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ANALYSES OF EUROPEAN TERMINAL AERODROME WEATHER FORECASTS IN 2022 AND 2023

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Abstract. Terminal Aerodrome Forecasts (TAFs) are essential components of aviation meteorology, providing critical information for flight safety and operational decision-making. This study conducts a comprehensive analysis of TAF for European airports during the years 2022 and 2023, leveraging Python functions accessible via a dedicated GitHub repository. The complexity inherent in TAF, characterized by diverse change groups, header formats, and regional variations, presents challenges for accurate interpretation.

The analysis focuses on key parameters within TAF, including the count of corrected messages and the frequency and types of change groups. The count of corrected messages serves as a metric for evaluating the quality of service provided, while the examination of change group utilization reveals distinct patterns and tendencies specific to each airport.

The findings underscore the significance of regional regulations, meteorologist decision-making, and adherence to International Civil Aviation Organization (ICAO) standards in shaping TAF. The GitHub repository and associated Python functions presented in this study provide valuable resources for meteorologists, researchers, and aviation personnel to conduct in-depth analyses and derive insights from TAF. Ultimately, this study identifies local differences and inconsistencies in the publication of TAF, laying the groundwork for enhancing their consistency and uniformity.

Keywords: TAF, aviation meteorology, terminal aerodrome forecast, change groups, European airports.

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1. Introduction

Aviation meteorological Terminal Aerodrome Forecasts (TAF), depicted in the Figure 1, serve as the cornerstone of aviation meteorological practice, crucially underpinning flight safety and operational decisions. Formulated in a concise code format, they encapsulate essential information indispensable for global aviation participants. This standardized format is universally adhered to by states aligned with the International Civil Aviation Organization (ICAO) or World meteorological organization (WMO) standards, supplying a diverse spectrum of recipients, encompassing civilian, military, professional, and recreational pilots, meteorologists, and external users alike.

Despite the growing trend towards automated meteorological observations, the production of TAF still relies significantly on meteorologist's expertise. Scrutinizing these forecasts and their underlying methodologies holds the potential to substantially refine their accuracy and uniformity. The TAF inherent irregularity poses a persistent challenge for automated interpretation, characterized by a series of distinctive complexities:

- Varied counts of change groups;
- Fluctuating numbers of elements within each group;
- Diverse header formats for predictions;
- Pervasive data availability issues, distinct from observations;
- Wide-ranging regional nuances and compliance mandates.

This study endeavours to deliver a vast analysis executed through Python functions shared within a GitHub repository (Sládek, 2024). These notebooks provide a tool for fellow meteorologists, offering a swift mechanism for dissecting a range of reports, as well as for researchers and aviation personnel. Comprehensive explanations of each function empower meteorologists to tailor these tools to their unique exigencies.

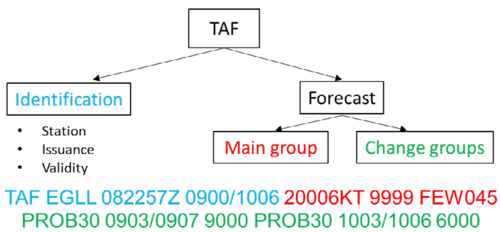

Figure 1. Schematic depiction of the TAF and its structure divided to the header (identification) and forecast part

Although TAF reports have been subjected to numerous analyses, they primarily find their place in technical reports, analyses, and safety assessments. Beyond the formulation of TAF detailed in ICAO Annex 3 (International Civil Aviation Organization [ICAO], 2018), the benchmark of quality is elucidated in Section 7.4 of ICAO Regulation 9873, the Manual on Quality (ICAO, 2010). This stipulates the overarching requisites that meteorological services and products must fulfil, including:

- Fulfilment of primary user (airlines/crews) requisites;
- Prompt assimilation of revised WMO/ICAO standards;
- Minimization of message correction or delay;
- Timely distribution of documentation to airline personnel;
- Punctual preparation of periodic summaries;
- Precision of issued forecasts.

Several papers have dealt in more detail with the actual methods for determining accuracy, e.g. (Mahringer, 2008; Sharpe et al., 2016; Novotny et al., 2021; Sladek, 2019, 2021). The focus of the research has been on quantifying the characteristics of forecasts regarding the minimization of message corrections (as referred to in the third bullet point) and, to some extent, the precision of issued forecasts (point 6). These studies recognize the inherent complexity of weather prediction, particularly evident in the TAF blend of deterministic and probabilistic predictions. Moreover, the incorporation of various factors to determine the periodicity of change adds further intricacy. Consequently, the establishment of standardized weights for these forecasts remains a work in progress, with ongoing research aimed at refining these methodologies.

Previous studies have emphasized the critical role of weather forecasting in optimizing aerodrome operations and ensuring safe air traffic management (Simone et al., 2022). While TAF are a routine operation for aerodrome systems, their accuracy and reliability remain paramount for effective decision-making. This paper proposes a performance-based analysis of weather forecast accuracy tailored to International Civil Aviation Organization (ICAO) standards, aiming to provide operational insights for both Weather Service Providers (WSP) and Air Navigation Service Providers (ANSP).

None of these studies focused on the overall attributes of the forecasts and how they change geographically and over time. This could be one of the key aspects of assessing the quality of forecasts. In addition to international regulations, there may be a number of internal regulations and guidelines, as well as changes.

An important consideration is the number of changes that can be introduced at the national level on a year-on-year basis. As an example of changes that can be made within one-year period, the changes implemented in the Czech Republic for the years 2022–2023 are exemplified through various modifications. This accents the need for continuous and coordinated international monitoring.

The primary and pivotal adjustment revolves around Václav Havel Airport Prague (LKPR), the largest international airport in the Czech Republic, boasting the highest traffic on runways and aprons. Initially, TAF were issued at six-hour intervals, with a forecast validity of thirty hours, occurring at 00:00, 06:00, 12:00, 18:00 UTC. In response to the request of the Czech Air Navigation Agency, and the commencement of the 2023 contract for aeronautical meteorological information and services by the Czech Meteorological Office, the frequency of sending TAF to LKPR was halved. Presently, these forecasts are dispatched at 00:00, 03:00, 06:00, 09:00, 12:00, 15:00, 18:00, and 21:00 UTC. This alteration has notably reduced the number of TAF AMD LKPR messages and significantly enhanced forecast accuracy.

Another notable transformation involved the reduction of the TAF validity period for civil, regional airports Karlovy Vary (LKKV), Brno (LKTB), and Ostrava (LKMT). Although the TAF sending times remain at 00:00, 06:00, 12:00, 18:00 UTC, the validity period was shortened from 30 hours to 24 hours. Consequently, TAF for LKKV, LKTB, and LKMT are now crafted for 24 hours, aligning with the validity of TAF for all military airports in the Czech Republic, namely Praha – Kbely (LKKB), Čáslav (LKCV), Náměšť (LKNA), Pardubice (LKPD).

The most recent innovation transpired in August 2023 when the Czech Meteorological Office assumed meteorological security responsibilities for České Budějovice Airport (LKCS). In collaboration with the airport operator and the Czech Air Traffic Control, the Czech Meteorological Office initiated the issuance of short TAF for LKCS, valid for only 9 hours. These forecasts are released at 06:00, 09:00, 12:00, 15:00, 18:00, 21:00 UTC, and exclusively when the airport is operational, potentially also unscheduled and upon special request from the airport operator.

