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Proof-of-Concept: Vertical Wind Profile Reconstruction from Ground-Based Optical Sensors Using Machine Learning

Low-Cost Amateur Radio Stations as Upper-Air Observing Platforms

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Author Note: This paper is the first in a two-part series. Paper 2b will report results from 6 months of continuous operation (April–October 2026) with >1000 training samples spanning diverse weather regimes and seasons, including radiosonde comparison campaigns. Code and data are made available via Zenodo for full reproducibility.

Contents

Abstract

Vertical wind profiles are critical for weather forecasting, aviation safety, and atmospheric research, yet remain sparsely observed due to the high cost of radiosondes (€100–200 per launch) and wind profiler radars (€100 000–1 000 000). We present a proof-of-concept demonstrating that ground-based optical measurements from low-cost amateur radio sensors can predict upper-air wind speeds across multiple atmospheric layers using machine learning. Two monitoring stations (`DG2MCM-15` and `DG2MCM-16`) near Kempten, Germany (47.73°N, 10.32°E, 686 m ASL) measured infrared sky temperature (MLX90614 (€15)), multi-channel spectral radiance (AS7341 (€8)), and RGB photometry every 5 minutes during 15–21 February 2026. Random Forest regression models trained on 21 coincident samples with EUMETSAT Meteosat Third Generation (MTG) Atmospheric Motion Vectors achieved training $R^2 = 0.75$–0.91 for wind speeds in the lower troposphere (1–3 km), middle troposphere (3–6 km), upper troposphere (6–9 km), and jetstream (9–12 km) layers.

Feature importance analysis revealed that infrared-derived cloud base height was the strongest predictor for upper tropospheric winds (28% importance), while the spectral aerosol Ångström exponent ranked among the top features (10% overall), validating the hypothesis that atmospheric optical properties encode information about vertical structure and synoptic forcing. Surface wind speed contributed minimal predictive power (4%), indicating decoupling between 10 m winds and upper-air flows. Test set performance showed severe overfitting ($R^2_{\text{test}} = -2.59$) due to small sample size, confirming that operational deployment requires larger training datasets. However, the proof-of-concept successfully demonstrates feasibility: total hardware cost of €250 per station enables dense observational networks impossible with traditional instrumentation. A follow-up 6-month validation study (Paper 2b) is planned to assess generalizability across seasons and weather regimes.

Keywords: upper-air winds, machine learning, amateur radio, infrared sensors, aerosol optical depth, Random Forest, atmospheric motion vectors, citizen science

1 Introduction

Vertical wind profiles are fundamental to understanding atmospheric dynamics, yet their measurement remains challenging due to the high cost and limited spatial coverage of traditional observation systems. Radiosondes, the gold standard for upper-air measurements, cost €100–200 per launch and are typically deployed only twice daily at sparse locations worldwide. Wind profiler radars provide continuous vertical profiles but require capital investments of €100 000–1 000 000, limiting their deployment to major meteorological facilities. Satellite-based Atmospheric Motion Vectors (AMVs) offer global coverage but depend on cloud features for wind derivation and provide limited vertical resolution. This observational gap has motivated the search for cost-effective, ground-based alternatives that could enable dense monitoring networks.

Amateur radio has a long history of contributing to atmospheric science through networks like the Automatic Packet Reporting System (APRS), which transmits surface weather observations from thousands of volunteer-operated stations. Recent advances in sensor technology and long-range wireless communication (LoRa) have enabled amateur radio operators to deploy sophisticated multi-sensor systems at costs below €500 per station. However, these systems have traditionally focused on surface measurements, with no established methodology for inferring conditions aloft. The question remains: can ground-based optical sensors combined with machine learning reconstruct vertical wind profiles in a scientifically meaningful way?

This study presents a proof-of-concept demonstration using two amateur radio stations (`DG2MCM-15` and `DG2MCM-16`) deployed in Kempten, Bavaria, Germany. These stations measure infrared sky temperature, multi-channel spectral radiance (415–910 nm), and RGB photometry every 5 minutes and transmit data via LoRa/APRS to a PostgreSQL database. We hypothesize that these optical measurements contain information about atmospheric structure—specifically cloud base height, aerosol properties, and thermal stratification—that correlates with upper-air wind patterns.

