
National Institute of Meteorological Sciences


SkySearch: Satellite Video Search at Scale

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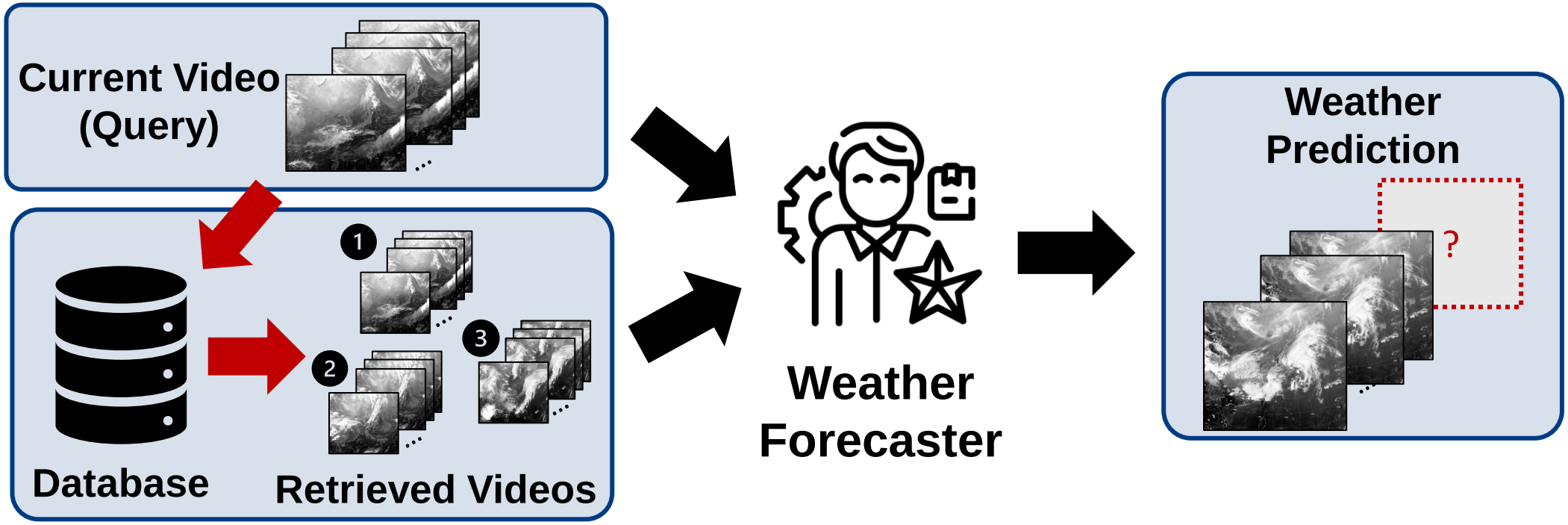
Motivations

- Weather patterns often **repeat**, making historical analysis essential.

Motivations

- Weather forecasters **refer to past satellite videos** to better understand and interpret current weather conditions.
- Our problem: Accurate and fast search of **similar satellite videos.**

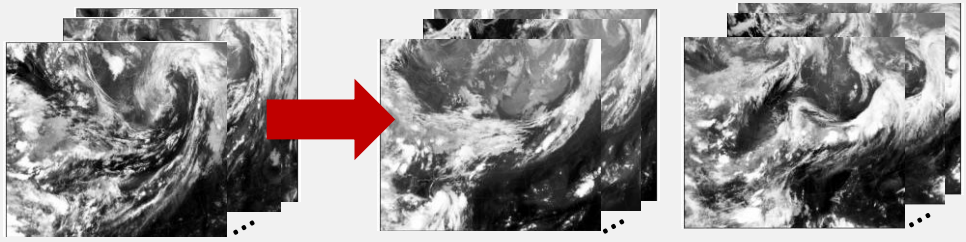


Challenges

- Satellite video retrieval presents **unique practical challenges**:
  1. **No ground truth for similarity**
  2. **Massive volume and resolution**

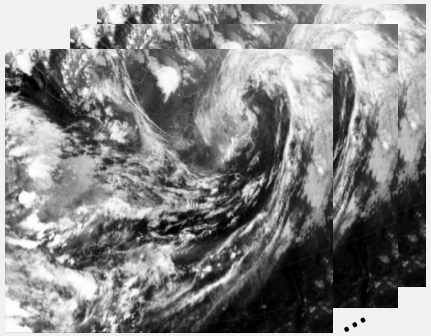
No Ground Truth for Similarity

"No label tells us which retrieved case is correct."

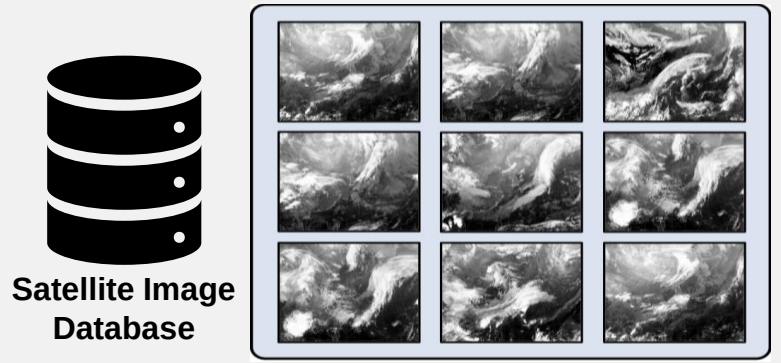


Query Video **Retrieved Cases**

Massive Volume and Resolution



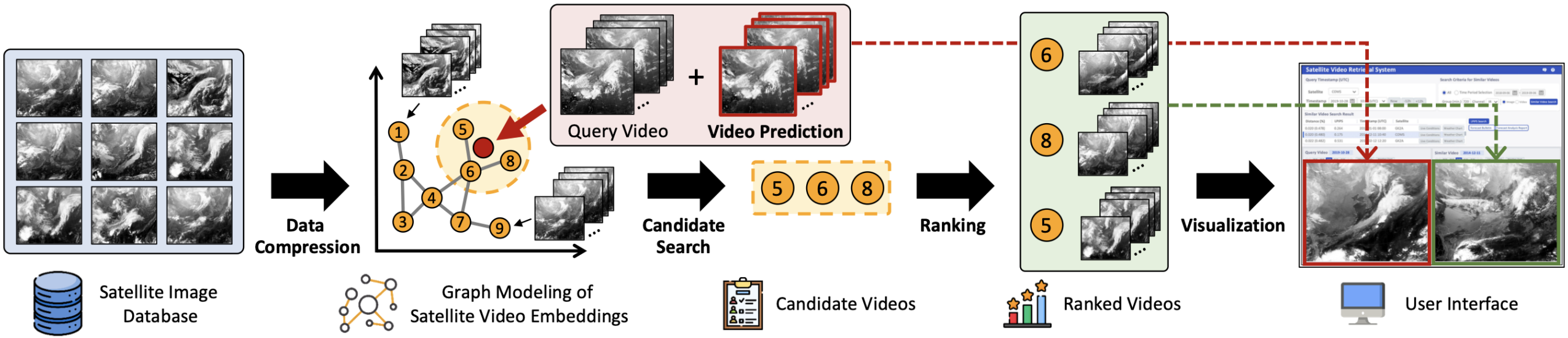
(600 ×748)×12 frames



Covers 12 years of data (2010–2021)