These adjustments underscore the necessity of conducting real-time or near-real-time evaluations of TAF forecasts, as any unforeseen alterations in national regulations markedly impact the airport's reliability for pilots. To implement such a system effectively, comprehensive analyses of the current state are imperative. In addition to providing tools for analyzing TAF, this study seeks to address a fundamental question: Can a comprehensive analysis of the nature of change groups serve as a robust indicator for mapping regulatory changes, internal directives compliance, adherence to ICAO regulations, and ultimately, the complexity of weather and aviation forecaster's performance when comparing airports in close proximity? By delving into the intricacies of change group dynamics, this research aims to shed light on the multifaceted challenges faced by aviation meteorologists and regulatory bodies, offering valuable insights for enhancing forecast accuracy and regulatory compliance across airport networks.

2. Data and methods

The primary data source in this study emanated from the universally employed standardized TAF (Figure 1). Regularly disseminated, these TAF adhere to ICAO guidelines and regional directives stipulated by the respective competent authorities, such as the Civil Aviation Authority in the Czech Republic. Manifesting in a standardized code format, the TAF concisely describe the prevailing atmospheric conditions and significant anticipated changes in selected meteorological parameters over the forecast duration.

Within the Czech Republic, aligned with recommendations in Annex 3, a TAF boasts a validity span of either 24 or 30 hours, necessitating issuance at intervals of 6 or 9 hours, with a release frequency of 3 hours. Geographical variations emerge across the globe, governed by distinctive national, regional, and local regulations.

Vital for maintaining its accuracy and compliance, the TAF remains subject to continuous monitoring, as dictated by regulations. Transgressing the thresholds set by binding regulations and agreements mandates the swift issuance of an Amendment. Notably, only one valid forecast for a specific airport can persist concurrently; hence, an amendment or a new forecast automatically cancels the preceding one.

In this research, TAF forecasts from 45 European airports (Figure 2) were analyzed.

Airports were selected from major European cities and this selection was augmented by including the three London airports (London Heathrow: EGLL, London Stansted: EGSS, and London Luton: EGGW). The aim was to investigate differences within proximity, where similar weather conditions could prevail.

Aggregate number of change groups (part of the forecast containing expected significant changes) become pivotal. This complexity is underscored in (Novotny et al., 2021). The authors emphasize that compliance with regulatory norms may occasionally hinder certain adjustments, even if these modifications align with meteorological insights. Basically, a forecast, despite capturing meteorological dynamics with precision, must adhere to formal principles to sustain clarity and intelligibility, necessitating a balance between technical precision and regulatory conformity.

2.1. Data acquisition

The initial phase encompassed the procurement of data, a pivotal endeavour executed through diverse databases. The dedicated notebook, titled "Taf_get_data.ipynb," (Sládek, 2024) specifically interacts with the Ogimet (Ogimet, 2024) database. This interaction leverages the Python modules "requests" (*Requests 2.31.0*, 2024) and "bs4" (*Beautifulsoup4 4.12.3*, 2024) (The Python Package index, 2024a, 2024b), enabling the extraction of pertinent text from the database (Figure 3). The user's role is straightforward and is limited to specifying the following parameters:

1. A compilation of desired ICAO indicators.
2. The initiation year and month (with data spanning the entirety of the month).
3. The designated storage location for the acquired dataset.

Figure 3 shows the flowchart of the function that automatically retrieves the data. The first step starts in the bottom left corner, using concatenation to create a URL based on user parameters. A Request to Ogimet database is entered, a bs4 object is created, which extracts the query

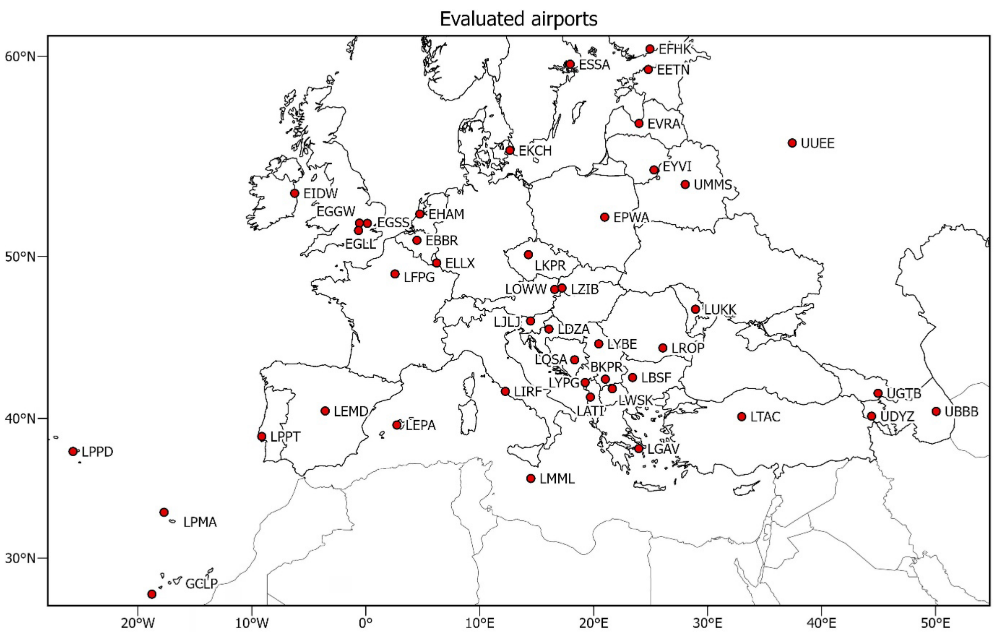

Figure 2. Analysed airports and their ICAO indicators

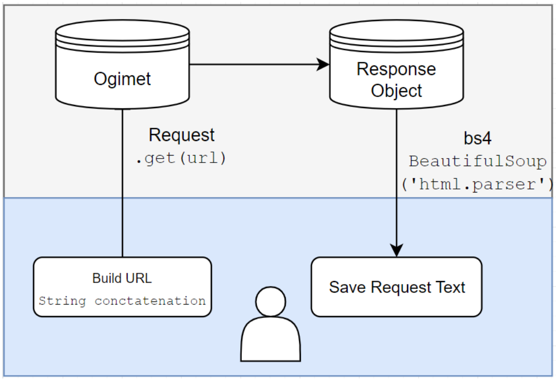

Figure 3. Scheme of retrieving data from the Ogimet database

text using an html parser. This text contains the one that would be displayed to the user on the page.

Given that the stored file exclusively contains unprocessed text, encompassing the introduction, page headers, and annotations, an indispensable data refinement function was devised. This function is integrated within the "Taf_clean.ipynb" notebook. The input is displayed in the Figure 4 and the outcome after cleaning and splitting by individual forecasts in the Figure 5.

Datasets sourced from different databases often encompass diverse forms of identifiers, headers, or accompanying textual information, as exemplified in Figure 4. However, the focus lies in extracting solely the encoded predictions from such datasets (Figure 5).

```
##############################################################
# Query made at 07/20/2023 09:29:20 UTC
# Time interval: from 07/01/2020 00:00  to 07/31/2020 23:59  UTC
##############################################################

##############################################################
# LATI, Tirana (Albania)
# WMO index: 13615. WIGOS ID: 0-20000-0-13615
# Latitude 41-19-59N. Longitude 019-46-59E. Altitude 89 m.
##############################################################

# No METAR/SPECI reports frome LATI in database.

# No short TAF reports from LATI in databse.

#####################################
#  large TAF from LATI
#####################################
202007010500 TAF LATI 010500Z 0106/0206 VRB04KT CAVOK
                       TX35/0112Z TN20/0204
                       TEMPO 0109/0112 34012KT=
202007011100 TAF LATI 011100Z 0112/0212 34010KT CAVOK
                       TX35/0112Z TN20/0204Z
                       BECMG 0117/0119 VRB03KT=
```

Figure 4. Ogimet File downloaded by the first Jupyter notebook

	TAF Forecast
0	202007010500 TAF LATI 010500Z 0106/0206 VRB04K...
1	202007011100 TAF LATI 011100Z 0112/0212 34010K...
2	202007011700 TAF LATI 011700Z 0118/0218 VRB03K...
3	202007012300 TAF LATI 012300Z 0200/0224 VRB02K...
4	202007020500 TAF LATI 020500Z 0206/0306 VRB02K...

