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Detecting Changes in Power Plant NO_x Emissions Using Deep Learning and TEMPO Satellite Imagery

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Abstract

NASA’s Tropospheric Emissions: Monitoring of Pollution (TEMPO) instrument provides hourly daytime observations of tropospheric nitrogen dioxide (NO_2) across North America. These observations could support independent, facility-level monitoring of power plant nitrogen oxides (NO_x) emissions, filling gaps when continuous emissions monitoring system (CEMS) measurements fail or facilities are not subject to hourly emissions reporting requirements. Previous studies have estimated hourly point-source emissions using inversion methods, which are highly sensitive to instrument retrieval uncertainty, changing atmospheric conditions, TEMPO’s coarse spatial resolution, signals from nearby emission sources, and temporal mismatch with hourly CEMS records. We instead formulate facility monitoring as change detection over sequences of TEMPO observations. This allows the model to learn relative emissions behavior rather than estimate exact emissions from noisy data. We develop a convolutional gated recurrent unit (ConvGRU) model that processes five consecutive TEMPO observations together with meteorological inputs, features representing plume transport, and tabular features encoding time of day and seasonality to classify power plant emission trajectories as increasing, steady, or decreasing. On a held-out evaluation set of more than 22,000 samples covering 116 active U.S. power plants observed between August 2023 and June 2026, the ConvGRU model achieved a macro-F1 score of 0.56, outperforming a baseline multilayer perceptron (MLP) trained only on the same time-derived features, which scored 0.45. Our findings suggest that the ConvGRU model can identify signals of power plant emissions from TEMPO observations beyond the time-derived features shared with the baseline MLP. More broadly, they indicate that change detection may offer a more tractable framework for modeling power plant activity from TEMPO observations than estimating absolute emissions.

1 Introduction

Based on U.S. Environmental Protection Agency (EPA) inventory data, power plants in the U.S. electricity generation sector emitted approximately 0.74 million short tons of NO_x in 2023, about 9.5% of national emissions [30]. NO_x emissions contribute to ground-level ozone and secondary particulate matter, pollutants that can inflame and damage the airways, reduce lung function, and aggravate asthma [28]. EPA regulations require most large U.S. fossil-fuel-fired generating units that produce electricity for sale to submit unit-level hourly emissions data on a quarterly basis [33]. However, monitoring equipment malfunctions and maintenance can make CEMS measurements unavailable or invalid, requiring plants to report

calculated substitute values instead of direct measurements [29]. Behind-the-meter generators that do not sell electricity, such as the natural gas turbines powering SpaceX’s Colossus 2 data center, can fall outside federal hourly reporting requirements [11]. Outside the United States, comparable public, hourly, unit-level emissions data are generally unavailable; global inventories typically provide only annual estimates [12]. Independent estimates could therefore fill reporting gaps and provide timely insight into facility operations ahead of the EPA’s quarterly release of hourly emissions data.

TEMPO is an ultraviolet-visible spectrometer hosted aboard a geostationary satellite that observes tropospheric vertical column densities (TVCDs) for various trace gases across North America during daylight hours [37]. Earlier polar-orbiting instruments, including the Ozone Monitoring Instrument (OMI) and Tropospheric Monitoring Instrument (TROPOMI), typically observe a given location once per day; TEMPO’s geostationary view provides approximately hourly scans with finer spatial resolution [15, 35, 37]. Hourly sampling captures intraday changes in emissions plumes and atmospheric transport that daily observations can miss. However, power plant emission signals in TEMPO NO_2 TVCDs can be weakened or obscured by factors including evolving meteorology and atmospheric chemistry, cloud cover, viewing geometry and retrieval uncertainty, dilution within TEMPO’s $2.0 \text{ km} \times 4.75 \text{ km}$ spatial resolution, and interference from nearby emission sources [11, 12, 25]. Comparisons with CEMS records, our most reliable ground truth, introduce an additional temporal mismatch because TEMPO observes a facility at a specific time during each hourly scan, whereas CEMS data aggregate emissions over an entire clock hour [25, 33].

Satellite instruments measure atmospheric column abundance rather than emissions directly. Inversion methods therefore infer source rates from the spatial structure of an observed plume and estimated winds. Cross-sectional flux (CSF) removes the background column, integrates the remaining enhancement across transects perpendicular to the plume, and multiplies the resulting line density by an effective wind speed. Under steady-state conditions, this flux approximates the source emission rate. The directional derivative approach (DDA) instead combines the wind field with spatial gradients in the observed column to estimate a local source term, which is then integrated around the facility [21, 24].

Although promising, these methods remain sensitive to source characteristics and observing conditions. Kuhlmann et al. applied CSF to TROPOMI NO_2 observations of 18 power plants in Europe and the United States, recovering seasonal NO_x emissions variability. However, the number of valid overpasses varied across plants, ranging from 38 to 170 per year depending on local cloud cover and interference from nearby plumes, with especially sparse winter

coverage. These sampling gaps, along with uncertainty in chemistry corrections, limited the ability to resolve short-term emissions fluctuations [14]. Using DDA with TEMPO observations, Sun et al. improved correlations with CEMS at 10 of 14 power plants by accounting for changes in NO_2 columns between scans, although their emissions estimates remained approximately four times lower than CEMS measurements [24]. Beaudry et al. estimated emissions using a rise-decay (RD) model that separately fits the increase in NO_2 line density immediately downwind of the source and its subsequent decay farther downwind. Their average emissions estimates were within 50% of CEMS values at 27 of 64 plants, but bias was substantial at plants emitting less than $250 \text{ kg NO}_2 \text{ h}^{-1}$ [3].

Machine learning (ML) studies have addressed several related point-source monitoring tasks. Huang and Wang trained a tabular MLP to predict whether a TROPOMI observation contained a detectable power plant NO_2 plume using 25 facility, meteorological, surface, and sensor variables sampled at the plant location [12]. Their models achieved F1 scores above 0.66, but detectability ranged from below 20% to above 60% for plants with similar emissions. Their interference filters also retained plants representing only 45.0% of U.S. and 21.1% of global NO_x emissions in their datasets. Alnaim et al. used stacked long short-term memory (LSTM) networks to predict next-day EPA-reported NO_2 emissions from seven-day sequences of tabular features comprising previous emissions, TROPOMI NO_2 column values extracted from areas surrounding each plant, MERRA-2 meteorology, aerosol measurements, and calendar variables [1]. Their best single-plant LSTM had an error near 40%, while multi-plant experiments exceeded 55% error and often underestimated extreme values. Finch et al. developed a convolutional neural network (CNN) using 6,086 manually labeled TROPOMI images, achieving greater than 90% test accuracy for NO_2 plume detection. However, reliance on manual annotation limits the scalability of label generation, and plume presence alone is not always a reliable proxy for emissions quantity or plant activity [10].

