FROM REGIONS TO DECISIONS: MULTIMODAL ADVERSARIAL ATTACKS ON REMOTE SENSING VISION-LANGUAGE MODELS

Anonymous authors
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ABSTRACT

Remote sensing vision–language models (RS-VLMs) translate wide-area Earth observations into disaster-related decisions, yet their predictions may hinge on sparse local evidence and subtle variations in prompt formulation. Existing attacks typically perturb images under fixed linguistic conditions or optimize surrogate representations, overlooking the evolving interaction between visual evidence and language. We propose RS-RDA, a region-to-decision white-box multimodal attack. RS-RDA localizes decision-relevant evidence by combining proposal reliability, vision–language relevance, and semantic complementarity, and then optimizes bounded perturbations within them. After each visual round, RS-RDA compares the clean and adversarial answer distributions together with regional gradients to identify the induced score shift, the dominant incorrect competitor, and the visual regions driving the decision change. These signals guide the generation and selection of semantics-preserving adversarial prompts, enabling the prompt attack to adapt to the evolving decision boundary. Across five heterogeneous RS-VLMs, RS-RDA achieves average attack success rates of 93.89%, 90.64%, and 97.29% on building-damage counting, disaster-type recognition, and object-relation reasoning, respectively. These results exceed the strongest task-level baseline averages by 52.09%, 35.50%, and 24.00%, respectively. These results establish RS-RDA as an effective method for evaluating the adversarial robustness of RS-VLMs in disaster-scene perception and reasoning tasks.

1 INTRODUCTION

Remote sensing vision–language models (RS-VLMs) jointly interpret imagery and natural-language instructions to perform perception, grounding, and reasoning over heterogeneous Earth observation data, providing valuable support for time-critical disaster-scene assessment (Liu et al., 2026c). In such safety-sensitive settings, reliability requires not only accuracy under routine inputs but also decision stability against subtle, directionally optimized perturbations (Zhao et al., 2023). If limited input changes can induce substantial prediction shifts, the resulting uncertainty may be amplified throughout subsequent analytical workflows and undermine the credibility of remote sensing interpretation (Dong et al., 2025). Nevertheless, existing research has primarily emphasized the task capabilities of RS-VLMs, leaving their decision stability and failure boundaries under controlled multimodal input perturbations insufficiently understood (Xiao et al., 2025). Characterizing these properties is therefore essential for assessing the security risks and operational reliability of RS-VLMs in disaster scenarios (Liu et al., 2024a).

This risk is closely associated with the distinctive spatial structure of remote sensing imagery. Remote sensing images commonly exhibit broad spatial coverage and a high background-to-target ratio, whereas the visual evidence supporting a particular disaster-related decision is often concentrated in a small number of local regions or distributed among several correlated objects (Zhang et al., 2026). Full-image attacks place all pixels within the same optimization domain, which enlarges the effective search space, disperses limited gradient updates over task-irrelevant content, and introduces unnecessary optimization overhead (Ming et al., 2024). Such indiscriminate perturbation also weakens the interpretive connection between the perturbed evidence and the resulting decision failure (Liu et al., 2026a). Moreover, remote sensing scenes frequently contain visually similar

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or semantically redundant regions. Selecting attack locations solely according to visual saliency may therefore repeatedly cover analogous objects while overlooking complementary evidence that is more influential to the task (Zhang et al., 2025). Jointly considering task relevance and semantic diversity among spatially coherent candidates can instead concentrate perturbations on regions most likely to influence the prediction, improving budget efficiency and clarifying the role of localized evidence in decision failures.

Regional localization determines where an attack should operate, but an RS-VLM decision is additionally governed by the interaction between the image and the prompt (Liu et al., 2026b). An image-only attack fixes the prompt and thus examines only a single linguistic slice of the multimodal decision space, whereas a prompt-only attack leaves the visual evidence unchanged and cannot exploit fine-grained perturbations in the image space (Li et al., 2024). More importantly, the effects of image perturbations and prompt variations are not independent. A prompt can alter how the model attends to visual regions and organizes the extracted evidence, while an evolving adversarial image changes the competition among candidate answers, making a prompt selected before image optimization progressively less compatible with the current attack state (Li et al., 2022; Zhou et al., 2022). Optimizing the two modalities separately may therefore produce inconsistent attack directions and fail to exploit the cross-modal coupling within the RS-VLM (Zhou et al., 2024). We address this limitation through adaptive image–prompt joint optimization, where prompts evolve with the adversarial image and decision state, while selected prompts guide subsequent visual updates. This alternating feedback coordinates both modalities toward a shared erroneous decision, overcoming the limitations of unimodal attacks and enabling a more faithful assessment of RS-VLM robustness.

To this end, we propose RS-RDA, a region-driven adaptive multimodal adversarial attack that establishes a direct pathway from task-relevant visual evidence to erroneous RS-VLM decisions. RS-RDA consists of two stages. The first stage constructs a compact key-region mask by jointly considering proposal reliability, task-conditioned vision–prompt relevance, and inter-region semantic complementarity, thereby concentrating the perturbation budget on informative visual content. The second stage performs adaptive image–prompt optimization in the target model's decision space. Regional image perturbations are optimized against calibrated answer rankings, while task-preserving adversarial prompts are dynamically generated and selected according to the decision shifts induced by the evolving adversarial image. The selected prompts subsequently guide the next visual optimization round, enabling the two attack branches to adapt jointly to the changing decision boundary.

Experiments on five heterogeneous RS-VLMs across building-damage counting (BDC), disaster-type recognition (DTR), and object-relation reasoning (ORR) demonstrate that RS-RDA consistently outperforms all competing attacks. It achieves the highest ASR for all three tasks on every evaluated RS-VLM, with task-level averages of **93.89%**, **90.64%**, and **97.29%**, respectively. Relative to the strongest baseline selected independently for each model–task pair, RS-RDA improves the average ASR by **50.87%**, **35.06%**, and **18.66%** across the three tasks, demonstrating substantial and consistent advantages across diverse model architectures and task formulations. Our main contributions are summarized as follows:

- We formulate localized, task-preserving multimodal attacks on RS-VLMs and propose RS-RDA, which directly optimizes erroneous decisions under a white-box threat model.
- We develop target-independent key-region discovery that combines proposal reliability, task-conditioned vision–prompt relevance, and semantic complementarity to construct compact perturbation support.
- We introduce closed-loop image–prompt optimization that couples calibrated answer ranking with decision-state-guided prompt evolution for joint multimodal adaptation.
- Experiments on five heterogeneous RS-VLMs across three disaster-scene tasks demonstrate the consistent superiority of RS-RDA over existing multimodal attacks.

2 Preliminaries and Threat model

Problem definition. Let $\mathcal{M}_\theta$ denote a target RS-VLM and $\mathcal{T}$ a downstream task. Each instance is represented by $\mathbf{z} = (\mathbf{x}, p, y)$, where $\mathbf{x} \in \mathcal{X}$ is the image, $p \in \mathcal{P}$ is the task prompt, and $y \in \mathcal{Y}_\mathcal{T}$ is the ground-truth outcome. Because an RS-VLM generates a textual response rather than a direct

task label, its task-level prediction is defined through a task-specific output mapping:

$$\hat{y} = \Gamma_{\mathcal{T}}\big(\mathcal{M}_\theta(\mathbf{x}, p)\big), \tag{1}$$

where $\Gamma_{\mathcal{T}}$ maps the generated response to the task-dependent output space $\mathcal{Y}_{\mathcal{T}}$. Given task $\mathcal{T}$ and an optional query q extracted from p, with $q = \varnothing$ when not required, the attack constructs a fixed task-conditioned mask $\mathbf{m}^* \in 0, 1^{H\times W}$. This mask defines the perturbable spatial support and is broadcast across image channels when applied to $\boldsymbol{\delta}$:

$$\mathbf{m}^* = \mathcal{R}(\mathbf{x}, \mathcal{T}, q), \qquad \mathbf{x}_{\mathrm{adv}}(\boldsymbol{\delta}) = \Pi_{\mathcal{X}}\big(\mathbf{x} + \mathbf{m}^* \odot \boldsymbol{\delta}\big), \qquad p_{\mathrm{adv}} \in \mathcal{P}_{\mathrm{sem}}(p), \tag{2}$$

where $\Pi_{\mathcal{X}}$ projects the perturbed image onto the valid input domain, and $\mathcal{P}_{\mathrm{sem}}(p)$ contains prompt reformulations that preserve the original task intent, answer space, and output protocol. The joint attack is formulated as:

$$\begin{aligned}(\boldsymbol{\delta}^*, p^*_{\mathrm{adv}}) = \arg\max_{\boldsymbol{\delta},\, p'} \quad & \mathcal{L}_{\mathrm{adv}}\big(\mathcal{M}_\theta(\mathbf{x}_{\mathrm{adv}}(\boldsymbol{\delta}), p'), y\big) \\ \text{s.t.} \quad & \|\mathbf{m}^* \odot \boldsymbol{\delta}\|_\infty \le \epsilon, \qquad p' \in \mathcal{P}_{\mathrm{sem}}(p),\end{aligned} \tag{3}$$

where ϵ bounds the effective regional perturbation and $\mathcal{L}_{\mathrm{adv}}$ denotes the differentiable surrogate objective for degrading the model's task decision.