SkySearch: Satellite Video Search at Scale

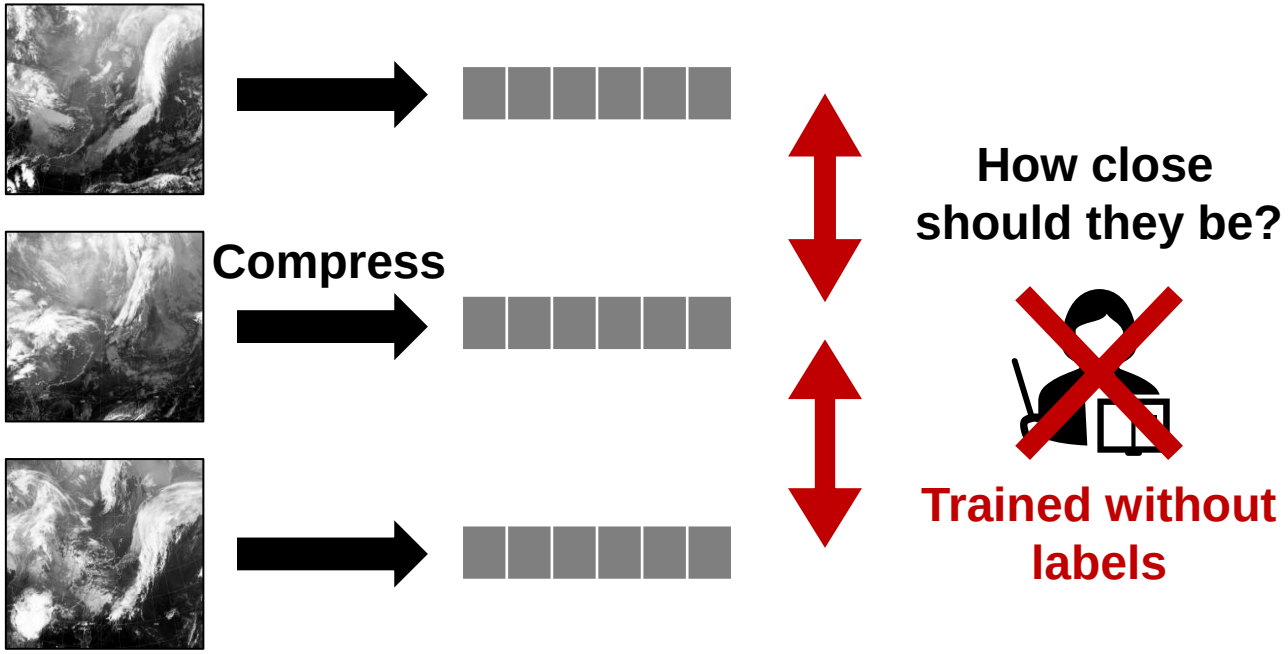
- An **unsupervised real-time satellite video search system** deployed at the Korea Meteorological Administration (KMA).



Key Components

- **SkySearch** has **three core** technical components,

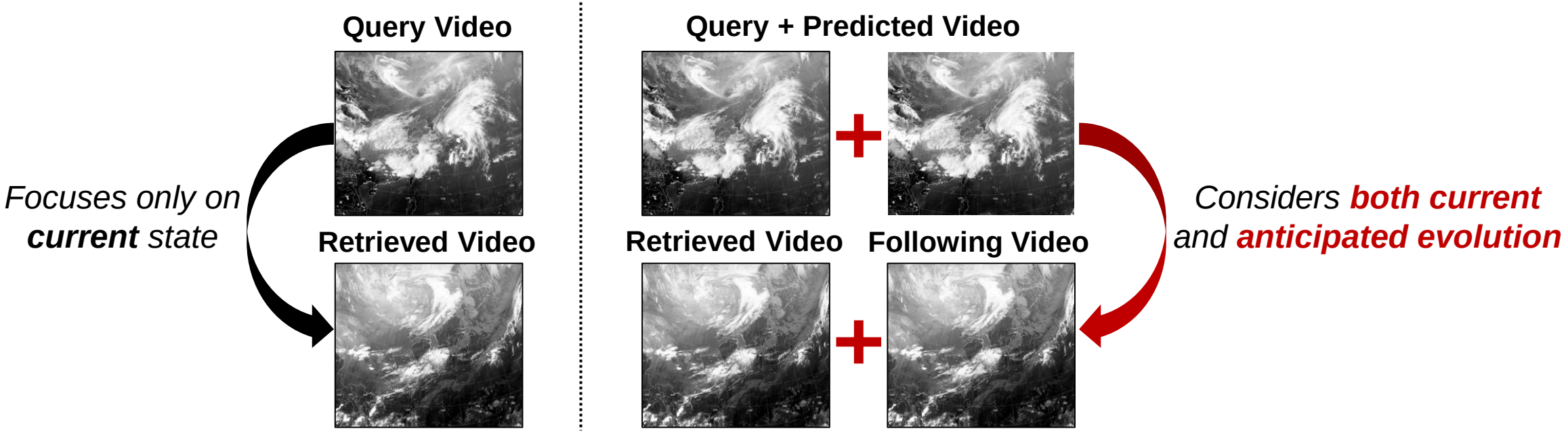
1. **Self-Supervised Video Compression:**
   Encode each video into **low-dimensional** vectors via **self-supervised learning**, capturing key spatiotemporal patterns **without labels**.



Key Components

- **SkySearch** has **three core** technical components,

2. **Prediction-Based Query Augmentation:**
   Predict future frames to **augment** the query, **enabling** retrieval aligned with **both current state and anticipated evolution**.

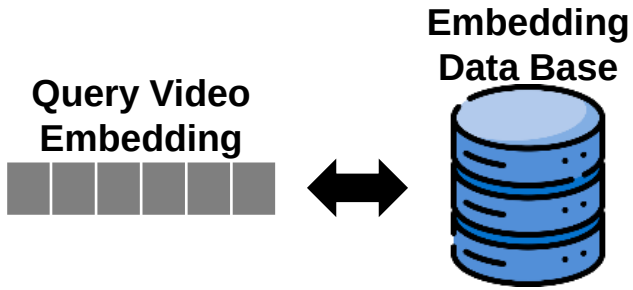


Key Components

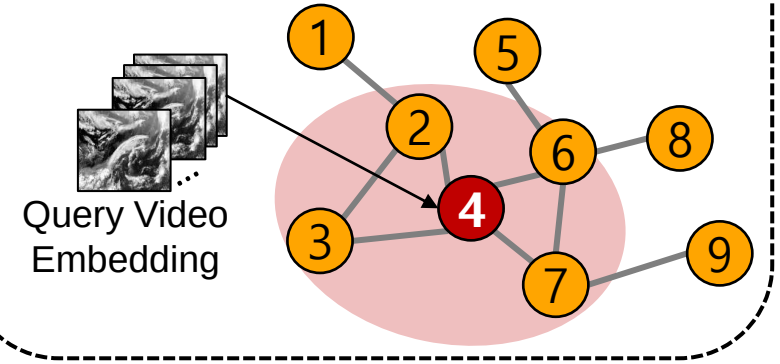
- **SkySearch** has **three core** technical components,

3. **Graph-Based Retrieval:**
   Traverse a **k-NN graph** in latent space to retrieve and rank similar past videos.

