Hedonic Forecast: ML Housing Prediction in Japan

CSE - 6242 FINAL PROJECT - TEAM 090

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Problem Definition

Japan's official price indices (JRPPI) lag by three months and report only broad regional aggregates, making them insufficient for timely, local decision-making. Investors, developers, and urban planners increasingly need ward-level and neighborhood-scale forecasts to identify emerging opportunities. However, current approaches either ignore spatial patterns (time-series models) or temporal dynamics (spatial ML), leaving no unified and interpretable solution. Besides, analysts require transparent, explainable predictions they can justify to investors and policymakers.

ML Model

Model Choices

- Linear Regression – fast, interpretable baseline for price momentum and structural signals.
- Random Forest (300 trees) – captures nonlinear patterns; strong performance on heterogeneous mesh data.
- LightGBM (600 trees) – handles sparse features and missingness; best accuracy–speed balance.
- LSTM (8-quarter window) – learns temporal patterns; reduced feature set (7 vars) for stability.

Data Collection & Overview

Source: Ministry of Land, Infrastructure, Transport and Tourism (MLIT) Real Estate Information Library

- Access Method: Retrieval via the MLIT public API
- Type: Residential transaction records (price, area, building year, coordinates)
- Fields Provided: Price, area, building year, latitude/longitude, transaction date

Coverage & Span:

- Geographic Scope: Tokyo's 23 wards + Sendai's main wards
- Availability: 2005-Q3 to 2025-Q1 (79 quarters; quarterly releases)

Scale & Structure:

- 485,093 transactions (~150MB)
- 3,000+ unique 250m × 250m JIS X 0410 mesh cells
- Ward panel: ~2,100 ward×quarter rows
- Mesh panel: ~37,900 mesh×quarter rows

Key Attributes:

Price per sqm, floor area, building age, lat/long, quarter/time trend, ward/mesh aggregates.

Key Innovations

- Direct 250m mesh encoding (no geocoding APIs)
- Hierarchical ward→mesh features to stabilize sparse grids
- Cold-start smoothing (Moving avg + volatility).
- SHAP explanations for all models, including LSTM
- Tokyo–Sendai metro vs. regional comparison

Comparison to Prior Work

Method	Resolution	Frequency	Our Contribution
JRPPI (official)	City	Monthly +3mo lag	250m, quarterly, no lag
Yoshida 2024	Building	Cross-sectional	Time-series forecasting
Chen 2017 LSTM	City	Monthly	Finer spatial granularity

Evaluation

Below are the 5 evaluation questions:

1) Feature importance: Which features drive prices?

2) Accuracy across scales: How accurate at ward vs mesh scales?

3) Granularity trade-off: insight vs noise

4) Efficiency and scaling: How does accuracy scale with more data?

5) Efficiency and scaling.: Which model balances accuracy and latency?

Key findings

1. Momentum drives forecasts: 1-quarter lags and 4-quarter moving averages dominate SHAP importance; structural features matter far less.
2. Performance varies by resolution: Linear Regression is best for wards, while Random Forest is clearly strongest for meshes.
3. Granularity trade-off: Mesh forecasts reveal neighbourhood hotspots but come with heavier error tails.
4. Efficiency: Linear Regression offers sub-millisecond inference; Random Forest gives the best accuracy–time balance once data coverage >50%.
5. Model accuracy: Linear Regression is strongest on wards and offers sub-millisecond latency; meshes require nonlinear models and Random Forest leads, LightGBM follows, and the LSTM struggles to generalise beyond momentum despite higher inference cost.

Methodology

Hedonic Price Index

We estimate municipality-level indices using two-way fixed effects (PanelOLS):

t

$$\ln(P_{it}) = \beta_0 + \beta_1 \ln(\text{Area}_{it}) + \beta_2 \text{Age}_{it} + \beta_3 \text{AgeUnknown}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Forecasting Workflow

1. Build quarterly ward and mesh indices from the hedonic regression.
2. Derive engineered features: lags, QoQ/YoY growth, moving averages, and volatility.
3. Train forecasting models on 2005–2019, with 2020–2021 as the validation period.
4. Generate one-quarter-ahead forecasts for the 2022–2025 test period.

