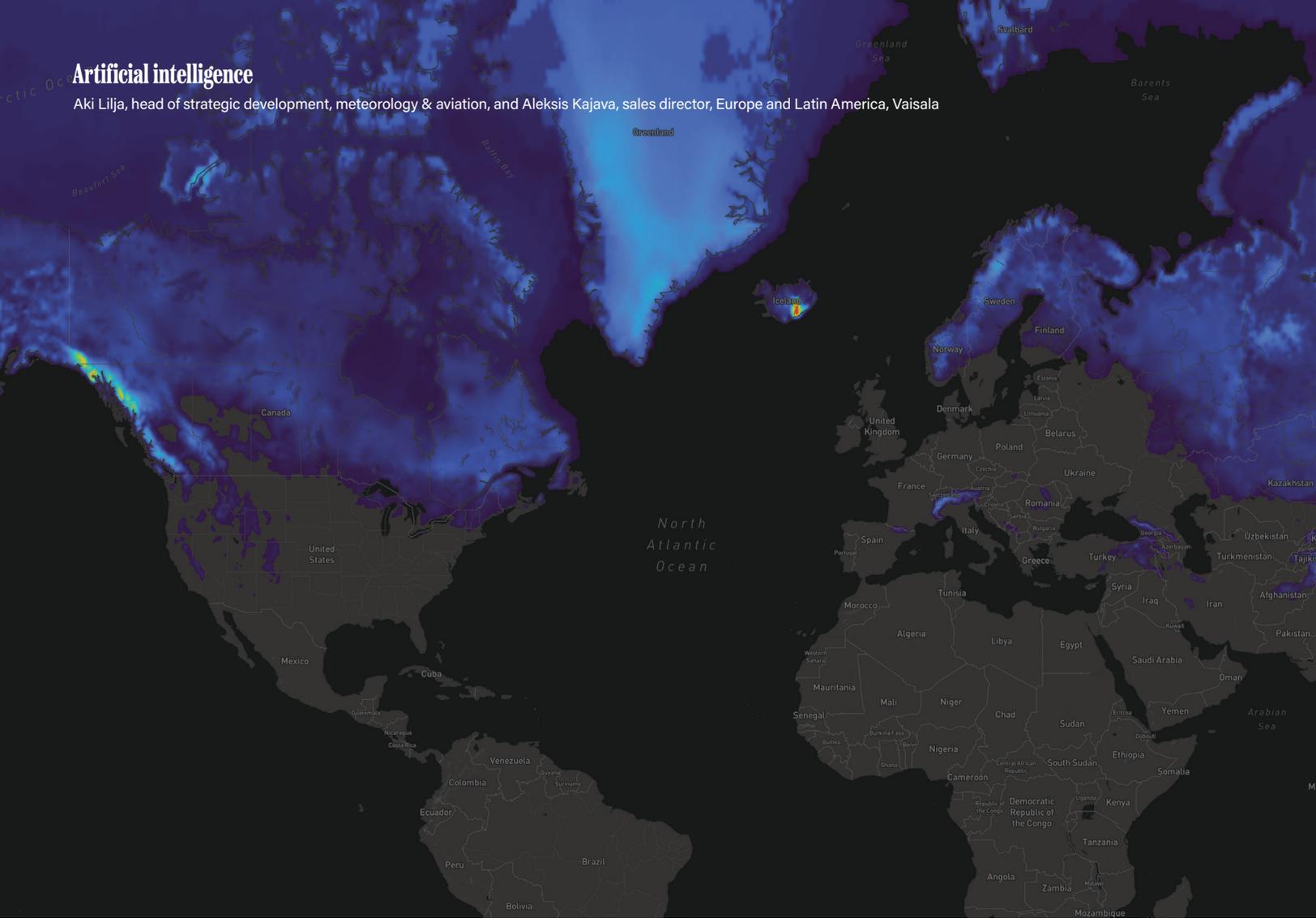


## Artificial intelligence

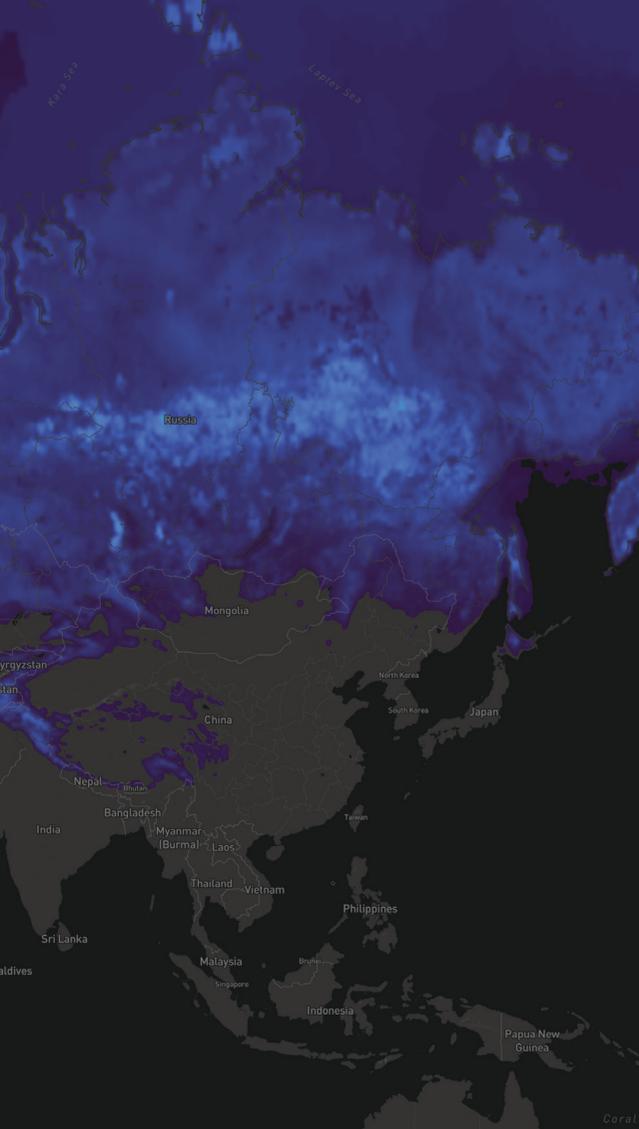
Aki Lilja, head of strategic development, meteorology & aviation, and Aleksis Kajava, sales director, Europe and Latin America, Vaisala



# SMARTER

## forecasts, smarter choices

AI is reshaping weather forecasting – not by replacing traditional models, but by enhancing them – and **Vaisala** is leading innovation with hybrid systems that deliver faster, smarter, more accessible atmospheric insights



// AI is not a silver bullet. The technology works best in tandem with physics-based models"

**W**hen you think about AI in weather forecasting, do you picture machine learning replacing traditional models entirely? Unfortunately, this

all-too-common misconception misses the remarkable innovation happening in the meteorology industry today. AI is not simply supplanting physics-based forecasting but reshaping how we extract value from observations, compress computational complexity and deliver actionable atmospheric insights at speed and scale.

AI's capacity to maximize the utility of existing atmospheric data while dramatically reducing the computational burden of generating weather forecasts offers a legitimate breakthrough. Where traditional numerical weather prediction (NWP) models might take hours to run on supercomputers, AI-powered systems can produce comparable results using just a fraction of the time and energy.

Efficiency gains enabled by AI and machine learning help democratize access to sophisticated forecasting abilities for authorities and entities that previously could not afford the computational infrastructure.

#### ABOVE LEFT:

By combining high-quality global sensor meteorological data with advanced AI tools, the industry can deliver precise and actionable weather insights

#### Fresh data, faster forecasts

AI does not eliminate uncertainty in the atmosphere, but the technology is changing the value chain of weather prediction. At the European Centre for Medium-Range Weather Forecasts, for example, the new AI Forecasting System (AIFS) produces forecasts in less than 1% of the computing time (and energy) needed for traditional runs.

That speed matters. Conventional models can take hours to generate results, meaning forecasts are already based on conditions that may be six hours old. AI enables fresher observations, as it completes the forward computation of the atmosphere much sooner than in the corresponding NWP models.