Naive Search:
Compare against entire database

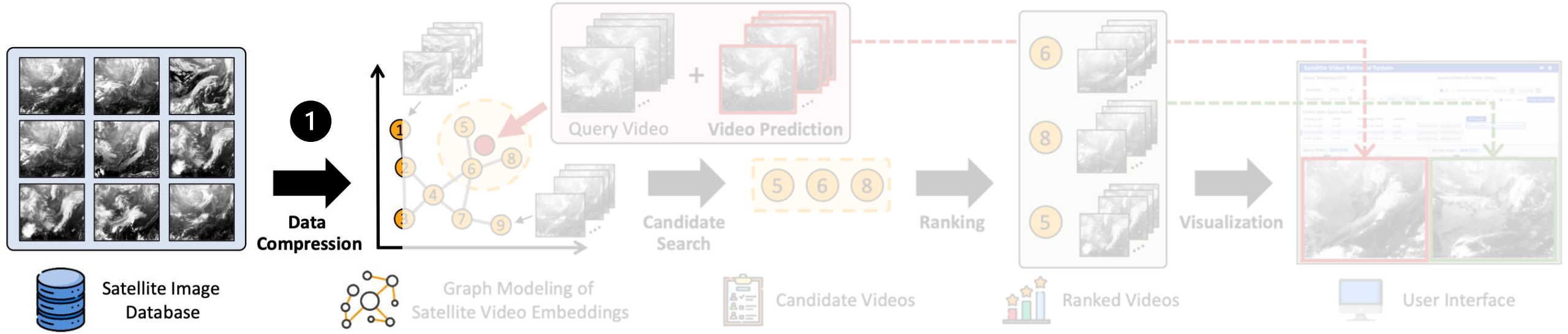


Graph-Based Retrieval:
Start from the query and explore its most similar neighbors



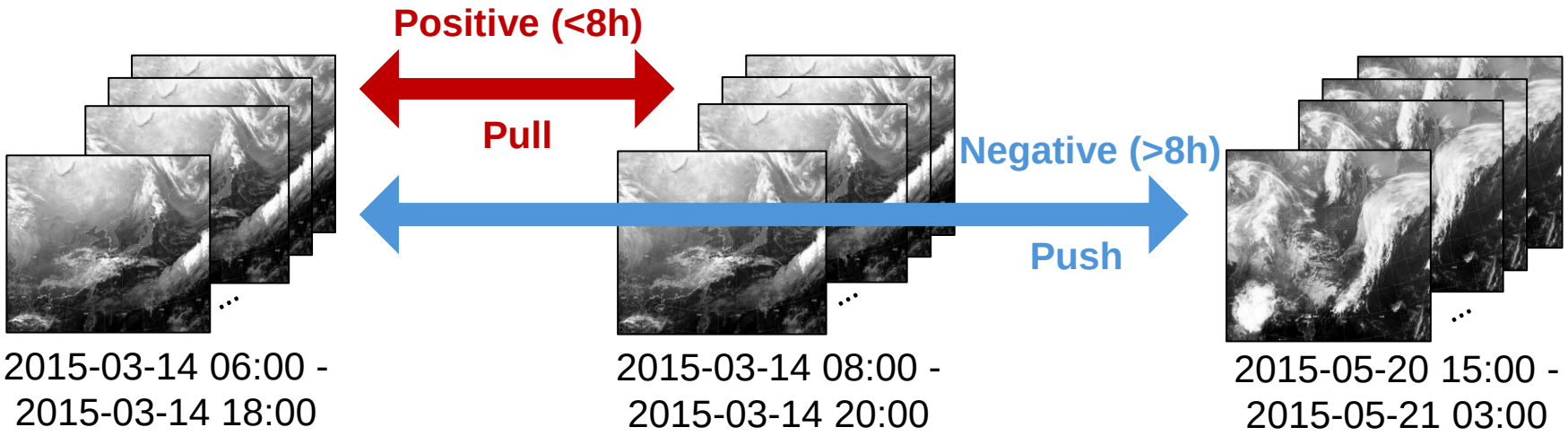
Step 1: Video Compression

- **Compression Objective:**
  - Compress satellite videos into **compact latent embeddings**.
  - Preserve **spatiotemporal similarity** between meteorologically similar videos.



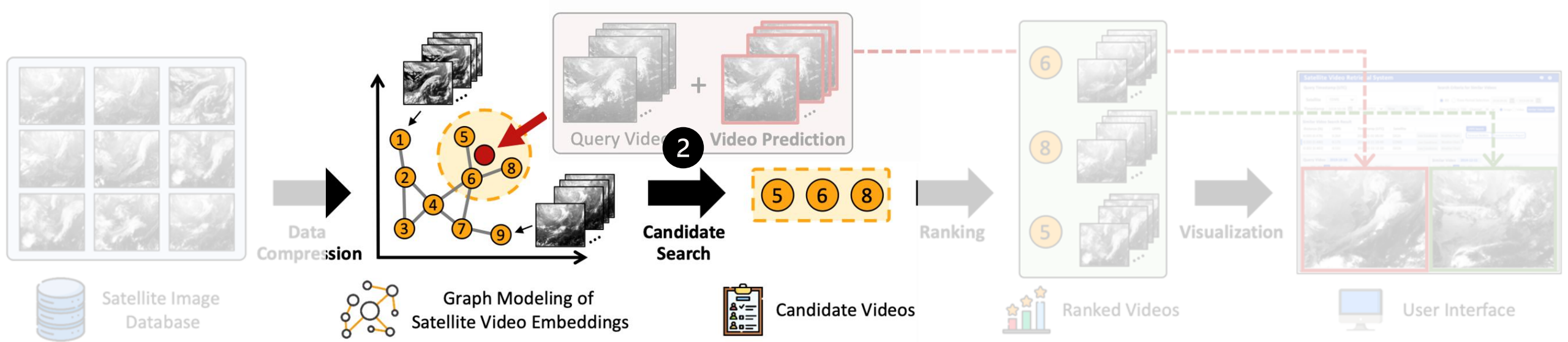
Step 1: Video Compression

- **Key Point:** Weather evolves **gradually** over time.
  → temporal proximity ≈ semantic similarity.
- **Contrastive Loss:** pull close positives, push away negatives.
  - **Positive Pairs:** videos within ±8 hours.
  - **Negative Pairs:** temporally distant videos.



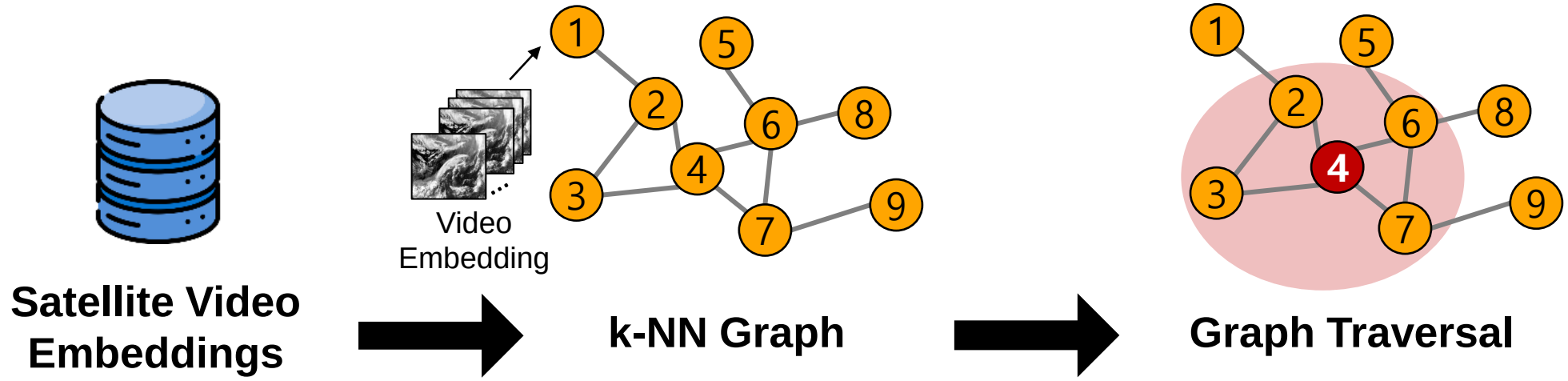
Step 2: Graph-Based Search

- **Goal: Efficiently** find videos most similar to a given query video.
- **Challenge**: Direct comparison with all videos is **too slow** for real-time use.
- **Solution**: Use **graph-based retrieval** to scale to large databases.



