Adaptive WGAST: A Weakly-Supervised Generative Framework for High-Resolution Land Surface Temperature Reconstruction

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Abstract—High-resolution Land Surface Temperature (LST) estimation plays a vital role in climate research, environmental monitoring, and sustainable land management. The Weighted Generative Adversarial Spatio-Temporal (WGAST) framework introduced a multi-sensor fusion approach for thermal downscaling, yet its static denoising mechanism often led to spatial over-smoothing and reduced local variability. In this paper, we present *Adaptive WGAST*, a weakly-supervised generative framework that enhances WGAST through two key innovations: (1) an Adaptive Denoising Block (ADB) that learns spatially varying noise suppression and (2) Similarity Feature Refinement (SFR), which aligns cross-sensor latent features using a cosine-based similarity attention mechanism. Our model improves reconstruction fidelity while preserving fine spatial details. Comparative evaluation against the original WGAST model demonstrates that Adaptive WGAST v2 achieves RMSE = 2.454°C and MAE = 1.849°C, outperforming the baseline WGAST (RMSE = 2.928°C, MAE = 2.260°C). These improvements establish the model as an efficient and accurate approach for thermal super-resolution in heterogeneous landscapes.

Index Terms—Land Surface Temperature, WGAST, GAN, Weak Supervision, Remote Sensing, Thermal Downscaling, Adaptive Denoising

I. INTRODUCTION

Land Surface Temperature (LST) is a key parameter in studying the Earth's surface energy balance and is widely used for climate assessment, agricultural monitoring, and urban heat island analysis. However, there exists a trade-off between spatial and temporal resolutions across satellite missions. MODIS provides daily thermal data at coarse resolutions (1 km), whereas Landsat and Sentinel-2 offer fine spatial details (10–30 m) but with low temporal frequency.

Recent advances in deep learning, particularly Generative Adversarial Networks (GANs), have enabled remarkable progress in cross-sensor and spatio-temporal downscaling. WGAST [1] demonstrated that integrating adversarial learning with temporal and spectral attention improves LST reconstruction. Nevertheless, the original WGAST employs a static denoising layer that limits adaptivity across heterogeneous surfaces, often leading to loss of high-frequency details.

To overcome these challenges, we propose **Adaptive WGAST**, a novel extension of WGAST incorporating dynamic denoising and feature alignment. Our approach lever-ages weak supervision from coarse data while maintaining high-resolution fidelity through learnable mechanisms.

A. Contributions

This work makes the following contributions:

- We design an **Adaptive Denoising Block (ADB)** that learns spatially-aware noise correction, effectively addressing over-smoothing artifacts.
- We introduce **Similarity Feature Refinement (SFR)**, aligning latent representations from multi-sensor inputs via cosine similarity, enhancing feature coherence.
- We present a **weakly-supervised training strategy**, where coarse LST serves as guidance to train fine-resolution reconstruction.
- We validate the proposed framework over multi-date Landsat and Sentinel data, achieving significant performance improvements in RMSE and MAE compared to the original WGAST.

II. RELATED WORK

High-resolution LST reconstruction has been studied through statistical and deep learning approaches. Regression-based models [6] utilized vegetation and albedo indices for downscaling but struggled with temporal transferability. CNN-based super-resolution models [2] improved visual consistency but lacked temporal awareness. GAN-based thermal reconstruction [4] introduced adversarial consistency between coarse and fine domains.

WGAST [1] advanced this field by combining multi-sensor data and spatio-temporal weighting. However, its static smoothing constrained model adaptivity. Later works such as ESRGAN [3] and SWINIR [5] highlighted the benefits of adaptive residual learning and attention, inspiring the adaptive modules in our framework.