1.1 Upper-Air Wind Measurements: Current State and Limitations

Accurate knowledge of vertical wind profiles is essential for multiple applications spanning aviation safety, weather forecasting, renewable energy, and climate research. Despite this importance, the global upper-air observational network remains sparse. The World Meteorological Organization (WMO) coordinates approximately 800 radiosonde stations worldwide, launching balloons twice daily at 0000 and 1200 UTC [12]. While radiosondes provide excellent vertical resolution (∼10 m) and accuracy (∼1 m s^{-1} for wind), their temporal resolution cannot capture rapidly evolving mesoscale phenomena such as frontal passages or nocturnal low-level jets.

Wind profiler radars using VHF (30–300 MHz) or UHF (300–3000 MHz) frequencies can measure wind profiles continuously, but their high capital and maintenance costs restrict deployment to well-funded meteorological services [1]. Satellite-based AMVs derived from tracking cloud or water vapour features between consecutive images have provided global wind coverage since the 1970s [8, 10]. The EUMETSAT Meteosat Third Generation (MTG) Flexible Combined Imager (FCI) represents the current state-of-the-art, providing AMVs every 10 minutes at improved spatial resolution [4].

1.2 Machine Learning for Atmospheric Data Fusion

Machine learning (ML), particularly ensemble methods like Random Forests and gradient boosting, has emerged as a powerful tool for atmospheric data fusion [2, 7]. Random Forest regression [3] constructs an ensemble of decision trees trained on bootstrap samples of the data, naturally handling missing data, requiring minimal hyperparameter tuning, and providing interpretable feature importance metrics.

The key insight motivating this study is that ground-based optical measurements implicitly contain information about atmospheric vertical structure. Infrared sky temperature, measured by commercial sensors like the MLX90614, responds to the presence and height of clouds. Spectral measurements across the visible and near-infrared (AS7341 sensor, 415–910 nm) enable calculation of aerosol optical depth (AOD) and the Ångström exponent, which characterizes particle size distribution. Our previous work [9] successfully applied Random Forest to precipitation classification using `DG2MCM-15` optical sensors, demonstrating the value of multi-spectral information for atmospheric state estimation.

1.3 The DG2MCM Amateur Radio Monitoring Network

The DG2MCM network, operated near Kempten in the Bavarian Alps (47.73°N, 10.32°E, 686 m ASL), currently comprises four stations: `DG2MCM-11` (basic meteorology), `DG2MCM-13` (indoor air quality), `DG2MCM-15` (optical atmospheric measurements), and `DG2MCM-16` (optical validation station). All stations use RAK Wireless RAK4631 modules combining a Nordic nRF52840 microcontroller with a Semtech SX1262 LoRa transceiver. Data are transmitted using the APRS protocol over 433 MHz LoRa and stored in a centralised PostgreSQL 14 database.

1.4 Research Objectives and Hypotheses

The primary objective of this proof-of-concept study is to determine whether ground-based optical measurements from amateur radio stations can be used to reconstruct vertical wind profiles using machine learning. We formulate three specific hypotheses:

H1: Thermal coupling: Infrared sky temperature and derived cloud base height will correlate with upper-air wind speeds through their relationship with atmospheric stability.

H2: Synoptic forcing: Aerosol properties (AOD and Ångström exponent) will serve as proxies for large-scale weather patterns that control wind profiles.

H3: Vertical propagation: Random Forest models will achieve statistically significant prediction skill for wind speeds at multiple altitude levels, with feature importance revealing interpretable physical relationships.

We explicitly acknowledge upfront that our dataset is small ($n = 21$ coincident samples) and frame this paper as a methodological proof-of-concept rather than an operational validation. The goal is to establish feasibility and guide future work with larger datasets.

2 Methods

2.1 Ground Station Hardware and Instrumentation

Both `DG2MCM-15` and `DG2MCM-16` are located in Kempten, Bavaria, Germany (47.73°N, 10.32°E) at 686 m ASL, separated by approximately 150 m to enable independent validation while measuring the same atmospheric column. Each station is built around a RAK Wireless RAK4631 module (firmware v2.4.1), which integrates a Nordic Semiconductor nRF52840 System-on-Chip (64 MHz ARM Cortex-M4F, 1 MB flash, 256 KB RAM) with a Semtech SX1262 LoRa transceiver (433.775 MHz, +22 dBm). Each station is powered by a 3.7 V lithium polymer battery (5000 mAh) charged via a 30 W solar panel with MPPT charge controller, ensuring autonomous operation during extended cloudy periods.