Figure 5. Ogimet File with cleaned and split data

Figure 4 and Figure 5 indicate that the databases are not always uniformly set up and a slightly modified reading algorithm must be created for each of them. In general, preprocessing and data cleaning is a very challenging job in data analysis. However, rigid approach in this phase provides much less difficulties in the subsequent analysis.

2.2. Decoding

The core of the entire procedure is captured in the third notebook. This notebook contains the pivotal function named "process_taf_to_df," (Figure 6) where the user's involvement is streamlined to a single parameter entry. This parameter involves the TAF as string, which was previously extracted.

Special attention should be paid here to the need to modify the BECMG groups (implying a gradual change of the conditions). They are perhaps a bit unexpectedly a problem for the regular decoding itself. Validity in the temporal determination of a given group never belongs to that group, but de facto limits the validity of the previous one (see Figure 7).

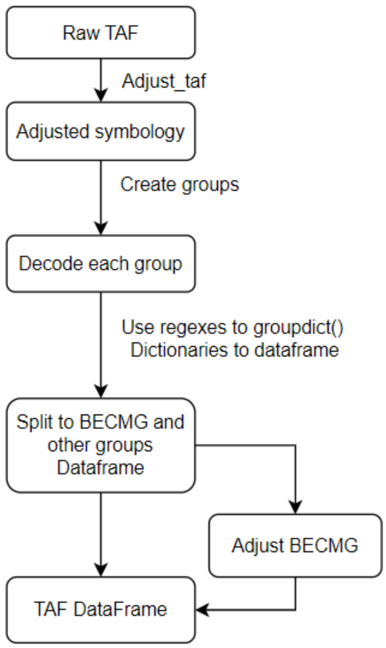

Figure 6. Flowchart of decoding TAF string adjusting it to the regular DataFrame object

TAF LKTB 1106/1206 15012KT CAVOK
BECMG 1114/1116 VRB02KT
meaning:

- 15012KT valid from 06 to 16 UTC
- CAVOK valid for all validity period
- 14–16 UTC, both wind values are valid

Figure 7. Example of simplified BECMG group understanding by human reading. Green values correspond to the green times of validity and yellow wind information corresponds to validity times that. Validity times are actually contained in the different groups than their wind information

Figure 7 illustrates a key challenge in understanding TAF forecasts. A sample forecast of SE winds of 12 knots, which will gradually calm to a variable wind direction of up to 2 knots in the afternoon was produced. While the main time indicator extends validity up to day 12, 6 hours, it is cut short by the BECMG change group. This indicates a change occurring between 2 and 4 pm on day 11. Consequently, after 4 pm, the wind forecast VRB02KT (variable wind, 2 knots) and CAVOK, mentioned in the main group, are already in effect. To facilitate machine processing, it was necessary to divide the entire TAF into temporary groups (TEMPO, PROB) containing only conditional changes, which then revert to the original conditions, and a sub-database of permanent changes (BECMG, FM) that entirely alter the conditions. As illustrated in Figure 6, the solution of the BECMG group involved dividing the sub-database into two segments. This approach facilitated the interchange of timestamp objects (such as form 1012/1016) and time data represented as datetime objects within the corresponding cells. However, this property of the TAF can be identified as a significant drawback. The need to use such a procedure is an example of the fact that TAF is not built for machine reading. In the case shown in Figure 7, it can be seen that the values and their validity times are not given within a single group at all. Thus, one only can create the whole picture once the whole forecast is read.

3. Results

To explore potential applications, an examination of specific parameters within the 2022–2023 TAF was conducted. The following parameters have been identified as primary focus points for analysis:

- Count of corrected/amended forecasts.
- Quantity and categories of change groups.

3.1. Amended and corrected forecasts

The TAF can be corrected in two ways:

- TAF AMD, called an Amendment: a forecast issued on the basis that the forecast values themselves do not match or differ significantly from observations.
- TAF COR, corrected: A forecast corrected for formal errors or typos.

The analysis also examined the number of AMD and COR forecasts issued by TAF (Figure 8 and Figure 9). This is because their number is a direct indicator of the quality of service provided. It is also defined as a quality indicator in ICAO Regulation 9873, Manual on Quality (ICAO, 2010), as mentioned at the beginning of the article.

Before the analysis, the data were removed from Oslo Airport (2022) due to faulty data in the database, where although the values are correct, a corrected message was automatically added to each message. Such input is probably due to a faulty data flow or checking the release time and automatically adding AMD/COR suffix to the header. Using the algorithm, it would be the need to design new code branch to mark the duplicate COR forecasts without this being necessary. In the 2023 data, this error was already corrected. By the Kyiv airport, significant part of the database is missing.

The number of COR reports alone indicates low forecasters' focus or low automation of report issuance; for AMD reports, changing conditions or lower staff experience may be to blame. These corrections/amendments are considerd together because, for example, the Paris airport (LFPG) does not issue COR reports but straight AMD reports, as do airports in Athens or Portugal.

- Looking at the map (Figure 8 and Figure 9), several findings are particularly visible. Substantial variations exist among London airports. Such proximity highlights potential inconsistencies in regional regulations or disparities in the quality of service delivery.

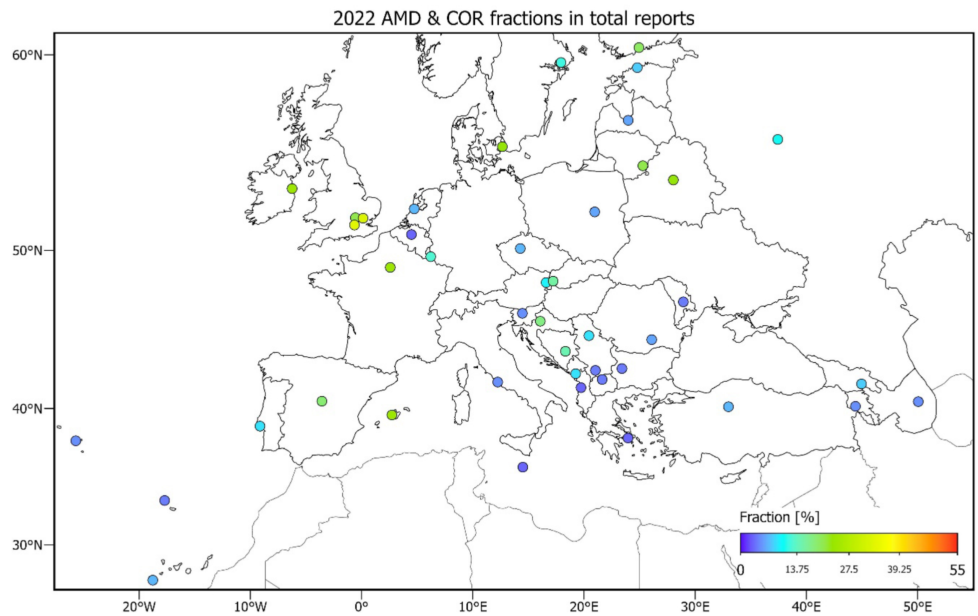

Figure 8. Proportion of the number of corrected (AMD or COR) forecasts out of the total number issued for 2022