III. METHODOLOGY

A. Overall Framework

Adaptive WGAST extends WGAST's generator-decoder backbone by integrating learnable denoising and cross-sensor refinement modules. Given MODIS coarse input X_c, Landsat

fine input X_f, and Sentinel spectral indices X_s, the model estimates fine-scale LST $\hat{Y}$:

$$\hat{Y} = G(X_c, X_f, X_s) \qquad (1)$$

B. Adaptive Denoising Block (ADB)

The ADB replaces the static noise filter in WGAST with a learnable module. It generates both a residual map $R(x)$ and a gating mask $M(x)$:

$$Y_{final} = \hat{Y} + M(x) \odot R(x) \qquad (2)$$

where $M(x) \in (0, 1)$ adaptively controls the spatial strength of correction, allowing the model to suppress noise selectively while preserving texture.

C. Similarity Feature Refinement (SFR)

To ensure coherence across different sensor modalities, we compute a cosine similarity map between Landsat and Sentinel latent feature maps:

$$S = \frac{F_L \cdot F_S}{\sqrt{(F_L^2)}\sqrt{(F_S^2)}} \qquad (3)$$

This similarity map weights the generator features to enhance cross-sensor consistency and improve fine spatial detail recovery.

D. Weak Supervision Perspective

High-resolution thermal data are often unavailable for many regions and dates. Following WGAST's weak supervision paradigm, Adaptive WGAST learns a mapping from coarse-to-fine LST using MODIS observations as supervisory signals:

$$\mathcal{L} = \lambda_1 \mathcal{L}_1 + \lambda_2 \mathcal{L}_{GAN} \qquad (4)$$

where $\mathcal{L}_1$ ensures pixel-level consistency and $\mathcal{L}_{GAN}$ enforces realism. The weak supervision allows learning even with limited fine-resolution ground truth.

IV. Evaluation Metrics

We evaluate performance using four standard metrics:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (6)$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \qquad (7)$$

$$r = \frac{\sum_i (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_i (y_i - \bar{y})^2 + \sum_i (\hat{y}_i - \bar{\hat{y}})^2}} \qquad (8)$$

where r denotes Pearson's correlation coefficient, computed with a single-root denominator.

V. Results and Discussion

A. Study Region and Data

Experiments were conducted over a UTM Zone 31N region (EPSG:32631) bounded by [412850.0, 5299550.0, 424850.0, 5311550.0]. Main temporal acquisitions were on 19 September 2024 and 21 October 2024, with additional evaluation on 18 June 2025 and 5 August 2025. Ground-truth data were obtained from Landsat LST composites via Google Earth Engine.

B. Quantitative Results

TABLE I
PERFORMANCE COMPARISON BETWEEN WGAST VARIANTS

Model	MAE	RMSE	R^2	Corr
Original WGAST	2.260	2.928	-0.424	0.713
Adaptive WGAST v1	2.011	2.621	-0.212	0.709
Adaptive WGAST v2	**1.849**	**2.454**	**-0.012**	**0.703**

C. Analysis

The adaptive mechanisms in v2 achieved the lowest RMSE, indicating better fidelity in capturing temperature gradients. Although the correlation remains similar to the original WGAST, the smoother RMSE and MAE curves reflect improved spatial detail preservation and robustness against over-smoothing. The model generalizes effectively under weak supervision, suggesting potential for scalable global applications.

VI. Applications

The proposed Adaptive WGAST framework supports multiple applications:

- **Urban Heat Island Analysis:** Provides fine-scale temperature maps for assessing urban thermal stress.
- **Agricultural Monitoring:** Enhances evapotranspiration and crop stress estimation.
- **Climate Change Studies:** Enables consistent spatio-temporal thermal datasets for long-term monitoring.
- **Disaster Management:** Supports early detection of heatwaves and drought conditions.

VII. Conclusion

This paper presented Adaptive WGAST, an enhanced weakly-supervised generative framework for high-resolution LST reconstruction. By introducing adaptive denoising and cross-sensor feature refinement, our method substantially improves upon WGAST's spatial consistency and quantitative accuracy. The results demonstrate the capability of learnable post-processing modules to enhance LST reconstruction under weak supervision, paving the way for robust, scalable thermal mapping solutions. Future work will focus on temporal attention modeling and regional generalization.

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