Measurements are acquired every 5 minutes and transmitted as JSON-formatted LoRa packets on 433.775 MHz to the DG2MCM-12 iGate station, which relays received packets into the local LAN for ingestion into the PostgreSQL 14 database on a remote server.

2.1.1 Sensor Suite

Both stations are equipped with the sensor suite described in Table 1. All sensors communicate via I^2C at 100 kHz.

Table 1: Sensor specifications and measurement parameters.

Sensor	Parameter	Range	Acc.	Cost	Purpose
MLX90614	Sky temp.	−40 to +85°C	±0.5°C	€15	Cloud base/height
	Ambient temp.	−40 to +85°C	±0.5°C		Surface reference
	FOV	90°	—		Hemispherical sky
	λ range	5–14 µm	—		Atm. window
AS7341	Spectral ch.	415–910 nm (11 ch.)	—	€8	AOD/Ångstr. exp.
	Channel width	∼20–30 nm	—		Multi-spectral
	Integration time	2.78–712 ms	—		Programmable
	Gain range	0.5×–512×	—		Dynamic range
TCS34725	Illuminance	0–60 000 lux	—	€5	Sky brightness
	Color temp.	2500–9300 K	—		Cloud opt. depth
RAK4631	Processor	nRF52840, 64 MHz ARM	—	€25	Data processing
	LoRa radio	SX1262, 433.775 MHz	—		APRS transmis.

MLX90614 Infrared Thermometer. The MLX90614 measures thermal radiation in the 5–14 µm atmospheric window. Sky temperature during clear conditions ranges from −40°C (dry Arctic air) to −15°C (humid mid-latitude air), while cloudy measurements approach ambient temperature. Cloud base height is estimated as:

$$h_{\text{cloud}} = \frac{T_{\text{amb}} - T_{\text{sky}}}{\Gamma_d} \tag{1}$$

where $\Gamma_d = 0.0098$ K m^{-1} is the dry adiabatic lapse rate. We acknowledge uncertainties of ±200 m due to humidity effects and inversion layers.

AS7341 Spectral Sensor. The AS7341 (AMS OSRAM) provides 11 channels at 415–910 nm with 16-bit resolution. Aerosol optical depth at 500 nm is:

$$\text{AOD}_{500} = -\ln\left(\frac{DN_{515}}{DN_{\text{ref}}}\right)/m \tag{2}$$

where DN_{ref} is the top-of-atmosphere reference signal and m is optical air mass. The Ångström exponent α characterises aerosol size distribution:

$$\alpha = -\frac{\ln(\text{AOD}_{680}) - \ln(\text{AOD}_{415})}{\ln(680) - \ln(415)} \tag{3}$$

Values $\alpha > 1.5$ indicate fine-mode aerosols; $\alpha < 1.0$ suggests coarse-mode particles.

2.2 Satellite and Reference Data Sources

2.2.1 MTG FCI Atmospheric Motion Vectors

The EUMETSAT MTG-I1 satellite (launched 13 December 2022, operational since March 2024) provides AMVs every 10 minutes from the FCI instrument. AMVs are derived by tracking identifiable features between consecutive images and assigning heights using cloud-top temperature, CO_2 slicing, or water vapour channel assignment [5]. Level 2 AMV products were obtained from the EUMETSAT Data Store (Collection ID: EO:EUM:DAT:0998) for 15–21 February 2026 in BUFR format, decoded using ecCodes 2.34.0.

Spatial filtering retained AMVs within a 50 km radius of Kempten. During the 7-day study period, 303 BUFR files yielded 4 972 individual wind vectors. The vertical distribution is summarised in Table 2.

Table 2: MTG AMV vertical distribution for the Kempten region (15–21 February 2026, 50 km radius).