Experiments & Results

Experimental Design

Split	Period	Ward	Mesh
Train	2005-Q3 to 2019-Q4	1,507	26,818
Validation	2020-Q1 to 2021-Q4	336	6,337
Test	**2022-Q1 to 2025-Q1**	**252**	**4,762**

Feature Engineering

- Ward: 15 features (momentum, liquidity, structure, time)
- Mesh: 13+ features (adds hedonic indices + missingness flags)
- LSTM: 7 features (reduced set for sequence modeling)

Evaluation Metrics

- MAE (JPY/m²) — Mean absolute error
- RMSE (JPY/m²) — Penalizes outliers
- R^2 — Coefficient of determination
- SHAP values computed on validation set (500-1000 samples)

Model Configuration

- Random Forest: 300 trees | LightGBM: 600 boosting rounds
- LSTM: 8-quarter window, 96 hidden units, dropout 0.3
- Early stopping: patience = 8 epochs on validation loss

Key Findings

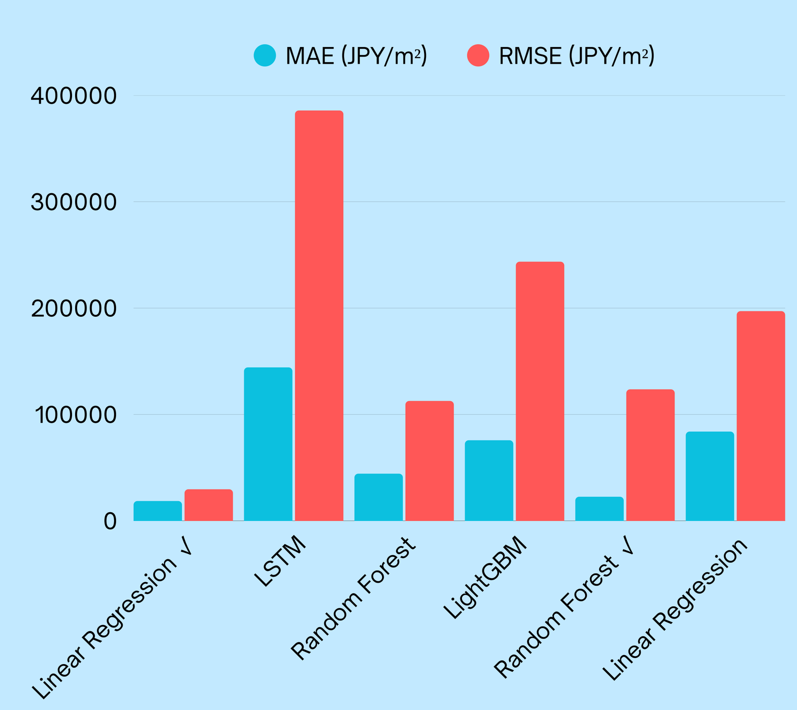
Ward: Linear Regression achieves MAE 18.6k, R^2=0.995 (momentum alone explains 99.5% variance)

Mesh: Random Forest cuts error 73% vs. linear (22.6k MAE, R^2=0.95)—nonlinear interactions matter at fine resolution

SHAP: 4Q moving average dominates (60-70% weight), structure features activate only when data is sparse

Speed: Linear <2ms | RF 40-80ms | LightGBM ~5ms (unstable on small samples)

Tokyo vs. Sendai: Dense markets favor all models; sparse markets perform well with random forest regularization

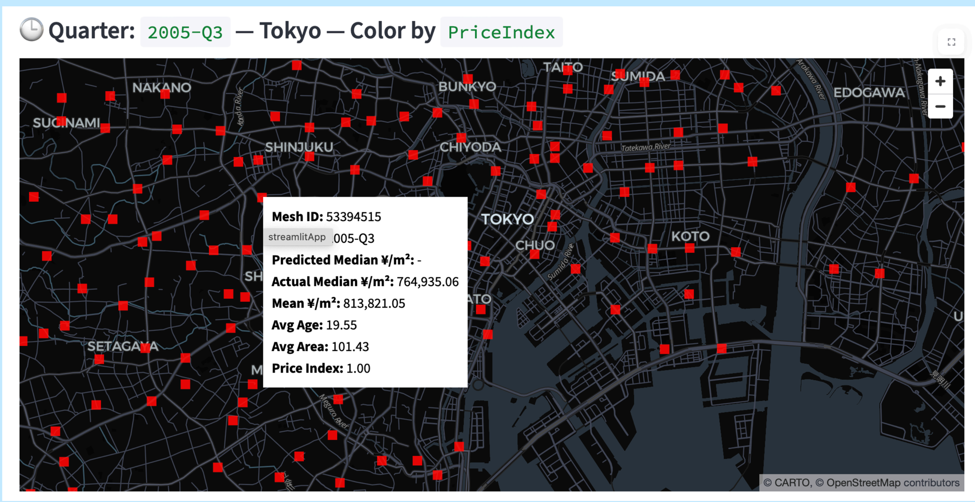


Level	Model	R^2	Inference Time
Ward	Linear Regression ✓	0.995	<2ms
Ward	LSTM	0.98	—
Ward	Random Forest	0.933	~80ms
Ward	LightGBM	0.928	~5ms
Mesh (250m)	Random Forest ✓	0.951	~140ms
Mesh (250m)	LightGBM	0.948	~47ms
Mesh (250m)	Linear Regression	0.876	~3ms
Mesh (250m)	LSTM	0.664	—