Threat Model. We consider a white-box adversary with access to the target RS-VLM's parameters, tokenizer, multimodal preprocessing pipeline, differentiable choice scores, and input gradients. Each target model is attacked independently through its native differentiable inference path. The adversary may apply bounded perturbations only within the fixed key-region mask and reformulate the user prompt within $\mathcal{P}_{\mathrm{sem}}(p)$. The original task semantics and answer space are preserved throughout the attack. Under this threat model, RS-RDA performs sample-specific untargeted evasion. An attack succeeds when the final task-level prediction differs from the ground-truth outcome:

$$\Gamma_{\mathcal{T}}\big(\mathcal{M}_\theta(\mathbf{x}_{\mathrm{adv}}(\boldsymbol{\delta}^*), p^*_{\mathrm{adv}})\big) \neq y. \tag{4}$$

The differentiable attack loss serves only as an optimization surrogate. Attack success is determined from the complete generated response through the task-specific output mapping $\Gamma_{\mathcal{T}}$.

3 Overview of RS-RDA

As illustrated in Figure 1, RS-RDA first discovers a compact task-relevant perturbation support and then alternates region-constrained visual optimization with image-adaptive prompt evolution. The current adversarial image guides prompt updates through its decision state, while the selected elite prompts condition the next visual round, forming a closed-loop multimodal attack.

Task-conditioned Key-region Discovery. Given a clean remote-sensing image, its task specification, and an optional query, this stage constructs a fixed binary key-region mask. The Segment Anything Model (SAM) (Carion et al., 2025) generates spatially coherent proposals without task-specific segmentation annotations, which are filtered by segmentation reliability and scale. RemoteCLIP (Liu et al., 2024b) evaluates their relevance to the task descriptions or query using remote-sensing-aligned image–text representations, while DINOv2 (Oquab et al., 2023) identifies semantic redundancy and promotes complementary selection. The selected regions are finally merged into a compact mask that defines the spatial support of subsequent visual perturbations. Because the entire process is independent of the target RS-VLM's internal signals, the resulting mask can be reused across different target models for the same image, task, and query.

Alternating Adaptive Attack. For each target RS-VLM, RS-RDA initializes an audited elite prompt set and a zero visual perturbation. At each round, the visual branch fixes the prompts and optimizes a calibrated answer-ranking loss over model-native choice scores, elite prompts, and task-compatible transformations. Momentum-based projected updates constrain the perturbation to the discovered key regions within the budget. The prompt branch then fixes the adversarial image and generates, audits, and evaluates new candidates using the current decision state. The resulting elite prompts guide the next visual update, yielding an adversarial image–prompt pair through alternating optimization.

Cross-Modal Feedback. The two branches exchange complementary attack-state information. The image branch summarizes answer-margin shifts, dominant incorrect options, and masked-gradient

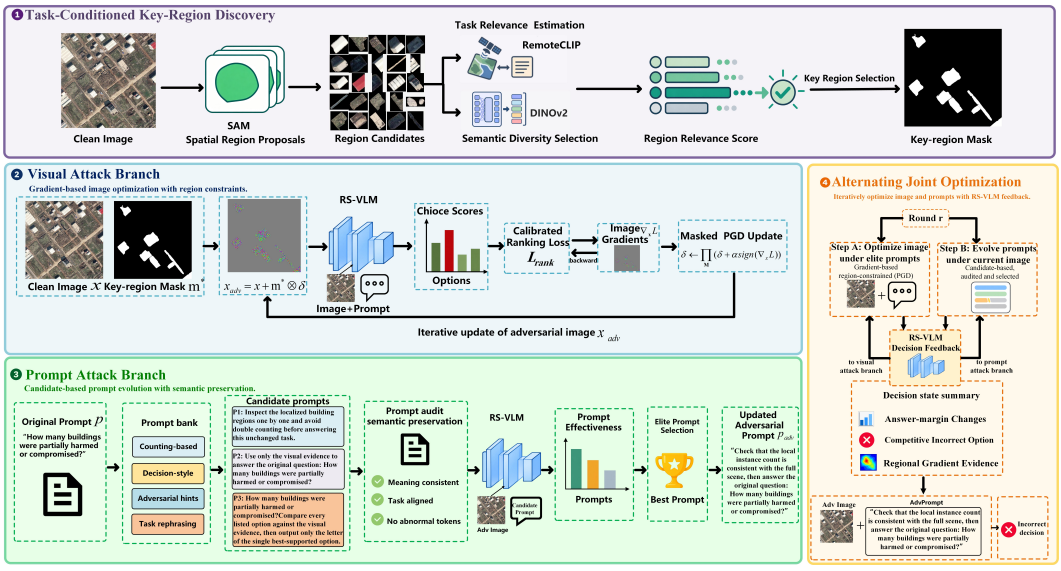


Figure 1: **Overview of RS-RDA.** RS-RDA localizes task-relevant regions and jointly optimizes regional perturbations and adaptive prompts via decision feedback.

statistics to guide semantics-preserving prompt evolution. In return, the updated elite prompts condition subsequent visual optimization, enabling regional perturbations to adapt to decision-effective formulations. Candidates are ranked by decision degradation, cross-modal interaction, gradient alignment, keeping both branches synchronized with the evolving decision boundary.

4 METHODOLOGY

4.1 TASK-CONDITIONED KEY-REGION DISCOVERY

Spatial Proposal Generation and Filtering. SAM generates spatially coherent proposals without task-specific segmentation annotations. Each proposal contains a binary mask $\mathbf{m}_i \in \{0,1\}^{H\times W}$, a predicted IoU score η_i, and a stability score ς_i. We define its normalized area ρ_i and segmentation reliability ω_i as:

$$\rho_i = \frac{\|\mathbf{m}_i\|_1}{HW}, \qquad \omega_i = \frac{\eta_i + \varsigma_i}{2}, \tag{5}$$

where ρ_i measures the relative mask area and ω_i denotes its segmentation reliability. We retain proposals whose indices form the set

$$\mathcal{I} = \{i \mid \rho_{\min} \le \rho_i \le \rho_{\max},\ \eta_i \ge \eta_{\min},\ \varsigma_i \ge \varsigma_{\min}\}. \tag{6}$$

This filtering removes out-of-scale or unstable masks. If $|\mathcal{I}| > N_{\max}$, only the top $N_{\max}$ proposals ranked by ω_i are retained for efficient feature extraction.

Task-conditioned Relevance Estimation. Each retained mask yields a regional crop $\widetilde{\mathbf{x}}_i$ by suppressing background pixels and extracting its bounding region. BDC and DTR use fixed task descriptors, while ORR derives them from query entities and relations, without reference answers or target-model outputs. RemoteCLIP scores each crop against the descriptor set $\mathcal{D}_{\mathcal{T}}(q)$:

$$r_i = \max_{d_\ell \in \mathcal{D}_{\mathcal{T}}(q)} \cos\left(E_I^R(\widetilde{\mathbf{x}}_i), E_T^R(d_\ell)\right), \qquad s_i = r_i + \lambda_{\text{qual}}\omega_i, \tag{7}$$

where E_I^R and E_T^R are the RemoteCLIP image and text encoders. Maximum similarity captures alignment with any task concept, while reliability differentiates semantically comparable proposals. RemoteCLIP provides cross-modal representations aligned with remote-sensing semantics.

Diversity-aware Region Selection. Ranking proposals solely by s_i may repeatedly select regions with similar visual content. We therefore use DINOv2 to estimate their pairwise semantic similarity:

$$\kappa_{ij} = \cos\left(E^D(\widetilde{\mathbf{x}}_i), E^D(\widetilde{\mathbf{x}}_j)\right), \tag{8}$$

where E^D denotes the DINOv2 encoder. RemoteCLIP thus measures task relevance, while DINOv2 identifies semantic redundancy among relevant candidates. Candidates are traversed in descending order of s_i and selected if their maximum similarity to existing selections is at most τ_{div}, until reaching budget K. If fewer than $\min(K, |\mathcal{I}|)$ qualify, the highest-scoring remaining candidates fill the budget. This balances task relevance and semantic diversity. Let $\mathcal{S}^* \subseteq \mathcal{I}$ denote the selected set; the final key-region mask is their pixel-wise union:

$$\mathbf{m}^* = \mathbb{I}\left[\sum_{i \in \mathcal{S}^*} \mathbf{m}_i > 0\right]. \tag{9}$$

The resulting mask defines the spatial support of the subsequent visual attack, ensuring that all bounded perturbations are restricted to the selected task-relevant regions.

4.2 Key-Region-Constrained Visual Attack

Scale-normalized answer-ranking objective. For the ordered answer set $\mathcal{A} = \{a_j\}_{j=1}^{J}$, a model-specific differentiable adapter extracts the option scores $\mathbf{z}_\theta(\mathbf{x}', p; \mathcal{A}) \in \mathbb{R}^J$ from the first-step log-probabilities of the answer labels. Let y denote the ground-truth option index and define the score scale as

$$d_\theta(\mathbf{x}', p) = \max\left(\text{Std}_j\left[z_{\theta,j}(\mathbf{x}', p)\right], \xi_{\text{s}}\right), \tag{10}$$

where $\xi_{\text{s}} > 0$ ensures numerical stability. RS-RDA maximizes the normalized score gaps between the competing and ground-truth options:

$$\mathcal{L}_{\text{rank}}(\mathbf{x}', p, y) = \log \sum_{j \neq y} \exp\left(\frac{z_{\theta,j}(\mathbf{x}', p) - z_{\theta,y}(\mathbf{x}', p)}{\tau d_\theta(\mathbf{x}', p)}\right), \tag{11}$$

where $\tau > 0$ controls the emphasis on the most competitive incorrect option. This objective suppresses the ground-truth option relative to its competitors and directly optimizes the option-ranking boundary induced by the target RS-VLM's differentiable scores.

