Original Article

Requirements for local production and consumption of time-series data in tourist destinations:

Insights from weather forecasting as a model of everyday data utilisation

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Abstract
The tourism industry is suffering from an acute labour shortage. To mitigate this gap, enhancing productivity through data-driven destination management has become imperative. Local communities therefore need to collect development-relevant data and leverage for planning and operations. Although data utilisation by non-expert users who manage tourist destinations is an important topic, only a limited number of studies have focused on it. In this research, we clarify the essential data utilisation requirements for non-expert users of urban time-series data. To derive these requirements, we examine weather forecasting, the most widely accepted and routinely employed form of time-series data utilisation. First, the end-to-end pipeline of meteorological information from data collection through analysis, prediction, and public dissemination was mapped. Next, we characterise the published data that constitute users' points of contact with weather services, focusing on attributes such as temporal granularity and measurement scales, and highlight key considerations for collaboration with private-sector providers. From this examination, eleven features of weather forecast that foster user engagement were distilled. These features inform a set of practical requirements for ordinary users managing tourist destinations, among which are: data should be collected centrally by a public authority rather than by individual users; the authority should publish not only raw figures but also processed analytics; providing daily updated forecasts of current and future data is most important for users; and users should develop intuitive understandings of higher-scale data through repeated exposure to past data. The results offer actionable guidance for designing data utilisation that empower non-expert users to enhance tourist destination management.

Keywords
data utilisation, non-expert, weather forecast, tourism, digital transformation

1. Introduction

Tourism is a key industry in Japan; however, it is currently suffering from an acute labour shortage owing to the shrinking working-age population and the out-migration of residents to metropolitan areas [Fujiyama, 2022]. To offset this shortage, productivity enhancement has become imperative, and data-driven, efficient management of tourist destinations is being pursued. In the Digital Garden City Nation Vision announced by the Cabinet Office in 2021, which aims to address regional social challenges through digital technologies, tourism digital transformation (DX) is positioned as one of the core initiatives. The vision calls for a thorough re-examination of data-based business strategies and the creation of new business models. The UNWTO likewise contends that the adoption of digital technologies can render destinations more attractive, efficient, inclusive, and sustainable [UN Tourism, n.d.].

To realise tourism DX, prior technical studies have estimated visitor numbers from Wi-Fi packet sensor data, among other approaches [Murai et al., 2022]. Nevertheless, research that examines how non-experts of tourist destinations, who do not specialise in data or its utilisation, should employ data in practice remains limited. Addressing the gap, this study focuses on weather forecasting, one of the most widely accepted forms of data utilisation in everyday life, and analyses the requirements needed to encourage data-driven practices among non-expert stakeholders.

2. Local production and consumption of data

Advances in information and communication technology (ICT), particularly artificial intelligence (AI), now allow us to collect and analyse not only structured data stored in computers but also unstructured data generated in the physical world. To promote sustainable community development, it is essential to practise "local production and consumption of data," to gather and utilise the data a community needs within the community itself. For example, individuals who feel it necessary can monitor their own sleep patterns and improve sleep quality by using Fitbit, a smartwatch marketed by Google. Likewise, Toi Labs has commercialised TrueLoo, an AI-equipped toilet seat that optically scans stools and urine; the device can be retrofitted to existing toilets and is currently installed in more than 50 senior-living facilities [Wilser, 2024]. On a larger scale, Walmart, the world's largest retailer, operates its Intelligent Retail Lab (IRL) in Levittown, New York, where ceiling-mounted cameras and sensors monitor inventory levels and shelf-restocking needs in real time, enabling staff to respond rapidly and thereby improving store operations [Smith, 2019].

These cases illustrate how the targeted collection and utilisation of data within an individual or a closed facility can be harnessed to improve personal or organisational conditions. Across many sectors, the demand for efficient, data driven decision-making is rising [Lawrence, 2024]. In tourism, too, DX initiatives aim to establish data-management platforms that gather regional data and enable communities to utilise data locally. By analogy with data practices at the individual and closed facility level, broader open entities—communities or "towns" composed of multiple individuals and organisations—must likewise pursue the local production and consumption of data: collecting the data essential for their own development and employing them to advance community planning and management.

3. Related work

A substantial body of research has examined data-driven community development in tourist destinations. Nevertheless, only a limited number of studies focus on the relationship between town-level data and the ordinary local people expected to use them, many of whom lack advanced data literacy.

Bekele et al. conducted a bibliometric review of tourism DX and, by analysing 1,303 scholarly works, demonstrated that recent research falls into four principal clusters: digital innovation, smart tourism ecosystem, eTourism, and smart destination experience [Bekele and Raj, 2024]. Within the smart tourism ecosystem cluster, studies seek to link tourism operators, destination management organisations (DMOs), and visitors through real-time collection, processing, and sharing of big data. To provide real-time information to these actors, researchers in this cluster strive to integrate systems, institutional frameworks, and technologies, and they develop and analyse methods for capturing behavioural data on-site at tourist destinations. Kawamura et al. demonstrated that visitor numbers can be estimated from Wi-Fi packet-sensor data and, with appropriate data extraction, separate counts for overnight and day-trip visitors can be obtained [Kawamura and Shioya, 2021]. Murai et al. applied the same sensing technology to an urban, open-air zoo and botanical garden, estimating gate-specific entries and visitor movement trajectories; by analysing length of stay and number of transfers, they captured year-long trends in attendance [Murai et al., 2022]. Yamamoto et al. used the Mobile Spatial Statistics provided by NTT DOCOMO to investigate tourists' movement patterns within destinations [Yamamoto et al., 2021]. Large-area analyses have also been performed by estimating pedestrian volumes from GPS traces and cellular base-station data [Ubukata and Sekimoto, 2013]. Kishi et al. evaluated the applicability of ETC 2.0 vehicle probe data for tourism behaviour analysis and showed that the system can almost completely identify the locations visited and routes taken by rental cars [Kishi et al., 2017]. Finally, Hernandez-Cabrera developed TOURETHOS, a platform that collects data on tourists' territorial movements by logging their connections to Wi-Fi networks [Hernandez-Cabrera et al., 2024].