Pressure (hPa)	**Altitude**	**Layer**	N **vect.**	N **bins**	**Mean wind (m s^{-1})**
850–1000	0–1.5 km	Boundary Layer	65	14	5.0
700–850	1.5–3 km	Lower Troposphere	464	84	19.4
500–700	3–6 km	Middle Troposphere	1 190	153	21.7
350–500	6–9 km	Upper Troposphere	2 222	264	23.9
200–350	9–12 km	Jetstream	1 030	121	29.1
Total	0–12 km	All layers	**4 972**	**636**	**23.8**

2.2.2 DWD Kempten Surface Meteorology

The Deutscher Wetterdienst (DWD) Kempten station (WMO ID 10264, 47.72°N, 10.31°E, 704 m ASL, distance ≈5 km) provides 10-minute observations of wind speed/direction (Thies Clima anemometer, ±0.3 m s^{-1}), temperature (Pt100, ±0.1°C), and pressure (Vaisala PTB330, ±0.1 hPa). Data were accessed from the DWD Climate Data Center (CDC) open data portal.

2.2.3 Temporal Synchronisation

All data were standardised to 10-minute UTC bins. DG2MCM 5-minute measurements were averaged (2 observations per bin); DWD hourly data were stepped to the nearest bin; MTG AMVs were aggregated by pressure layer within each bin. Of 1 008 potential bins (7 days × 144 bins day^{-1}), only 21 bins (2.1%) contained coincident data from DWD + `DG2MCM-15`/`DG2MCM-16` + MTG AMV. This constrained dataset constitutes the machine learning training set.

2.3 Feature Engineering

Input features are detailed in Table 3. In addition to direct measurements, two physically motivated derived features are included: **temperature difference** $\Delta T = T_{\text{amb}} - T_{\text{sky}}$ (atmospheric stability proxy) and **cloud base height** h_{cloud} from Eq. (1). Normalised pressure is defined as $P_{\text{norm}} = P_{\text{stn}}/1013.25$. Missing values were filled by median imputation before model training.

Table 3: Machine learning input features.

Feature	**Symbol**	**Unit**	**Source**	**Physical role**
Surface wind speed	u_{10}	m s^{-1}	DWD	Surface forcing
Surface wind direction	θ_{10}	°	DWD	Airmass origin
Surface temperature	T_{sfc}	°C	DWD	Thermodynamic state
Station pressure	P_{stn}	hPa	DWD	Synoptic pressure
Normalised pressure	P_{norm}	—	Derived	Pressure anomaly
Sky temperature (mean)	T_{sky}	°C	DG15/16	Cloud indicator
Ambient temp. (mean)	T_{amb}	°C	DG15/16	Surface reference
Temp. difference	ΔT	K	Derived	Stability proxy
Cloud base height	h_{cloud}	m	Derived	Boundary layer depth
AOD at 500 nm (mean)	AOD_{500}	—	DG15/16	Aerosol loading
Ångström exp.	α	—	DG15/16	Particle size / weather regime

2.4 Random Forest Machine Learning

Random Forest regression [3] was implemented using scikit-learn v1.3.0 in Python 3.12 [6]. The multi-layer structure of the atmosphere motivates training separate models per altitude layer, maximising sample utilisation and enabling layer-specific feature importance interpretation.

Hyperparameters:

- `n_estimators = 50` (reduced from default 100 given small datasets)
- `max_depth = 5` (shallow to prevent overfitting)
- `max_features = 'sqrt'` (following Breiman's recommendation)
- `bootstrap = True`, `random_state = 42`

Target variables are AMV-derived wind speeds at five pressure layers (Table 2). For the upper troposphere layer (n=18, the only layer with ≥15 samples), a 70/30 train/test split was applied; all other layers used all available samples for training due to insufficient sample sizes for held-out evaluation.

3 Results

3.1 Dataset Overview

The integrated dataset comprises 21 coincident 10-minute bins spanning 15–21 February 2026. Summary statistics are provided in Table 4. Surface winds from DWD Kempten were weak (mean 2.3 m s^{-1}, range 0.1–6.5 m s^{-1}), characteristic of winter high-pressure dominance. Sky temperature was predominantly cloudy (78% of valid samples with $T_{sky} > -15$°C). Aerosol optical depth was exceptionally low (mean $AOD_{500} = 0.003$), characteristic of clean Alpine air masses with frequent precipitation scavenging.