Task-Aware Ensemble Visual Objective. At attack round r, the elite prompts $\mathcal{E}_r = \{p_{r,e}\}_{e=1}^{E}$ remain fixed as conditions for visual optimization. Let $\Omega_{\mathcal{T}}$ denote the distribution of task-compatible transformations. For $\zeta \sim \Omega_{\mathcal{T}}$, the conditional attack loss is

$$\ell_{e,\zeta}(\boldsymbol{\delta}) = \mathcal{L}_{\text{rank}}\left(\mathsf{T}_\zeta^{\mathcal{T}}\left(\mathbf{x} + \boldsymbol{\delta}; \mathbf{m}^*\right), p_{r,e}, y\right). \tag{12}$$

The visual objective aggregates this loss over transformed views and elite prompts:

$$\mathcal{L}_{\text{vis}}(\boldsymbol{\delta}; \mathcal{E}_r) = \mathbb{E}_{\zeta \sim \Omega_{\mathcal{T}}}\left[\frac{\beta}{E}\sum_{e=1}^{E} \ell_{e,\zeta}(\boldsymbol{\delta}) + (1-\beta)\,\text{SoftMin}_\gamma\left(\{\ell_{e,\zeta}(\boldsymbol{\delta})\}_{e=1}^{E}\right)\right], \tag{13}$$

where β balances average attack effectiveness and robustness to the least vulnerable prompt, while γ controls the smooth minimum. Transformations affect only visual-gradient computation and do not update the elite prompts; their task-specific configurations are detailed in the appendix.

Support-Restricted Momentum Optimization. Let $\overline{\mathbf{m}}^* = \mathbf{m}^* \otimes \mathbf{1}_C$ be the key-region mask broadcast across image channels. The feasible perturbation set is

$$\Delta_\epsilon(\mathbf{m}^*) = \left\{\boldsymbol{\delta} \;\middle|\; \boldsymbol{\delta} = \overline{\mathbf{m}}^* \odot \boldsymbol{\delta},\ \|\boldsymbol{\delta}\|_\infty \leq \epsilon,\ \mathbf{x} + \boldsymbol{\delta} \in [0,1]^{H \times W \times C}\right\}. \tag{14}$$

RS-RDA maximizes $\mathcal{L}_{\text{vis}}$ through masked momentum projected updates:

$$\begin{aligned} \mathbf{g}_t &= \overline{\mathbf{m}}^* \odot \nabla_{\boldsymbol{\delta}_t} \mathcal{L}_{\text{vis}}, \\ \mathbf{v}_{t+1} &= \mu \mathbf{v}_t + \text{Norm}_{\mathbf{m}^*}(\mathbf{g}_t), \\ \boldsymbol{\delta}_{t+1} &= \Pi_{\Delta_\epsilon(\mathbf{m}^*)}\left(\boldsymbol{\delta}_t + \alpha\ \text{sign}(\mathbf{v}_{t+1})\right). \end{aligned} \tag{15}$$

Normalization and projection enforce regional support, the ℓ_∞ budget, and valid pixel values. Each attack round is warm-started from the preceding solution to adapt to the updated elite prompts. The final image is $\mathbf{x}_{\text{adv}} = \mathbf{x} + \boldsymbol{\delta}$. The ranking loss is used only for optimization, whereas attack success is assessed from the target RS-VLM's complete response.

4.3 Adaptive Prompt Attack

Image-Adaptive Prompt Evolution. At attack round r, let $\mathbf{x}_r^{\mathrm{adv}}$ and $\boldsymbol{\delta}_r$ denote the current adversarial image and perturbation. Using the option scores $\mathbf{z}_\theta$ and scale factor d_θ defined above, the normalized answer margin is

$$m_\theta(\mathbf{x}', p; y) = \frac{z_{\theta,y}(\mathbf{x}', p) - \max_{j \neq y} z_{\theta,j}(\mathbf{x}', p)}{d_\theta(\mathbf{x}', p)}. \tag{16}$$

A smaller margin indicates stronger decision degradation. At generation step k, the current prompt $p_{r,k-1}$ is evaluated on both clean and adversarial images to construct the attack state

$$\begin{aligned} \Delta m_{r,k} &= m_\theta(\mathbf{x}_r^{\mathrm{adv}}, p_{r,k-1}; y) - m_\theta(\mathbf{x}, p_{r,k-1}; y), \\ j_{r,k}^- &= \arg\max_{j \neq y} z_{\theta,j}(\mathbf{x}_r^{\mathrm{adv}}, p_{r,k-1}), \\ \mathbf{g}_{r,k} &= \overline{\mathbf{m}}^* \odot \nabla_{\mathbf{x}_r^{\mathrm{adv}}} \mathcal{L}_{\mathrm{rank}}(\mathbf{x}_r^{\mathrm{adv}}, p_{r,k-1}, y), \\ \mathcal{H}_{r,k} &= \left\{ m_\theta(\mathbf{x}_r^{\mathrm{adv}}, p_{r,k-1}; y), \Delta m_{r,k}, j_{r,k}^-, \phi(\boldsymbol{\delta}_r, \mathbf{m}^*), \psi(\mathbf{g}_{r,k}) \right\}. \end{aligned} \tag{17}$$

Here, $\Delta m_{r,k}$ captures the image-induced margin shift, $j_{r,k}^-$ identifies the strongest incorrect option, and $\phi(\cdot)$ and $\psi(\cdot)$ summarize perturbation utilization and masked-gradient distribution. Starting from $\mathcal{E}_{r,0} = \mathcal{E}_r$, candidates are evolved from the attack state and audited as

$$\mathcal{P}_{r,k} = \mathrm{Audit}_{p_0,\mathcal{A}} \left(\mathrm{Evolve} \left(\mathcal{E}_{r,k-1}, \mathcal{H}_{r,k} \right) \right), \tag{18}$$

where p_0 is the original prompt and $\mathcal{A}$ is the ordered answer set. The audit rejects candidates that alter task semantics, answer content or order, response protocol, or expose answer cues.

Cross-Modal Prompt Selection. Each audited candidate p' is scored by its decision degradation and compatibility with the current perturbation:

$$\begin{aligned} Q_{\mathrm{dec}}(p') &= \mathcal{L}_{\mathrm{rank}}(\mathbf{x}_r^{\mathrm{adv}}, p', y), \\ Q_{\mathrm{int}}(p') &= \Big[\mathcal{L}_{\mathrm{rank}}(\mathbf{x}_r^{\mathrm{adv}}, p', y) - \mathcal{L}_{\mathrm{rank}}(\mathbf{x}, p', y) \Big] \\ &\quad - \Big[\mathcal{L}_{\mathrm{rank}}(\mathbf{x}_r^{\mathrm{adv}}, p_0, y) - \mathcal{L}_{\mathrm{rank}}(\mathbf{x}, p_0, y) \Big], \\ Q_{\mathrm{grad}}(p') &= \frac{\langle \mathbf{g}_r(p'), \boldsymbol{\delta}_r \rangle}{\|\mathbf{g}_r(p')\|_2 \|\boldsymbol{\delta}_r\|_2 + \xi}, \\ Q_{\mathrm{div}}(p' \mid \mathcal{E}_{r,k-1}) &= 1 - \max_{e \in \mathcal{E}_{r,k-1}} \mathrm{Sim}_{\mathrm{text}}(p', e), \end{aligned} \tag{19}$$

where

$$\mathbf{g}_r(p') = \overline{\mathbf{m}}^* \odot \nabla_{\mathbf{x}_r^{\mathrm{adv}}} \mathcal{L}_{\mathrm{rank}}(\mathbf{x}_r^{\mathrm{adv}}, p', y). \tag{20}$$

These terms quantify decision degradation, image–prompt interaction, perturbation–gradient alignment, and linguistic diversity, respectively. In particular, Q_{int} isolates the perturbation gain over p_0, while Q_{grad} estimates compatibility with subsequent visual updates. After candidate-pool normalization, the utility is

$$J_{r,k}(p') = \lambda_{\mathrm{dec}} \widehat{Q}_{\mathrm{dec}}(p') + \lambda_{\mathrm{int}} \widehat{Q}_{\mathrm{int}}(p') + \lambda_{\mathrm{grad}} \widehat{Q}_{\mathrm{grad}}(p') + \lambda_{\mathrm{div}} \widehat{Q}_{\mathrm{div}}(p'), \tag{21}$$

with non-negative coefficients. The top-E candidates update the elite set:

$$\mathcal{E}_{r,k} = \mathrm{Top}_E \left(\mathcal{P}_{r,k}; J_{r,k} \right), \qquad p_{r,k} = \arg\max_{p' \in \mathcal{E}_{r,k}} J_{r,k}(p'). \tag{22}$$

After N_{prompt} generations, $\mathcal{E}_{r+1} = \mathcal{E}_{r,N_{\mathrm{prompt}}}$ conditions the next visual round, aligning prompt evolution with the image-induced decision boundary.

