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Nowcasting Meso-Level Industrial Production Using Multi-Source Satellite Data and Hybrid DFM–Machine Learning Framework

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Abstract

Official industrial statistics are released with delays, creating a need for timely complementary information. This study evaluates whether freely available multi-source satellite observations can nowcast Japan's Index of Industrial Production (IIP) and production indicators for chemicals, ordinary steel, and four-wheel motor vehicles. Daily VIIRS nighttime-light and Sentinel-5P/TROPOMI NO₂ observations from major production sites over July 2018–December 2025 were summarized using dynamic factor models (DFMs). Ridge regression and LightGBM were evaluated against direct-regression and autoregressive benchmarks using cross-validation. The optimal specification differed across targets. The IIP was best predicted by LightGBM using nighttime lights, NO₂, lagged IIP, and five factors without blocks. Chemicals favored NO₂, lagged target values, regional factors, and ridge regression; steel favored combined satellite data, firm-level factors, and ridge regression without lagged targets. For automobiles, ridge regression using nighttime lights from selected Toyota and Mazda plants outperformed both the all-firm satellite model and AR(1) benchmark. DFM-based models reduced RMSE relative to direct regression for all targets. These findings show that free satellite data provide useful predictive information, but effective nowcasting requires target-specific choices of satellite signals, factor structure, prediction model, and observation sites.

Introduction

Nowcasting economic indicators has become increasingly important for detecting changes in economic and industrial activity at an early stage [1–3]. Governments and firms require timely assessments of current and near-term economic conditions when making decisions concerning production, investment, inventories, and related activities [1,2]. Economic activity can be examined at different levels of aggregation. At the macro level, gross domestic product (GDP) summarizes economy-wide activity, whereas micro-level analyses focus on individual firms, establishments, or production sites. Previous studies using conventional and alternative data have extensively examined national and regional economic conditions as well as increasingly granular firm- and establishment-level activity [3,4].

Between these macro- and micro-level perspectives lies the production activity of industries comprising multiple firms and production sites. In this study, we refer to indicators that aggregate production trends for an individual industry or a group of industries as “meso-level indicators.” We examine monthly production

indicators for three major Japanese manufacturing industries: automobiles, chemicals, and steel. The analysis also includes the Index of Industrial Production (IIP), which summarizes production activity across a broad range of manufacturing industries [5–8].

Meso-level production indicators are potentially important for both macroeconomic and microeconomic analysis. At the macro level, aggregate economic fluctuations emerge from changes in activity across individual industries, and conventional GDP nowcasting models therefore make extensive use of monthly production and other sectoral indicators [1,31–33]. Recent studies further show that timely alternative data can provide additional information beyond conventional monthly indicators, particularly during periods in which official statistics for the current quarter have not yet been released [9–11]. In Japan, for example, credit-card, retail-sales, Internet-search, and other high-frequency data have been shown to improve the timeliness or accuracy of economic assessment when combined with conventional information [9,10]. These findings suggest that more timely estimates of industry-level production could themselves provide useful inputs for broader macroeconomic nowcasting.

Industry-level information may also be useful for understanding developments at individual firms. Previous research has shown that industry-level information can improve forecasts of some dimensions of firm performance, including long-term growth and earnings, and that analysts use both industry-wide and firm-specific information when forming expectations about individual companies [12–15]. Thus, timely information on meso-level production activity may contribute not only to macroeconomic nowcasting but also to assessments of changes occurring at individual firms and production sites.

A major difficulty, however, is the publication lag of official statistics. The IIP provides monthly information on Japanese manufacturing production by industry, but preliminary values become available only after the reference period has ended [5]. Similar publication lags apply to the Current Survey of Production and monthly industry statistics for automobiles and steel [6–8]. Consequently, although these statistics provide detailed measures of actual industrial production, they cannot directly reveal production conditions during the interval between economic activity and official publication. This creates an information gap that is particularly relevant for real-time economic monitoring and nowcasting.

Various forms of alternative data have been used to reduce this information gap. Examples include point-of-sale and payment transactions, credit-card data, Internet searches, and human-mobility information [9,10,16–19]. Such data can provide high-frequency signals before conventional statistics become available. Their usefulness, however, may depend on the coverage, historical availability, continuity, and accessibility of individual data providers [4,11]. Satellite-based Earth-observation data provide a complementary source of information because they enable repeated observations over broad geographic areas, and several important satellite products are publicly accessible. In particular, the Visible Infrared Imaging Radiometer Suite (VIIRS) provides systematic measurements of nighttime lights [21], whereas the Tropospheric Monitoring Instrument (TROPOMI) aboard Sentinel-5 Precursor measures atmospheric constituents including nitrogen dioxide (NO₂) [22]. Advances in these observational systems have substantially expanded the use of remotely sensed information for socioeconomic analysis [20,23,24].

Satellite data have already demonstrated considerable potential for economic measurement. At the macro

and regional levels, nighttime-light observations have been used to estimate or supplement conventional measures of economic activity and economic growth [25–27]. Atmospheric observations have also been linked to changes in economic activity. Recent evidence from Japan, for example, shows that satellite-derived NO₂ contains information related to regional and sectoral economic conditions [28]. At a substantially finer spatial scale, satellite data have been used to monitor activity at individual firms and establishments. Bilicka and Seidel [29] show that nighttime-light emissions from automobile manufacturing plants contain information about plant-level economic activity, while Feng and Fay [30] use satellite-derived parking-lot traffic to predict retailer performance. Satellite imagery has also been used to measure activity in ports and other economic infrastructure [42].

