

Introduction

Exploring the **dynamics of live poultry trade** is crucial for understanding and managing public health risks, especially those related to the spread of avian influenza viruses. The primary aim is to evaluate whether **these models can accurately describe and predict poultry trade flows** between producing upazilas and marketing cities, based on area characteristics and distances. Success in this endeavour could enable the application of these models **to areas lacking specific poultry-trade data**.

Materials and methods

Gravity models (linear regression), commonly used in economic trade analysis, and machine learning techniques (random forest and boosted regression tree) were used to predict poultry trade flows in Bangladesh. This approach is grounded in the analysis of data from a comprehensive cross-sectional study conducted between 2015 and 2016, which provides the quantity, species, and origins of poultry traded in Dhaka and Chittagong (Fig. 1).

Key variables such as driving distance, travel time, poultry population, and competitiveness indices are used to train the models. These variables are crucial for understanding their correlation with the volume of chicken exports to major cities, thereby offering predictive insights into trade flow dynamics.

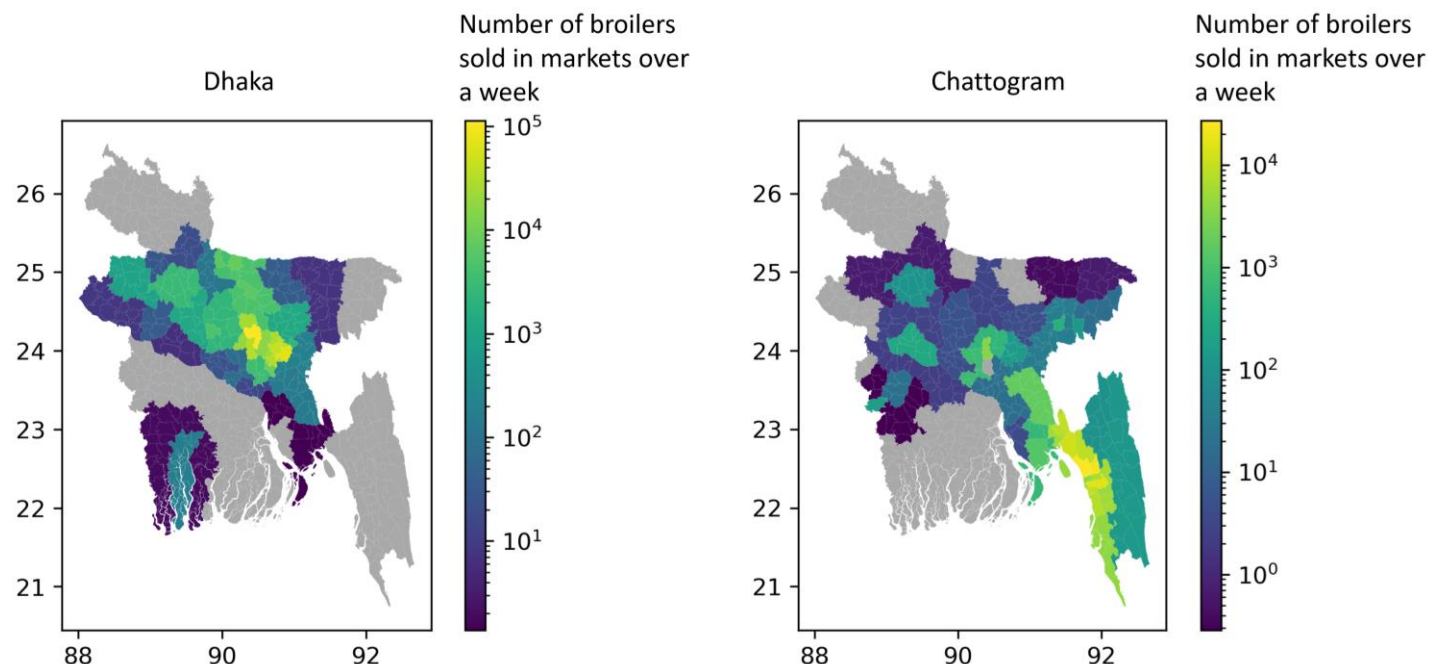


Figure 1: Origins of exotic broilers sold in markets in Dhaka (left plot) and Chattogram (right plot). Data were collected during the Balzac study.

Results

Performance of the models

Model	Predictors													RMSE	R ² Log10(Actual) vs Log10(Predicted)	R ² Actual vs Predicted			
	Road distance (km)	Travel time (min)	Broiler population at origin	Broiler farms at origin	Urban pop at origin	Urban pop at destination	Poverty pop at origin	Poverty pop at destination	% rate_poverty at origin	attractor_index_urb_pop	Chickenmeat consumption	Mean chicken meat conso	total chicken meat conso_j				conso_mean_j		
Linear	✓	✓			✓	✓		✓									0.932	0.505	0.285
Random Forest	✓	✓	✓	✓					✓	✓	✓	✓					0.534	0.837	0.600
Gradient Boosting	✓	✓	✓	✓			✓		✓	✓	✓						0.456	0.881	0.680

The table summarizes the inclusion of predictors in different models—Linear, Random Forest, and Gradient Boosting—and their respective predictive performance metrics. The Gradient Boosting Regression (GBR) showed a higher R² value (0.68) in predicting actual values, indicating strong predictive accuracy.