5 Results

5.1 Experiment Setup

Target RS-VLMs. We evaluate RS-RDA on five heterogeneous RS-VLMs: EarthDial (Soni et al., 2025), EarthMind (Shu et al., 2025), GeoChat (Kuckreja et al., 2024), TEOChat (Irvin et al., 2025), and TerraScope (Shu et al., 2026).

Table 1: Comparison with competing attacks across five RS-VLMs. ASR denotes attack success rate; MAE and MRE denote counting errors; Macro-F1 measures DTR performance. ASR and MRE are reported in percentage.

Model	Method	BDC			DTR		ORR
		ASR	MAE	MRE	ASR	Ma-F1	ASR
GeoChat	Co-Attack	50.89	4.97	42.30	9.15	0.88	64.10
	SGA	48.48	4.84	55.41	20.92	0.59	58.12
	VQAttack	48.48	5.18	40.21	34.64	0.56	71.79
	LSSA	51.40	5.08	51.57	21.57	0.57	70.09
	GLEAM	52.28	5.57	39.53	56.21	0.41	84.62
	RS-RDA	**94.67**	**8.27**	**195.67**	**92.81**	**0.05**	**96.58**
TEOChat	Co-Attack	47.21	6.34	39.58	9.42	0.85	72.67
	SGA	49.34	6.95	51.62	14.14	0.78	73.29
	VQAttack	46.15	6.71	39.46	34.03	0.65	75.78
	LSSA	46.82	6.90	45.24	17.28	0.73	75.16
	GLEAM	46.15	7.27	26.70	42.93	0.55	91.93
	RS-RDA	**84.75**	**10.57**	**145.96**	**73.30**	**0.24**	**92.55**
EarthDial	Co-Attack	23.47	2.80	26.22	26.09	0.76	58.33
	SGA	24.67	2.90	28.73	31.52	0.68	50.00
	VQAttack	20.67	2.69	20.49	65.22	0.38	43.75
	LSSA	26.40	2.93	30.68	29.89	0.66	55.21
	GLEAM	27.87	2.95	18.32	63.04	0.34	60.42
	RS-RDA	**94.00**	**9.57**	**183.95**	**89.29**	**0.09**	**98.96**
TerraScope	Co-Attack	64.02	5.16	75.34	51.85	0.49	91.30
	SGA	50.90	3.98	80.09	48.15	0.47	96.74
	VQAttack	47.62	5.16	153.45	28.15	0.56	86.96
	LSSA	63.92	4.64	62.82	43.70	0.50	91.30
	GLEAM	52.06	4.28	66.17	62.22	0.35	71.74
	RS-RDA	**97.04**	**14.22**	**343.51**	**97.78**	**0.03**	**98.91**
EarthMind	Co-Attack	20.60	2.26	21.37	17.31	0.81	59.43
	SGA	21.59	1.76	26.42	19.87	0.78	52.57
	VQAttack	20.40	2.17	17.19	39.10	0.59	54.29
	LSSA	20.50	1.81	23.09	21.15	0.73	54.29
	GLEAM	20.40	1.24	15.90	51.28	0.38	57.71
	RS-RDA	**99.01**	**16.85**	**303.72**	**100.00**	**0.00**	**99.43**

Baselines. We compare RS-RDA with five multimodal attacks: Co-Attack (Zhang et al., 2022), SGA (Lu et al., 2023), VQAttack (Yin et al., 2024), LSSA (Liu et al., 2025a), and GLEAM (Liu et al., 2025b). All methods follow a unified target-side protocol, with experimental settings and fairness controls detailed in Appendix E.1 and evaluation metrics in Appendix E.4.

5.2 RS-RDA Attack Performance

Comparison. Table 1 reports the attack performance on the clean-correct subsets of five RS-VLMs. RS-RDA achieves the strongest result for every reported model–task metric. Averaged across the victim models, its ASR reaches 93.89%, 90.64%, and 97.29% on BDC, DTR, and ORR, respectively. Compared with the strongest competing result for each model, the corresponding average improvements are 50.87%, 35.06%, and 18.66%. The simultaneous gains in ASR, counting errors, and classification degradation show that RS-RDA induces not only frequent prediction changes but also substantial task-level decision failures.

Why is RS-RDA more effective? The performance advantage of RS-RDA arises from complementary alignment at the decision and spatial levels. Decision alignment reduces the discrepancy between attack optimization and task failure: rather than maximizing surrogate feature divergence, RS-RDA directly suppresses the ground-truth option relative to its strongest competitors in the target model's native answer-ranking space. Meanwhile, spatial focus confines perturbations to task-relevant regions, suppressing background-gradient dispersion and concentrating optimization on predictive evidence. Moreover, cross-modal adaptation tracks non-stationary image–prompt in-

Table 2: Component ablation of RS-RDA across five RS-VLMs on the BDC task. ASR (%) is independently evaluated on the clean-correct subset at each attack step.

Model	Variant	ASR			
		Step 5	Step 10	Step 20	Step 30
EarthDial	**RS-RDA**	70.83	83.33	91.67	91.67
	w/o Key Region	75.76	78.79	78.79	78.79
	w/o Adaptive Prompt	40.81	54.08	66.33	70.41
	w/o Alternating Optimization	40.21	53.61	65.98	70.10
	w/o Task-aware EOT	47.96	61.22	58.16	60.20
EarthMind	**RS-RDA**	77.32	88.66	94.85	97.94
	w/o Key Region	72.73	79.80	86.87	88.89
	w/o Adaptive Prompt	42.39	47.83	53.26	53.26
	w/o Alternating Optimization	42.39	47.83	51.09	54.35
	w/o Task-aware EOT	39.13	42.39	42.39	42.39
GeoChat	**RS-RDA**	70.71	90.20	93.33	93.33
	w/o Key Region	67.41	78.18	87.18	87.18
	w/o Adaptive Prompt	66.28	83.67	88.57	86.11
	w/o Alternating Optimization	70.79	89.36	89.58	89.58
	w/o Task-aware EOT	67.42	76.27	83.33	83.33
TEOChat	**RS-RDA**	60.41	64.21	72.84	84.36
	w/o Key Region	71.13	81.25	85.00	89.47
	w/o Adaptive Prompt	60.20	63.92	69.23	73.03
	w/o Alternating Optimization	60.20	63.92	71.43	71.91
	w/o Task-aware EOT	59.18	58.76	58.24	58.43
TerraScope	**RS-RDA**	93.00	98.32	98.99	100.00
	w/o Key Region	99.00	100.00	100.00	100.00
	w/o Adaptive Prompt	92.93	98.00	98.21	98.00
	w/o Alternating Optimization	92.78	94.25	98.95	100.00
	w/o Task-aware EOT	96.11	94.00	99.00	96.77

teractions: decision shifts guide prompt evolution, while selected prompts condition subsequent visual updates. This alternating feedback synchronizes both modalities with the evolving decision boundary and reduces reliance on fixed linguistic formulations.

5.3 Effectiveness of RS-RDA Components

Comparison. Table 2 reports the component ablation results on BDC. At step 30, RS-RDA achieves the highest or tied ASR on four of the five target models, with an average ASR of 93.46%. Ablating adaptive prompt optimization, alternating optimization, and task-aware EOT lowers the average ASR by 17.30%, 16.27%, and 25.24%, respectively, highlighting their complementary roles in adaptive multimodal optimization. Additional DTR and ORR results are provided in Appendix F.

Effectiveness of Adaptive Feedback and Regional Constraints. Adaptive prompt and alternating optimization form a coupled feedback loop: evolving prompts track image-induced decision shifts and subsequently guide visual updates, as supported by their comparable ablation drops. Task-aware EOT mitigates transformation-specific overfitting and stabilizes optimization; its removal produces the largest average degradation and stronger checkpoint fluctuations. Although removing the key-region mask enlarges the perturbable support, regional optimization improves the final ASR by 12.88%, 9.05%, and 6.15% on EarthDial, EarthMind, and GeoChat, respectively, by suppressing task-irrelevant gradients. The full-image variant benefits TEOChat due to potentially dispersed evidence, while both variants saturate at 100% ASR on TerraScope. Key-region optimization balances attack effectiveness and perturbation locality, with its distortion advantage reported in Table 4.

5.4 Effectiveness of Region Selection

Comparison. Table 3 compares region-selection strategies on DTR. We set $K = 8$ for all Top-K variants to ensure a consistent region budget, retaining all valid candidates when fewer than eight are available. RS-RDA achieves the highest ASR on four models and ties for the best result on

Table 3: Comparison of region-selection strategies on DTR.

Region Strategy	EarthDial	EarthMind	GeoChat	TEOChat	TerraScope
Random Spatial	89.24	89.00	68.50	35.50	87.00
Random SAM	86.45	93.50	67.00	36.00	84.50
SAM Quality Top-K	83.12	82.00	55.00	38.00	85.00
Semantic Top-K	88.74	95.00	73.00	43.00	91.00
Semantic + Quality Top-K	89.29	93.00	71.00	44.00	77.00
RS-RDA	**90.00**	**100.00**	**76.00**	**51.00**	**91.00**

Table 4: Perturbation reduction of key-region RS-RDA over full-image attacks.

Model	BDC		DTR		ORR	
	RMSD	LPIPS	RMSD	LPIPS	RMSD	LPIPS
EarthDial	18.85%	14.98%	39.62%	52.67%	32.20%	33.04%
EarthMind	25.15%	35.10%	37.37%	47.19%	42.55%	54.86%
GeoChat	19.85%	20.31%	23.65%	11.62%	23.34%	14.40%
TEOChat	23.29%	23.93%	24.98%	21.27%	35.19%	53.99%
TerraScope	42.07%	56.01%	32.75%	45.58%	52.44%	70.93%

TerraScope, yielding the highest average ASR of 81.60%. Additional BDC and ORR results are provided in Appendix G.