More recent studies have moved closer to industry-level production measurement. Satellite imagery has been used to nowcast cement production, demonstrating that remotely sensed information can capture short-term fluctuations in production at the industry level [43]. Geospatial information, including nighttime lights and atmospheric or environmental signals, has also been combined with machine-learning methods to estimate production activity in the steel industry [44]. In addition, recent macroeconomic studies have combined multiple satellite-derived indicators, such as nighttime lights and atmospheric information, with statistical and machine-learning approaches for economic nowcasting [45]. These developments indicate that both multi-source satellite data and machine-learning methods can provide substantial predictive information about economic and industrial activity.

Nevertheless, several important questions remain unresolved. Existing satellite-economics studies have often focused either on aggregate macroeconomic outcomes, such as GDP and regional economic activity, or on individual sectors, firms, and facilities [25–30,43–45]. Much less is known about whether a common satellite-based framework can be used to nowcast monthly production indicators across multiple industries and, more importantly, whether the optimal satellite information and modeling architecture systematically differ across industries. Studies showing that satellite information is useful for a particular industry do not necessarily imply that the same satellite variable, aggregation method, or prediction model will perform well in another industry because production technologies, energy use, emissions, operating schedules, spatial concentration, and firm organization differ substantially across sectors.

This issue is particularly important when multiple satellite signals are available. Nighttime lights provide a direct measure of artificial illumination and have been extensively associated with human and economic activity [21,23–27]. Plant-level evidence further suggests that variation in nighttime illumination can reflect manufacturing activity [29]. NO₂, by contrast, is associated with anthropogenic combustion, transportation, energy consumption, and industrial processes [22,28,39]. Changes in industrial activity can therefore potentially alter satellite-observed NO₂ concentrations, although such observations are also affected by meteorological and atmospheric conditions [39]. Nighttime lights and NO₂ thus capture different physical dimensions of industrial activity and may provide complementary information. However, there is little reason to expect the relative information content of the two signals to be identical across industries.

A second unresolved issue concerns how satellite observations from multiple production sites should be aggregated. In macroeconomic forecasting, dynamic factor models (DFMs) are widely used to summarize

shared movements in large sets of time-series variables [1,31–33]. By extracting a small number of latent common factors, DFMs reduce dimensionality and separate common temporal variation from idiosyncratic fluctuations. Such properties may be particularly useful when satellite observations are collected from multiple factories because individual-site measurements may contain both common industry-level activity and plant-specific noise.

At the same time, machine-learning methods have increasingly been applied to economic nowcasting. Recent studies show that machine-learning models can outperform conventional linear or DFM-based approaches in some prediction settings, although their relative advantage depends on the information available, the prediction horizon, and the structure of the target variable [34–36]. To examine whether the relationship between satellite-derived factors and production indicators is better represented by linear or nonlinear models and whether this differs across industries, we compare ridge regression, a regularized linear model [37], with LightGBM, a nonlinear gradient-boosting model [38].

A third issue concerns spatial selection of observation sites. Using all available production sites may increase the amount of information available to a nowcasting model, but it may also introduce noise when individual factories respond differently to firm-specific or product-specific conditions. This issue may be particularly relevant to automobile manufacturing. Steel and chemical production is often geographically concentrated in large industrial areas in which material, energy, and by-product flows connect multiple establishments [40]. Automobile manufacturing, by contrast, serves a highly differentiated product market in which demand varies across manufacturers and vehicle models [41]. Production movements at individual automobile plants may therefore contain substantial manufacturer- or model-specific variation rather than moving uniformly across all producers. Accordingly, the most informative subset of factory observations for predicting aggregate automobile production may differ from the complete set of available plants.

Against this background, the central objective of this study is not simply to determine whether satellite data can predict industrial production, but to identify which combination of satellite signals, aggregation methods, prediction models, and, where relevant, observation sites is most effective for nowcasting different meso-level production indicators. We examine four targets: the IIP and production indicators for the automotive, chemical, and steel industries. These targets allow us to compare predictive performance across industries with different production technologies, emission characteristics, spatial structures, and patterns of firm heterogeneity.

The analysis evaluates the general hypothesis that the optimal nowcasting system for meso-level industrial production is industry-specific rather than universal. More specifically, we examine five related hypotheses. First, satellite observations contain predictive information beyond that available from the target indicator's own historical values. Second, the relative value of nighttime lights, NO₂, and their combination differs across industries because they capture different physical aspects of production activity. Third, the relative performance of linear and nonlinear machine-learning models differs across industries. Fourth, DFM-based extraction of shared movements improves prediction when satellite observations from multiple production sites contain a sufficiently strong common component. Fifth, in automobile manufacturing, selecting informative factory locations can improve nowcasting performance relative to using all available plants.

This study makes three main contributions:

- First, it provides a systematic evaluation of freely accessible multi-source satellite data for nowcasting monthly meso-level production indicators across multiple Japanese manufacturing industries within a common empirical framework.
- Second, it distinguishes predictive gains attributable to satellite information from those attributable to factor extraction and prediction models by comparing autoregressive, direct-regression, and DFM-based specifications, with and without lagged official statistics.
- Third, it examines target-specific model design by comparing satellite signals and factor structures across industries and evaluating whether the selection of target-relevant manufacturing locations improves automobile-production nowcasts.