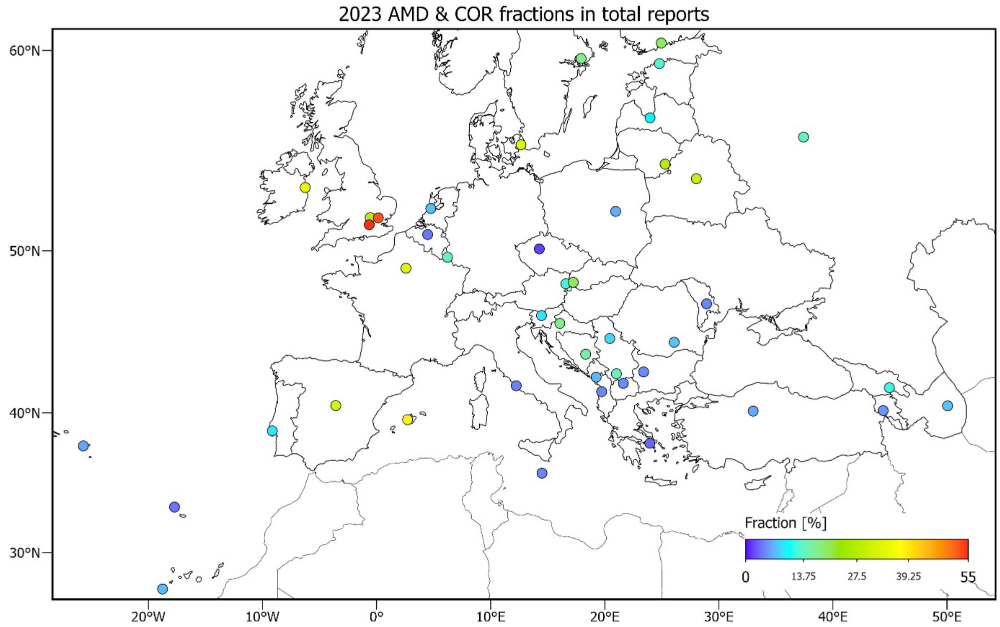

Figure 9. Proportion of the number of corrected (AMD or COR) forecasts out of the total number issued for 2023

- London Stansted (EGSS) and London Luton (EGGW) AMD/COR numbers raised between 2022 and 2023.
- Balkans, Prague or Brussels possess quite low AMD/COR fraction without significant shift between the years.

It should be borne in mind that numbers alone may not be indicative. It is only the statistics on how many forecasts were amended and how many of them should have been actually amended. Analysis including observations comparison would indicate the accuracy of the reporting or amending of the forecasts.

For a detailed overview of how many COR and AMD forecasts have been issued, see Table A2 and Table A4. It can be seen that some airports (e.g. all three Portuguese airports) do not issue COR forecasts at all, but straight AMD forecasts (Table 1). This supports the assertion of the importance of local agreements and regulations that may mandate the use of AMD only.

For Portuguese airports, it can be assumed that the use of AMD may be governed by national regulations. The other possibility is that some automatic system is used in Portugal to correct formal errors. In the case of France and Greece, the further analysis must be carried out formulate the anticipations about the absence of COR forecasts.

An interesting change is the increase in the percentage of corrected messages at London airports. The magnitude of the changes in Europe is expressed by the percentage difference from 2023 minus 2022 (Figure 10).

Figure 10 presents a comparison of 2022–2023 changes, revealing that numerous airports, particularly those in London, have experienced an incline in forecast correction percentage by 10 percent or more. This suggests the possibility of changes in directives or internal regulations within these airports. Interestingly, airports in Madrid or Mallorca have shown an increase in the frequency of issuing AMDs and CORs. This trend may be attributed to either more diligent work by meteorologists regarding corrections or the implementation of new regulations or significant weather changes. However, identifying the specific causes behind these trends requires further investigation in separate research.

Table 1. Selection of exceptional airports with a high difference in AMD usage and COR forecasts

ICAO	Location	TAF	COR	AMD	% of AMD/COR
EVRA	Riga	2811	1	190	6%
LFPG	Paris	1250	0	405	24%
LGAV	Athens	1417	0	48	3%
LPPT	Lisbon	1326	0	129	9%
LPMA	Madeira	1418	0	54	4%
LPPD	Ponta Delgada	1290	0	70	5%

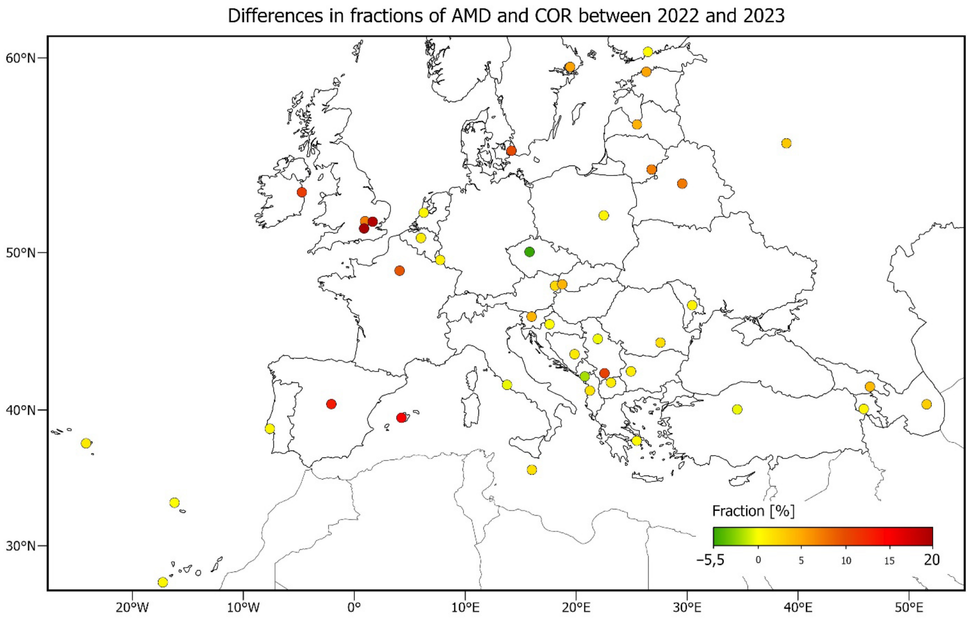

Figure 10. Yearly differences between fractions of AMD/COR forecasts in 2022 and 2023. Higher value stands for increase in fraction of the AMD/COR percentage

3.2. Change groups count

As part of the analysis, it is valuable to examine the frequency of change groups within each TAF forecast. Following the guidelines outlined in ICAO Annex 3, it is advised to limit the utilization of change groups to a maximum of four (ICAO, 2018). Excessive utilization of change groups can diminish the forecast's clarity and typically leads to decreased accuracy, thereby resulting in heightened instances of false alarms.

The number of change groups per forecast is shown in the following maps (Figure 11 and Figure 12).

In terms of year-on-year changes, the most interesting situation is in London, where the number of change groups has almost doubled (Figure 13). This may be due to a new directive or national regulations coming into force. All three airports have increased their average numbers and it would not be expected that such a shift in weather variability would occur in these two years.

The high number of change groups can be attributed to one of three influences:

- Very difficult situations where it is not possible to express the forecast more concisely.