Interactive Dashboard

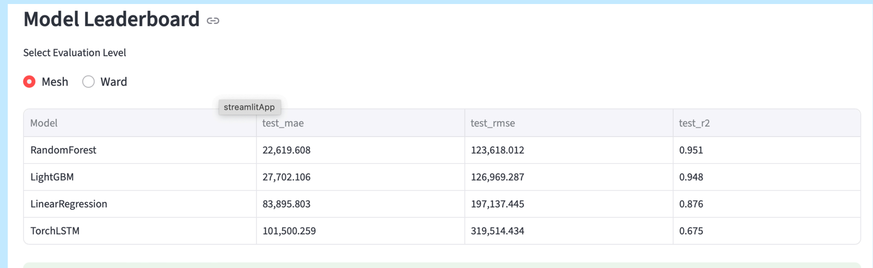
Feature 1:

Interactive 250 m mesh map with city/model/quarter controls and hover tooltips showing predicted vs actual prices, building age, floor area, and hedonic index. Supports quarter-by-quarter animation.



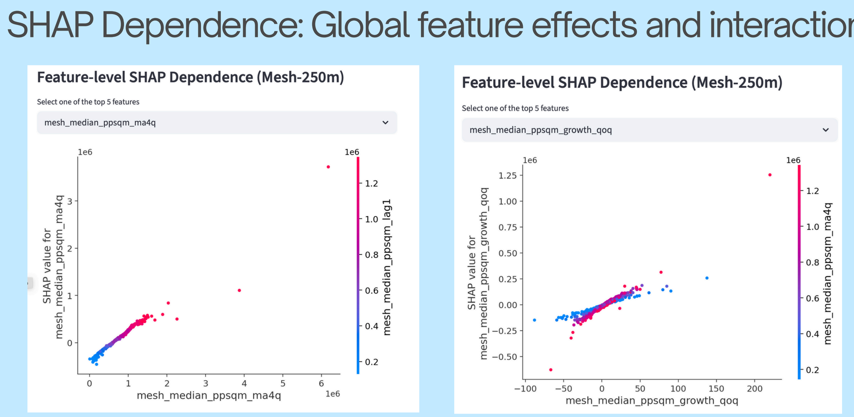
Feature 2:

Model leaderboard with MAE, RMSE, and R^2, highlighting the best model for Mesh/Ward.



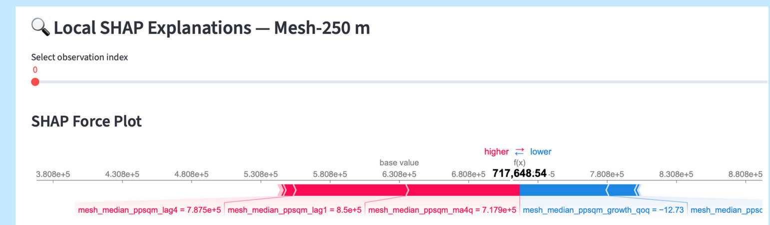
Feature 3:

SHAP Dependence: Global feature effects and interactions.



Feature 4.1 :

SHAP Dependence: Global feature effects and interactions.

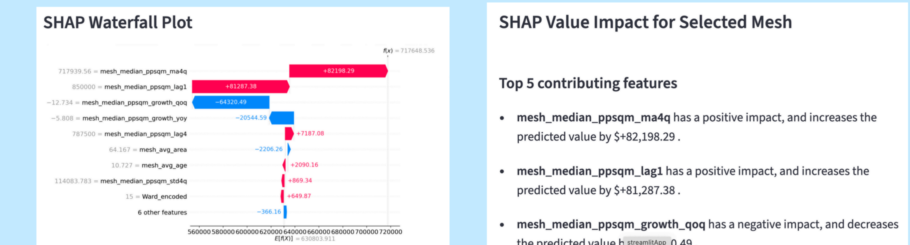


Key insights (1)

- Strong long-term momentum pushes the prediction up (lag-1, lag-4, MA-4q).
- Short-term QoQ growth pushes the prediction down slightly.
- Positive historical effects outweigh the negative short-term signal.
- Result: the mesh's past price strength leads to a higher-than-baseline prediction.

Feature 4.2 :

Local SHAP: Mesh-level explanations via force, waterfall, and impact plots.



Key insights (2)

- Long-term momentum is the main driver; The 4-quarter moving average and lag-1 price strongly increase the predicted value (+82k, +81k).
- Short-term weakness reduces the prediction; QoQ and YoY growth contribute large negative impacts (–64k, –20k).

Scan QR to launch app

Key Reference

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