Benefits of Diversity-Aware Selection. Random selection lacks task awareness, quality-based selection ignores decision relevance, and Semantic Top-K may retain redundant evidence. RS-RDA integrates spatial reliability, task relevance, and semantic complementarity to construct compact yet informative perturbation support. It outperforms the strongest alternative by 3.00 and 7.00 percentage points on GeoChat and TEOChat, respectively, while achieving the best or tied-best ASR across all five models. These results demonstrate that diversity-aware selection provides more consistent decision-relevant coverage across heterogeneous RS-VLMs.

5.5 Perturbation Efficiency of Key-Region Attacks

Comparison. As shown in Table 4, key-region attacks reduce RMSD and LPIPS by 31.55% and 37.06% on average across all model–task settings, with positive reductions in every case. The gains are largest on ORR, reaching average reductions of 37.14% and 45.44%, respectively. These results demonstrate that RS-RDA induces decision errors with substantially less distortion.

Sources of perturbation efficiency. Full-image optimization expands the search space over extensive task-irrelevant backgrounds, introducing low-utility gradient directions. RS-RDA instead restricts optimization to semantically relevant and complementary regions, concentrating updates on decision-critical evidence while avoiding redundant modifications. This compact, evidence-aligned support increases the influence on answer rankings per unit distortion. Moreover, the larger reduction in LPIPS than in RMSD indicates that the efficiency gain extends beyond pixel-level sparsity to perceptual feature preservation. The consistent improvements across heterogeneous visual encoders therefore demonstrate a more favorable attack effectiveness–distortion trade-off.

6 Conclusion

We presented RS-RDA, a region-driven adaptive multimodal attack for evaluating RS-VLM decision robustness in disaster-scene perception and reasoning. It combines task-conditioned region discovery with alternating regional visual optimization and image-adaptive prompt evolution, directly linking localized evidence to the target model's decision boundary. Experiments across heterogeneous RS-VLMs validate the effectiveness and complementarity of these components. RS-RDA thus provides a region-to-decision framework for characterizing adversarial vulnerabilities and guiding robust multimodal decision systems in disaster scenarios.

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A Appendix

B Related Work

B.1 Remote-Sensing Vision–Language Models

Existing studies examine RS-VLM reliability from three complementary perspectives. Truthfulness-oriented methods improve response calibration when questions contain false premises or refer to unobservable content; corruption-based evaluations measure degradation under predefined appearance, geometric, and linguistic variations; and adversarial studies construct optimized, sensor-specific perturbations to expose worst-case model behavior (Pang et al., 2025; Li et al., 2025; Min et al., 2026; Su et al., 2026). These directions show that strong clean-input performance does not imply stable multimodal reasoning. However, they do not jointly examine where task-relevant evidence is located, how bounded modifications to this evidence alter the answer boundary, and how semantics-preserving instructions interact with the evolving visual perturbation. RS-RDA addresses this gap by evaluating localized worst-case decision robustness under a task-preserving image–prompt threat model.

B.2 White-Box Attacks on Vision–Language Models

White-box attacks can be characterized by their optimization targets and perturbation supports. Representation-oriented methods differentiate through visual or cross-modal encoders to disrupt feature geometry and image–text alignment, while transfer-oriented extensions diversify optimization paths or input transformations to reduce surrogate-model overfitting (Lu et al., 2023). Generation-oriented attacks instead propagate gradients through multimodal projectors and language decoders to induce specified responses or general prediction failures (Qi et al., 2024; Wang et al., 2024). Support-constrained attacks restrict modifications to visual tokens or local patches, improving sparsity and perceptual plausibility (Fu et al., 2022; Kong et al., 2024). Their supports, however, are commonly determined by fixed geometry or victim-dependent activations and need not coincide with spatially coherent, task-relevant, and semantically complementary evidence. RS-RDA links target-independent region discovery to answer-space optimization on each target RS-VLM.

B.3 Multimodal Adversarial Attacks

Multimodal attacks coordinate perturbations across visual and linguistic inputs. Co-Attack, VLAttack, and VQAttack exploit cross-modal interactions through staged or alternating image–text updates (Zhang et al., 2022; Yin et al., 2023; 2024). Transfer-oriented methods further use set-level guidance, local sampling, and global–local augmentation to improve cross-model effectiveness (Liu et al., 2025a). Prompt-coupled attacks incorporate learnable prompts or model feedback into visual optimization, enhancing cross-prompt transferability or multimodal jailbreak performance (Luo et al., 2024; Ying et al., 2025). These approaches primarily target representation transfer, prompt generalization, or safety bypass. In contrast, RS-RDA adapts task-preserving prompts to the evolving answer boundary induced by localized visual perturbations.

C Additional Method Details

C.1 Optimization Procedure

Algorithm 1 summarizes the complete execution order of RS-RDA. The key-region mask is discovered once and remains fixed, whereas the visual perturbation and elite prompt set are updated alternately. Each visual round is warm-started from the preceding perturbation, and the updated elite prompts condition the subsequent visual optimization.

C.2 Masked Gradient Normalization and Feasible-Set Projection

Masked Gradient Normalization. Let $\mathbf{m}^*$ be the binary key-region mask broadcast over the C image channels. The masked gradient is normalized by its mean absolute magnitude over the

Algorithm 1 Overall Optimization Procedure of RS-RDA

Input: Target RS-VLM M_θ with differentiable option scorer $\mathbf{z}_\theta$; task $\mathcal{T}$; clean instance $(\mathbf{x}, p_0, y)$ with question q and ordered answer set $\mathcal{A}$; region selector $\mathcal{R}$; seed prompt bank $\mathcal{B}$.
Parameters: Attack rounds R, image steps N_{img}, prompt generations N_{prompt}, elite size E, perturbation budget ϵ, step size α, momentum coefficient μ, and utility weights $\{\lambda_u\}$.
Output: Adversarial pair $(\mathbf{x}^{\text{adv}}, p^{\text{adv}})$.
$\mathbf{m}^* \leftarrow \mathcal{R}(\mathbf{x}, \mathcal{T}, q)$
$\mathcal{P}_0 \leftarrow \text{Audit}_{p_0,\mathcal{A}}(\mathcal{B} \cup \{p_0\})$
$\mathcal{E}_1 \leftarrow \text{SelectInitialElites}(\mathcal{P}_0, \mathbf{x}, \mathbf{z}_\theta, y, E)$
$\boldsymbol{\delta}_0 \leftarrow \mathbf{0}$
for $r = 1, \ldots, R$ **do**
  $\boldsymbol{\delta}_{r,0} \leftarrow \boldsymbol{\delta}_{r-1}$; $\mathbf{v}_{r,0} \leftarrow \mathbf{0}$
  for $t = 0, \ldots, N_{\text{img}} - 1$ **do**
    $\mathbf{g}^{\text{vis}}_{r,t} \leftarrow \mathbf{m}^* \odot \nabla_{\boldsymbol{\delta}_{r,t}} \mathcal{L}_{\text{vis}}(\boldsymbol{\delta}_{r,t}; \mathcal{E}_r)$
    $\mathbf{v}_{r,t+1} \leftarrow \mu \mathbf{v}_{r,t} + \text{Norm}_{\mathbf{m}^*}(\mathbf{g}^{\text{vis}}_{r,t})$
    $\boldsymbol{\delta}_{r,t+1} \leftarrow \Pi_{\Delta_\epsilon(\mathbf{m}^*)}(\boldsymbol{\delta}_{r,t} + \alpha \,\text{sign}(\mathbf{v}_{r,t+1}))$
  end for
  $\boldsymbol{\delta}_r \leftarrow \boldsymbol{\delta}_{r,N_{\text{img}}}$; $\mathbf{x}^{\text{adv}}_r \leftarrow \mathbf{x} + \boldsymbol{\delta}_r$
  $\mathcal{E}_{r,0} \leftarrow \mathcal{E}_r$; $p_{r,0} \leftarrow \mathcal{E}_{r,0}[1]$
  for $k = 1, \ldots, N_{\text{prompt}}$ **do**
    $m^{\text{adv}}_{r,k} \leftarrow m_\theta(\mathbf{x}^{\text{adv}}_r, p_{r,k-1}; y)$
    $\Delta m_{r,k} \leftarrow m^{\text{adv}}_{r,k} - m_\theta(\mathbf{x}, p_{r,k-1}; y)$
    $j^-_{r,k} \leftarrow \arg\max_{j \neq y} z_{\theta,j}(\mathbf{x}^{\text{adv}}_r, p_{r,k-1})$
    $\mathbf{g}^{\text{state}}_{r,k} \leftarrow \mathbf{m}^* \odot \nabla_{\mathbf{x}^{\text{adv}}_r} \mathcal{L}_{\text{rank}}(\mathbf{x}^{\text{adv}}_r, p_{r,k-1}, y)$
    $\mathcal{H}_{r,k} \leftarrow \left\{ m^{\text{adv}}_{r,k}, \Delta m_{r,k}, j^-_{r,k}, \phi(\boldsymbol{\delta}_r, \mathbf{m}^*), \psi(\mathbf{g}^{\text{state}}_{r,k}) \right\}$
    $\mathcal{P}_{r,k} \leftarrow \text{Audit}_{p_0,\mathcal{A}}(\text{Evolve}(\mathcal{E}_{r,k-1}, \mathcal{H}_{r,k}))$
    Compute $J_{r,k}(p')$ for $p' \in \mathcal{P}_{r,k}$
    $\mathcal{E}_{r,k} \leftarrow \text{Top}_E(\mathcal{P}_{r,k}; J_{r,k})$
    $p_{r,k} \leftarrow \arg\max_{p' \in \mathcal{E}_{r,k}} J_{r,k}(p')$
  end for
  $\mathcal{E}_{r+1} \leftarrow \mathcal{E}_{r,N_{\text{prompt}}}$
end for
$\mathbf{x}^{\text{adv}} \leftarrow \mathbf{x}^{\text{adv}}_R$; $p^{\text{adv}} \leftarrow p_{R,N_{\text{prompt}}}$
return $(\mathbf{x}^{\text{adv}}, p^{\text{adv}})$