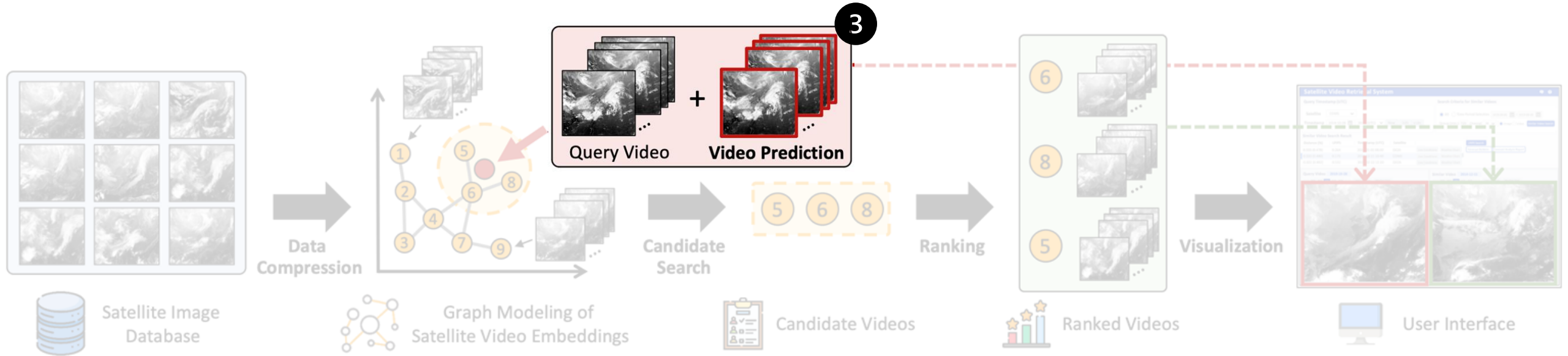
Step 2: Graph-Based Search

- **Candidate Search: Efficient and Time-Aware**
  - Build a **k-NN graph** from all video embeddings.
  - Start search from the query and **traverse nearby neighbors**.
  - **Restrict search** to videos from the **user-defined time window**.
  - Return a small set of highly similar candidates.



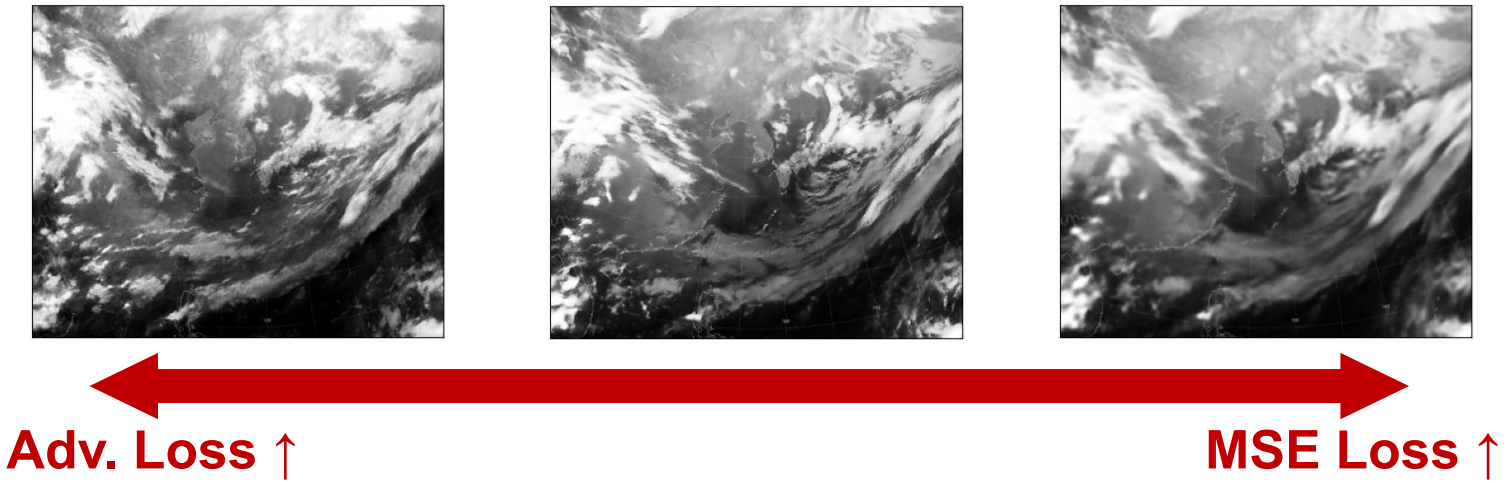
Step 3: Video Prediction

- **Goal:** Augment query videos with predicted future frames.
- **Purpose:** Retrieve past cases matching **both current and future conditions** to support forecast reasoning.



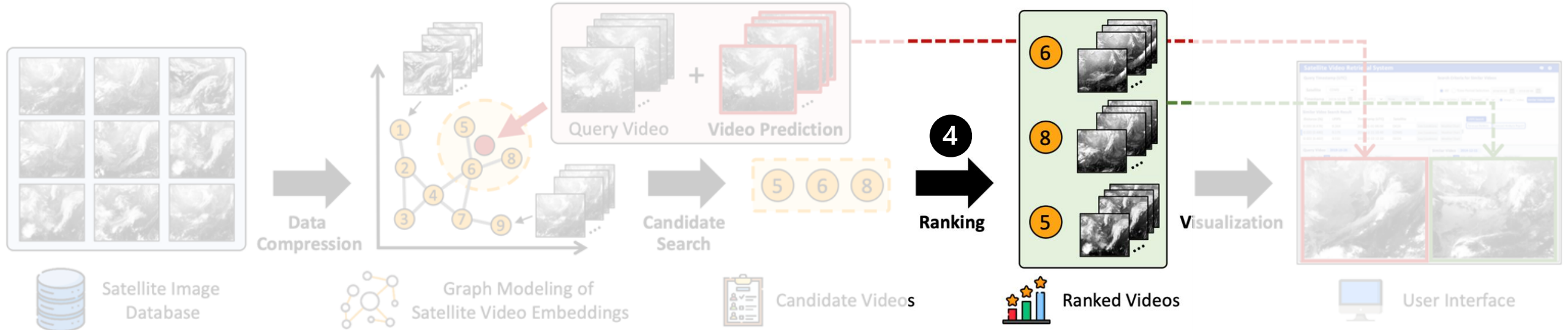
Step 3: Video Prediction

- **Backbone: SimVP**, a strong baseline for video prediction.
- **Challenge: Blurry** results on high-resolution satellite videos.
- **Solution:** Balance MSE and adversarial losses.
  - **MSE Loss:** Ensures pixel-level accuracy.
  - **Adversarial Loss:** Improves visual realism and sharpness.