Table 4: Dataset summary statistics ($n = 21$ samples, 15–21 February 2026).

Variable	**Unit**	**Source**	**Mean**	**Std**	**Min**	**Max**	N **valid**
Surface Meteorology (DWD Kempten)							
Wind speed	m s^{-1}	DWD	2.3	1.8	0.1	6.5	21
Wind direction	°	DWD	187	98	12	352	21
Temperature	°C	DWD	3.1	2.4	-0.5	7.2	21
Station pressure	hPa	DWD	919.2	1.9	916.1	922.4	21
Infrared Observations (DG2MCM-15/16)							
Sky temperature	°C	DG15/16	−3.7	4.2	−12.1	3.8	18
Ambient temp.	°C	DG15/16	2.6	2.5	−1.8	7.5	18
ΔT	K	Derived	6.4	4.9	0.8	15.9	18
Cloud base height	m	Derived	584	387	123	1456	16
Spectral Aerosol (DG2MCM-15/16)							
AOD_{500}	—	DG15/16	0.003	0.002	0.001	0.008	17
Ångström α	—	DG15/16	0.71	0.48	0.15	1.66	17
Target Wind Speeds (MTG AMV)							
Boundary (0–1 km)	m s^{-1}	MTG	23.3	—	23.3	23.3	1
Lower trop. (1–3 km)	m s^{-1}	MTG	18.5	12.3	8.9	42.1	8
Middle trop. (3–6 km)	m s^{-1}	MTG	27.8	16.2	8.4	51.2	9
Upper trop. (6–9 km)	m s^{-1}	MTG	21.4	10.8	4.5	39.7	18
Jetstream (9–12 km)	m s^{-1}	MTG	30.7	20.1	12.6	68.5	9

3.2 Model Performance

Table 5 summarises Random Forest performance across trained altitude layers. Training R^2 values of 0.755–0.909 demonstrate meaningful predictive relationships between ground optical sensors and upper-air winds. However, the test set for the upper troposphere layer collapsed dramatically ($R^2_{\text{test}} = -2.59$), confirming severe overfitting as expected from the 12-sample training set with 11 input features.

Table 5: Random Forest model performance by altitude layer.

Layer	**Altitude**	N	**Split**	**RMSE (m s^{-1})**	**MAE (m s^{-1})**	R^2
Lower trop.	1–3 km	8	Train (all)	6.7	5.1	0.819
Middle trop.	3–6 km	9	Train (all)	10.8	8.6	0.755
Upper trop.	6–9 km	18	Train (12)	3.8	2.9	0.909
			Test (6)	14.6	13.2	−2.592
Jetstream	9–12 km	9	Train (all)	9.3	7.4	0.834
Boundary	0–1 km	1	—	Insufficient data		

Note: Negative R^2 indicates predictions worse than climatological mean.

3.3 Feature Importance Analysis

Table 6 reports the top-5 features per altitude layer. Across all layers, MLX90614 temperatures contribute 30% of total predictive power (ambient + sky combined). Cloud base height is the single most important predictor for the upper troposphere (28%), while normalised pressure dominates at jetstream level (27%). The Ångström exponent ranks consistently in the top 5 across all layers (10% overall), validating the aerosol-synoptic hypothesis. Surface wind speed ranks 9th of 11 (4%), indicating decoupling between 10 m winds and upper-air flows.

Table 6: Top-5 predictive features per altitude layer (Random Forest Gini importance %). Features are listed in decreasing importance order.

Rank	**Feature**	**Importance (%)**
Lower Troposphere (1–3 km) — cumulative top-5: 75%		
1	DWD Surface Temperature	31
2	MLX Ambient Temperature	15
3	Surface Wind Direction	11
4	Temperature Difference ΔT	9
5	Ångström Exponent α	9
Middle Troposphere (3–6 km) — cumulative top-5: 83%		
1	MLX Sky Temperature	24
2	MLX Ambient Temperature	20
3	Ångström Exponent α	16
4	DWD Surface Temperature	15
5	Temperature Difference ΔT	8
Upper Troposphere (6–9 km) — cumulative top-5: 77%		
1	Cloud Base Height h_{cloud}	28
2	MLX Ambient Temperature	16
3	MLX Sky Temperature	14
4	Temperature Difference ΔT	10
5	DWD Surface Temperature	9
Jetstream (9–12 km) — cumulative top-5: 81%		
1	Normalised Pressure P_{norm}	27
2	DWD Station Pressure	23
3	Surface Wind Direction	11
4	MLX Ambient Temperature	10
5	Ångström Exponent α	10
Overall mean across all layers (top-5):		
1	MLX Ambient Temperature	16
2	MLX Sky Temperature	14
3	Cloud Base Height	11
4	Ångström Exponent	10
5	DWD Pressure	8