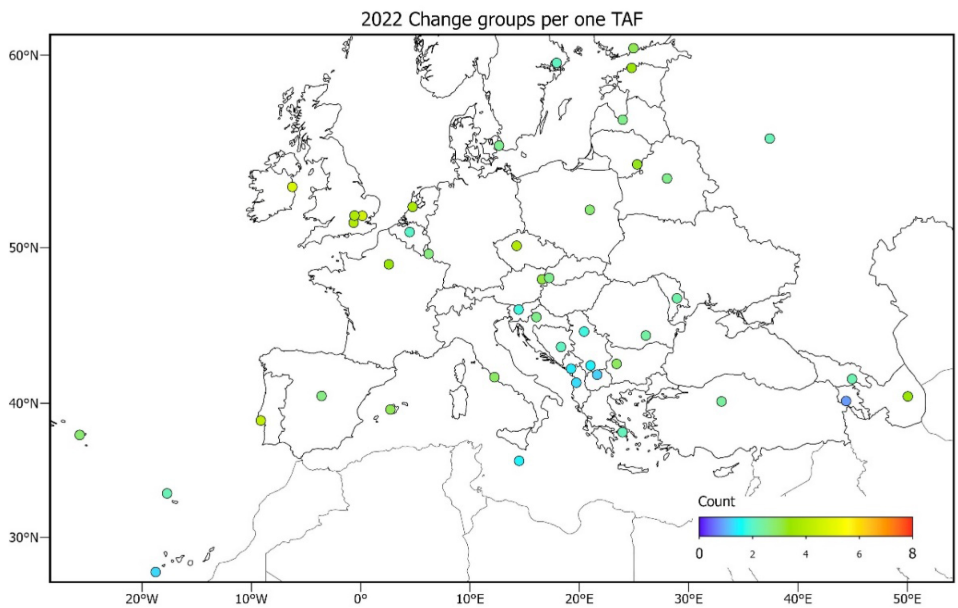

Figure 11. Frequency of change groups per Issued TAF Forecast in 2022. London, Dublin, and Prague exhibit the highest average numbers, suggesting a more frequent utilization of change groups

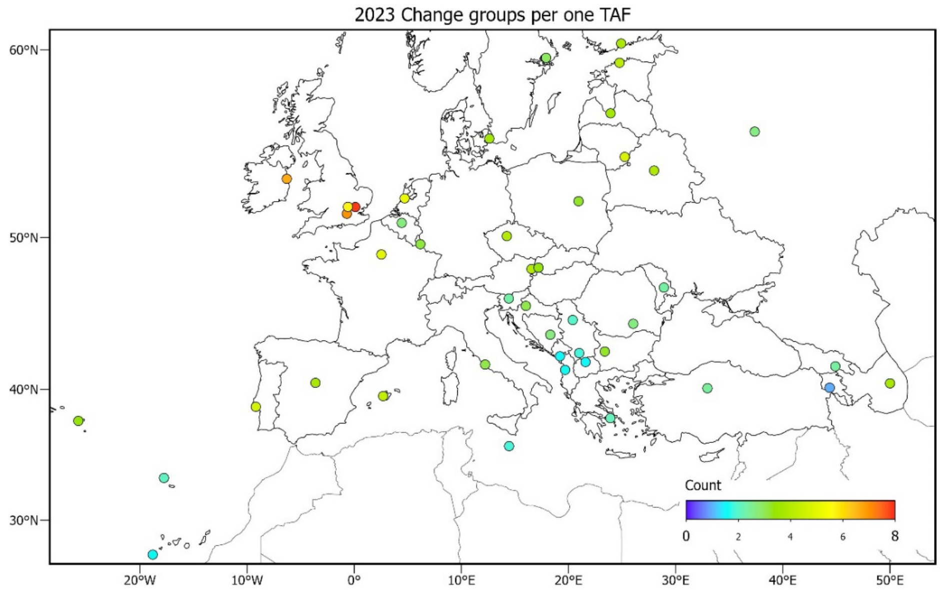

Figure 12. Frequency of change groups per Issued TAF Forecast in 2023. London, Dublin, and Amsterdam exhibit the highest average numbers, suggesting a more frequent utilization of change groups

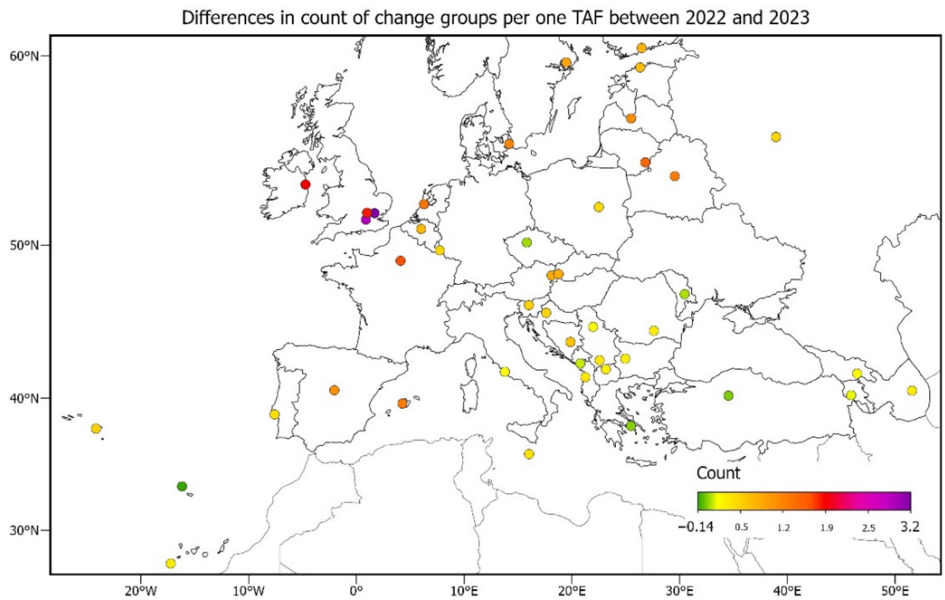

Figure 13. Difference in the use of change groups per one issued TAF Forecast in 2022–2023

- Regional specificities of the regulations that add criteria when a change group needs to be included, beyond those defined in ICAO Annex 3.
- Excessive apprehension of meteorologists and their protection against error. That is the placement of multiple values so that at least some are correct.

Since the professional forecasters are directed to follow ICAO quality standards, it is correct to expect that the first two points are primarily to blame. A change in the approach of the forecasters or a change in the team would not have had such a significant impact. There are still more people involved in the service, and individual differences would probably not manifest themselves as significantly in changes in both the number of AMD/CORs (Figure 10), and the number of change groups.

Analysis of the second point is challenging because Annex 3 (ICAO, 2018) acknowledges regional and individual agreements between the user and the weather service provider on several points. These agreements are an integral part of the provision of aviation meteorological services. However, they are often written in local language and are not published comprehensively within ICAO.

The first point, on the other hand could be examined through the statistical comparison of the observations or numerical model forecasts. Such as research could reveal how much the TAF characteristics are dependent on the observations and source data, i.e. how complicated the situation was.

3.3. Change groups type

It is also noteworthy to identify which specific groups are employed most frequently (Figure 14 and Figure 15). In certain airports, the absence of probability groups contributes to a diminished deterministic aspect of the forecast or its level of certainty.

The outcomes can be further scrutinized in the appended Table A1 and Table A3. Even at an initial glance, it becomes evident that certain airports exhibit a tendency to indicate changes through the TEMPO indicator, while others utilize the BECMG indicator equally. Notably, some airports choose to omit probabilities entirely. It is important to note that the directive does not directly address these variations; instead, it interprets the nature of change groups, leaving it to individual meteorologists to determine how to articulate the nature of the change. It was selected interesting cases:

1. Yerevan Zvarnots (UDYZ) uses primarily TEMPO indicator over BECMG.
2. Stockholm (ESSA) uses only PROB40 group, but not PROB40 TEMPO in 2022, but in 2023, also PROB40 TEMPO is used.
3. Riga (EVRA), Copenhagen (EKCH), Baku (UBBB) and Minsk (UMMS) never use PROB30 nor PROB30 TEMPO.
4. Rome Fiumicino (LIFR) and Vilnius (EYVI) do not use solely PROB30 and PROB40 groups, but they use PROB30/40 TEMPO.

