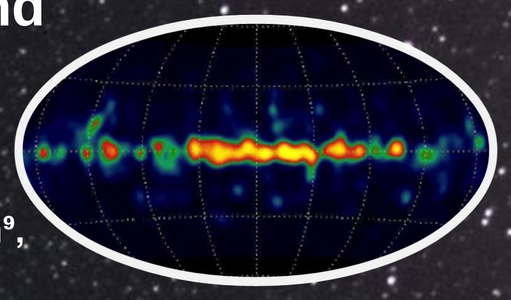
Machine Learning Models for Predicting the COSI Background for Gamma-Ray Burst Detection

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Summary

The **Compton Spectrometer and Imager (COSI)** is a NASA Small Explorer mission surveying the **0.2–5 MeV gamma-ray sky**. Using three months of DC4 background-only simulations, we model ARM-selected 1-s background light curves from spacecraft and orbital parameters. Poisson Regression and four-component GMR show comparable performance, with Poisson Regression retained as the simpler reference model. This work supports future blind GRB detection and localization across the COSI FoV.



Introduction

The **Germanium Compton Telescope (GCT)** on COSI consists of **16 high-purity germanium detectors** and provides an instantaneous FoV greater than **25% of the sky**, enabling localization of gamma-ray transients such as GRBs [1,2]. The COSI background varies with orbital and observing conditions, requiring accurate time-dependent background estimation for transient searches [2,3]. For a given sky direction, the **Angular Resolution Measure (ARM)** is the difference between the geometrically and kinematically reconstructed Compton scatter angles, $\Delta\phi_{\{ARM\}} = \phi_{\{geo\}} - \phi_{\{kin\}}$, as illustrated in Fig. 1 [3].

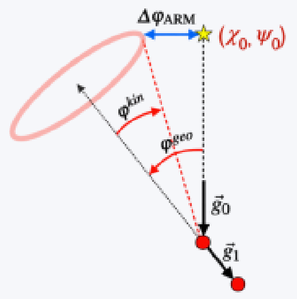


Fig. 1. Definition of the ARM

Methods

Dataset & Preprocessing: We use three months of COSI DC4 background-only simulations. ARM-selected 1-s light curves are extracted for HEALPix directions using |ARM| ≤ 13°; one representative sky direction is shown here. The first 100 orbits are excluded due to short-lived isotope activation. Figure 2 shows the long-term background evolution and subsequent stabilization. After quality and SAA cuts, ≈4.89 million valid samples remain.

DC4 Background (3-month simulation) → **HEALPix Directions** (Trial sky directions) → **ARM selection |ARM| ≤ 13°** (Selected events) → **1-s Light Curves** (Binned counts) → **Data Filtering** (First 100 orbits + SAA/invalid bins removed 4.89M valid samples)

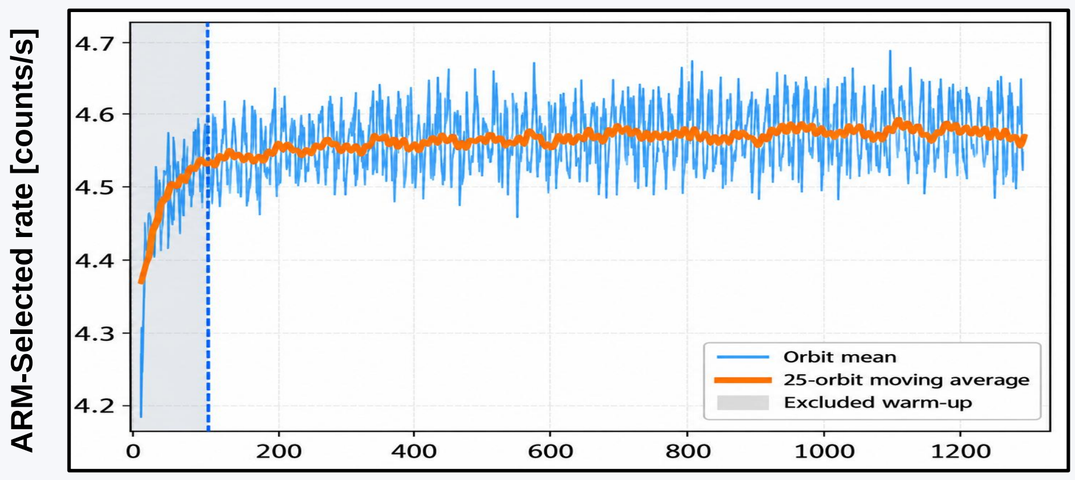


Fig. 2. Long-term ARM-selected background evolution; first 100 orbits excluded.