Map of residuals

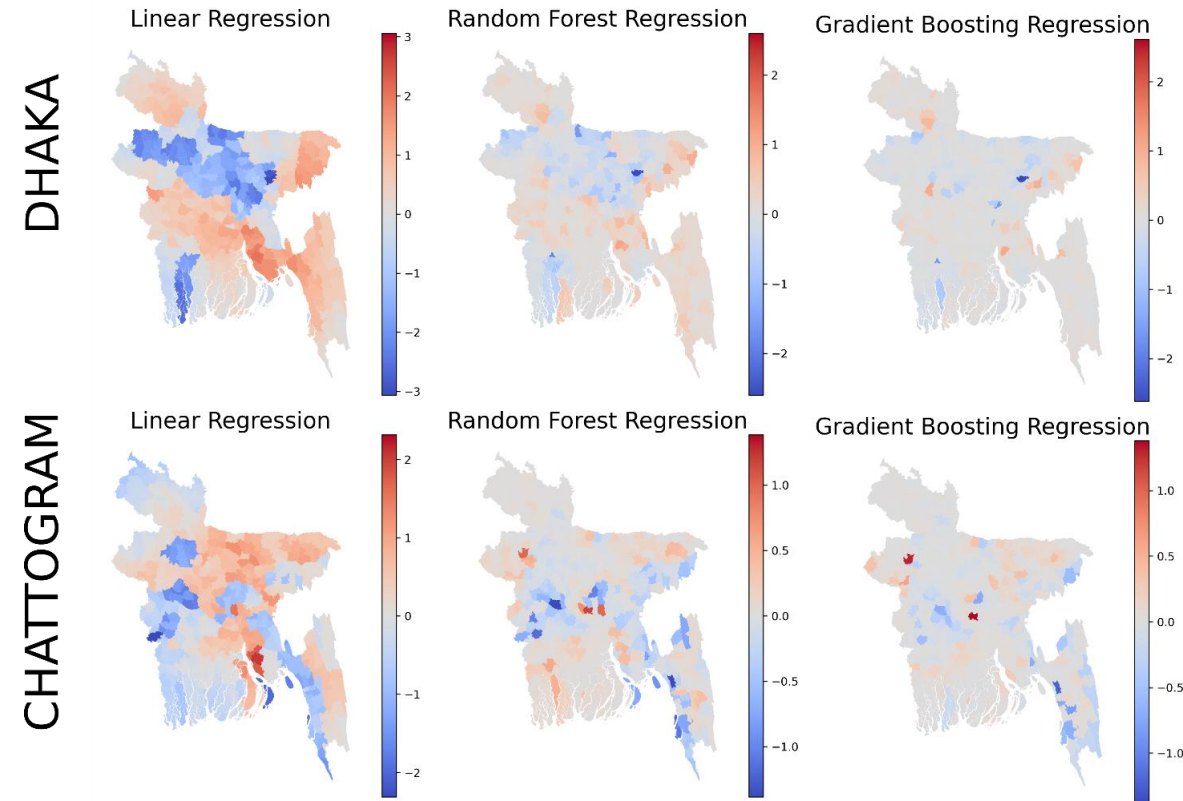


Figure 2: Residuals are color-coded, where red indicates overestimation, and blue represents underestimation of the model relative to actual broiler exports. These maps are critical in identifying regions where the models are not accurately predicting production levels. In the linear model, we observed interesting patterns: the model overestimates the exports to Dhaka from regions north to this city, while it underestimates the exports to Dhaka from regions in the South.

Discussion and conclusion

Among the three models analyzed for predicting the origins of broilers sold in Dhaka and Chattogram, linear regression demonstrates the least effectiveness. In the case of the Random Forest and Gradient Boosting models, the residuals maps show certain areas where broiler exports are under-predicted (regions with concentrated presence of blue). These discrepancies highlight potential areas for improving model accuracy, possibly by incorporating additional predictors or fine-tuning model parameters. The contrast between the different models' performance underscores the complexity of modeling agricultural systems, where multiple factors interact in nuanced ways to influence trade patterns.

The predictive power of these models allows us to identify likely catchment areas of cities that were not surveyed (Figure 3), and to inform the H9N2 phylogeography analyses.

Figure 3: Predictions of the models in three cities in Bangladesh, and comparison to data collected through Round 1 Hub field studies (LT R1).

Predictions in other cities of interest