The technology's speed advantage cascades through the entire forecasting chain. Decision-makers can access nowcasts and short-range forecasts for analytics without waiting for massive computational resources to churn through complicated equations. Developing countries that historically lacked the infrastructure for sophisticated forecasting can now deploy AI-enhanced systems using existing radar and satellite data to create early severe weather warning capabilities.

When AI systems can process observations in near real time, meteorologists can capture rapidly evolving weather patterns that traditional models might miss between cycles. But AI is not a silver bullet. The technology works best in tandem with physics-based models, raising questions about validation, training data and trust.

#### Garbage in, garbage out

Even though AI enables the use of more diverse data sources, it heightens the importance of data quality and traceability. In traditional NWP, meteorologists trust the underlying physics. With machine learning approaches, on the other hand, success depends entirely on the trustworthiness of the target dataset used in training.

Machine learning 'learns' patterns from past events. It cannot invent atmospheric truth from nothing. The old adage of garbage in, garbage out remains. A strongly biased or variable dataset does more harm than no data at all.

Surprisingly, conventional data sources such as radiosonde measurements and surface weather station observations remain crucial for optimal AI performance. Rather than eliminating the need for robust and accurate observational networks, AI technology amplifies their importance.

Metadata emerges as equally fundamental in the AI era. Information about sensor characteristics, calibration history, uncertainty estimates and installation dates provides context that AI models can leverage to better understand the quality and reliability of data.

However, validation and verification processes cannot be overlooked. Meteorology is a regulated field, especially in aviation, where decisions must

be based on traceable, physically sound processes. For training target data and validation datasets, physical traceability of observations helps prevent the introduction of systematic biases into these advanced systems. While predictor data used for inference might allow more flexibility, the foundational measurements that define what constitutes 'correct' weather must maintain rigorous calibration standards.

AI cannot be allowed to hallucinate outcomes. Models must remain anchored to accurate observations, validated against trusted benchmarks and used responsibly.

**Extending lidar measurements with AI**

Practical AI applications in meteorological observations demonstrate the role of machine learning in enhancing rather than replacing traditional measurement. Consider wind lidar systems, which use laser pulses to measure atmospheric conditions. These solutions apply threshold-based filtering to determine whether return signals contain reliable data. Signals above a certain strength threshold are deemed good, and anything below is discarded as noise.

By analyzing multiple variables related to each measurement, such as signal strength, atmospheric conditions, background noise and beam geometry, machine learning models can recover useful data from signals that traditional methods would discard, delivering a more nuanced evaluation.

The result resembles adding more power to the laser system without actually modifying the lidar equipment. In practical terms, AI extends wind lidar measurement range from approximately 1,500m to more than 2,000m.

For renewable energy operators, an extended measurement range means accessing wind data at the nacelle heights of modern turbines, maximizing the availability and accuracy of wind resource assessments. Aviation applications benefit from windshear detection and warnings

**BELOW:** Wind lidar Doppler data filtered with basic threshold (left) and with a multivariate AI model trained by specialist-assessed spectra (right). AI filtering can identify more good data (black points) while also eliminating unwanted data (red points)

// As AI takes on a more prominent role, expectations for observation networks will evolve"

at greater distances and higher altitudes. Now, airports with multiple long runways can provide comprehensive coverage using fewer lidar systems, reducing infrastructure costs while improving safety margins. With lidar, AI is not inventing data. It simply refines the classification of what is usable, rescuing observations that would otherwise be lost.