Methods

Scope of Analysis and Data Structure

This study analyzes Japan's automotive, chemical, and steel industries. Together, these sectors account for approximately 40% of national manufacturing shipments and can be directly linked to official industry-level production statistics. The analysis covers July 2018 through December 2025. Explanatory variables consist of site-level daily nighttime-light and tropospheric NO₂ observations from major plants, aggregated to monthly dynamic factor estimates (DFM).

Target variables include the aggregate Index of Industrial Production (IIP) and three sector-specific indicators: the Shipment Index of Major Chemical Products, four-wheel motor-vehicle production, and ordinary-steel production volume. The IIP models use satellite series from sites across all three industries, while industry-specific models use series corresponding to their respective sectors. For the automotive sector, we evaluate both a comprehensive plant set and a refined subset focused on major finished-vehicle assembly facilities.

To evaluate nowcasting potential, we compare satellite-only specifications against models incorporating target-variable lags available through two months prior to the nowcast month, reflecting actual official publication delays.

Nighttime-Light Data

For nighttime lights, we used the VNP46A2 Gap-Filled DNB BRDF-Corrected Nighttime Lights product derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi National Polar-orbiting Partnership satellite. VNP46A2 is a daily product derived from the VIIRS Day/Night Band (DNB) and corrected for moonlight, atmospheric effects, and the bidirectional reflectance distribution function (BRDF). It is provided at an approximate spatial resolution of 500 m. Data were obtained from NASA's LAADS DAAC; the Near Real-Time (NRT) product was used for the most recent periods for which the standard product had not yet been released.

For each factory or industrial site, we defined a polygonal area of interest and extracted pixels whose centers

fell within the polygon. Pixels with a Mandatory Quality Flag of 0 were treated as valid observations. A day's observation was retained when valid pixels accounted for at least 50% of all pixels in the area; days below that threshold were excluded. After limiting the influence of extremely bright pixels, we constructed a daily site-level series from a representative value of the pixels within each area.

NO₂ Data

For NO₂, we used the near-real-time COPERNICUS/S5P/NRTI/L3_NO2 product from the TROPOspheric Monitoring Instrument (TROPOMI) aboard Sentinel-5 Precursor. The analyzed variable was tropospheric_NO2_column_number_density, which represents tropospheric NO₂ column density, including the near-surface atmosphere. The data were obtained through Google Earth Engine. Pixels with a qa_value below 0.75 are excluded from this product. Because NO₂ is generated by high-temperature fuel combustion, it may serve as a proxy for combustion associated with factory boilers, furnaces, and captive power-generation equipment.

For each factory or industrial site, we defined an area of interest covering the plant and its surroundings and calculated a daily representative value from available pixels. A day was treated as missing when all pixels within the area were missing. This procedure produced a daily series for each site. NO₂ observations reflect not only factory emissions but also wind direction and speed, precipitation, seasonality, road traffic, and other nearby emission sources. We therefore do not interpret a single site's observations directly as production volume; instead, we use a DFM to extract shared variation across multiple site-level series for nowcasting.

Data Integration and Preprocessing

The site-level nighttime-light and NO₂ series were joined by date to construct a daily satellite dataset. Before being entered into the DFM, each variable was standardized over the full study period to have a mean of zero and a standard deviation of one.

Target Variables

Monthly statistics representing aggregate and industry-specific production activity were used as target variables. Aggregate activity was measured by the IIP. The industry-specific targets were the Shipment Index of Major Chemical Products for chemicals, four-wheel motor-vehicle production for automobiles, and ordinary-steel production volume from the Current Survey of Production of the Ministry of Economy, Trade and Industry for steel. Because all target series are monthly, the daily factors extracted by the DFM were subsequently aggregated to a monthly frequency and aligned with the target variables by year and month.

The models directly **predicted** the original levels of all target variables without transformations such as log differencing. The aim is to estimate the unreleased production index or production volume itself rather than its month-on-month growth rate.

Dynamic Factor Model

A dynamic factor model (DFM) was used to summarize shared movements across numerous site-level series in a small number of latent factors.

DFMs have been widely applied to macroeconomic monitoring, including forecasting, time-series interpolation, and the construction of coincident indicators. A prominent application is nowcasting, which integrates large numbers of frequently released time series to generate real-time estimates of lower-frequency headline indicators such as GDP. A DFM is formulated as a state-space model and estimated using the Kalman filter together with a numerical solution method. The expectation-maximization (EM) algorithm is widely used in economics because of its robust numerical properties.