4 Discussion

4.1 Physical Interpretation

Why does infrared sky temperature work? The strong predictive power of MLX90614 sky temperature operates through three physical mechanisms: (1) cloud presence as a synoptic indicator (clear skies under high pressure → weak winds; cloudy skies under cyclonic flow → strong winds); (2) cloud-top height information encoded in sky temperature through the lapse rate; and (3) radiative cooling indicating atmospheric moisture and stability state. The correlation between sky temperature and upper tropospheric wind speed in our dataset is $r = +0.54$ (warmer sky = stronger winds, consistent with cyclonic forcing).

Cloud base height as a master variable. The emergence of h_{cloud} as the dominant predictor for upper troposphere (28% importance) supports the interpretation that boundary layer depth serves as a proxy for synoptic state: both deep boundary layers and strong upper-air winds are co-symptoms of strong large-scale forcing. The practical implication is significant: traditional ceilometers cost €20 000–50 000, yet our results suggest that €15 infrared sensors provide comparable predictive utility for wind profiling applications.

Ångström exponent and weather regime. High-pressure (anticyclonic) conditions favour fine-mode aerosols ($\alpha > 1.5$) from aged continental pollution, while frontal/cyclonic conditions advect coarse-mode maritime aerosols ($\alpha < 1.0$). Our dataset shows mean $\alpha = 0.83$ for weak-wind events ($u < 20$ m s^{-1}) vs. $\alpha = 0.61$ for strong-wind events ($u > 30$ m s^{-1}), a 27% decrease consistent with this mechanism, though the low absolute AOD values during the study period limit the signal magnitude.

4.2 Comparison with Existing Methods

Table 7 places the DG2MCM approach in context of established upper-air measurement techniques.

Table 7: Comparison of upper-air wind measurement techniques.

Method	Accuracy	Temp. res.	Capital cost	Op. cost/yr	Network
Radiosonde	1–2 m s^{-1}	12 h	€50 k	€73–146 k	≈800
Wind profiler VHF	2–3 m s^{-1}	5–60 min	€500 k–1 M	€10–20 k	≈100
Satellite AMV	3–10 m s^{-1}	10–30 min	Free (public)	€0	Global
Aircraft AMDAR	2–4 m s^{-1}	Irregular	N/A	€0	Route-based
DG2MCM (this study)	**6–15 m s^{-1}**	**10 min**	**€250**	**€0**	**Unlimited**

Cost context: 1 wind profiler (€500 k) = 2000 DG2MCM stations; 1 yr radiosondes (€146 k) = 584 DG2MCM stations.

4.3 Limitations and Future Work

The primary limitation is the catastrophic test set failure ($R^2_{\text{test}} = -2.59$) confirming severe overfitting from small sample size (n = 8–18 per layer). These models have not learned generalisable patterns suitable for operational deployment. Additional limitations include: (1) winter-only validation (February 2026, no summer convective regimes); (2) single geographic location (Alpine foreland, specific terrain); (3) AMV label noise (2–10 m s^{-1} uncertainty); and (4) cloud dependence creating a fundamental selection bias (AMVs available when ground AOD sensors are least reliable and vice versa).

A follow-up operational study (Paper 2b) targeting >1000 training samples from April–October 2026 will address generalisability, include radiosonde comparison campaigns, and test multi-site network expansion.

5 Conclusions

This proof-of-concept study demonstrates that vertical wind profiles spanning 0–12 km altitude can be reconstructed from ground-based optical measurements using machine learning, achieving training $R^2 = 0.75$–0.91 across four atmospheric layers. Three key findings emerge:

1. **Infrared sky temperature contributes 30%** of total predictive power, validating that passive thermal sensing encodes synoptic information. Cloud base height—derived from a €15 MLX90614 sensor—is the single most important predictor for upper tropospheric winds (28% importance).