The studies reviewed above do not jointly model the spatial structure and temporal evolution of consecutive trace gas satellite rasters. We instead formulate facility monitoring as a sequence classification task, where we classify plant emissions trajectories as increasing, steady, or decreasing over sequences of five TEMPO observations. This formulation takes advantage of TEMPO’s hourly temporal resolution and reduces reliance on estimating exact emissions from noisy observations by instead learning relative emissions behavior.

To model spatial patterns and their evolution across TEMPO observations, we consider two families of neural networks: convolutional recurrent neural networks (CRNNs) and spatiotemporal vision transformers (ViTs). At each timestep, a CRNN combines features from the current raster with a spatially structured hidden state carried from the preceding timestep. Convolution operations update the hidden state at each location by combining information from a local neighborhood in both the current input and the previous hidden state. Two common variants are convolutional long short-term memory (ConvLSTM) and convolutional gated recurrent unit (ConvGRU) networks. ConvLSTM maintains separate cell and hidden states, with gates controlling how information is retained, updated, and exposed. ConvGRU maintains a single hidden state controlled by reset and update gates, reducing the

number of parameters relative to a comparably configured ConvLSTM [2, 23]. Spatiotemporal ViTs divide each raster into patches and use self-attention to combine information across patches and timesteps. This allows the model to relate spatially distant regions across observations without processing the sequence recurrently. Compared with convolutional models, spatiotemporal ViTs have a weaker locality bias and typically require more training samples to learn relationships among patches across input timesteps [4].

We select ConvGRU for the balance it offers between modeling capacity and parameter efficiency. Each input sequence contains only five timesteps, so we favor ConvGRU’s simpler memory structure over ConvLSTM’s additional cell state, which increases the parameter count and may offer limited benefit for such short sequences. The input rasters are also relatively small (24×24 pixels), and the spatial continuity of power plant plumes makes local convolutional operations well suited to modeling their evolution across observations. TEMPO’s approximately three-year observational history also limits the available training data, motivating our choice of a compact ConvGRU that captures spatiotemporal patterns with relatively few parameters.

2 Data Sources

2.1 TEMPO NO_2 Data

NASA distributes TEMPO NO_2 retrievals in two formats: Level 2 data on the instrument’s native measurement footprints and Level 3 data regridded from each east-to-west scan [25]. We downloaded version 4 Level 2 NO_2 retrievals from August 2023 through June 2026. Along with NO_2 TVCDs, the product provides metadata including native footprint geometry, mirror-step observation times, main data quality flags, and effective cloud fractions, which we later use for regridding, quality filtering, and temporal alignment with CEMS records.

2.2 CEMS Records

From the EPA’s Clean Air Markets Program Data (CAMPD) APIs, we downloaded hourly emissions records for individual U.S. power plant units from August 2023 through June 2026 and annual facility and unit attributes [34]. From the hourly records, we use facility and unit identifiers, reporting date and hour, NO_x mass and its measurement flag, and operating time. From the annual attributes, we use facility coordinates.

2.3 HRRR Weather Data

The High-Resolution Rapid Refresh (HRRR) is a weather prediction model updated hourly that covers the contiguous United States at a spatial resolution of 3 km [18]. From NOAA’s public HRRR archive, we downloaded hourly 2 m air temperature and eastward and northward wind components at 80 m above ground for August 2023 through June 2026 [19].

3 Methods

3.1 AOI Construction

For each power plant, we define a $72 \text{ km} \times 72 \text{ km}$ area of interest (AOI) centered on the facility and divide it into a 24×24 grid of $3 \text{ km} \times 3 \text{ km}$ cells. For each AOI-hour, we sum the unit-level NO_x

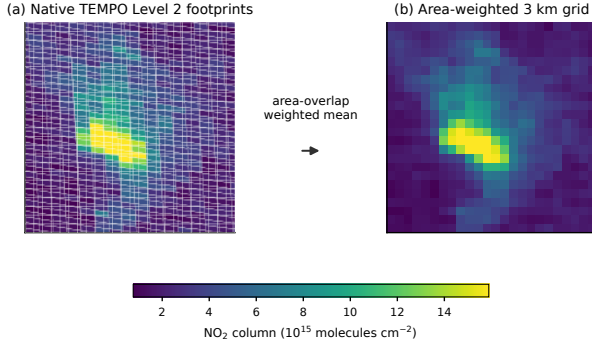


Figure 1: TEMPO NO₂ regridding within a 72 km × 72 km area centered on a power plant. (a) Native Level 2 footprints overlaid with the target grid. (b) Footprint values averaged by area of overlap onto a 24 × 24 grid of 3 km × 3 km cells.

mass reported by all facilities in the AOI and discard the hour if any contributing measurement is invalid or unavailable. We score each AOI using its median total NO_x mass across hours whose mean unit operating time meets or exceeds the AOI-specific median. We retain the highest-scoring 50% to focus the dataset on emissions signals more likely to be detected by TEMPO.

3.2 TEMPO Regridding and Quality Filtering

TEMPO Level 2 observations lie on irregular native footprints, whereas our model uses a fixed spatial grid. We project the footprint boundaries and AOI grid to the contiguous-U.S. Albers equal-area coordinate system. We then assign each AOI grid cell an NO₂ TVCD by averaging the TEMPO footprints that intersect it, weighted by their area of overlap. Figure 1 illustrates this mapping from native footprints to the fixed AOI grid.

A footprint contributes to the NO₂ average only when its main data quality flag equals zero, indicating a reliable retrieval, and its effective cloud fraction does not exceed 0.20. Grid cells without an accepted footprint overlap remain masked, and we retain a binary mask of the original valid cells. We use bilinear interpolation to fill masked NO₂ pixels for downstream modeling.

3.3 Sample Construction

Each sample contains five consecutive observations of one AOI, indexed from t_0 to t_4 . We retain a sequence only when each pair of adjacent TEMPO scans is separated by 40–70 minutes and every NO₂ raster has valid pixel coverage of at least 85%. At each timestep, we pair the TEMPO raster with the HRRR temperature and wind rasters from the closest hour and interpolate them to the same 24 × 24 raster size and spatial coverage as the NO₂ rasters.