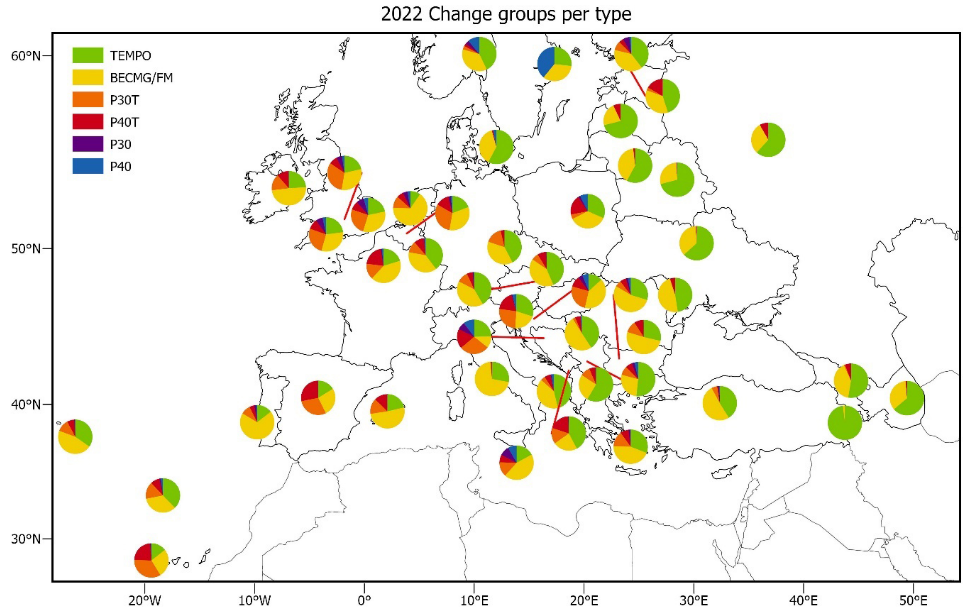

Figure 14. Pie Charts of usage change groups at airports in 2022

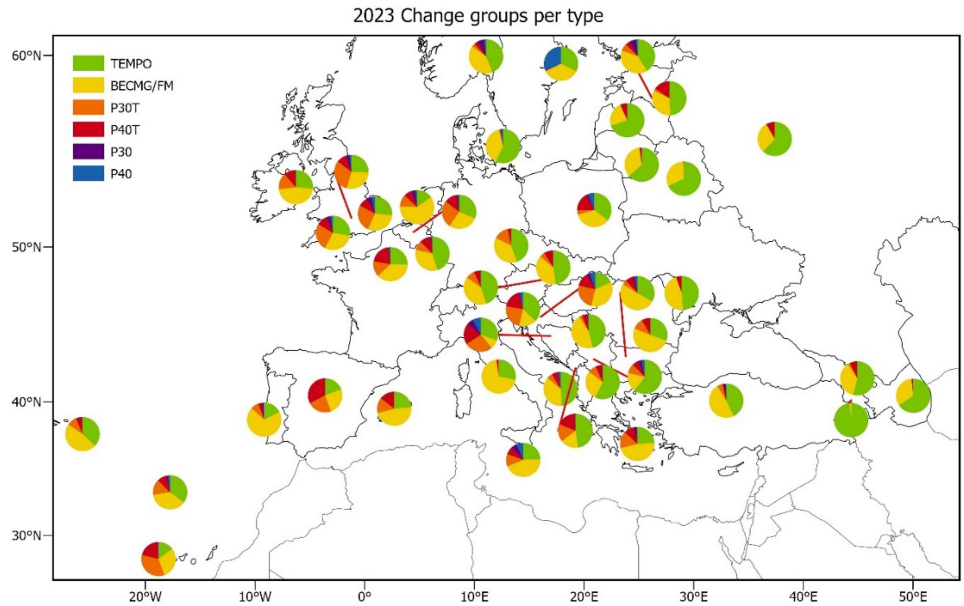

Figure 15. Pie Charts of usage change groups at airports in 2023

These differences may indicate variations in local directives or practices regarding the involvement of change groups. A notable example is Rome, where it is possible to anticipate absence of phenomena suitable for decreased probability of occurrence and continuous presence, such as fog. These phenomena are often indicated by the PROB30 and PROB40 groups.

3.4. Code exception as a result

Even errors (exceptions) of the code run can be seen as useful. With deeper analysis, it can lead to more profound check of the TAF databases. Table 2 presents exceptions yielded by the algorithm, detecting some errors in the TAF forecasts:

These exceptions generated by the code can be also used for spotting formal error – in all cases, problem was in the timer of the group (extra number), and therefore algorithm was not able to decode it unambiguously. Resulting errors (called exceptions) can be redirected to a service branch of the code, identify the problem, and resolve it.

To take advantage of these formal errors, two solutions are being proposed:

- Marking the error as correctable/uncorrectable for the case when there is a possibility to correct the error with high probability or when it is not possible to determine the correct value (e.g. typos in BKN - BNK, etc.)
- Marking an error as corrected/neglected. The algorithm would check the following report to see if it used COR or AMD to correct the error. The result would be an indicator of the consistency of the service in correcting formal errors.

Overall, it is recommended to include a separate algorithm when making predictions so that there are as few typos and formal errors as possible. However, by using error detection and automatic error correction, it would be possible at least produce detailed statistics of minor (and correctable) or major errors, as suggested by a previous study (Novotny et al., 2021). It is necessary to recognise that formal errors must be carefully identified and rigorously analysed before any summary statistics can be drawn. Failure to do so may compromise the quality of the results and potentially truncate the results of the methodology by not accounting for all possible scenarios.

4. Discussion

TAFs are pivotal in aviation meteorology, crucial for ensuring flight safety and facilitating operational decision-making at airports. Despite advancements in automated meteorological observations, TAF continue to heavily rely on the expertise of meteorologists.

The investigation into TAFs is characterized by its technical complexity, necessitating an understanding of the intricacies of meteorological data analysis and regulatory compliance. This study employs Python functions shared via GitHub repositories to conduct an overall analysis of TAF forecasts, focusing on tangible findings grounded in two years of the European data.

Regulatory compliance, as stipulated by the International Civil Aviation Organization (ICAO), serves as a cornerstone for assessing the consistency of TAF forecasts. Acknowledging the need of adherence to ICAO regulations and standards, the study provides concrete insights into the regulatory landscape governing aviation meteorology. Real findings emerge from the analysis of changes in forecast issuance frequency and validity periods across various airports, revealing notable shifts in regulatory mandates and forecasting practices over time.

Decoding TAF forecasts poses several challenges due to their inherent complexity. Factors such as varying counts of change groups, fluctuating elements within each group, diverse header formats, data availability issues, and regional nuances contribute to this complexity. Moreover, the use of change groups, integral to TAF forecasts, is influenced by regulations and regional conventions, further complicating interpretation. The paper provides readers with the necessary tools to decode irregular BECMG groups reliably, addressing potential challenges for non-professional users. Furthermore, cleaning and splitting functions are available in the referenced Python notebooks, accessible in the referenced GitHub repository.