complete image domain:

$$\text{Norm}_{\mathbf{m}^*}(\mathbf{g}) = \frac{\mathbf{m}^* \odot \mathbf{g}}{\frac{1}{HWC} \|\mathbf{m}^* \odot \mathbf{g}\|_1 + \xi_g}, \tag{23}$$

where $\xi_g = 10^{-12}$ prevents numerical instability. This operation preserves the selected support while reducing sensitivity to model- and task-dependent gradient scales.

Feasible-Set Projection. For an unconstrained update $\mathbf{u}$, RS-RDA applies

$$\Pi_{\Delta_\epsilon(\mathbf{m}^*)}(\mathbf{u}) = \mathbf{m}^* \odot \left[\text{clip}_{[0,1]} \left(\mathbf{x} + \mathbf{m}^* \odot \text{clip}_{[-\epsilon,\epsilon]}(\mathbf{u}) \right) - \mathbf{x} \right]. \tag{24}$$

The projection jointly enforces regional support, $\|\boldsymbol{\delta}\|_\infty \leq \epsilon$, and the valid image domain $\mathbf{x} + \boldsymbol{\delta} \in [0,1]^{H \times W \times C}$.

C.3 Attack-State Statistics

The perturbation summary records budget utilization and spatial support:

$$\phi(\boldsymbol{\delta}_r, \mathbf{m}^*) = \left(\|\boldsymbol{\delta}_r\|_\infty, \frac{\|\boldsymbol{\delta}_r\|_1}{HWC}, \frac{\|\mathbf{m}^*\|_0}{HWC} \right). \tag{25}$$

Table 5: Default configuration of adaptive prompt evolution.

Configuration	Value
Seed prompt templates	3
Elite-set size E	3
Children per elite	4
Prompt generations per round	2
Maximum candidate population	32

To characterize the spatial distribution of the masked gradient, the image is partitioned into a 4×4 grid. For grid cell $\mathcal{G}_b$, we compute

$$e_b = \sum_{(i,j)\in\mathcal{G}_b} m^*_{ij} \left(\frac{1}{C} \sum_{c=1}^{C} |g_{ijc}| \right), \qquad \rho_b = \frac{e_b}{\sum_{b'} e_{b'} + \xi_g}. \tag{26}$$

The gradient summary is

$$\psi(\mathbf{g}^{\text{state}}_{r,k}) = \left(\frac{\|\mathbf{g}^{\text{state}}_{r,k}\|_1}{HWC}, \|\mathbf{g}^{\text{state}}_{r,k}\|_\infty, \sum_{b\in \text{Top}_2(\boldsymbol{\rho})} \rho_b, \{e_b, \rho_b\}_{b=1}^{16} \right). \tag{27}$$

The first two components measure global gradient magnitude, whereas the top-two concentration and grid profile distinguish localized evidence from spatially distributed decision sensitivity.

C.4 Prompt Evolution, Normalization, and Semantic Auditing

Prompt evolution is deterministic in the default implementation. The question stem, option labels, option contents, and option order remain fixed, while the response and evidence-inspection instruction is reformulated according to the current attack state. Mutation operators emphasize localized evidence, choice-wise comparison, local–global consistency, or neutral visual-evidence inspection.

Candidates are rejected if they change the ordered answer set, alter the task semantics or output protocol, contain an empty instruction, introduce an unexpected image token, exceed 4096 characters, or expose an explicit answer cue. Duplicate candidates are removed after surface normalization. No external language-model proposer or stochastic text sampler is used.

For linguistic diversity, let $\mathcal{W}(p)$ be the set of lowercase alphanumeric tokens extracted from the question and instruction of prompt p. Because the answer options remain fixed, they are excluded from the similarity calculation. We use

$$\text{Sim}_{\text{text}}(p_i, p_j) = \frac{|\mathcal{W}(p_i) \cap \mathcal{W}(p_j)|}{|\mathcal{W}(p_i) \cup \mathcal{W}(p_j)|}. \tag{28}$$

Consistent with the normalized utility in the main text, each utility component is min–max normalized within the current candidate pool:

$$\widehat{Q}_u(p) = \frac{Q_u(p) - \min_{c\in\mathcal{P}_{r,k}} Q_u(c)}{\max_{c\in\mathcal{P}_{r,k}} Q_u(c) - \min_{c\in\mathcal{P}_{r,k}} Q_u(c) + \xi_q}, \quad u \in \{\text{dec}, \text{int}, \text{grad}, \text{div}\}, \tag{29}$$

where $\xi_q > 0$ handles degenerate candidate pools. The final utility is

$$J_{r,k}(p) = \lambda_{\text{dec}}\widehat{Q}_{\text{dec}}(p) + \lambda_{\text{int}}\widehat{Q}_{\text{int}}(p) + \lambda_{\text{grad}}\widehat{Q}_{\text{grad}}(p) + \lambda_{\text{div}}\widehat{Q}_{\text{div}}(p), \tag{30}$$

which follows the four-term objective defined in the main text.

D Unified Decision Interface across RS-VLMs

D.1 Differentiable Option Scoring

The evaluated RS-VLMs use different visual preprocessors, conversation templates, and multimodal forward APIs. For target model M_{θ_m}, image $\mathbf{x}$, prompt p, and ordered answer set $\mathcal{A} = \{a_j\}_{j=1}^{J}$, a

Table 6: Differentiable adapters for the evaluated RS-VLMs.

Model	Input adaptation	Differentiable forward path
EarthDial-4B-RGB	Dynamic image tiling, normalization, and native chat template.	Model-consistent visual tokens are passed through the official multimodal forward interface.
EarthMind-4B	EarthMind-specific visual preprocessing and prompt serialization.	A dedicated scorer adapter is integrated with the shared ranking loss and alternating optimizer.
GeoChat-7B	Square-padded CLIP input and the `llava_v1` conversation template.	Projected CLIP features replace the image token before language decoding.
TEOChat	Native resizing, center cropping, normalization, and video-language template.	Image-tower features are projected and fused with textual embeddings.
TerraScope-8B	Dynamic tiling with tile-aligned `<IMG_CONTEXT>` tokens.	Multimodal logits are obtained through the native differentiable `_llm_forward` interface.

model-specific adapter exposes

$$\mathbf{z}_{\theta_m}(\mathbf{x}, p; \mathcal{A}) = \mathcal{S}_m\left(\mathcal{P}_m^I(\mathbf{x}), \mathcal{P}_m^T(p, \mathcal{A})\right) \in \mathbb{R}^J, \tag{31}$$

where $\mathcal{P}_m^I$, $\mathcal{P}_m^T$, and $\mathcal{S}_m$ denote the native image processor, prompt serializer, and differentiable scorer. The attack core therefore accesses each model through

$$\texttt{score_choices}(\mathbf{x}, p, \mathcal{A}) \to \mathbf{z}_{\theta_m},$$

while keeping all model parameters frozen and preserving gradients with respect to the image.

The scorer uses the first-step log-probability of the canonical answer labels $L_j \in \{\mathrm{A}, \ldots, \mathrm{E}\}$:

$$z_{\theta_m, j}(\mathbf{x}, p; \mathcal{A}) = \log P_{\theta_m}\left(L_j \mid \mathbf{x}, p, \mathcal{A}\right). \tag{32}$$

Model-specific leading-space tokenization is resolved inside the adapter, and ground-truth fields are mapped to a canonical label before optimization. The score normalization and ranking objective follow Eqs. (10)–(11) in the main text and are not repeated here.

D.2 Model-Specific Adapters

All targets use `bfloat16` precision, greedy decoding (`num_beams` $= 1$), and at most 16 newly generated tokens. The native input resolution is 448 pixels, except for GeoChat, which uses 504 pixels. Dynamic tiling uses 1–6 patches with thumbnail augmentation where supported. These interface-level differences do not change the attack objective, perturbation budget, or optimization schedule.

D.3 Native Generation and Answer Parsing

Differentiable scores are used only during optimization. Final predictions are obtained from each model's native generation interface:

$$r_m = \mathcal{G}_m(\mathbf{x}^{\mathrm{adv}}, p^{\mathrm{adv}}), \qquad \widehat{y}_m = \Gamma_T(r_m), \tag{33}$$

where Γ_T maps the complete response to the task answer space. It returns the invalid state $\perp$ when no legal option can be recovered from an empty, malformed, or unavailable response. This separation provides a shared white-box objective while retaining the native inference behavior of every RS-VLM.