Because CEMS records correspond to clock hours rather than TEMPO scan times, we linearly interpolate the AOI-hour NO_x emissions between the surrounding hourly CEMS records at each scan time. Let E_i denote the interpolated emissions at time t_i . For scans t_a through t_b , we calculate the time-weighted mean

$$\bar{E}_{a:b} = \frac{\sum_{i=a}^{b-1} (t_{i+1} - t_i)(E_i + E_{i+1})/2}{t_b - t_a}. \quad (1)$$

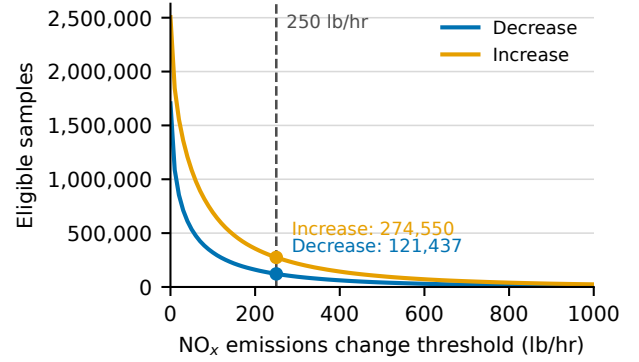


Figure 2: Eligible increase and decrease sample counts across NO_x emissions change thresholds, before raster quality filtering and class balancing.

We define the sequence change as $\Delta E = \bar{E}_{2:4} - \bar{E}_{0:2}$ and use the threshold $\theta = 250 \text{ lb h}^{-1}$ to assign its category:

$$c = \begin{cases} \text{increase,} & \Delta E \geq \theta, \\ \text{steady,} & -\theta < \Delta E < \theta, \\ \text{decrease,} & \Delta E \leq -\theta. \end{cases} \quad (2)$$

We chose the threshold $\theta = 250 \text{ lb h}^{-1}$ based on the balance between valid sample counts across classes and separability between classes from larger emissions deltas, which we visualize in Figure 2.

Requiring a substantial emissions change helps select samples with discernible visual evidence of emissions trajectories in the TEMPO observations. However, factors such as atmospheric transport and retrieval uncertainty can still obscure this signal, even for samples with substantial emissions changes. The two increase-labeled sequences in Figure 3 illustrate how visual agreement with CEMS-derived trajectories can vary even between samples with similar emissions changes.

Figure 4 displays a complete five-observation training sample, combining its NO₂ sequence with the other model inputs and its derived label.

3.4 Transport Model

Emissions change signals in consecutive NO₂ rasters can be degraded by movement and decay of the existing plume. For each pair of consecutive NO₂ rasters, we use a simple transport model to predict the next observation without new emissions in the AOI. We then subtract this prediction from the observed next raster to obtain a transport residual, which separates plume structure explained by modeled advection, horizontal dispersion, and chemical decay from remaining variation that may reflect emissions changes within the AOI.

For the interval $\Delta t_i = t_{i+1} - t_i$, let $N_i(\mathbf{x})$ and $N_{i+1}(\mathbf{x})$ denote the earlier and later NO₂ rasters, $\mathbf{u}_i(\mathbf{x})$ and $\mathbf{u}_{i+1}(\mathbf{x})$ their wind fields, and B_i the median NO₂ value along the boundary of the earlier raster. Using these quantities, we construct the transported prediction and residual as follows:

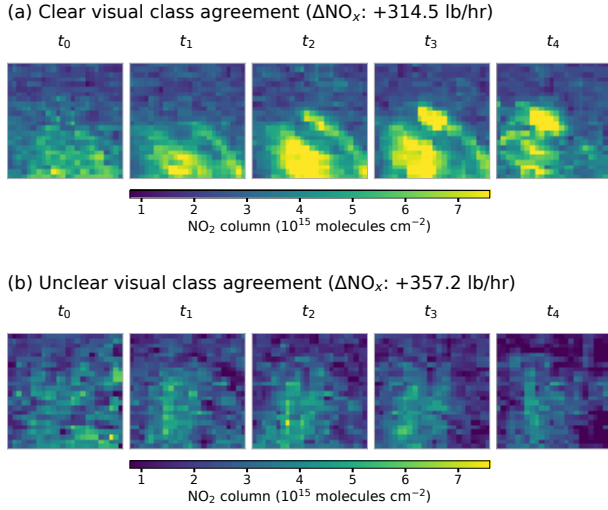


Figure 3: Two five-observation TEMPO NO₂ sequences with CEMS-derived increase labels. (a) An AOI centered on the Victor H. Braunig Power Station in San Antonio, Texas, observed on August 25, 2023, shows a clear visual pattern of increasing emissions. (b) An AOI centered on the High Bridge Generating Station in St. Paul, Minnesota, observed on September 16, 2025, shows little visual evidence of increasing emissions. Both sequences exceed the 250 lb h⁻¹ NO_x emissions change threshold.

$$\begin{aligned}
 \text{(i)} \quad & \bar{\mathbf{u}}_i = \gamma[(1 - \lambda)\mathbf{u}_i + \lambda\mathbf{u}_{i+1}] \\
 \text{(ii)} \quad & A_i(\mathbf{x}) = N_i(\mathbf{x} - \bar{\mathbf{u}}_i(\mathbf{x})\Delta t_i) \\
 \text{(iii)} \quad & \sigma_i = \sigma_0 \sqrt{\frac{\Delta t_i}{1 \text{ h}}} \\
 \text{(iv)} \quad & D_i = B_i + G_{\sigma_i} * (A_i - B_i) \\
 \text{(v)} \quad & \hat{N}_{i+1} = B_i + \exp\left(-\frac{\Delta t_i}{\tau}\right)(D_i - B_i) \\
 \text{(vi)} \quad & R_i = N_{i+1} - \hat{N}_{i+1}.
 \end{aligned}$$

We selected the values of λ , γ , σ_0 , and τ using the tuning procedure described in Section 3.8. Equations (i) and (ii) represent wind-driven advection. Satellite columns do not resolve the vertical distribution of plume mass, so point-source methods commonly use an effective wind to approximate its mean transport speed [17, 21]. We approximate this wind by averaging the fields at the two endpoints ($\lambda = 0.5$) and applying a modest speed correction ($\gamma = 0.8$). Equation (ii) then applies semi-Lagrangian advection by tracing each destination cell backward along the effective wind over Δt_i and bilinearly sampling the earlier raster at the resulting departure location.

Equations (iii) and (iv) approximate unresolved turbulent horizontal dispersion. Gaussian plume representations are widely used in satellite point-source studies [17, 21]. We set σ_0 to one 3 km grid cell after one hour and increase the width with $\sqrt{\Delta t_i}$. Applying the

Gaussian kernel to $A_i - B_i$ spreads the plume enhancement while preserving the estimated background.