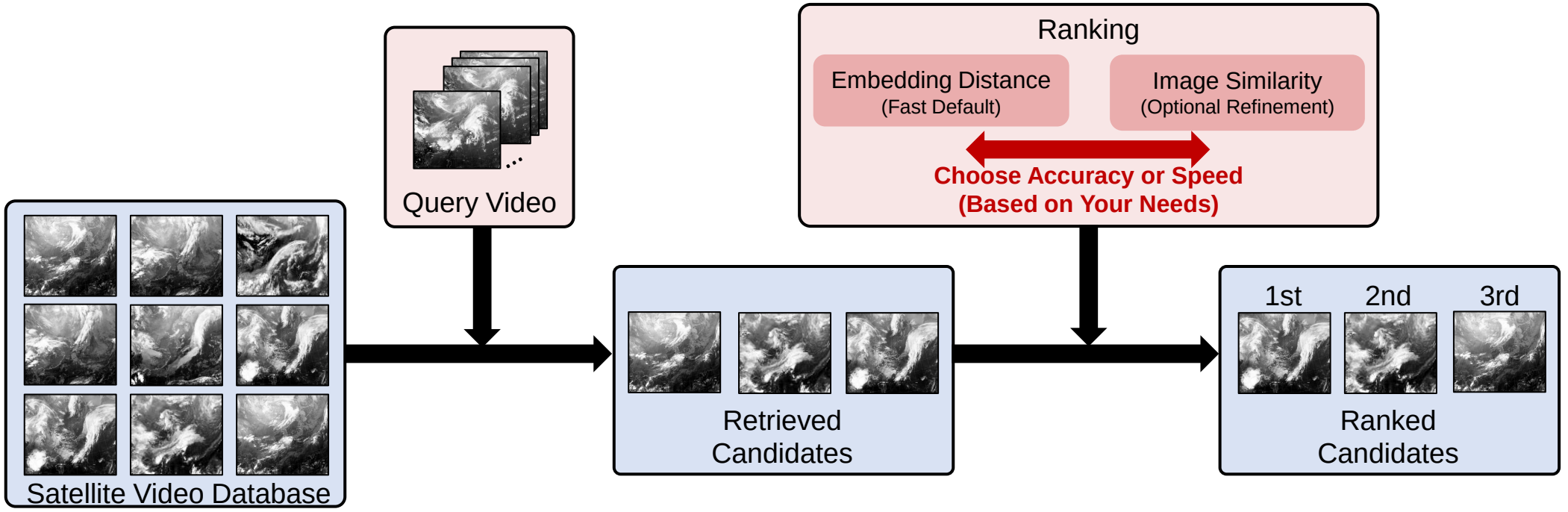
Step 4: Ranking

- **Goal**: Retrieved candidates are ranked by embedding distance or perceptual similarity to **prioritize** relevant results.



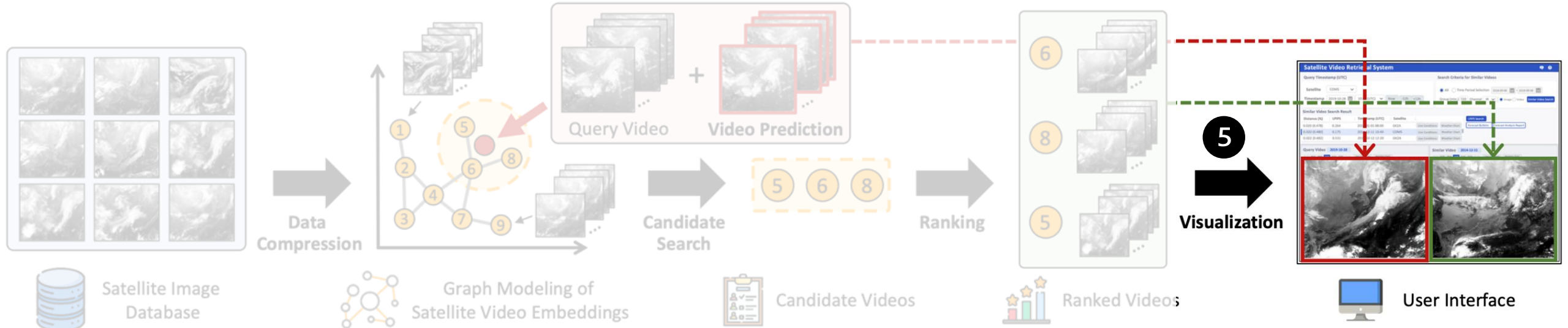
Step 4: Ranking

- **Default Ranking**: Use Euclidean distance between embeddings for speed.
- **Refined Ranking:** Optionally apply LPIPS, FSIM, or SSIM for better accuracy.
- **Trade-off:** Perceptual metrics improve relevance but increase computation time.



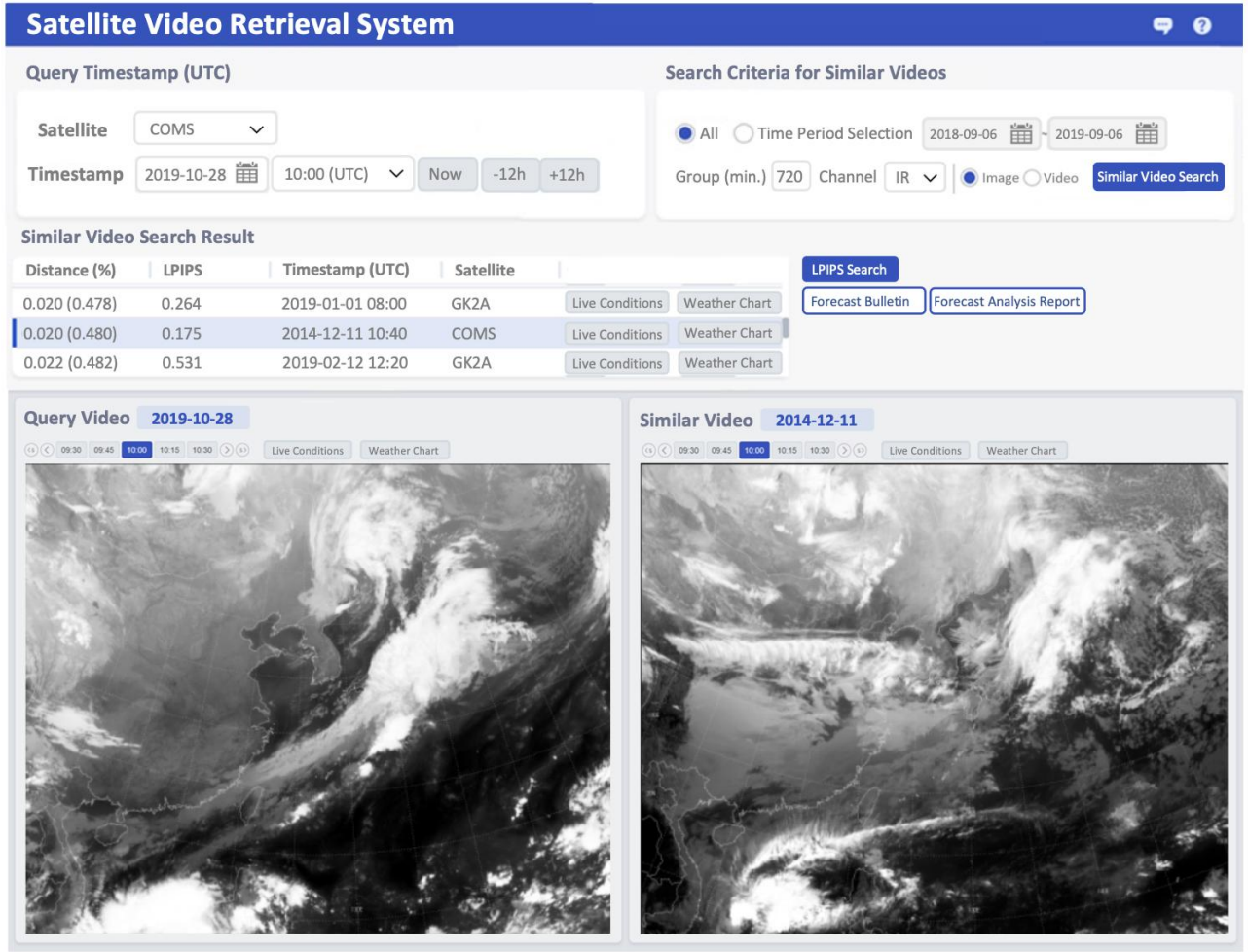
Step 5: Visualization

- **Goal**: The retrieved results are displayed through a **user interface** deployed at KMA.