A standard baseline dynamic factor model can be written as follows:

$$x_t = \Lambda f_t + \varepsilon_t \quad (1)$$

$$f_t = \sum_{j=1}^p A_j f_{t-j} + u_t, u_t \sim N(0, Q) \quad (2)$$

where the idiosyncratic components follow series-specific AR(1) processes:

$$\varepsilon_{(i,t)} = \rho_i \varepsilon_{(i,t-1)} + e_{(i,t)}, e_{(i,t)} \sim N(0, R) \quad (3)$$

The symbols are defined as follows:

- x_t : $n \times 1$ vector of observed series at time t , for which missing observations are permitted
- f_t : $q \times 1$ vector of latent factors at time t
- Λ : $n \times q$ factor-loading matrix
- A_j : $q \times q$ factor-transition matrix at lag j
- ε_t : $n \times 1$ vector of serially correlated idiosyncratic components
- ρ_i : AR(1) coefficient of the idiosyncratic component for series i
- u_t : $q \times 1$ vector of factor innovations with covariance matrix Q
- e_t : $n \times 1$ vector of idiosyncratic innovations with covariance matrix R
- Q : $q \times q$ covariance matrix of the factor innovations
- R : $n \times n$ diagonal covariance matrix of the idiosyncratic innovations

Factor Blocks

We compare two approaches to specifying the factor structure: a block structure that groups observed series by industry or firm, and an unrestricted structure that extracts common factors from all series without predefined blocks. To retain industry- or firm-specific variation, the block specifications extract either one or two factors per block. The no-block specification aggregates common variation across all observed series into five factors without imposing industry classifications. This comparison tests whether industry-specific or cross-industry common variation is more informative for prediction.

In specifications that include the target variable, the monthly target series is shifted by two months before being entered into the daily DFM. Each lagged target value is entered only on its corresponding observation date and is treated as missing on all other days; it is not repeated across days. Consequently, factor extraction at time t uses satellite observations available at t and target values available through $t - 2$, while the contemporaneous target value at t is never used.

Prediction Models

Ridge Regression

Ridge regression is used as the linear prediction model. By penalizing the sum of squared regression coefficients, ridge regression stabilizes coefficient estimates under multicollinearity. Its objective function is $\min_{\beta} \sum_i (y_i - \beta_0 - x_i^T \beta)^2 + \alpha \|\beta\|_2^2$.

The regularization parameter α is selected from a set of candidate values using RidgeCV. Features supplied to the regression model are standardized using the mean and standard deviation of the corresponding training sample.

LightGBM

LightGBM is used to capture nonlinear relationships. It is a gradient-boosting method that sequentially adds decision trees to correct errors from preceding stages. Given the limited sample size, we restrict the tree depth, number of leaves, and number of trees. A comparison with ridge regression indicates whether the relationship between satellite factors and production indicators is adequately represented by a linear model or benefits from a nonlinear specification.

Benchmark Models

- Direct regression: To evaluate the effect of DFM aggregation, we estimate models that enter monthly site-level nighttime-light and NO₂ observations directly into ridge regression or LightGBM without factor transformation. Using the same data configurations for the DFM and direct-regression models isolates the effect of factor extraction on predictive performance.
- Autoregressive model (AutoReg): As a benchmark for assessing the contribution of satellite data, we use an AR(1) model based solely on the first lag of the target variable.

Evaluation Procedure

Predictive performance is evaluated using three-fold expanding-window cross-validation. Each training period begins in August 2018 and expands sequentially, and the immediately following 22 months constitute the corresponding test period. Model estimation and hyperparameter selection are conducted using only the training period, and random partitioning is not used.

$$\text{RMSE} = \sqrt{[(1/N) \sum_{t=1}^N (y_t - \hat{y}_t)^2]}$$

where y_t is the observed value, $\hat{y}_t$ is the predicted value, and N is the number of observations in the test period. Because RMSE places greater weight on large prediction errors, it is used for the main model comparisons. For each model, we calculate the RMSE in each fold together with the mean and standard deviation across the three folds.

Experiments

Experimental Objectives

The experiments evaluate the extent to which freely available nighttime-light and NO₂ data are useful for nowcasting the IIP and industry-specific production indicators. In particular, they assess the predictive information contained in satellite data alone, their incremental value over lagged target values, the effect of DFM-based factor extraction, and performance differences between linear and nonlinear models.

Study Period and Nowcast Targets

The analysis covers July 2018 through December 2025, the period for which both nighttime-light and NO₂ observations are available. The IIP is used as an aggregate indicator, and monthly production indicators corresponding to the automotive, chemical, and steel industries serve as industry-specific targets. Dates are standardized to the first day of each month, and satellite-derived features are aligned with the target variables at a monthly frequency.

Input-Data Configurations

Two input-data configurations are examined: satellite data alone, comprising nighttime lights and NO₂, and satellite data augmented with the most recently published target values. In the latter specification, a two-month publication lag is assumed, and the target series is shifted by two months.

Three DFM factor structures are evaluated: (1) one factor extracted from each industry or firm block; (2) two factors extracted from each such block; and (3) five factors extracted from all series without blocks. The contemporaneous factors and their first lags are used as predictors in ridge regression or LightGBM models.

Model Configurations Compared

To assess the effect of DFM-based dimension reduction, direct-regression models that enter the satellite series into ridge regression or LightGBM without factor extraction are included as benchmarks. Direct regression is evaluated both with satellite data alone and with target values available through two months earlier. An AR(1) model using only the target's autocorrelation is included as an additional benchmark.

For ridge regression, the explanatory variables are standardized and the regularization parameter is selected within the training sample. LightGBM is likewise fitted using training-period data only. Predictive accuracy is measured by RMSE, with lower values indicating smaller nowcast errors.