Equation (v) applies first-order loss to the above-background enhancement. The effective timescale $\tau = 8$ h represents the combined persistence of the observed NO₂ plume under chemical removal and other unresolved losses. Exponential loss is commonly used to describe the downwind decay of satellite-observed NO_x plumes, whose effective lifetimes vary with meteorology and plume chemistry [17]. Equation (vi) subtracts the resulting transport-only prediction from the next observation.

Each five-observation sample produces four transport-residual rasters, one for each pair of consecutive NO₂ rasters. For each pair, we advect and diffuse the earlier observation’s validity mask alongside its NO₂ raster, then multiply it by the later observation’s mask to form the residual’s quality mask. Figure 4 shows all four residuals for the example sample.

3.5 Dataset Stratification

Our split design has three goals: prevent leakage from overlapping AOIs, produce an approximately 70%/15%/15% stratification of samples, and construct class distributions that support balanced training and comparable evaluation across the held-out splits. We group overlapping AOIs into connected clusters and treat each cluster as an indivisible assignment unit. Because each cluster contains an arbitrary number of AOIs, samples, and class instances, cluster-level assignment cannot generally meet every target exactly.

We use mixed-integer linear programming (MILP) to assign each cluster to exactly one split while minimizing normalized deviations from target counts of AOIs and eligible samples. The first optimization targets a 70%/15%/15% sample stratification using AOI and sample counts, after which we fix the training clusters. A second optimization assigns the remaining clusters equally between validation and test while balancing AOI, sample, and per-class counts. It also constrains both held-out splits to have the same median number of plant units per AOI as the combined held-out pool.

We then uniformly downsample each training class to the size of the smallest class. In validation and test, we retain every increase and decrease sample and uniformly subsample steady samples to at most the size of the larger non-steady class.

We then apply the raster filtering described in Section 3.3. Across the three splits, 19.4% of selected decrease samples, 25.5% of steady samples, and 32.4% of increase samples are retained through raster filtering. The retention pattern is primarily driven by seasonal cloud cover: decrease samples occur more often in winter, steady samples are less seasonally concentrated, and increase samples occur more often in summer. Table 1 reports the final dataset and class counts.

3.6 ConvGRU Model

Each sample supplies five 24 × 24 observation frames and four transport-residual frames, one for each consecutive NO₂ transition. An observation frame contains NO₂, its binary validity mask, eastward and northward winds at 80 m, and air temperature at 2 m. A residual frame contains the transport residual and an associated quality channel indicating support from valid observations. The model also receives four time-derived tabular features computed at the sequence midpoint.

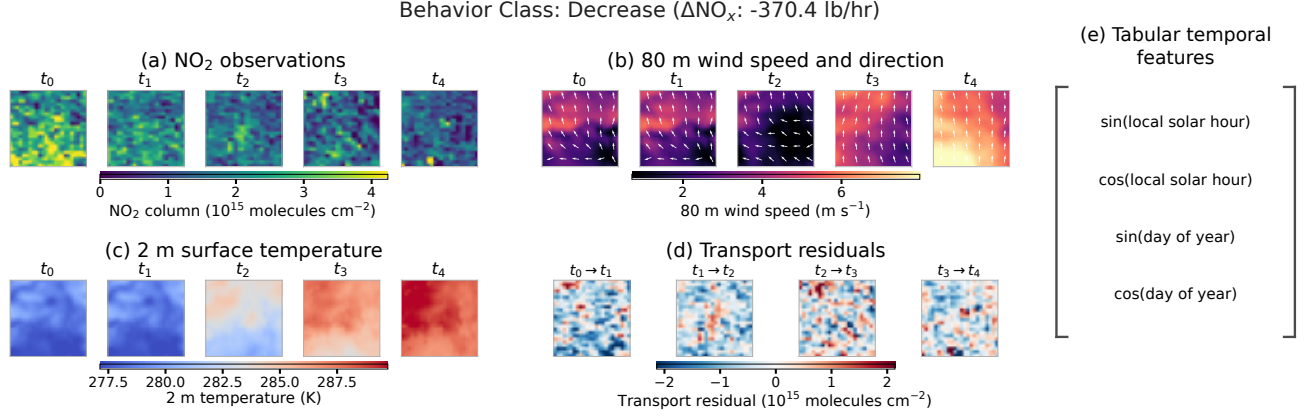


Figure 4: Five-observation training sample (validity masks excluded) from an AOI centered on the Hugh L. Spurlock Generating Station in Maysville, Kentucky, observed on February 26, 2025. Panels (a)–(c) show the NO₂, wind, and temperature inputs at t_0 – t_4 ; (d) shows the four residuals between adjacent observations; and (e) shows the temporal features.

Separate convolutional encoders process the observation and residual frames, sharing weights across time within each branch. A ConvGRU updates a spatial hidden state over four transitions. The model then combines the final visual representation with the time-derived features to classify emissions change behavior. Figure 5 shows the architecture and one ConvGRU cell.

We denote the observation and residual encoders E_x and E_r , respectively, in Figure 5(a). Separate encoders account for the different meanings of their inputs. Both encoders begin with a 5×5 convolution that produces 32 channels, followed by five residual blocks. Strided blocks increase the channel width from 32 to 48 and then 64 while reducing each 24×24 raster to a feature map with 64 channels and a spatial size of 6×6 . Each residual block applies two 3×3 convolutions with group normalization, a SiLU activation after the first convolution, and another SiLU activation after adding the skip connection. Blocks that change channel width or spatial resolution use a 1×1 convolution on the skip path.

As shown in Figure 5(a), the encoded t_0 observation initializes the hidden state, so the model does not synthesize a residual before the first observation. At each subsequent timestep t_i , the model concatenates the encoded observation with the encoded residual for $t_{i-1} \rightarrow t_i$. A 1×1 projection fuses the two encoded feature maps before the recurrent update.

Figure 5(b) expands one recurrent update. Let f_i denote the fused input and h_{i-1} the previous hidden state, a $64 \times 6 \times 6$ feature map that carries spatial information from earlier observations. The ConvGRU computes

$$[r_i, z_i] = \sigma(W_g * [f_i, h_{i-1}] + b_g), \quad (3)$$

$$\tilde{h}_i = \tanh(W_h * [f_i, r_i \odot h_{i-1}] + b_h), \quad (4)$$

$$h_i = (1 - z_i) \odot h_{i-1} + z_i \odot \tilde{h}_i, \quad (5)$$

where the subscripts g and h denote the gate and candidate-state convolutions, respectively. W_g and W_h are their learned 3×3 kernels, while b_g and b_h are the corresponding biases. The symbol $*$ denotes convolution, and $[\cdot, \cdot]$ denotes channel-wise concatenation. The

reset gate r_i controls how much previous spatial information contributes to the candidate state, while the update gate z_i determines how much of that candidate replaces the previous state.