Step 5: Visualization

- **Input:** satellite, channel, timestamp and the desired time range.
- **Output:** list of similar videos with date & similarity score.



Deployment at KMA

National Institute of Meteorological Sciences

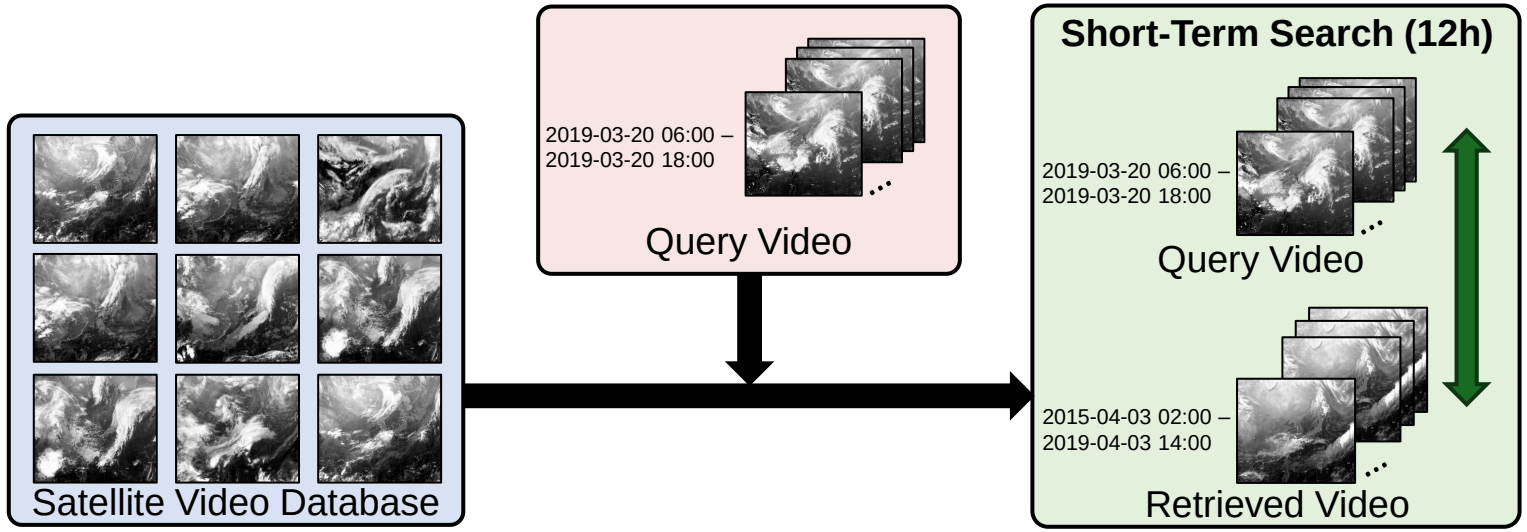
- **Satellite Sources**:
  - COMS (2010–2020): general-purpose satellite.
  - GK2A (2018–present): specialized for weather monitoring.
- **Supported Channels**:
  - IR (Infrared), SWIR (Shortwave IR), WV (Water Vapor).
- **Temporal Coverage**:
  - Dataset spans 12 years: Sep 2010 – Jun 2021.
  - Image intervals: 15 min (COMS), 10 min (GK2A).
- **Resolution & Scale**:
  - Original: 1300×1500, downsampled to 600×748.
  - Each video = 12 frames, totaling 5.4M pixels per video.

Evaluation of Final Outcomes

- **Evaluation Setup**
  - **Compare SkySearch with pre-trained and fine-tuned baselines**.
    - ResNet, EfficientNet, VideoMAE, TimeSformer
  - **Query Set:** 2,000 IR-channel COMS videos (2019–2020), 12h duration.
  - **Database:** 2014–2018 IR COMS videos.
  - **Metrics:** LPIPS, FSIM, SSIM over aligned frame pairs.

Evaluation of Final Outcomes

- **Short-Term Search Evaluation**
  - **Goal:** Retrieve visually similar past videos.
  - Compare retrieved 12h video with query 12h video.
  - Evaluates **current pattern matching** ability.



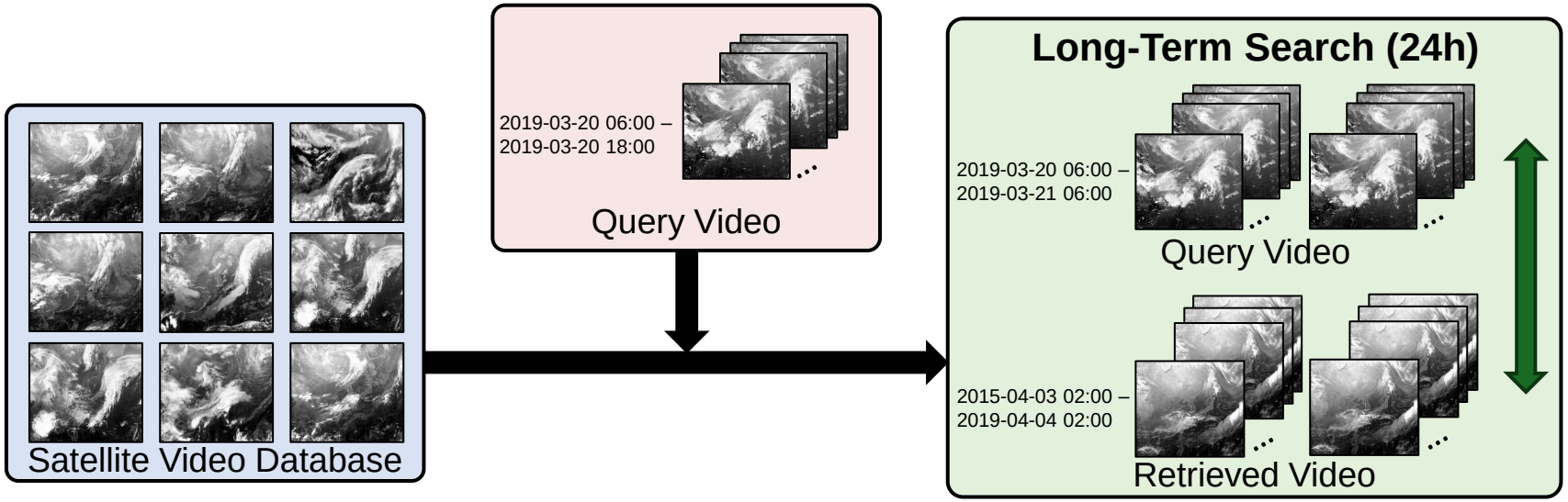
Evaluation of Final Outcomes

- **Short-Term Search Evaluation**
  - **SkySearch** achieves the **best** performance across all metrics.
  - The version without video prediction achieves the best results, demonstrating **strong representation quality**.

Model	Short-Term Search Accuracy (12 Hours)		
	LPIPS (↓)	FSIM (↑)	SSIM (↑)
Random	0.2406 ± 0.0364	0.3350 ± 0.0126	0.2249 ± 0.0609
ResNet (Pre-Trained)	0.2086 ± 0.0396	0.3465 ± 0.0159	0.2635 ± 0.0780
ResNet (Fine-Tuned w/ SimCLR)	0.2034 ± 0.0342	0.3487 ± 0.0149	0.2713 ± 0.0753
EfficientNet (Pre-Trained)	0.2087 ± 0.0376	0.3461 ± 0.0150	0.2633 ± 0.0751
EfficientNet (Fine-Tuned w/ SimCLR)	0.2039 ± 0.0365	0.3479 ± 0.0151	0.2703 ± 0.0767
VideoMAE (Pre-Trained)	0.2039 ± 0.0401	0.3486 ± 0.0164	0.2712 ± 0.0812
TimeSformer (Pre-Trained)	0.2090 ± 0.0395	0.3466 ± 0.0163	0.2627 ± 0.0782
SkySearch (w/o Video Prediction)	**0.1943 ± 0.0355**	**0.3502 ± 0.0150**	**0.2784 ± 0.0767**
SkySearch (w/ Video Prediction)	0.1960 ± 0.0356	0.3495 ± 0.0151	0.2775 ± 0.0759

Evaluation of Final Outcomes

- **Long-Term Search Evaluation**
  - **Goal:** Retrieve past videos that resemble **both current and future trends**.
  - **Tests whether retrieved video evolves similarly**.