Experimental Specifications

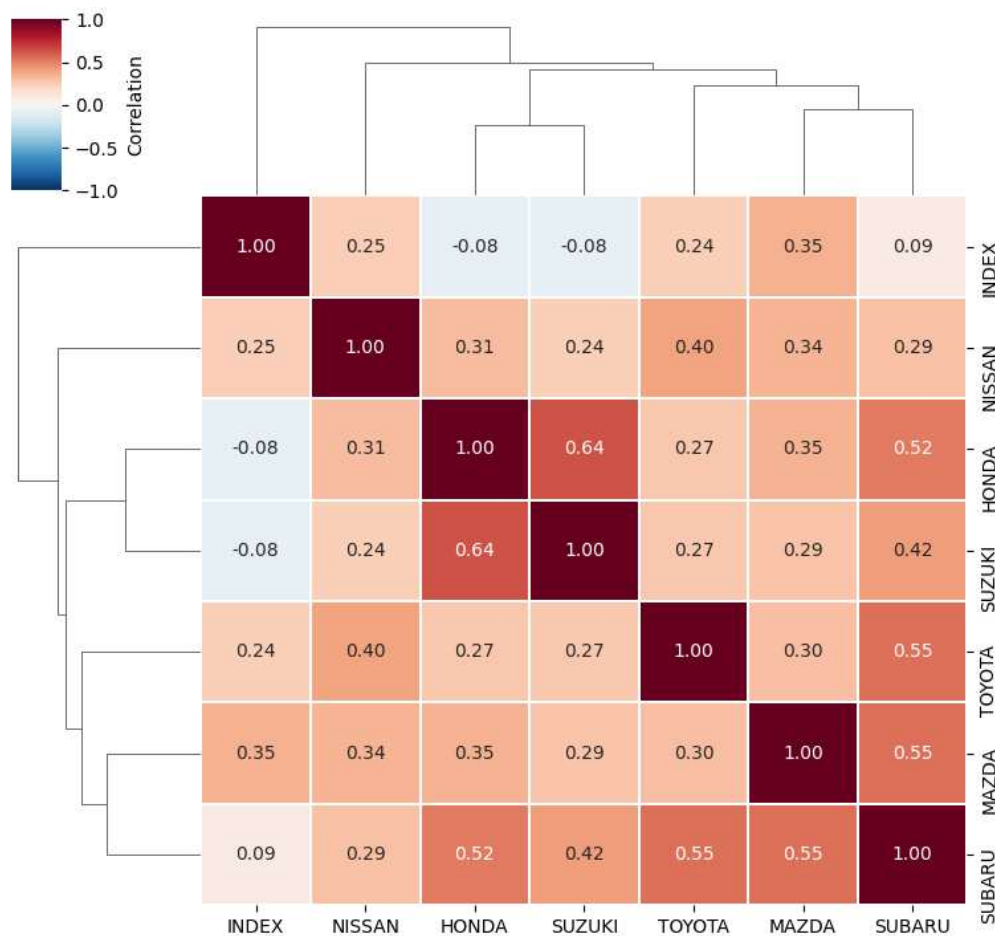
The experiments compare combinations of DFM factor structure, inclusion or exclusion of lagged target values, and prediction model. The evaluated specifications comprise one- and two-factor industry or firm blocks, five factors without blocks, direct regression, and AR(1).

Selection of Observation Sites for Four-Wheel Motor-Vehicle Production

Because the target variable is domestic four-wheel motor-vehicle production, observation sites were selected according to their relevance to domestic finished-vehicle production rather than indiscriminately including

all plants.

For each firm, a monthly average nighttime-light series was constructed from its plants, and its correlation with four-wheel motor-vehicle production was calculated.



The correlations were 0.35 for Mazda, 0.25 for Nissan, and 0.24 for Toyota. Toyota accounted for approximately 40% of the domestic output of Japan's eight passenger-vehicle manufacturers in 2025 and had the largest production volume. Based on these results and the firms' production structures, Toyota, Mazda, and Nissan were selected as candidate firms.

The evaluated configurations comprised Toyota's major domestic plants, Mazda's Hiroshima and Hofu plants, and Nissan Motor Kyushu. Nighttime-light series from these plants were aggregated using the DFM, and the extracted factors were used to nowcast four-wheel motor-vehicle production.

Time-Series Cross-Validation

The evaluation sample contains 89 months, from August 2018 through December 2025. The three expanding-window folds are defined as follows:

- Fold 1: August 2018–June 2020 (training); July 2020–April 2022 (test)
- Fold 2: August 2018–April 2022 (training); May 2022–February 2024 (test)
- Fold 3: August 2018–February 2024 (training); March 2024–December 2025 (test)

RMSE is calculated for each fold, and the arithmetic mean across the three folds is used as the principal

evaluation statistic.