After the fourth recurrent update, global average and maximum pooling summarize distributed and localized evidence, respectively, in the final hidden state. The model concatenates their outputs and projects them into a visual embedding. A feedforward encoder maps four time-derived tabular features (the sine and cosine of local solar hour and of day of year) into a tabular embedding. The model concatenates the tabular embedding with the visual embedding after recurrent processing, keeping the tabular features out of the spatial state updates. The fused representation passes through a classification head to produce one logit for each emissions-change class: increasing, steady, or decreasing.

3.7 Baseline MLP Model

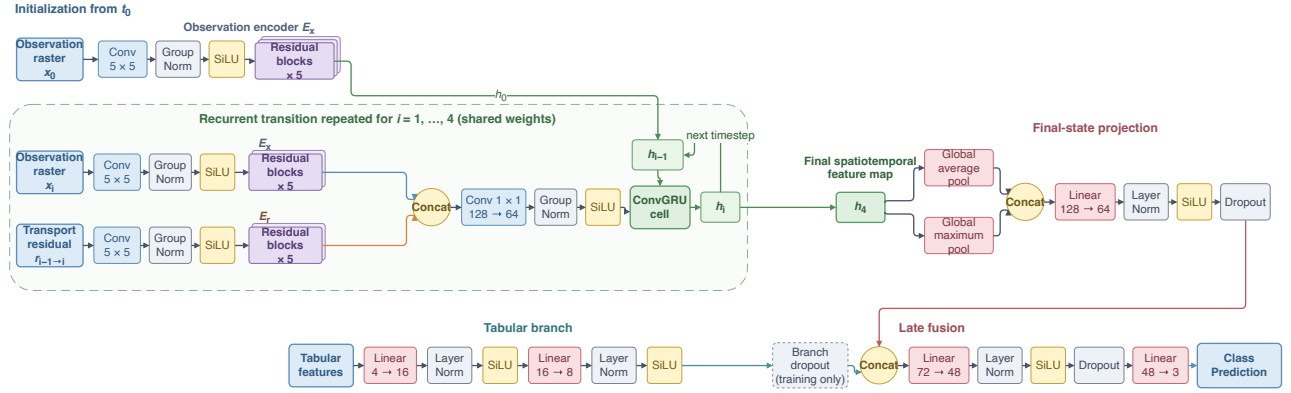
We use a lightweight baseline MLP to gauge how much emissions change behavior can be predicted from recurring daily and annual patterns without satellite or weather inputs. It uses the same four time-derived tabular features as the ConvGRU. The baseline MLP maps these features through 16- and 8-unit hidden layers, each with layer normalization and a SiLU activation, followed by a linear layer that produces logits for the three behavior classes.

3.8 Transport Model Parameter Tuning

We tuned the transport model on steady samples from the validation split to assess its ability to predict NO₂ plume evolution during periods of relatively stable NO_x emissions. We sampled 2,500 records and randomly selected one consecutive NO₂ raster transition from each record.

We evaluated the wind-blending factor λ , wind-speed scale γ , dispersion width σ_0 , and decay timescale τ using the L1 loss between the transport model’s predicted NO₂ raster $\tilde{N}_{i+1}$ and the observed raster N_{i+1} . The parameter set $\lambda = 0.5$, $\gamma = 0.8$, $\sigma_0 = 1$, and $\tau = 8$ yielded the lowest error from this procedure.

(a) ConvGRU architecture



(b) ConvGRU cell

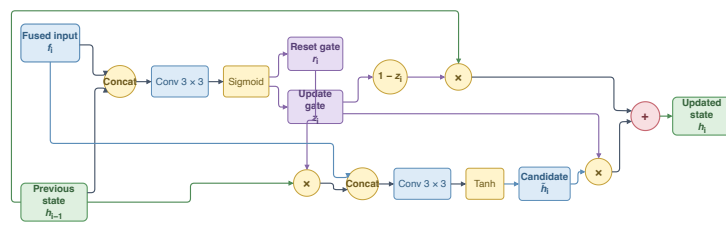


Figure 5: ConvGRU architecture for emissions change classification. (a) Observation and transport-residual encoders, four recurrent transitions, and late fusion with time-derived tabular features. (b) Reset, update, and hidden-state operations within one ConvGRU cell.

Table 1: Final modeling dataset composition by split and behavior class. AOIs are distinct 72 km × 72 km bounding boxes centered on power plants. An active plant has nonzero operating time during at least one observed hour in the dataset.

Split	AOIs	Active plants	Decrease	Steady	Increase	Total
Training	469	530	17,130	23,289	29,888	70,307
Validation	100	109	3,240	7,648	9,902	20,790
Test	98	116	3,142	8,722	10,602	22,466
Total	667	755	23,512	39,659	50,392	113,563

3.9 Training Procedure

We standardize the NO_2 , wind, temperature, and transport residual rasters and the tabular inputs in every split using means and standard deviations computed from the training split.

We conducted hyperparameter optimization for the ConvGRU by varying model width, initial learning rate, weight decay, and activation dropout, selecting the configuration with the highest validation macro-F1. Table 2 reports the selected hyperparameters and other training settings.

For the ConvGRU model, we also apply tabular branch dropout during training: for each sample, the tabular embedding is fully zeroed with probability 0.25 before late fusion. This discourages the classifier from relying on the time-derived tabular features alone.

Both classifiers use inverse-frequency class weights computed from the final training split and minimize weighted cross-entropy.

Table 2: Training parameters and setup details for the baseline MLP and ConvGRU. Dashes indicate parameters not used by the MLP. Asterisks denote parameters selected through hyperparameter optimization for ConvGRU.

