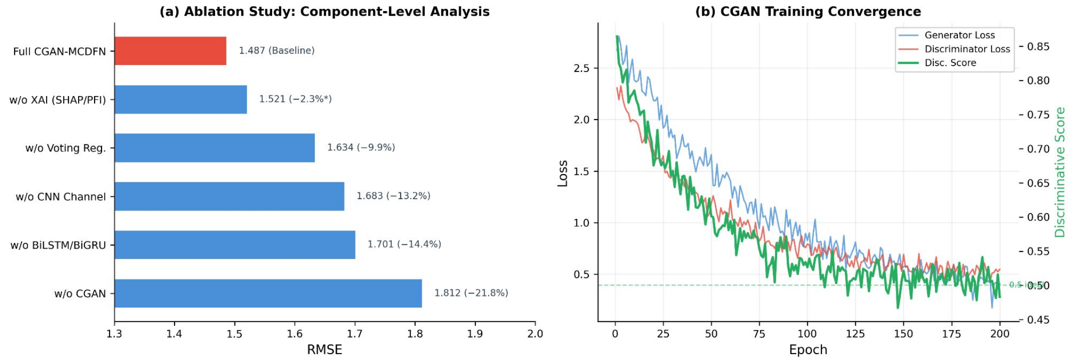

Figure 1: **Supplementary Figure S1. Ablation study and CGAN training convergence.** **(a)** Component-level ablation analysis showing RMSE on the M5 test set when individual components are removed. CGAN augmentation contributes the largest improvement (−21.8%), followed by BiLSTM/BiGRU (−14.4%) and CNN (−13.2%). **(b)** CGAN training curves showing generator loss, discriminator loss, and discriminative score convergence toward the ideal 0.5 over 200 epochs.

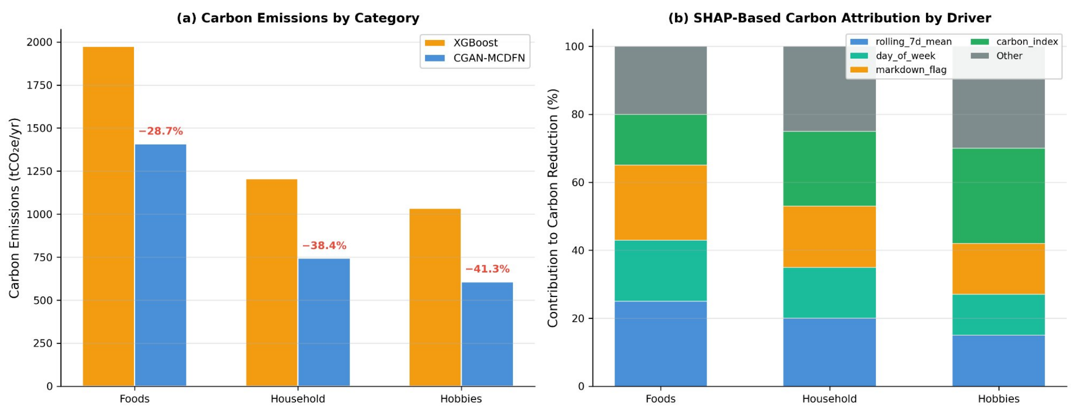

Figure 2: **Supplementary Figure S2. Product-category-level carbon analysis.** **(a)** Carbon emissions comparison between XGBoost baseline and CGAN-MCDFN by product category. Foods contributes the largest absolute carbon reduction (−28.7%) due to its higher emission factor, while Hobbies shows the largest percentage reduction (−41.3%) driven by CGAN augmentation of sparse SKUs. **(b)** SHAP-based carbon attribution decomposed by demand driver for each category. The carbon_index feature (green) contributes disproportionately in the Hobbies category.

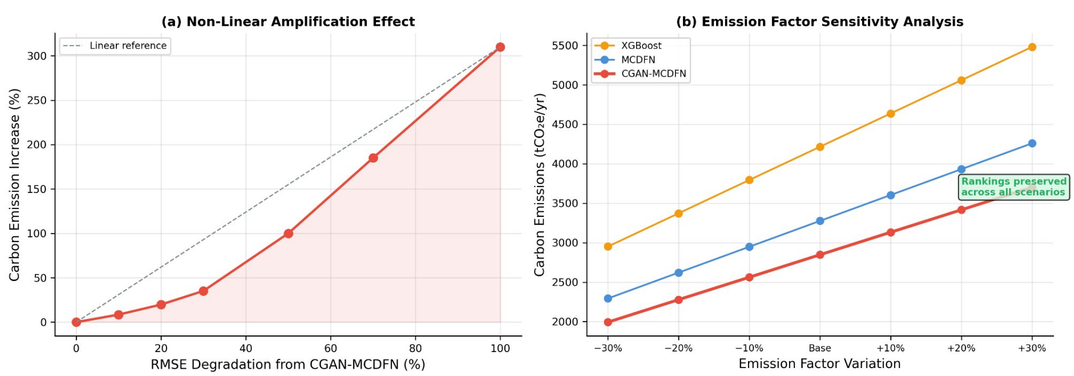

Figure 3: **Supplementary Figure S3. Scenario and sensitivity analysis. (a)** Non-linear amplification effect: carbon emission increase as a function of RMSE degradation from CGAN-MCDFN baseline. The dashed grey line shows a linear reference, highlighting the super-linear relationship. A 50% RMSE degradation produces a 100% carbon increase. **(b)** Emission factor sensitivity analysis under $\pm 30\%$ variation. While absolute estimates shift proportionally, the relative ranking of models (CGAN-MCDFN $<$ MCDFN $<$ XGBoost) remains preserved across all scenarios.