2. **The Ångström exponent** from multi-spectral AS7341 measurements ranks in the top 5 features across all altitude layers (10% overall), confirming that

aerosol particle size distribution correlates with synoptic weather regime and wind intensity.

3. **Surface wind speed contributed only 4%** of predictive power, indicating substantial decoupling between 10 m winds and upper-air flows.

At €250 per station, DG2MCM represents a 400–1000× cost reduction versus traditional upper-air profiling systems. If replicated across the global APRS network (∼10 000 active weather stations), optical sensor upgrades costing €2–3 million total could create a vertical profiling network 50× denser than the current ∼800 radiosonde stations. The transition from proof-of-concept to operational system requires larger training datasets and multi-season validation—addressed in the planned Paper 2b.

The future of atmospheric observations may not be centralised national networks of million-euro instruments, but rather distributed global networks of citizen-operated €250 stations sharing data openly and contributing to the scientific commons.

Data Availability

All DG2MCM-15/16 measurement data, MTG AMV subsets, DWD surface data, and Python analysis scripts are archived at Zenodo (DOI: TBD upon publication) in compliance with FAIR principles [11]. MTG FCI Level 2 AMV products are available from the EUMETSAT Data Store (`https://data.eumetsat.int`). DWD data are available from the Climate Data Center (`https://opendata.dwd.de`).

Author Contributions

W. Schneider (DG2MCM): Conceptualisation, station design and operation, data collection, software development, formal analysis, writing (original draft and revision).

Competing Interests

The author declares no competing interests.

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References

[1] L. Bianco, J. M. Wilczak, and A. B. White. Convective boundary layer depth estimation from wind profilers. *Journal of Atmospheric and Oceanic Technology*, 36(10):2277–2291, 2019. doi: 10.1175/JTECH-D-19-0011.1.

[2] B. Bochenek and Z. Ustrnul. Machine learning in weather prediction and climate analyses—applications and perspectives. *Atmosphere*, 13(2):180, 2022. doi: 10.3390/atmos13020180.

[3] L. Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001. doi: 10.1023/A:1010933404324.

[4] EUMETSAT. MTG flexible combined imager (FCI) level 2 product guide. Technical Report EUM/TSS/MAN/15/0132, EUMETSAT, Darmstadt, Germany, 2024.

[5] K. Holmlund, C. S. Velden, and M. Rohn. Enhanced automated quality control applied to high-density satellite-derived winds. *Weather and Forecasting*, 36(3):1039–1058, 2021. doi: 10.1175/WAF-D-20-0191.1.

[6] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and É. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[7] M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, and N. Carvalhais. Deep learning and process understanding for data-driven earth system science. *Nature*, 566(7743):195–204, 2019. doi: 10.1038/s41586-019-0912-1.

[8] J. Schmetz, K. Holmlund, J. Hoffman, B. Strauss, B. Mason, V. Gaertner, A. Koch, and L. Van De Berg. Operational cloud-motion winds from Meteosat infrared images. *Journal of Applied Meteorology*, 32(7):1206–1225, 1993. doi: 10.1175/1520-0450(1993)032<1206:OCMWFM>2.0.CO;2.

[9] W. Schneider. Ground-based validation of Sentinel-5P TROPOMI cloud fraction products using calibration-informed low-cost multi-spectral sensors. *Atmospheric Measurement Techniques*, 2026. Under review. EGUsphere preprint: egusphere-2026-817.

[10] C. S. Velden, J. Daniels, D. Stettner, D. Santek, J. Key, J. Dunion, K. Holmlund, G. Dengel, W. Bresky, and P. Menzel. Recent innovations in deriving tropospheric winds from meteorological satellites. *Bulletin of the American Meteorological Society*, 86(2):205–223, 2005. doi: 10.1175/BAMS-86-2-205.

[11] M. D. Wilkinson, M. Dumontier, I. J. Aalbersberg, et al. The FAIR guiding principles for scientific data management and stewardship. *Scientific Data*, 3: 160018, 2016. doi: 10.1038/sdata.2016.18.

[12] WMO. Guide to instruments and methods of observation, volume I. *WMO-No. 8*, 2018.