Parameter	Baseline MLP	ConvGRU
Trainable parameters	291	724,939
Model width*	–	64
Optimizer	AdamW	
Batch size	128	128
Initial learning rate*	10^{-3}	6.04×10^{-5}
Weight decay*	10^{-4}	10^{-4}
Activation dropout*	–	0.20
Tabular branch dropout	–	0.25
Gradient-norm limit		5.0
LR scheduler	Reduce on plateau	
LR reduction factor	0.5	
Scheduler patience	5 epochs	
Selection metric	Validation macro-F1	
Early-stopping patience	10 epochs	
Hardware	1 NVIDIA RTX A5000 GPU	

4 Results

4.1 Classification Performance

We use F1 to summarize the balance between precision and recall for each behavior class, and macro-F1 to give the three classes equal weight despite unequal sample counts. Figure 6 compares the

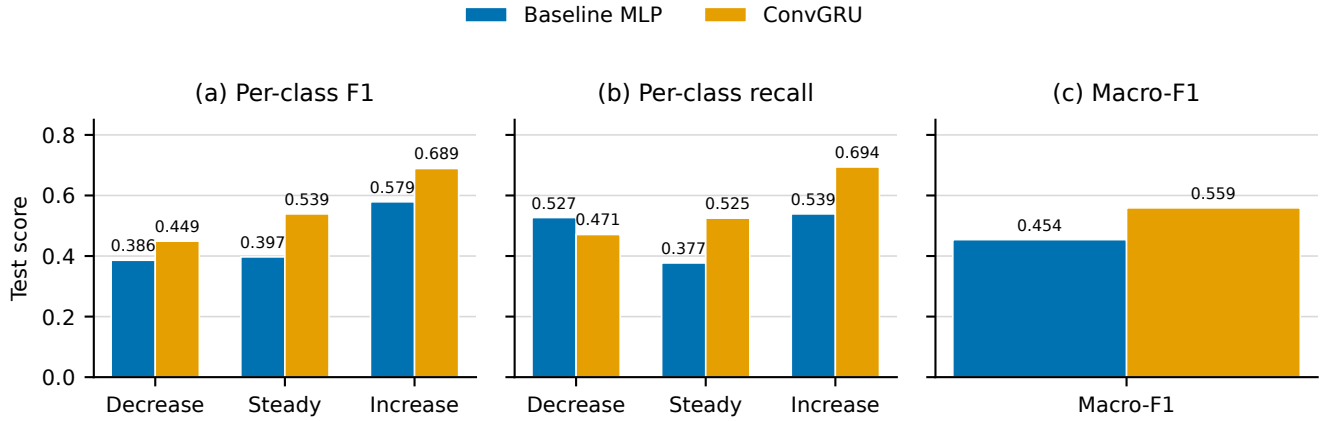


Figure 6: Test set performance of the baseline MLP and ConvGRU for emissions change classification. (a) F1 and (b) recall for the decrease, steady, and increase classes; (c) macro-F1 across classes.

models on the test set. The ConvGRU achieves a macro-F1 of 0.56, compared with 0.45 for the baseline MLP.

ConvGRU achieved a training macro-F1 of 0.62 and a validation macro-F1 of 0.60, compared with 0.53 and 0.53 for the baseline MLP. Its macro-F1 decreased by 0.06 from training to test, compared with a decrease of 0.08 for the MLP. On the test set, the ConvGRU outperformed the baseline in F1 across all three classes, with its largest advantage for steady samples: an absolute F1 difference of 0.14. Decrease remained the ConvGRU's weakest class, with test recall of 0.47 versus 0.53 for the baseline MLP. Detecting decreases may be more difficult because fewer decrease samples are available for training and previously emitted NO₂ can remain visible after emissions decline as the plume advects, disperses, and decays.

4.2 Performance Across Evaluation Strata

4.2.1 Performance Across Months. Figure 7 shows that ConvGRU classification accuracy is more stable across seasons than that of the baseline MLP. Their results are closest in summer, but ConvGRU accuracy exceeds MLP accuracy by 0.28 in April and 0.32 in November. Panel (b) shows that increases are especially common in summer, while steady samples make up a larger share in spring and late fall, when the models differ more. This pattern is consistent with the MLP relying on seasonal class prevalence, whereas the ConvGRU can also use raster inputs to identify plant activity.

4.2.2 Performance by Local Solar Hour. Figure 8 shows that the ConvGRU outperforms the baseline MLP at nearly all local solar hours. Both models show a generally decreasing trend in accuracy from morning to late afternoon. Panel (b) shows that sample counts peak around 10:00–11:00 and are sparse at the earliest and latest hours; the class mix also changes through the day. These aggregate results therefore do not isolate an effect of solar hour from differences in class composition.

4.2.3 Performance by Census Region. Figure 9 shows ConvGRU macro-F1 of 0.57 in the South, 0.51 in the West, and 0.46 in the Midwest, while the baseline MLP remains near 0.45 in all three regions. The ConvGRU's regional pattern broadly tracks the class

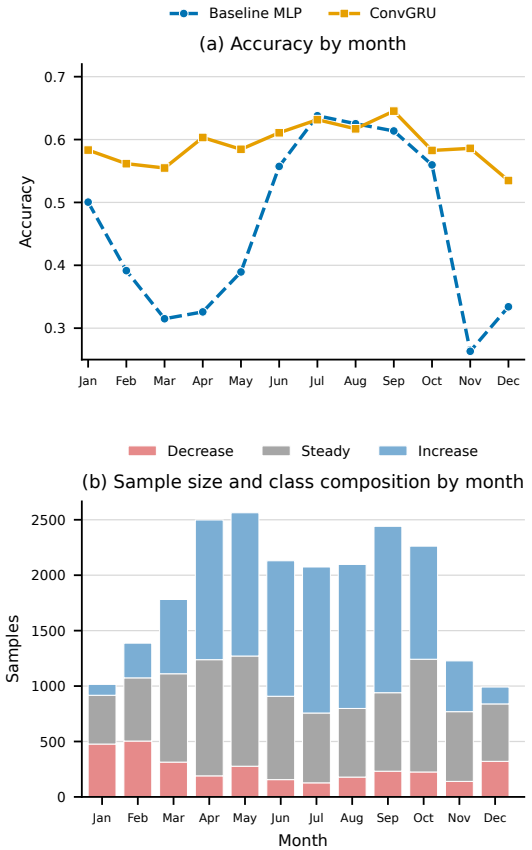


Figure 7: Test set performance and class composition by month. (a) Classification accuracy of the baseline MLP and ConvGRU. (b) Number of samples in each emissions change class (decrease, steady, and increase) by month.