Results

Overview of the Results

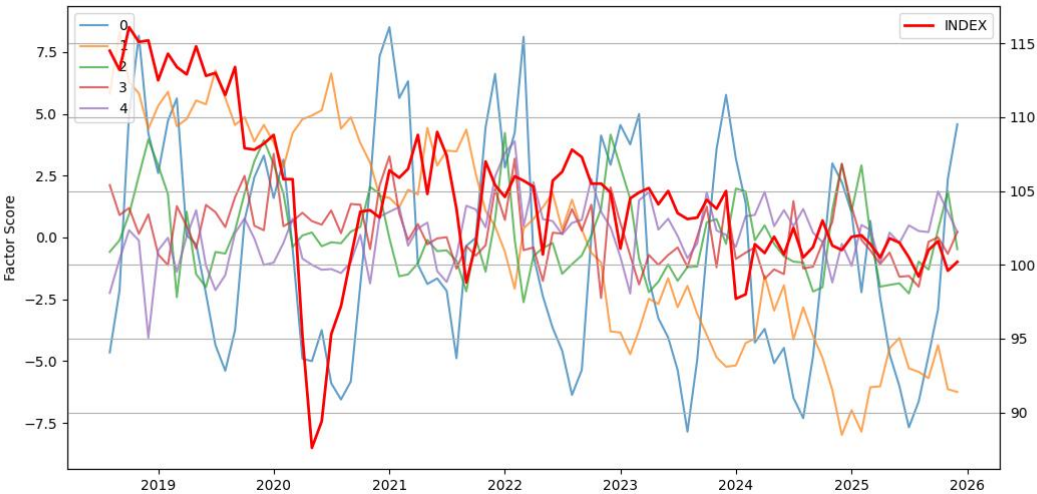
This section reports time-series cross-validation results for the IIP, the Shipment Index of Major Chemical Products, ordinary-steel production volume, and four-wheel motor-vehicle production. For each target, we compare alternative DFM factor structures, satellite-data sources, inclusion of lagged target values, and prediction models. The specification with the lowest mean RMSE across folds is designated the best-performing model.

Nowcasting Results for the IIP

For the IIP, the best-performing specification extracted five factors from the satellite series without industry-specific factor blocks. The inputs were nighttime lights, NO₂, and lagged published target values, and LightGBM was used for prediction. The mean RMSE was 3.580.

Table 1. Nowcasting results for the IIP

Best-performing model specification	Mean RMSE
Satellite data + lagged target (no blocks; five factors; LightGBM)	3.580

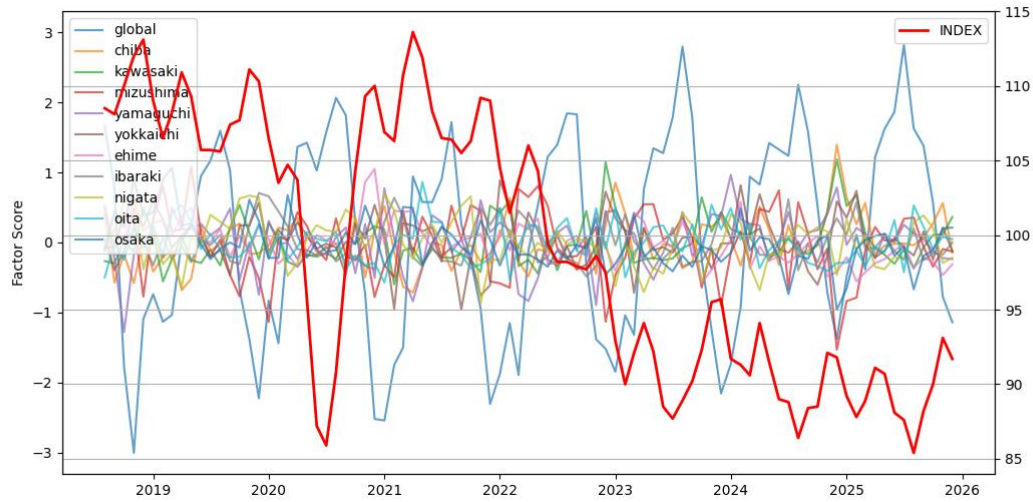


Nowcasting Results for the Shipment Index of Major Chemical Products

For the Shipment Index of Major Chemical Products, the best-performing specification was ridge regression using NO₂ and lagged published target values, with one factor extracted from each regional block. Its mean RMSE was 3.455.

Table 2. Nowcasting results for the Shipment Index of Major Chemical Products

Best-performing model specification	Mean RMSE
NO ₂ + lagged target (one factor per regional block; ridge)	3.455

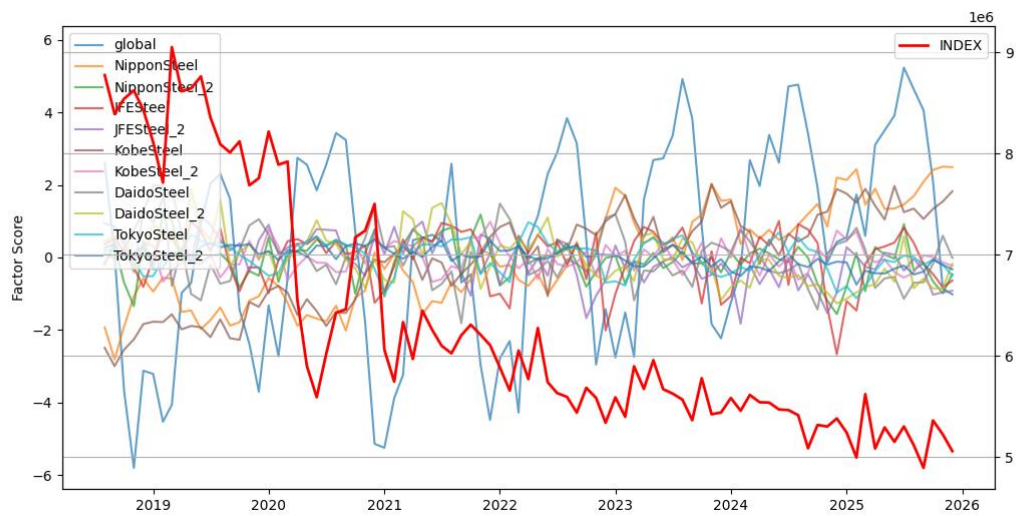


Nowcasting Results for Ordinary-Steel Production (Current Survey of Production, METI)