E Reproducibility and Evaluation Details

E.1 Target-Model and Baseline Configurations

Experiments use post-disaster RGB images from the DisasterM3 test split and cover Building Damage Counting (BDC), Disaster Type Recognition (DTR), and Object-Relation Reasoning (ORR). For every model–task pair, attacks are evaluated on the clean-correct subset defined in the main text.

Table 7: Principal configurations of the compared attacks.

Method	Visual attack	Textual attack	Surrogate/settings
Co-Attack	$\epsilon = 2/255$, 10 iterations, random start, and internal step size $0.25/255$.	BERTAttack with Top-$K = 10$ and maximum length 30; official joint mode `adv=4` with $\alpha = 3.0$.	ALBEF with the MSCOCO retrieval checkpoint and official `Retrieval_coco` configuration.
SGA	$\epsilon = 2/255$, $\alpha = 0.5/255$, 10 steps, random start, and scales $\{0.5, 0.75, 1.25, 1.5\}$.	One textual perturbation, Top-$K = 10$, score threshold 0.3, and maximum length 30.	ALBEF with the MSCOCO retrieval checkpoint and official set-level guidance attacker.
VQAttack	$\epsilon = 16/255$, $\alpha \approx 1.275/255$, 40 steps, and an ℓ_∞ constraint.	MLM Top-$K = 5$, score threshold 0.3, USE similarity threshold 0.95, and maximum question length 25.	ALBEF pretraining checkpoint with a question-conditioned multimodal objective.
LSSA	$\epsilon = 2/255$, $\alpha = 0.5/255$, 10 steps, scales $\{0.5, 0.75, 1.25, 1.5\}$, and 20 VT samples.	At most one textual modification, MLM Top-$K = 10$, score threshold 0.3, and maximum length 30.	ALBEF with the MSCOCO retrieval checkpoint and local-shuffle sample-based optimization.
GLEAM	$\epsilon = 8/255$, $\alpha = 6/255$, 10 steps, and 20 NURBS warpings with a 30×30 mesh.	One textual perturbation, Top-$K = 10$, threshold 0.3, and maximum length 77.	CLIP-RN101 and BERT-base-uncased; $\rho = 100$, noise scale 2.0, $\beta = 1.5$, and 20 neighbors.

Table 8: Core hyperparameters of RS-RDA.

Component	Configuration
Visual optimization	$\epsilon = 8/255$, $\alpha = 1/255$, $\mu = 0.9$, 30 total updates, checkpoints $\{5, 10, 20, 30\}$
Ranking/ensemble	$\tau = 1.0$, mean coefficient $\beta = 0.7$, SoftMin temperature $\gamma = 0.5$
Task-aware EOT	4 label-preserving views per update; low-frequency noise standard deviation $2/255$
Region discovery	Region budget $K = 8$; DINOv2 diversity threshold $\tau_{\text{div}} = 0.92$
Prompt evolution	$E = 3$; 4 children per elite; 2 generations per alternating block; maximum population 32
Prompt utility	$(\lambda_{\text{dec}}, \lambda_{\text{int}}, \lambda_{\text{grad}}, \lambda_{\text{div}}) = (0.45, 0.35, 0.10, 0.05)$
Decision scoring	First-token option scoring

Co-Attack, SGA, VQAttack, LSSA, and GLEAM retain their original objectives, surrogate architectures, and recommended configurations whenever available. Visual budgets are reported in the normalized $[0, 1]$ image domain. Textual modifications are restricted to the question or response instruction; answer labels, answer contents, option order, and task semantics remain fixed.

E.2 Core Hyperparameters and Task-Aware EOT

RS-RDA uses the same attack-side hyperparameters across all target RS-VLMs and tasks. The perturbation is restricted to the selected support under an ℓ_∞ budget of $8/255$. We perform 30 visual updates and save checkpoints at steps $\{5, 10, 20, 30\}$. Each visual block is warm-started from the preceding perturbation, while prompt evolution transfers the elite set between alternating blocks.

At each visual update, four independently sampled, label-preserving views are drawn from Ω_T. The ensemble contains the identity view and low-frequency perturbed views with standard deviation $2/255$. Transformations affect only visual-gradient estimation and do not alter the question, answer options, prompt elite set, or final evaluation input.

E.3 Fairness and Evaluation Protocol

For each target RS-VLM, all attacks share the same evaluation cohort, native visual processor, conversation template, decoding configuration, and answer parser. Prompt modifications must preserve the task semantics, ordered answer options, and output protocol. All selected samples remain in the ASR denominator, and every checkpoint is evaluated independently without success inheritance. RS-RDA differentiates through the target model under the stated white-box threat model, whereas transfer-based baselines access only their prescribed surrogate models. The protocol therefore standardizes target-side evaluation while retaining each method's original access assumptions.

E.4 Evaluation Metrics

Evaluation protocol. At each checkpoint s, the complete model response is independently generated and mapped to the task answer space by Γ_T. Empty, unparseable, or illegal responses, inference exceptions, and missing checkpoint outputs are mapped to the invalid state $\perp$. All selected samples remain in the denominator, and success is not inherited from earlier checkpoints.

Attack Success Rate. For model m and task T, ASR is

$$\mathrm{ASR}_{m,T}^{(s)} = \frac{100}{N_{m,T}} \sum_{i=1}^{N_{m,T}} \mathbf{1}\left[\widehat{y}_{m,i}^{(s)} \neq y_i\right], \tag{34}$$

where $\widehat{y}_{m,i}^{(s)} \in \mathcal{Y}_T \cup \{\perp\}$. A legal but incorrect option or the invalid state $\perp$ is counted as an attack success.

Counting Errors. For BDC, each legal option is mapped to its numerical value. Let c_i and $\widehat{c}_{m,i}^{(s)}$ be the ground-truth and predicted counts, and let $\mathcal{V}_{m,T}^{(s)}$ be the set of valid numerical predictions. We use

$$\mathrm{MAE}_m^{(s)} = \frac{1}{|\mathcal{V}_{m,T}^{(s)}|} \sum_{i \in \mathcal{V}_{m,T}^{(s)}} \left|\widehat{c}_{m,i}^{(s)} - c_i\right|, \tag{35}$$

$$\mathrm{MRE}_m^{(s)} = \frac{100}{|\mathcal{V}_{m,T}^{(s)}|} \sum_{i \in \mathcal{V}_{m,T}^{(s)}} \frac{\left|\widehat{c}_{m,i}^{(s)} - c_i\right|}{\max(|c_i|, 1)}. \tag{36}$$

Invalid outputs contribute to ASR but are excluded from MAE and MRE because they cannot be mapped to numerical counts.

Classification Performance. For DTR, Macro-F1 is

$$\text{Macro-F1}_m^{(s)} = \frac{1}{C} \sum_{k=1}^{C} \frac{2\,\mathrm{TP}_{m,k}^{(s)}}{2\,\mathrm{TP}_{m,k}^{(s)} + \mathrm{FP}_{m,k}^{(s)} + \mathrm{FN}_{m,k}^{(s)}}, \tag{37}$$

where C is the number of disaster classes. An invalid prediction contributes a false negative to its ground-truth class.

Perturbation Distortion. For $\mathbf{x}_i \in [0,1]^{H \times W \times C}$ and its adversarial counterpart,

$$\mathrm{RMSD}_i = \sqrt{\frac{\|\mathbf{x}_i^{\mathrm{adv}} - \mathbf{x}_i\|_2^2}{HWC}}. \tag{38}$$

LPIPS measures the corresponding discrepancy in the feature space of a fixed pretrained perceptual network. Both metrics are averaged over the evaluated samples and computed on the complete image domain.

For $Q \in \{\mathrm{RMSD}, \mathrm{LPIPS}\}$, the relative reduction of key-region optimization over full-image optimization is

$$\mathrm{Reduction}_Q = 100 \frac{\overline{Q}_{\mathrm{full}} - \overline{Q}_{\mathrm{key}}}{\overline{Q}_{\mathrm{full}}}. \tag{39}$$

The two averages are computed on identical paired samples; a positive value indicates lower distortion under key-region optimization.

F Additional Component Ablations

Results on DTR and ORR. Tables 9 and 10 extend the component analysis to DTR and ORR. At step 30, RS-RDA achieves the best or tied-best ASR on four of the five models for each task, averaging 96.46% on DTR and 95.87% on ORR. Removing adaptive prompt optimization, alternating optimization, and task-aware EOT decreases the DTR average by 31.64, 18.67, and 27.75 percentage points, respectively; the corresponding reductions on ORR are 12.94, 14.48, and 17.52 points.

Table 9: Component ablation of RS-RDA across five RS-VLMs on the DTR task. ASR (%) is independently evaluated on the clean-correct subset at each attack step.