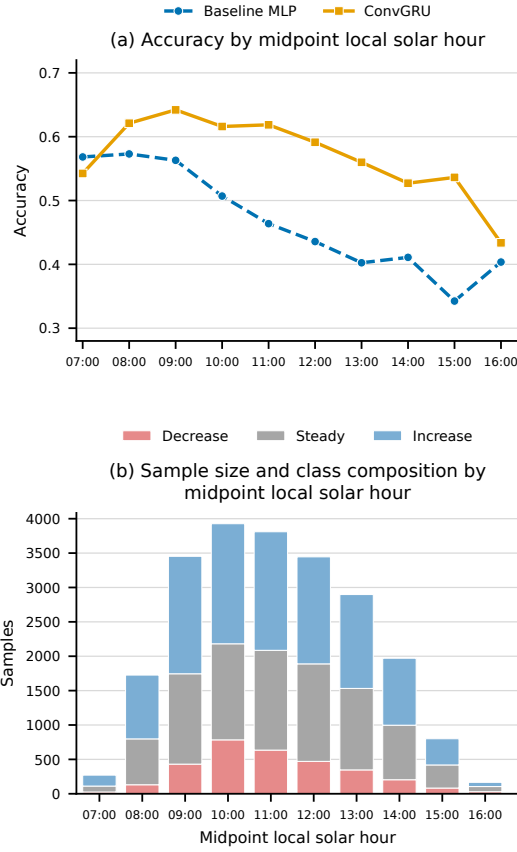


Figure 8: Test set performance and class composition by local solar hour at the sequence midpoint. (a) Classification accuracy of the baseline MLP and ConvGRU. (b) Number of samples in each emissions change class (decrease, steady, and increase) by hour.

mix in panel (b): its score is highest where increase samples are most prevalent and lowest where decrease samples have the largest share. The West, where steady samples dominate, falls between them. Class composition may contribute to these differences, though this comparison does not isolate its effect. The test split contains no Northeastern AOIs.

4.2.4 Performance by NO_x Change Magnitude. Figure 10 shows that lower-magnitude decreases are the ConvGRU’s weakest group among those plotted: its score is 0.59, compared with 0.69 for larger decreases. The baseline MLP scores 0.68 on smaller decreases, while the models perform similarly on larger decreases. By contrast, the ConvGRU’s scores for smaller and larger increases are nearly identical (0.81 and 0.83). Smaller decreases may therefore be a principal source of its weaker performance on decrease events overall. This pattern is consistent with a lag in the raster response: NO_2 emitted before a unit’s emissions decline or stop can remain visible as it advects and decays, making smaller decreases harder to distinguish.

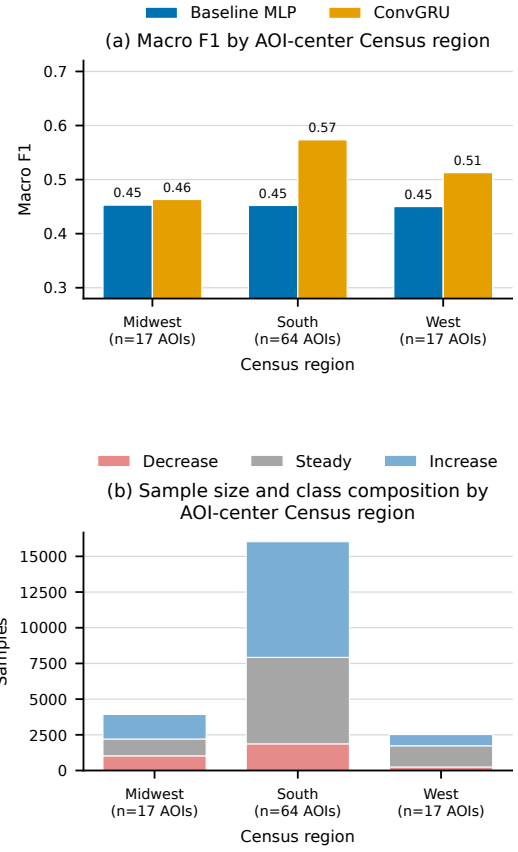


Figure 9: Test set performance and class composition by Census region of the AOI center. (a) macro-F1 of the baseline MLP and ConvGRU. (b) Number of samples in each emissions change class (decrease, steady, and increase) by region.

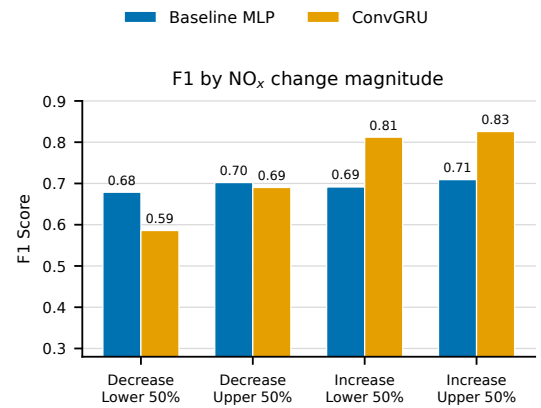


Figure 10: Test set performance by NO_x emissions change magnitude within increase and decrease classes. Within each class, samples are split into lower and upper halves at the median absolute emissions change.

Table 3: ConvGRU ablation performance on the test set. Each ablated model was retrained with the listed input zeroed out for all samples. Baseline is the full-input ConvGRU.

Input feature removed	macro-F1	Decrease F1	Steady F1	Increase F1
Baseline	0.56	0.46	0.52	0.69
Wind rasters	0.56	0.46	0.54	0.67
Temperature rasters	0.51	0.42	0.53	0.57
Transport residuals	0.43	0.36	0.31	0.62
Tabular features	0.55	0.46	0.51	0.68
t_1 observation	0.54	0.44	0.56	0.62
t_2 observation	0.54	0.47	0.54	0.62
t_3 observation	0.53	0.45	0.50	0.63
t_4 observation	0.54	0.47	0.51	0.64

4.3 Ablation Study

We retrain the ConvGRU for each ablation in Table 3, zeroing the listed input for every sample. For timestep ablations, we zero the NO₂ and weather rasters but retain overlapping transport residuals. We omit t_0 because it initializes the hidden state, making its removal different from removing later observations.

Removing transport residuals causes the largest drop in test macro-F1 (12.58 percentage points), including a fall in steady F1 from 0.52 to 0.31. This suggests the model uses deviations from predicted plume transport to distinguish emissions changes from plume transport. Removing temperature costs 4.87 points and particularly hurts increase F1 (0.69 to 0.57). Temperature may help the model interpret atmospheric effects in the rasters, although it could also act as a proxy for electricity demand. Removing tabular features costs only 0.74 points, supporting the view that the ConvGRU identifies emissions trajectories primarily from visual inputs rather than seasonal timing alone. Removing wind rasters costs only 0.27 points, but wind also enters the transport residual calculation, so this does not establish that wind is uninformative.

5 Discussion

5.1 Evaluation of Model Results

The ConvGRU uses raster information about power plant activity beyond time of day and seasonality. Its advantage over the baseline MLP is greatest for steady samples, where features derived from time are less informative. Transport residuals contribute most to the model’s performance in the ablation study, particularly for steady samples. This suggests that accounting for plume transport helps the model distinguish emissions behavior from changes in atmospheric conditions. The ConvGRU performs worse on decreases than on increases, possibly because decreases are less common in the training set and previously emitted NO₂ can remain visible after emissions fall.