For ordinary-steel production, the best-performing specification used ridge regression with nighttime lights and NO₂ only and two factors extracted from each firm block. Its mean RMSE was 526,318.778. Lagged published target values were not included in the best-performing model.

Table 3. Nowcasting results for ordinary-steel production

Best-performing model specification	Mean RMSE
Satellite data only (two factors per firm block; ridge)	526,318.778



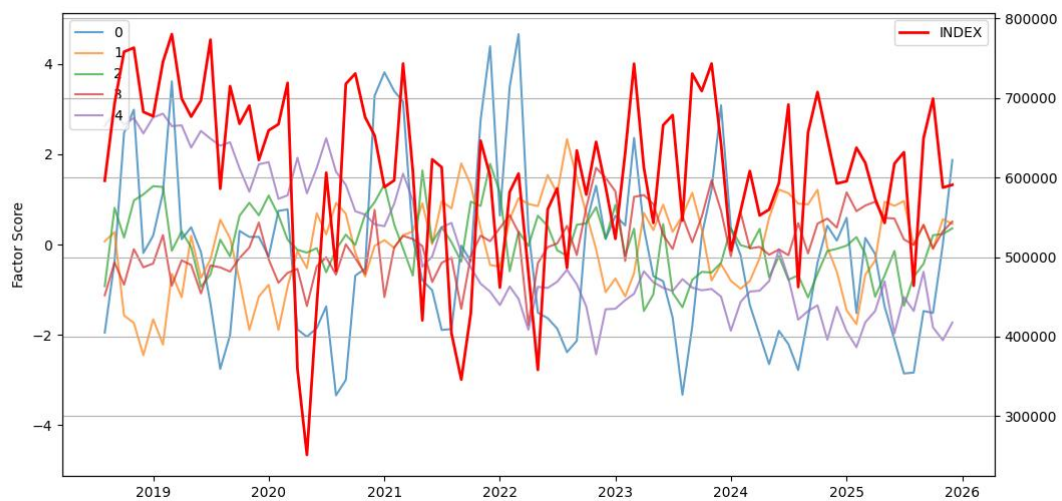
Nowcasting Results for Four-Wheel Motor-Vehicle Production

Automotive firms differ in their domestic–overseas production mix, production systems, and the roles of individual plants. Plants also differ in whether they produce finished vehicles, engines, or components. Because the target is domestic four-wheel motor-vehicle production, firms and plants closely linked to domestic finished-vehicle production were selected as observation sites based on firm-level domestic production volumes and shares and the correlation analysis of firm-average nighttime-light series.

The best-performing site-selection specification used major domestic plants operated by Toyota and Mazda and extracted DFM factors from their nighttime-light series. Its mean RMSE was 87,688.741 vehicles, lower than that of both the satellite model using sites from all firms (103,227.205 vehicles) and the AR(1) benchmark (101,718.427 vehicles).

Table 4. Nowcasting results using selected automotive firms

Observed firms	Model	Mean RMSE
Toyota + Mazda (nighttime lights only)	Ridge	87,688.741



Summary of Results

The best-performing data, factor structure, and prediction model differed across targets. For the IIP, LightGBM with five factors extracted without blocks from multi-industry observations and augmented with lagged published target values performed best. For the Shipment Index of Major Chemical Products, the best model was ridge regression with one factor per regional block using NO₂ and lagged target values. For ordinary-steel production, the best model was ridge regression with two factors per firm block using satellite data alone and excluding lagged target values.

For four-wheel motor-vehicle production, ridge regression using nighttime lights alone from the selected Toyota and Mazda sites produced the lowest mean RMSE.

Discussion

This study evaluated five questions concerning the use of freely available nighttime-light and NO₂ observations for nowcasting the IIP and production indicators for chemicals, steel, and automobiles. The results show that the predictive value of satellite data, the preferred satellite signal, the nowcasting model, the DFM structure, and the appropriate observation sites all depend on the target. The following discussion addresses these five questions in the order presented in the Introduction.

Satellite-based specifications achieved the lowest mean RMSE among the candidate models for all four targets. For the IIP and the Shipment Index of Major Chemical Products, the best models combined satellite factors with target values available with a two-month lag, indicating that the two information sources were complementary. For ordinary-steel production, satellite data alone produced the best result, whereas adding the lagged target did not improve accuracy. For four-wheel motor-vehicle production, the satellite model based on selected domestic plants outperformed the AR(1) benchmark. These results indicate that satellite observations provide useful information before official statistics are published, although their incremental value differs across targets.