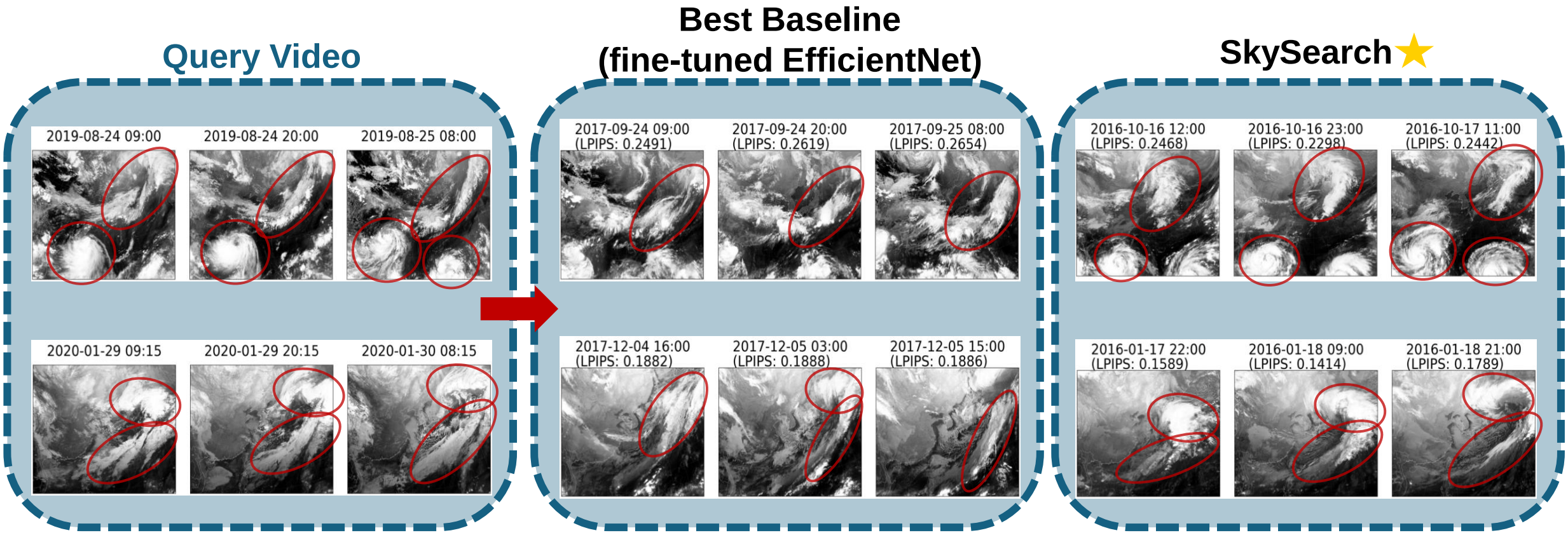
Evaluation of Final Outcomes

- **Long-Term Search Evaluation**
  - **SkySearch outperforms** all baselines by a clear margin.
  - The video prediction module enables alignment with future trends, boosting accuracy in long-term retrieval.

Model	Long-Term Search Accuracy (24 Hours)		
	LPIPS (↓)	FSIM (↑)	SSIM (↑)
Random	0.2405 ± 0.0356	0.3348 ± 0.0122	0.2248 ± 0.0595
ResNet (Pre-Trained)	0.2100 ± 0.0388	0.3459 ± 0.0154	0.2626 ± 0.0765
ResNet (Fine-Tuned w/ SimCLR)	0.2051 ± 0.0335	0.3478 ± 0.0144	0.2687 ± 0.0737
EfficientNet (Pre-Trained)	0.2103 ± 0.0367	0.3452 ± 0.0145	0.2619 ± 0.0739
EfficientNet (Fine-Tuned w/ SimCLR)	0.2047 ± 0.0357	0.3476 ± 0.0146	0.2690 ± 0.0751
VideoMAE (Pre-Trained)	0.2051 ± 0.0390	0.3480 ± 0.0159	0.2692 ± 0.0791
TimeSformer (Pre-Trained)	0.2102 ± 0.0388	0.3460 ± 0.0160	0.2615 ± 0.0763
SkySearch (w/o Video Prediction)	0.1974 ± 0.0349	0.3490 ± 0.0147	0.2751 ± 0.0750
SkySearch (w/ Video Prediction)	**0.1965 ± 0.0347**	**0.3494 ± 0.0146**	**0.2766 ± 0.0750**

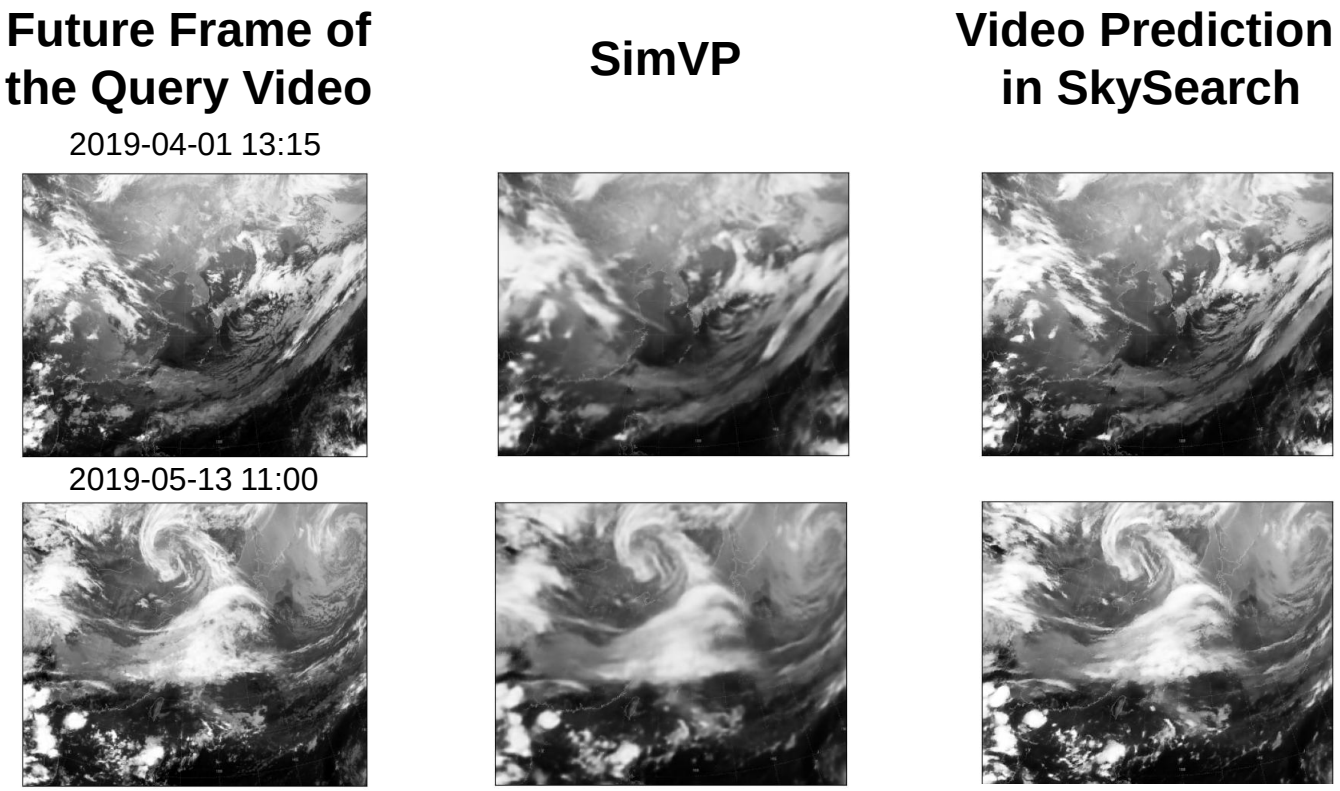
Evaluation of Final Outcomes

- SkySearch retrieves the **most visually coherent** past events.