The analysis of TAF from 2022 to 2023 reveals basic insights into their quality and characteristics. Examining the frequency of corrected and amended forecasts provides general overview of the service quality. Additionally, studying change group utilization across different airports unveils various approaches to the structuring TAF forecast. Some airports exhibit a higher frequency of change groups, influenced by factors such as complexity of situations, regional regulations, and forecaster decision-making. Remarkably,

Table 2. Exceptions occurred during the run of the code exposing formal errors (marked yellow)

Excepting TAF	202301181130 TAF BKPR 181130Z 1812/1912 21008KT 9999 SCT030 BKN050 TEMPO 18127/1818 24022KT PROB40 TEMPO 1812/1816 SHRA=
Error	'NoneType' object has no attribute 'groupdict'
Excepting TAF	Excepting TAF is 202301031700 TAF EYVI 031700Z 0318/0418 28014KT 9000 OVC012 TEMPO 0318/0322 5000 RA BR BKN005 BECMG 0401/0403 VRB04KT BKN015 TEMPO 04003/0406 SCT005=
Error	'NoneType' object has no attribute 'groupdict'

the investigation uncovers instances where certain airports entirely forego the utilization of specific change group indicators, such as PROB30. A brief discussion follows on the potential reasons behind these omissions, suggesting that they may stem from a combination of factors including the unsuitability of certain indicators based on the occurrence of phenomena, as well as adherence to national, internal, and local regulations. Moreover, the lack of standardization in change group directives allows individual meteorologists to express changes based on their judgment. This variability in interpretation poses challenges in forecast consistency and decision-making processes, highlighting the need for standardized guidelines.

In conclusion, this analysis highlights the fundamental bottleneck in understanding TAF forecasts in aviation meteorology. By understanding the challenges in decoding and interpreting TAF, the intricacies involved and work towards improving forecast quality and reliability can be better appreciated. This framework also introduced method for reshaping irregular forecast to the format suitable for database and ML processing.

5. Conclusions

The findings underscore the delicate balance between technical precision and regulatory conformity in producing accurate and intelligible TAF. The Python functions shared in the code repository provide forecasters with tools to dissect and analyse various aspects of TAF. While TAF have undergone previous analyses, this study offers a comprehensive approach that extends beyond technical reports, focusing on practical applications and implications for the forecaster's performance improvement. The key conclusions that emerge from the analysis and that were identified as critical to the perceived readability and quality of the forecasts issued are:

1. Variability in TAF Forecasts: TAF forecasts can exhibit significant differences, even among closely located areas such as London airports. This underscores the importance of considering regional nuances and microclimates in forecast interpretation.
2. Impact of Standards and Guidelines: National standards and internal guidelines exert a notable influence on TAF forecast counts. Standardized practices are essential to ensure consistency and reliability across diverse forecasting entities.
3. Call for Standardization of Change Groups: There is a clear need to define the utilization of change groups in international guidelines. Standardization in this aspect would enhance clarity and comprehension, particularly for forecast users and stakeholders.
4. Advocacy for Unified Quality Assessment Tool: Developing a unified tool for assessing basic forecast characteristics globally is crucial. Such a tool would serve as a valuable indicator of service quality changes, enabling benchmarking and improvement initiatives.
5. Potential of TAF Forecasts as Weather Complexity Indicators: Standardized TAF forecasts hold promise as indicators of weather complexity. This has significant implications for aviation operations and safety, providing valuable insights into atmospheric conditions.

In conclusion, this study contributes to improving the uniformity of TAF while emphasizing the importance of regional considerations, regulatory compliance, and expert judgment. The availability of Python functions in the GitHub repository enhances accessibility for meteorologists, researchers, and aviation personnel, facilitating deeper insights and applications of TAF. Overall, this study provides code and overall analysis as an effective tool to increase standardization, interpretation of TAF predictions, as well as their processing into ML systems in the future.

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Notation

Abbreviations

AMD – Amended
ANSP – Air Navigation Service Provider
BCMG – Becoming
CAVOK – Clouds And Visibility OK
COR – Corrected
ICAO – International Civil Aviation Organization
KT – Knots, velocity unit
ML – Machine Learning
TAF – Terminal Aerodrome Forecast
TEMPO – Temporary
UTC – Universal Time Coordinated
WMO – World meteorological organization
WSP – Weather Service Provider

Appendix

Table A1. Complete results of change groups count 2022. Dates columns contain count of unique issue dates (even duplicate without duplicate forecasts)

ICAO	NAME	Dates	TEMPO	P30	P30T	P40	P40T	BECMG/FM
LATI	Tirana	1486	872	14	81	48	110	759
UDYZ	Yerevan	1483	1166	0	0	0	0	23
LOWW	Vienna	2402	3127	70	787	35	420	3087
UBBB	Baku	1482	3231	0	0	3	68	1762
UMMS	Minsk	1297	2323	0	0	10	16	929
EBBR	Brussels	1379	521	63	832	44	347	913
LQSA	Sarajevo	1456	726	214	830	308	545	326
LBSF	Sofia	1475	1275	85	256	115	251	2308
LDZA	Zagreb	1668	558	172	1088	261	434	1706
LKPR	Prague	1461	2420	8	924	0	204	2167
EKCH	Copenhagen	1857	2678	0	0	143	56	1757
EETN	Tallinn	1465	2292	2	141	3	840	1802
EFHK	Helsinki	3538	4182	654	908	202	468	4153
LFPG	Paris Charles de Gaulle	1655	1124	59	839	97	1126	2321
UGTB	Tbilisi	1477	1693	0	35	3	184	1301
LGAV	Athens	1458	947	56	445	10	240	1366
EIDW	Dublin	1737	1979	16	1269	19	917	4067
LIRF	Rome Fiumicino	1504	1210	0	31	0	41	3033
BKPR	Pristina	1637	1212	64	196	81	149	645
EVRA	Riga	2998	5419	0	0	3	537	1671
EYVI	Vilnius	1607	3059	0	6	0	90	2123
ELLX	Luxembourg	1476	1554	18	423	53	371	1493
LMML	Malta	1435	355	191	287	171	148	923
LUKK	Chisinau	1500	1602	0	12	1	161	1600
LYPG	Podgorica	1511	877	13	311	3	397	477
EHAM	Amsterdam Schiphol	1404	521	237	601	143	336	3530
LWSK	Skopje	2930	2055	5	325	14	209	904
EPWA	Warsaw	2816	2444	144	342	579	1457	2791
LPPT	Lisbon	1439	882	110	546	60	280	4204
LPMA	Madeira	1451	1183	40	504	66	272	1072
LPPD	Ponta Delgada	1341	1298	21	435	14	254	1722
LROP	Bucharest H. Coanda	1488	990	2	384	8	307	1773
UUEE	Moscow Sheremetyevo	2900	3806	0	1	13	497	1844
LYBE	Belgrade Nikola Tesla	1520	1088	10	67	26	136	1340
LZIB	Bratislava	1632	1786	8	275	10	341	1682
LJLJ	Ljubljana	1398	738	18	647	94	451	519
GCLP	Gran Canaria	1554	281	14	669	10	454	523
LEMD	Madrid Barajas	1533	655	12	1177	5	1118	1064

End of Table A1

ICAO	NAME	Dates	TEMPO	P30	P30T	P40	P40T	BECMG/FM
LEPA	Palma de Mallorca	1764	1132	13	780	3	658	2723
ESSA	Stockholm Arlanda	3192	1725	0	0	2521	0	2196
LTAC	Ankara Esenboga	1544	1504	38	194	14	41	1866
EGLL	London Heathrow	1743	1450	355	2155	165	532	2120
EGGW	London Luton	2032	1858	534	2101	271	781	2544
EGSS	London Stansted	1997	2000	657	2339	402	754	3043