Across the monthly, hourly, and regional subsets, both models tend to perform better when increases are more prevalent than when decreases are more prevalent. The ConvGRU’s advantage tends to grow as the share of steady samples rises. A binary task with classification labels of increase and non-increase might therefore be easier to learn, since it would not require the model to

distinguish decreases from steady periods. Future work could test this framing during operating hours when ramp-up activity is more common (e.g., in the morning) for a clearer visual signal across the dataset.

5.2 Implications for Power Plant Monitoring

Satellite plume inversion depends on observations that distinguish a plant’s plume from nearby emissions. Low source emissions, nearby sources, cloud screening, and very low or high wind speeds can reduce the number of usable observations or increase uncertainty in emission-rate estimates [12, 14, 21]. Our model instead classifies relative emissions changes across 72 km × 72 km AOIs while accounting for transport dynamics. This design could extend activity monitoring to some clustered or urban settings where plume inversion is difficult, although we have not directly evaluated that comparison.

This modeling approach could support identification of power plant shutdowns and restarts associated with planned maintenance, equipment failures, or periods when units are available but not dispatched. Public access to individual generator outage records varies across grid operators. For example, CAISO publishes daily outage reports identifying individual generating resources and their unavailable capacity. ERCOT publishes unplanned outage and derating records with a three-day delay for individually identified generating resources, which can represent individual units or groups of units. PJM publishes daily regional and system-wide outage-capacity totals while generally keeping individual generator outages confidential [5, 7, 20]. For facilities covered by EPA reporting programs, quarterly submissions of hourly operating and emissions data provide a retrospective record of nonoperation and subsequent restarts [31, 34]. Our current model predicts aggregate emissions changes across each AOI. An extension could jointly predict the emissions-change class and a spatial contribution raster, supervised using facility-level emissions changes derived from CEMS. This could potentially help the model monitor emissions changes at the granularity required to identify when a specific facility is undergoing shutdown or restart behavior.

Another potential application is monitoring substantial changes in generating output from one or more units within an AOI. In response to dispatch instructions, operating units may increase or decrease their output without an entire facility shutting down or restarting. These adjustments can produce substantial emissions changes even while other units in the AOI maintain their operating levels. Hourly generation totals for balancing authority areas, including breakdowns by energy source, are public, but timely output data for individual generators are less consistently available. For example, PJM treats individual generator output as confidential, while ERCOT releases resource-specific dispatch targets and telemetered output with a 60-day delay [6, 20, 26]. EPA records also provide historical hourly generation information for many covered units through quarterly reporting [31, 34]. The joint prediction of emissions trajectories and per-pixel spatial contributions discussed above could also help identify facilities exhibiting behavior consistent with substantial dispatch-related changes in generating output before corresponding operational records become publicly available.

Growing electricity demand from data centers is driving the deployment of dedicated natural gas power plants located at or near computing facilities. These installations can comprise multiple gas turbines or natural gas-fired piston engines connected to electrical generators. For example, SpaceXAI’s Colossus 2 data center draws power from a dedicated installation of natural gas turbines in Southaven, Mississippi [11, 27]. Some dedicated data center power facilities may lack the publicly available hourly emissions records provided by EPA’s power sector reporting programs, creating an opportunity for independent satellite monitoring [32]. At facilities without publicly available CEMS records, our approach could provide information about short-term emissions trajectories and associated operational changes. Although ground-truth data for these facilities may be scarce, our model could complement methods that estimate absolute emissions by providing additional transparency into their short-term emissions activity.

5.3 Limitations and Future Work

The available TEMPO observation history limits the size and coverage of the modeling dataset. Our observations span August 2023 through June 2026, which covers the full range of dates with both TEMPO observations and quarterly CEMS data available at the time of study. Cloud cover and pixel validity requirements further reduced the number of usable five-observation sequences. As the TEMPO and EPA CEMS records grow, more sequences may meet our sampling requirements. Beyond North America, GEMS observations could be paired with South Korea’s publicly released stack NO_x measurements, while Sentinel-4 observations could be paired with European generation data for large individual units [8, 9, 13, 36]. These extensions would require new label construction and validation because the available ground data differ from EPA CEMS. Improved NO_2 retrieval and cloud-correction algorithms may also make changes in plume structure more discernible across our raster sequences [22].

Transport residuals produced the largest gain in our ablation study, but their calculation uses one effective wind field, simplified horizontal dispersion, and a fixed decay timescale. A future model could interpolate wind vector data based on stack height, account for boundary-layer mixing and plume rise, and model NO_2 chemistry as it varies with sunlight and temperature [12, 17]. Better predictions of how existing plumes move and persist could reduce transport-related variation in the residuals, making emissions changes easier to detect, especially decreases obscured by lingering NO_2 .

Our labels aggregate emissions from all facilities within each AOI. When nearby units change activity in opposing directions, their signals can partly cancel, weakening visual evidence of the aggregate label. The current model cannot identify which facility drove a predicted change or what caused it. Future work could jointly predict the activity label and a per-pixel spatial contribution map to help associate the observed signal with specific facilities in an AOI.

6 Conclusion

We formulate short-term power plant monitoring as detecting changes across sequences of TEMPO NO_2 observations rather than

estimating an exact emission rate from each scan. On more than 22,000 held-out samples covering 116 active U.S. plants, the ConvGRU achieved a macro-F1 of 0.56, compared with 0.45 for a baseline using only time-derived features. This gain suggests that the raster sequences contain information beyond recurring daily and seasonal patterns, even though retrieval uncertainty, changing atmospheric conditions, and nearby sources can obscure individual plumes. Transport residuals compare each scan with a prediction of how an existing plume should move and decay, and our ablation study identified them as the most important model input. These findings suggest that change detection may be a more tractable framework for modeling short-term emissions from noisy satellite observations than direct regression of absolute emissions. This approach could support independent monitoring of plant activity during CEMS failures, before quarterly CEMS data are released publicly, and at facilities not subject to hourly reporting requirements.

Code and data availability

The code used in this study is available at <https://github.com/pranav-walimbe/powerplant-modeling>. The processed modeling dataset is available from the corresponding author upon request. The source data are publicly available: TEMPO Level 2 NO_2 retrievals (version 4) through NASA Earthdata [16], HRRR meteorological fields through NOAA’s public HRRR archive [19], and hourly CEMS emissions and operating records through the EPA’s Clean Air Markets Program Data portal [34].

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