Model Inputs & Feature Representation: The model uses **12 input features per 1-s bin**: elapsed time, altitude, sine/cosine of orbital latitude and longitude, and Cartesian **(x,y,z)** components of the spacecraft **X- and Z-axis pointing vectors**. Sine/cosine encoding preserves angular periodicity and avoids boundary discontinuities, while Cartesian coordinates preserve the full **3D pointing direction** without angular singularities.

Background Models: Predict the full conditional distribution $\mathbf{p}(N_t \mid x_t)$ of ARM-selected background counts in each 1-s bin, rather than only their mean.

1. Poisson Regression

$$N_t \mid x_t \sim \mathbf{Poisson}(\lambda_t),$$
$$\log(\lambda_t) = \beta_0 + \beta^T x_t$$

A probabilistic count model in which the predicted mean and variance are both equal to λ_t.

2. Gaussian Mixture Regression

$$p(N_t \mid x_t) = \sum_{k=1}^{4} \pi_{k(x_t)} \mathcal{N}\left(N_t \mid \mu_{k(x_t)}, \left[\sigma_{k(x_t)}\right]^2\right)$$

GMR provides flexible background prediction with uncertainty.

Output: Expected background and predictive uncertainty for **transient-search significance calculations**.

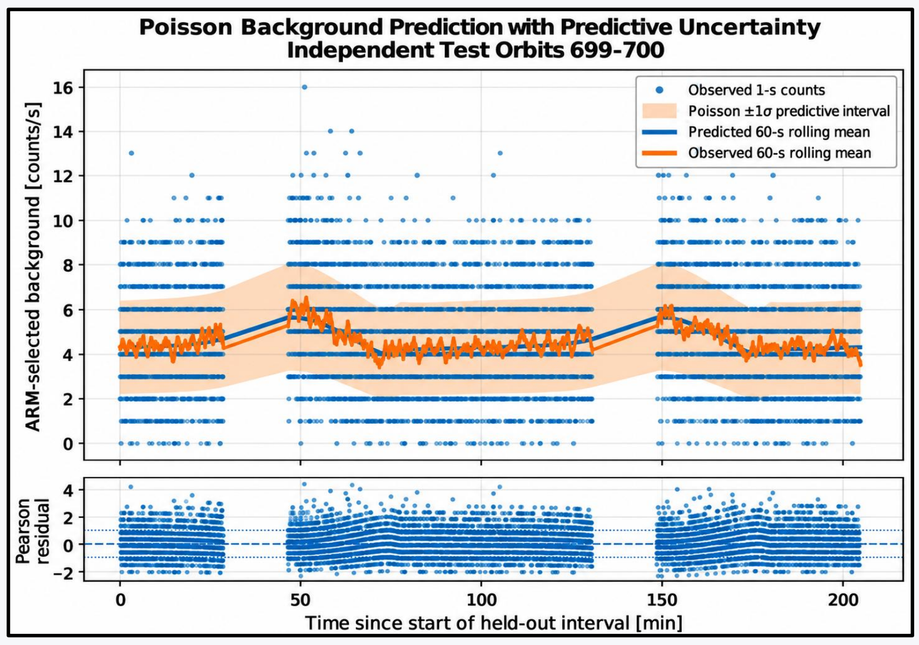
Temporal Validation: orbits **699–700** are reserved as an unseen continuous test interval (**10,152 one-second samples**). Performance evaluated at **1, 5, 10** and **100 s** using deviance, RMSE, MAE, bias and Poisson residuals.

Results

Independent temporal test — orbits 699–700 · 10,152 unseen 1-s samples

Model	Bias [counts/s]	MAE [counts/s]	RMSE [counts/s]	Poisson deviance
Poisson regression	+ 0.047	1.691	2.116	1.040
4-component GMR	− 0.003	1.697	2.116	—

Held-out Orbit Prediction: Fig. 3 shows that Poisson regression follows the background evolution over unseen **orbits 699–700.**



Poisson temporal calibration over held-out windows

Scale	Deviance	RMSE	MAE	Bias [counts/window]
1 s	1.052	2.116	1.696	−0.010
5 s	0.992	4.709	3.741	−0.048
10 s	1.007	6.717	5.334	−0.092
100 s	1.107	22.338	17.630	−0.766

1–10 s: well calibrated; 100 s: mild extra variance, stable mean.

Conclusions

Conclusions: Poisson regression reproduces the ARM-selected COSI background at the representative sky direction across multiple orbits and remains stable from **1–10 s**, with only mild extra variance at **100 s**. This study uses **DC4 background-only simulations** and tests eight HEALPix directions, while one representative direction is shown here. The validated background model provides a basis for future **GRB injection, blind-search tests, localization across the COSI FoV, and validation with real COSI data.**

Ref

[1] Tomsick et al. — The Compton Spectrometer and Imager
[2] Neights et al. — Predictions for Short Gamma-Ray Burst Detections by COSI
[3] Kierans, Takahashi & Kanbach — Compton Telescopes for Gamma-ray Astrophysics

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