Model	Variant	ASR			
		Step 5	Step 10	Step 20	Step 30
EarthDial	**RS-RDA**	91.75	94.85	100.00	100.00
	w/o Key Region	64.58	69.39	71.76	78.79
	w/o Adaptive Prompt	43.30	55.10	61.22	62.24
	w/o Alternating Optimization	42.85	53.61	60.20	61.78
	w/o Task-aware EOT	56.04	56.38	59.55	62.50
EarthMind	**RS-RDA**	70.10	77.66	83.64	100.00
	w/o Key Region	67.06	77.01	81.57	100.00
	w/o Adaptive Prompt	31.58	31.25	47.37	51.35
	w/o Alternating Optimization	35.71	49.40	61.54	92.30
	w/o Task-aware EOT	52.17	70.77	75.32	82.28
GeoChat	**RS-RDA**	66.67	80.23	97.90	97.75
	w/o Key Region	68.37	82.47	96.81	97.96
	w/o Adaptive Prompt	41.76	51.04	55.91	62.20
	w/o Alternating Optimization	41.77	49.40	53.85	64.10
	w/o Task-aware EOT	44.30	46.99	52.38	50.00
TEOChat	**RS-RDA**	53.25	61.04	80.51	84.53
	w/o Key Region	50.65	64.94	83.52	83.70
	w/o Adaptive Prompt	34.07	37.23	41.23	49.48
	w/o Alternating Optimization	60.20	63.92	71.43	71.91
	w/o Task-aware EOT	40.00	45.45	42.55	50.00
TerraScope	**RS-RDA**	91.67	95.23	100.00	100.00
	w/o Key Region	98.08	98.11	100.00	100.00
	w/o Adaptive Prompt	98.68	98.14	98.76	98.83
	w/o Alternating Optimization	96.55	98.21	98.96	98.85
	w/o Task-aware EOT	98.36	98.88	98.84	98.77

Cross-task Observations. The relative contributions vary with task structure. Prompt adaptation is most influential on DTR, where visual perturbations continuously alter the competition among disaster categories. In contrast, ORR benefits more from task-aware EOT and alternating optimization, reflecting its dependence on stable gradients and coordinated evidence across spatial entities. Removing the key-region constraint produces smaller average differences of 4.37 points on DTR and 2.55 points on ORR. The marginal reversals on GeoChat–DTR and TerraScope–ORR are only 0.21 points, consistent with the enlarged search space of full-image attacks and performance saturation. Overall, these results confirm that RS-RDA preserves competitive attack effectiveness while restricting perturbations to compact, task-relevant support.

G Additional Region-Selection Results

G.1 Results on BDC and ORR

Tables 11 and 12 report the region-selection results on BDC and ORR, respectively. RS-RDA achieves average ASRs of 87.20% and 94.69%, outperforming the strongest competing strategy on each task by 2.10 and 2.99 percentage points, respectively. It obtains the best or tied-best result on every target model for both tasks. These results indicate that integrating region reliability, task relevance, and semantic complementarity produces compact perturbation support capable of capturing distributed counting evidence and cross-region relational cues.

G.2 Cross-Task Analysis

The supplementary results are consistent with the DTR findings in Section 5.4. Random strategies lack task alignment, quality-only selection ignores decision relevance, and semantic Top-K may retain redundant evidence. RS-RDA instead combines spatial reliability, task-conditioned rele-

Table 10: Component ablation of RS-RDA across five RS-VLMs on the ORR task. ASR (%) is independently evaluated on the clean-correct subset at each attack step.

Model	Variant	ASR			
		Step 5	Step 10	Step 20	Step 30
EarthDial	**RS-RDA**	91.01	95.51	100.00	100.00
	w/o Key Region	89.47	94.74	100.00	100.00
	w/o Adaptive Prompt	71.70	77.36	84.91	86.79
	w/o Alternating Optimization	74.58	83.05	88.14	88.14
	w/o Task-aware EOT	74.32	71.62	78.38	78.38
EarthMind	**RS-RDA**	82.61	86.96	91.30	95.65
	w/o Key Region	81.25	81.25	87.50	93.75
	w/o Adaptive Prompt	78.95	84.21	89.47	94.74
	w/o Alternating Optimization	65.31	67.35	73.47	73.47
	w/o Task-aware EOT	62.75	68.63	72.00	72.54
GeoChat	**RS-RDA**	49.33	56.72	86.57	93.33
	w/o Key Region	50.00	71.42	75.00	85.71
	w/o Adaptive Prompt	41.76	53.57	57.13	65.22
	w/o Alternating Optimization	35.90	53.85	69.23	78.95
	w/o Task-aware EOT	35.42	55.10	62.03	82.61
TEOChat	**RS-RDA**	71.91	78.95	91.30	91.67
	w/o Key Region	73.47	78.79	88.24	88.24
	w/o Adaptive Prompt	60.82	65.96	69.47	69.07
	w/o Alternating Optimization	58.43	64.04	67.42	69.66
	w/o Task-aware EOT	58.16	58.33	59.38	60.42
TerraScope	**RS-RDA**	94.81	97.40	98.67	98.70
	w/o Key Region	91.30	95.65	97.83	98.91
	w/o Adaptive Prompt	91.21	98.14	98.76	98.83
	w/o Alternating Optimization	96.55	95.56	96.67	96.74
	w/o Task-aware EOT	93.48	95.65	97.82	97.82

Table 11: Comparison of region-selection strategies on BDC. All entries are ASR (%).

Region Strategy	EarthDial	EarthMind	GeoChat	TEOChat	TerraScope
Random Spatial	79.00	86.50	89.50	74.50	96.00
Random SAM	74.00	85.00	88.00	74.50	93.50
SAM Quality Top-K	69.00	72.00	90.00	74.00	93.00
Semantic Top-K	78.50	84.00	88.00	77.00	95.00
Semantic + Quality Top-K	79.00	85.50	89.00	75.00	97.00
RS-RDA	**82.00**	**87.00**	**91.00**	**79.00**	**97.00**

vance, and inter-region complementarity, producing compact support that generalizes across counting, recognition, and relational reasoning tasks.

H Qualitative Attack Examples

Figures 2–4 illustrate successful RS-RDA attacks on BDC, DTR, and ORR. In each case, the jointly optimized regional perturbation and semantics-preserving prompt shift the RS-VLM from the correct clean prediction to an incorrect task decision while retaining the original task objective, answer space, and output protocol. These examples demonstrate the effectiveness of cross-modal optimization across remote-sensing perception and reasoning tasks.

Table 12: Comparison of region-selection strategies on ORR. All entries are ASR (%).

Region Strategy	EarthDial	EarthMind	GeoChat	TEOChat	TerraScope
Random Spatial	85.42	100.00	79.50	91.00	97.28
Random SAM	79.69	99.50	89.50	92.00	97.83
SAM Quality Top-K	78.65	97.00	85.54	92.00	92.93
Semantic Top-K	84.38	100.00	84.94	92.00	95.65
Semantic + Quality Top-K	77.08	98.00	83.73	91.00	95.65
RS-RDA	**90.62**	**100.00**	**93.00**	**92.00**	**97.83**



Clean Input



Adversarial Input

CLEAN PROMPT

How many buildings were partially harmed or compromised?

Options

A. 69 B. 96
C. 82 D. 42
E. 56

Answer only with one option letter from the choices. Do not output any explanation.

ADVERSARIAL PROMPT

Use only the visual evidence to answer the original question: How many buildings were partially harmed or compromised?

Options

A. 69 **B. 96**
C. 82 D. 42
E. 56

Select exactly one option and output only its letter.

Figure 2: Successful RS-RDA attack on BDC, changing the correct count (green) to an incorrect prediction (red) while preserving task semantics.



Clean Input

CLEAN PROMPT

What disaster has happened in this area?

Options

A. Tornado B. Hurricane
C. Explosion D. Volcano
E. Tsunami

Select exactly one option. Return only the option letter.



Adversarial Input

ADVERSARIAL PROMPT

Use the most diagnostic localized visual evidence in the scene to answer the original disaster-recognition question: What disaster has happened in this area?

Options

A. Tornado B. Hurricane
C. Explosion D. Volcano
E. Tsunami

After comparing the choices, output only the capital letter of the single best-supported option.

Figure 3: Successful RS-RDA attack on DTR, shifting the correct disaster class (green) to an incorrect prediction (red) under a semantics-preserving prompt.



Clean Input

CLEAN PROMPT

Describe the spatial relationship between object in the red box and object in the blue box.

Options

A. The inundated road in the red box is situated within the harmed residential area in the blue box.
B. The flooded road in the red box runs between the intact building in the blue box with a grey roof and several houses to the west.
C. Damaged house in the red box with a red roof is adjacent to the intact house in the blue box with a white roof near the left center of the image.
D. The intact parking lot in the red box is southeast of the flooded intersection in the blue box in the lower right section of the image.
E. Flooded street in the red box surrounds the cluster of intact houses in the blue box in the middle of the lower half of the image.

This is a remote-sensing Relational Reasoning task. Use the image to determine the spatial relationship of the red-box object(s) relative to the blue-box object(s).Answer only with one option letter from A/B/C/D/E. Do not output any explanation.



Adversarial Input

ADVERSARIAL PROMPT

Use both the marked local geometry and the full-scene context without swapping the target and reference: Describe the spatial relationship between object in the red box and object in the blue box.

Options

A. The inundated road in the red box is situated within the harmed residential area in the blue box.
B. The flooded road in the red box runs between the intact building in the blue box with a grey roof and several houses to the west.
C. Damaged house in the red box with a red roof is adjacent to the intact house in the blue box with a white roof near the left center of the image.
D. The intact parking lot in the red box is southeast of the flooded intersection in the blue box in the lower right section of the image.
E. Flooded street in the red box surrounds the cluster of intact houses in the blue box in the middle of the lower half of the image.

Resolve the choice using the diagnostic evidence, then give one option letter only.

Figure 4: Successful RS-RDA attack on ORR, changing the correct spatial relation (green) to an incorrect prediction (red) without altering the queried objects.