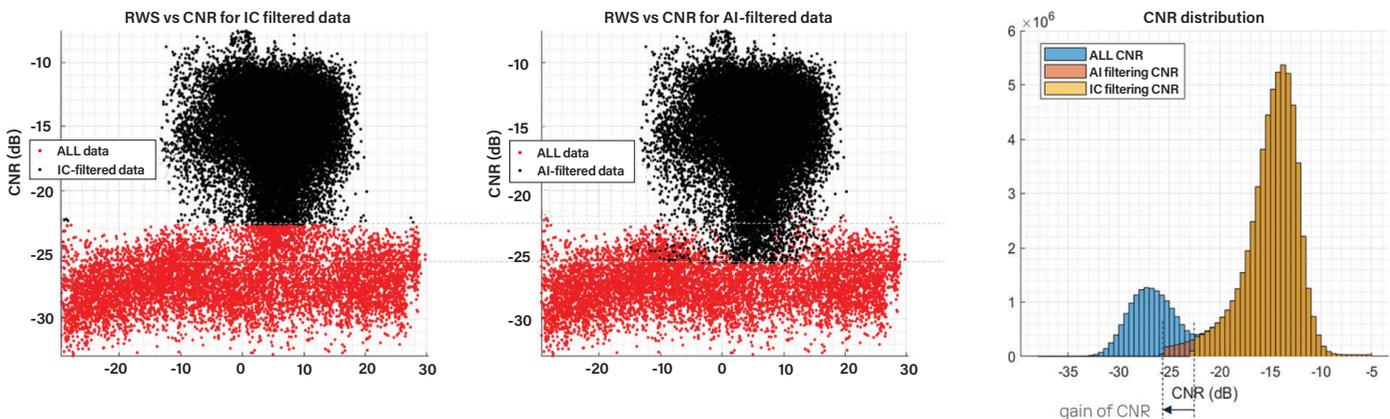
**AI-enhanced radar propels smarter nowcasting**

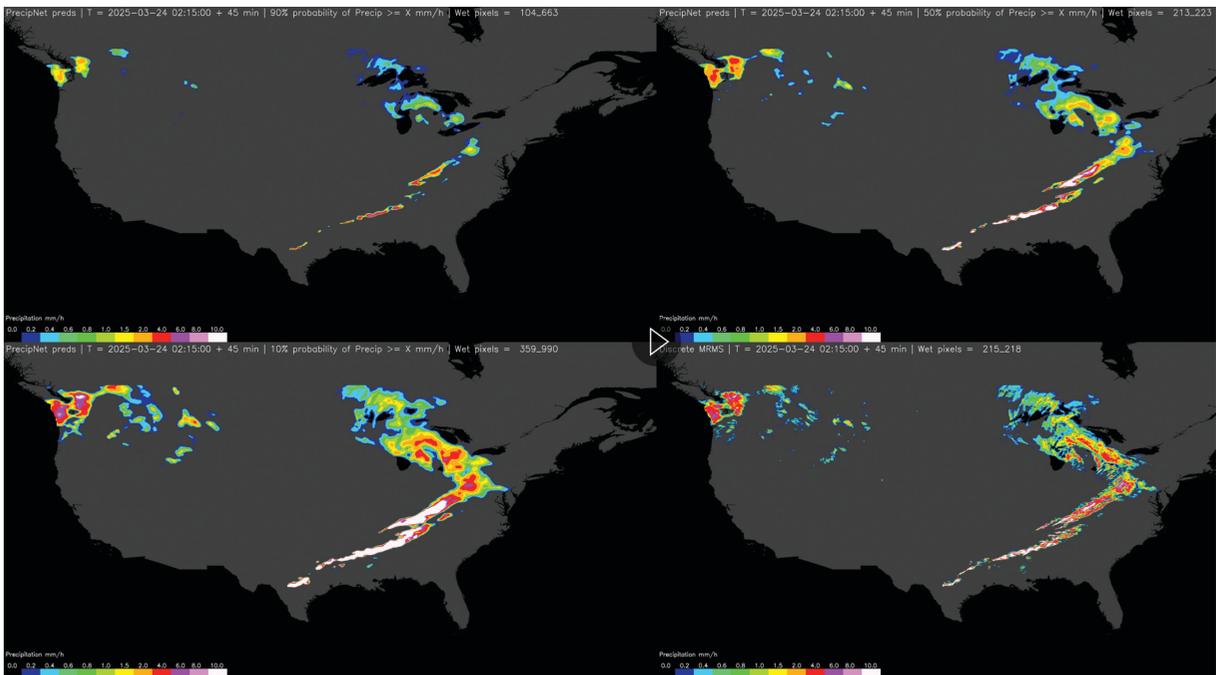
Another frontier lies in weather radar. Traditionally, radars provide snapshots of precipitation that numerical models must assimilate and project forward. But without mathematical extrapolation, however, physics-based methods struggle to follow how rain showers and convective storms move, intensify, dissipate and reform.