The most informative satellite input also differed across targets. The best IIP and steel models combined nighttime lights and NO₂, suggesting that illumination and combustion-related signals provided complementary information for these broad or energy-intensive production measures. For chemicals, NO₂ alone performed best, consistent with the relevance of combustion and process-related emissions to chemical production. By contrast, nighttime lights alone were most effective for automobiles. Automobile output is affected by assembly schedules, model mix, and supply-chain conditions that may not generate a sufficiently distinct NO₂ signal at the observed spatial scale. The results therefore do not support a universal satellite input; the physical relationship between each signal and the production process should guide data selection.

The preferred **prediction model** varied across targets. LightGBM performed best for the IIP, whereas ridge regression performed best for chemicals, steel, and automobiles. Because the IIP aggregates activity across multiple industries, LightGBM may have captured nonlinear interactions among heterogeneous satellite factors and lagged production information. The industry-specific indicators may have had more stable relationships with a smaller set of factors, while ridge regularization was advantageous given the limited monthly sample. These interpretations remain tentative, but the results show that nonlinear models do not invariably outperform regularized linear models in industrial nowcasting.

DFM-based specifications produced lower mean RMSEs than direct regressions using the observed satellite series for every target. With the input data and nowcasting model held constant, the reductions were approximately 34.0% for the IIP, 33.6% for chemicals, 6.1% for steel, and 2.4% for automobiles. The larger improvements for the IIP and chemicals suggest that factor extraction effectively reduced redundant and site-specific variation in their satellite series. The smaller automotive gain indicates that factor aggregation alone was less important than selecting sites that corresponded to the production target.

The preferred factor structure also reflected the aggregation scope of each target. The IIP used five factors extracted without blocks, preserving common variation across industries. Chemicals used one factor per regional block, whereas steel used two factors per firm block, retaining variation specific to groups of

production sites. Thus, the value of the DFM depended not only on dimension reduction but also on aligning the factor structure with the economic and spatial scope of the target.

The automotive results address the fifth question. Restricting the input to major domestic plants operated by Toyota and Mazda produced a lower mean RMSE than using observations from all available firms. Because the target measures domestic finished-vehicle production, this restriction may have reduced variation associated with overseas-oriented activity, components, and plant roles outside the target's coverage. Although Nissan's firm-average nighttime lights were correlated with automobile production, part of their industry-wide information may already have been represented by Toyota and Mazda, limiting their incremental contribution. The result indicates that adding more sites is not necessarily beneficial; observation sites should be selected according to their physical and economic correspondence with the target.

Satellite observations contain variation unrelated to production, and the short monthly sample limits the stability of the factor and prediction models. The automotive site-selection result should therefore be interpreted as evidence that target-aligned site design matters, rather than as a fixed ranking of firms or plants. Future research should assess the robustness of these findings using longer samples and site-selection criteria defined within each training period.

Conclusion

This study aggregated freely available nighttime-light and NO₂ satellite observations using a DFM and evaluated their ability to nowcast the IIP, the Shipment Index of Major Chemical Products, ordinary-steel production, and four-wheel motor-vehicle production. Models based on DFM-extracted factors achieved the lowest mean RMSE among the compared specifications for the IIP, chemicals, and steel. For the IIP, the best specification used LightGBM with five factors extracted without blocks and included lagged published target values. For chemicals, the best specification used ridge regression with one factor per regional block, NO₂, and lagged target values. For ordinary-steel production, the best specification used ridge regression with two factors per firm block and satellite data alone, combining nighttime lights and NO₂.

Relative to direct regression on the observed satellite series, DFM-based specifications produced lower mean RMSEs for every target, demonstrating the value of aggregating numerous satellite series into common factors. The optimal factor structure nevertheless differed by target: cross-industry common factors were effective for the IIP, whereas factors specific to groups of firms and plants were effective for chemicals and steel. DFM implementation therefore requires not only selecting the number of factors but also aligning the factor structure with the aggregation scope of the target.

For four-wheel motor-vehicle production, restricting observation sites to reflect domestic production yielded the lowest mean RMSE for ridge regression using nighttime lights alone from Toyota and Mazda sites. This finding indicates that satellite-based nowcasts of industrial indicators depend not simply on the number of observation sites but on their correspondence with the target's coverage and with industry-, firm-, and plant-level characteristics.

Overall, freely available satellite data may provide predictive information that complements meso-level official statistics, and the DFM is an effective means of aggregating common variation across satellite series.

Nowcast performance, however, depends on the industry, factor structure, use of lagged target values, model, and correspondence between the target's scope and the observed sites. The automotive analysis in particular highlights the importance of designing observation-site sets that match the target. Future work should test the reproducibility of site selection based on ex ante criteria, select and weight factors using loadings and variable importance, introduce estimation methods suited to small samples, and extend the analysis to additional industries and periods to identify more precisely the conditions under which satellite data and DFMs are effective.

Data availability

The VIIRS VNP46A2 nighttime-light data used in this study are available from NASA's LAADS DAAC. The Sentinel-5P NRTI NO₂ data are available from the Google Earth Engine Data Catalog. The IIP and Current Survey of Production data are available from the Ministry of Economy, Trade and Industry of Japan. Motor-vehicle production data are available from the Japan Automobile Manufacturers Association, and monthly steel statistics are available from the Japan Iron and Steel Federation. The processed datasets generated for the analysis are available from the corresponding author upon reasonable request.

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