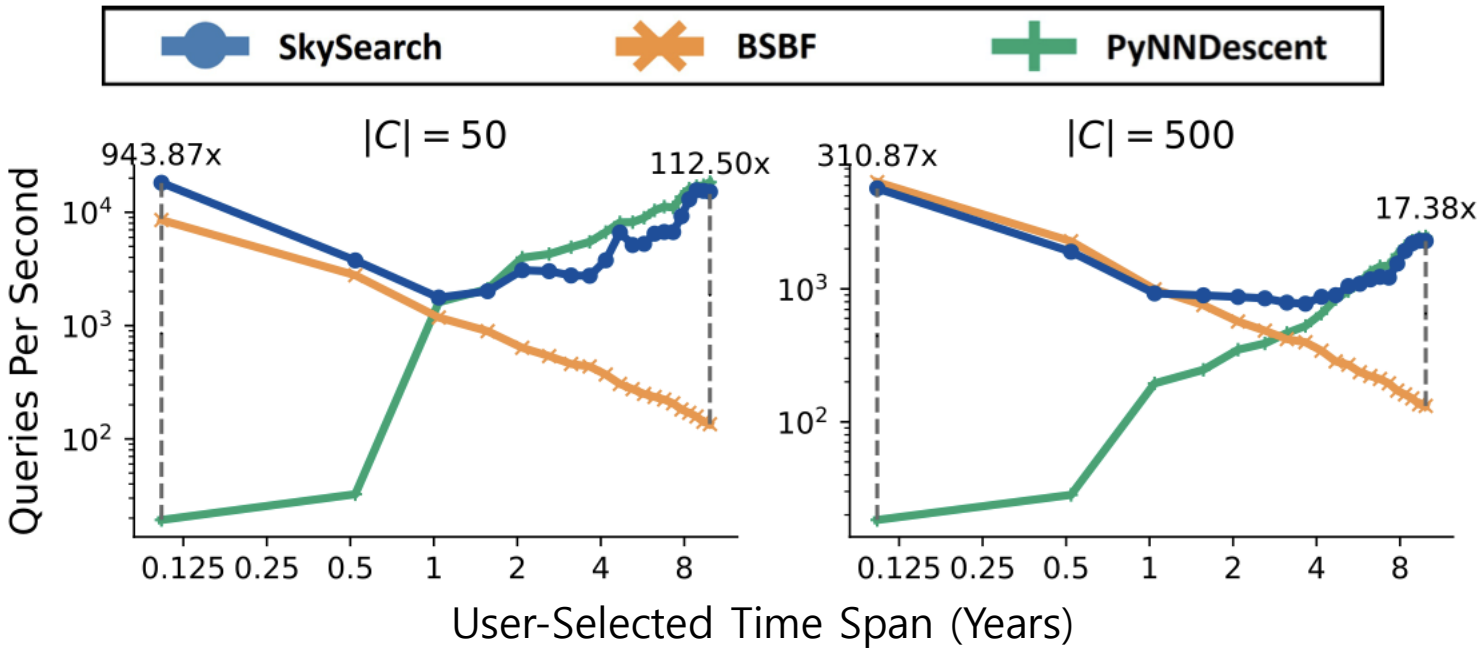
Evaluation of Components

- **Video prediction with adversarial loss** improves sharpness and realism.
- Achieves significantly **lower LPIPS** than SimVP: 0.2170 vs. 0.3907.



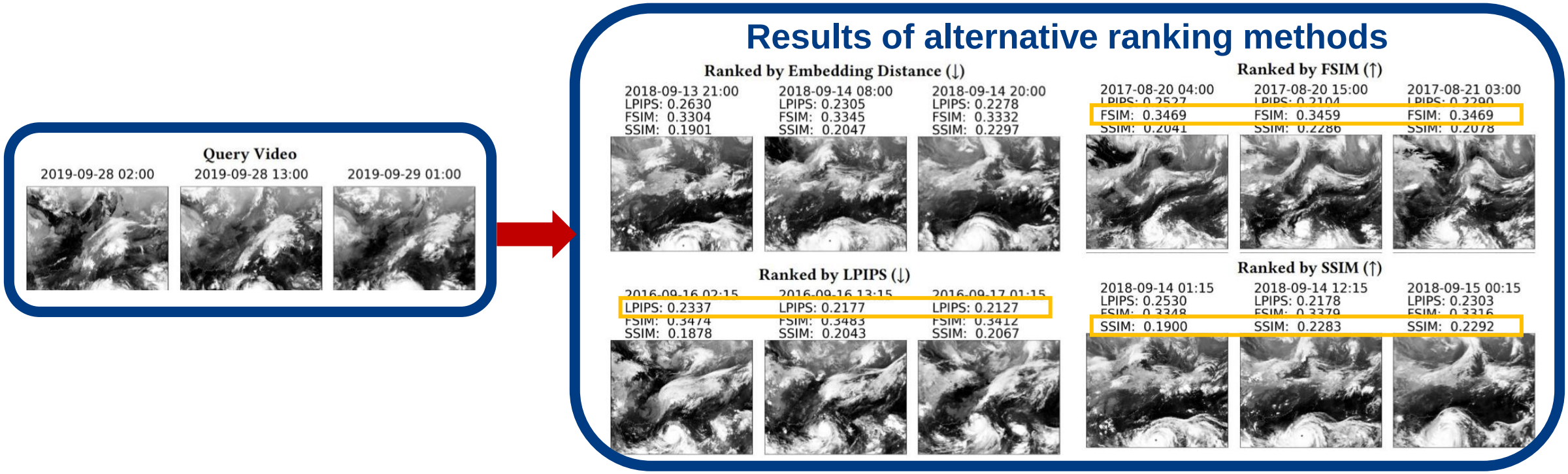
Evaluation of Components

- **Graph-based candidate search is fast and accurate**, even when users search across different time ranges.
- SkySearch achieves up to **943× faster** search than PyNNDescent, especially when the search is limited to recent years or specific seasons.



Evaluation of Components

- **SkySearch offers flexible ranking**: fast **embedding-based** by default, or **refined with LPIPS, FSIM, SSIM** for better visual alignment.
- **Users can trade off speed and accuracy** depending on their needs.



Conclusion

SkySearch, a large-scale satellite video retrieval system deployed at the Korea Meteorological Administration (KMA), offers the following advantages:

- **Efficient**: SkySearch processes queries from massive databases and provides results **within seconds**.
- **Accurate**: SkySearch retrieves videos that closely align with the input query video, **both numerically and visually**.
- **Unsupervised**: SkySearch employs **self-supervised learning** to address the lack of labeled data.

For reproducibility, we release our code and online appendix at https://github.com/geon0325/skysearch.