Machine learning approaches overcome these limitations by learning from historical precipitation patterns rather than attempting to recreate physical processes from first principles. Advanced weather and environmental data monitoring systems such as Vaisala Xweather combine high-resolution rapid-refresh model data, satellite observations and weather radar measurements through trained neural networks to predict precipitation patterns up to four hours ahead at 15-minute intervals.

When sufficient training data is available, AI models demonstrate superior performance over traditional nowcasting methods for forecasts extending up to eight hours – a timeframe vital for emergency management operations.

For customers, the appeal is not AI for AI's sake but better insights, from clearer flood warnings to more accurate rainfall totals to improved short-range aviation forecasts. Still, deploying these state-of-the-art systems requires calibration and care. Lamentably, it's not as simple as attaching an algorithm to a radar feed because models must be trained, validated and adjusted to local conditions.





**ABOVE:** Example of AI-based precipitation nowcast with confidence limits. The upper left pane shows the dry scenario, “at least this much rain”, while the lower left pane shows the wet scenario, “not more than this”. The upper right shows the predicted most likely rain amount, while the lower right pane has the Multi-Radar Multi-Sensor system of NOAA ground truth for the same time

### Opportunities and misconceptions

The most significant misconception about AI in meteorological applications is the belief that it can create accurate forecasts without quality input data. AI systems excel at finding patterns and relationships in data, but they cannot generate reliable atmospheric information from inadequate observations. Plus, global observation networks are not evenly distributed. Large gaps remain, especially across oceans and in developing regions. AI cannot compensate for missing data entirely, and reliance on commercial or intermittent datasets raises concerns about continuity.

Another common misconception suggests that AI will always outperform traditional deterministic forecasting methods. Reality proves that some situations favor physics-based approaches while others benefit from machine learning techniques. Optimal forecasting often leverages the strengths of each approach for different aspects of prediction.

Simply combining radar systems with AI algorithms doesn't automatically produce superior nowcasts and forecasts. Successful deployment requires a genuine understanding of local atmospheric patterns, validating model performance against high-quality ground truth observations and continuously refining system parameters to improve predictions.

### Evolving expectations

As AI takes on a more prominent role, expectations for observation networks will evolve. Instead of focusing solely on assimilation into physics-based models, datasets must also serve as training and validation targets.

Target data for model training must be representative, trustworthy and meteorologically meaningful, as the quality of this data directly determines the maximum achievable forecast accuracy. Predictor data for training and inference must comprehensively describe atmospheric states, requiring continued investment in

observational networks even as AI reduces computational requirements.

Validation and verification data maintains its conventional role of assessing model performance but becomes more critical as AI systems learn relationships that aren't explicitly physics based. Regular retraining with new datasets and model architectures will become standard practice, creating dynamic requirements for observational data that may shift over time.

This duality – continuity on the one hand, experimentation on the other – will shape how meteorologists view global observation strategies in the years ahead.

### Forecasts of the future

What will a typical forecast look like in 2035? Ten years from now, weather forecasts will likely demonstrate improved accuracy metrics, for example, in precipitation estimation and short-term predictions. Machine learning models will better use existing radar and satellite data, extracting more value from current observational investments. Seasonal and subseasonal forecasting may improve as AI systems learn to model complex interactions between atmospheric, oceanic and biospheric components.

However, the chaotic nature of atmospheric systems won't disappear. Weather forecasts beyond a couple of weeks will have very little skill over climatology, regardless of any technological advances. The real transformation? Industries will receive customized weather predictions for the next hours and days – tailored to their specific needs, along with improved estimates on the impact of the weather forecast for their operations, rather than relying on generic public information.

The future belongs not to AI or traditional forecasting alone but to their intelligent integration, powered by quality observations, guided by physical understanding and delivered through systems that transform atmospheric data into decisions that protect lives and property. ■

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