Table A2. Count and percentage of AMD and COR forecasts 2022

ICAO	NAME	TAF	COR	AMD	% of A/C
LATI	Tirana	1445	11	33	3%
UDYZ	Yerevan	1417	35	39	5%
LOWW	Vienna	2163	36	210	10%
UBBB	Baku	1411	27	47	5%
UMMS	Minsk	997	6	298	23%
EBBR	Brussels	1336	26	19	3%
LQSA	Sarajevo	1243	133	87	15%
LBSF	Sofia	1422	12	43	4%
LDZA	Zagreb	1371	44	256	18%
LKPR	Prague	1361	4	96	7%
EKCH	Copenhagen	1435	9	421	23%
EETN	Tallinn	1347	41	78	8%
EFHK	Helsinki	2849	52	642	20%
LFPG	Paris Charles de Gaulle	1250	0	405	24%
UGTB	Tbilisi	1366	53	65	8%
LGAV	Athens	1417	0	48	3%
EIDW	Dublin	1322	31	393	24%
LIRF	Rome Fiumicino	1437	11	63	5%
BKPR	Pristina	1576	20	47	4%
EVRA	Riga	2811	1	190	6%
EYVI	Vilnius	1266	108	236	21%
ELLX	Luxembourg	1285	75	120	13%
LMML	Malta	1394	14	30	3%
LUKK	Chisinau	1437	19	44	4%
LYPG	Podgorica	1384	59	73	9%
EHAM	Amsterdam Schiphol	1312	56	39	7%
LWSK	Skopje	2829	42	68	4%
EPWA	Warsaw	2649	13	156	6%
LPPT	Lisbon	1326	0	129	9%
LPMA	Madeira	1418	0	54	4%
LPPD	Ponta Delgada	1290	0	70	5%
LROP	Bucharest H. Coanda	1403	16	80	6%
UUEE	Moscow Sheremetyevo	2616	21	297	11%
LYBE	Belgrade Nikola Tesla	1381	71	73	9%
LZIB	Bratislava	1368	34	230	16%
LJLJ	Ljubljana	1332	4	63	5%
GCLP	Gran Canaria	1459	6	102	7%
LEMD	Madrid Barajas	1250	36	255	19%
LEPA	Palma de Mallorca	1353	21	405	24%
ESSA	Stockholm Arlanda	2810	17	372	12%
LTAC	Ankara Esenboga	1441	9	106	7%
EGLL	London Heathrow	1395	17	347	21%
EGGW	London Luton	1358	10	688	34%
EGSS	London Stansted	1354	10	657	33%

Table A3. Complete results of change group count 2023. Dates columns contain count of unique issue dates (even duplicate without duplicate forecasts)

ICAO	NAME	Dates	TEMPO	P30	P30T	P40	P40T	BECMG/FM
LATI	Tirana	1476	1140	15	124	73	136	874
UDYZ	Yerevan	1446	1339	0	0	0	0	22
LOWW	Vienna	3004	5347	52	1010	57	706	4773
UBBB	Baku	1470	3601	0	1	2	88	1787
UMMS	Minsk	1470	3827	0	0	5	16	1790
EBBR	Brussels	1497	1239	58	1031	69	473	1117
LQSA	Sarajevo	1403	1158	245	1008	269	741	321
LBSF	Sofia	1474	1560	88	210	142	351	2373
LDZA	Zagreb	1515	837	123	1148	209	602	1657
LKPR	Prague	2979	5257	27	1674	23	360	4455
EKCH	Copenhagen	1525	3196	0	0	142	57	2215
EETN	Tallinn	1492	3039	1	144	5	947	2072
EFHK	Helsinki	2981	4588	725	769	242	477	4420
LFPG	Paris Charles de Gaulle	1409	1823	26	1061	60	1456	2664
UGTB	Tbilisi	1398	1765	4	63	7	234	1203
LGAV	Athens	1485	750	90	501	24	300	1463
EIDW	Dublin	1435	2552	19	1485	26	1070	4418
LIRF	Rome Fiumicino	1477	1268	0	31	0	82	3139
BKPR	Pristina	1466	1558	85	231	101	154	472
EVRA	Riga	2979	7587	0	0	31	733	2523
EYVI	Vilnius	1453	4388	0	32	0	129	2380
ELLX	Luxembourg	1413	2015	25	384	49	480	1475
LMML	Malta	1464	639	141	311	211	198	1169
LUKK	Chisinau	1480	1660	0	13	12	179	1555
LYPG	Podgorica	1455	1014	12	353	4	387	367
EHAM	Amsterdam Schiphol	1484	1148	285	848	156	580	4647
LWSK	Skopje	2937	2482	16	338	6	267	1220
EPWA	Warsaw	2981	3361	164	394	733	1651	3268
LPPT	Lisbon	1467	1192	97	512	51	238	4705
LPMA	Madeira	1482	1058	46	442	40	269	1142
LPPD	Ponta Delgada	1469	1814	13	447	19	277	2318
LROP	Bucharest Henri Coanda	1460	1170	10	405	11	301	1956
UUEE	Moscow Sheremetyevo	2918	4695	0	0	12	615	2266
LYBE	Belgrade Nikola Tesla	1426	1286	4	79	8	144	1261
LZIB	Bratislava	1485	2367	3	246	0	428	1902
LJLJ	Ljubljana	1451	1230	33	813	78	607	556
GCLP	Gran Canaria	1482	341	11	799	13	467	686
LEMD	Madrid Barajas	1451	1041	18	1235	13	1732	1352
LEPA	Palma de Mallorca	1435	1443	9	905	0	877	2923
ESSA	Stockholm Arlanda	2970	2612	0	0	3112	62	2845
LTAC	Ankara Esenboga	1480	1498	86	183	16	20	1689
EGLL	London Heathrow	1503	2200	308	2670	103	793	2490
EGGW	London Luton	1495	2876	360	2697	248	1078	3136
EGSS	London Stansted	1489	3129	527	3092	283	1076	3581

Table A4. Count and percentage of AMD and COR forecasts 2023

ICAO	NAME	TAF	COR	AMD	% of A/C
LATI	Tirana	1542	29	37	4%
UDYZ	Yerevan	1523	37	40	5%
LOWW	Vienna	3366	38	324	12%
UBBB	Baku	1582	23	89	8%
UMMS	Minsk	1917	7	440	30%
EBBR	Brussels	1554	40	17	4%
LQSA	Sarajevo	1626	123	100	16%
LBSF	Sofia	1544	11	59	5%
LDZA	Zagreb	1784	43	226	18%
LKPR	Prague	3024	2	43	2%
EKCH	Copenhagen	2031	21	485	33%
EETN	Tallinn	1688	54	142	13%
EFHK	Helsinki	3574	35	558	20%
LFPG	Paris Charles de Gaulle	1881	0	472	33%
UGTB	Tbilisi	1564	81	85	12%
LGAV	Athens	1529	0	44	3%
EIDW	Dublin	1940	45	460	35%
LIRF	Rome Fiumicino	1541	13	51	4%
BKPR	Pristina	1683	91	126	15%
EVRA	Riga	3287	4	304	10%
EYVI	Vilnius	1863	101	309	28%
ELLX	Luxembourg	1606	58	135	14%
LMML	Malta	1531	35	32	5%
LUKK	Chisinau	1546	15	51	4%
LYPG	Podgorica	1554	36	63	7%
EHAM	Amsterdam Schiphol	1591	57	50	7%
LWSK	Skopje	3077	68	72	5%
EPWA	Warsaw	3170	21	168	6%
LPPT	Lisbon	1602	2	133	9%
LPMA	Madeira	1537	5	50	4%
LPPD	Ponta Delgada	1556	3	84	6%
LROP	Bucharest Henri Coanda	1571	16	95	8%
UUEE	Moscow Sheremetyevo	3326	34	374	14%
LYBE	Belgrade Nikola Tesla	1545	50	69	8%
LZIB	Bratislava	1786	43	258	20%
LJLJ	Ljubljana	1584	1	132	9%
GCLP	Gran Canaria	1587	15	90	7%
LEMD	Madrid Barajas	1923	47	425	33%
LEPA	Palma de Mallorca	1992	29	528	39%
ESSA	Stockholm Arlanda	3481	5	506	17%
LTAC	Ankara Esenboga	1573	10	83	6%
EGLL	London Heathrow	1929	20	406	28%
EGGW	London Luton	2309	12	802	54%
EGSS	London Stansted	2272	10	773	53%