Although such studies are invaluable for collecting and analysing real-world data in the pursuit of technological innovation, they seldom address the practical digitalization challenges encountered on site at tourist destinations. As a result, research that centres on how ordinary, non-expert stakeholders can leverage local data for destination management remains scarce. Tourism is often cited as a sector in which data-driven practices have been slow to mature [Fujiu et al., 2018]. Most of the people responsible for managing tourist destinations are not specialists in data or its application. Rather than leaving data utilisation solely to data experts, practitioners in other fields must also employ data within their respective domains. Consequently, frameworks are needed that allow a much wider range of stakeholders, not only those already proficient in data analytics, to harness data effectively.

In this research, we clarify the essential data utilisation requirements for non-expert users of urban data, so that a system can be established which facilitates broader data utilisation by a wider audience. The analysis centres on urban time-series data, because tourism is inherently seasonal and indicators such as pedestrian counts, bus ridership, and inbound visitor numbers are among the most valuable data for destination management. To derive these requirements, this study examines weather forecasting, the most widely accepted and routinely employed form of time-series data utilisation. Weather forecasts exert a profound influence on individual and policy-level decisions [Diehl et al., 2013; Ramar and Mirnalinee, 2014]. Today, people of all ages access forecasts effortlessly via television, newspapers, and smartphone applications, often without even recognising that they are engaging in data-driven behaviour. Accordingly, weather forecasting represents one of the most pervasive and successful examples of time-series data use in contemporary society, making it an ideal analogue for promoting data utilisation among non-experts.

4. Weather forecasting and data utilisation

Even before the advent of scientific methods, weather forecasts—however rudimentary—were crucial for anticipating natural threats and ensuring human survival [Eminger, 2011]. The earliest forecasting relied mainly on personal experience. In the 4th century BC, Aristotle wrote Meteorologica entirely from observation rather than experiment; although largely inaccurate, the work was accepted for nearly two millennia [Moore, 2015]. In the 19th century, still working with intuition and experience, the British naval captain Robert FitzRoy, Charles Darwin's skipper, began issuing storm warnings. In 1854 he established fifteen coastal observation stations, and by 1860 he was using the telegraph to gather real-time weather reports and broadcast alerts when storms threatened. The following year he introduced public forecasts extending two days ahead. Believing that weather forecasting should be a public service, FitzRoy arranged for government-sanctioned daily forecasts to appear in The Times newspaper, where they rapidly gained popularity [BBC News, 2015; Lawrence-Mathers, 2021; Eden, 2009]. FitzRoy's forecasts were empirical, but in the early 20th century Norwegian meteorologist Vilhelm Bjerknes and British physicist Lewis Fry Richardson laid the groundwork for modern scientific and ultimately numerical forecasting. Bjerknes showed that atmospheric processes could be solved using classical mechanics, providing the theoretical basis for numerical weather prediction [Bjerknes, 2009; Nitta, 2009]. In 1922, Richardson published a comprehensive numerical method of weather prediction [Platzman, 1967; Richardson, 2007].

Thus, modern scientific weather forecasting, an exercise in time-series data analysis, has been practiced since the early 20th century. It has continued to advance, and today people of all ages consult forecasts effortlessly, often without realising they are engaging in data-driven behaviour. Weather forecasting has therefore become one of the most pervasive and successful examples of time-series data utilisation. In Japan, the Japan Meteorological Agency (JMA), and in the United Kingdom, the Met Office, spearhead the collection and analysis of meteorological data and disseminate the results to the public, where both individuals and businesses depend on them for day-to-day decisions.

The way ordinary people engage with data through weather forecasts parallels the local production and consumption of data envisioned for community development in tourist destinations. By analysing weather forecasting from a data-utilisation perspective, this study aims to identify the requirements for leveraging time-series data by ordinary people in destination management. Accordingly, the following chapters first map the end-to-end pipeline of meteorological information from data collection through analysis, prediction, and public dissemination. Next, we characterise the published data that constitute users' points of contact with weather services, focusing on attributes such as temporal dimension and measurement scales, and highlight key considerations for collaboration with private sector providers. On the basis of this analysis, the features of weather forecasting that foster user engagement with data are distilled and, in turn, the requirements for making effective use of urban time-series data by ordinary people in destination management are derived.

5. Overview of weather forecasting

5.1 Meteorological data collection, analysis, forecasting, and dissemination

In this study, we use a data workflow centred on the JMA as a representative example. Japan is a global leader in numerical weather prediction [Matsueda and Nakazawa, 2015], and the JMA's extensive collaboration with private sector companies offers insights that can be transferred to data utilisation for community development in tourist destinations. Note that this paper does not address emergency alerts such as earthquake early warnings; instead, it focuses on routine weather forecasting, because everyday data utilisation is the primary concern.

At the JMA, the production of weather forecasts proceeds through the following steps (Figure 1) [Weather Business Consortium, 2019].

(1) The JMA serves as the central hub for observing and collecting a wide range of domestic and international meteorological data.
(2) Using super-computers, the JMA analyses the future state of the atmosphere.
(3) Through the Japan Meteorological Business Support Centre, the JMA releases the collected observational data as numerical datasets to private weather-service providers.

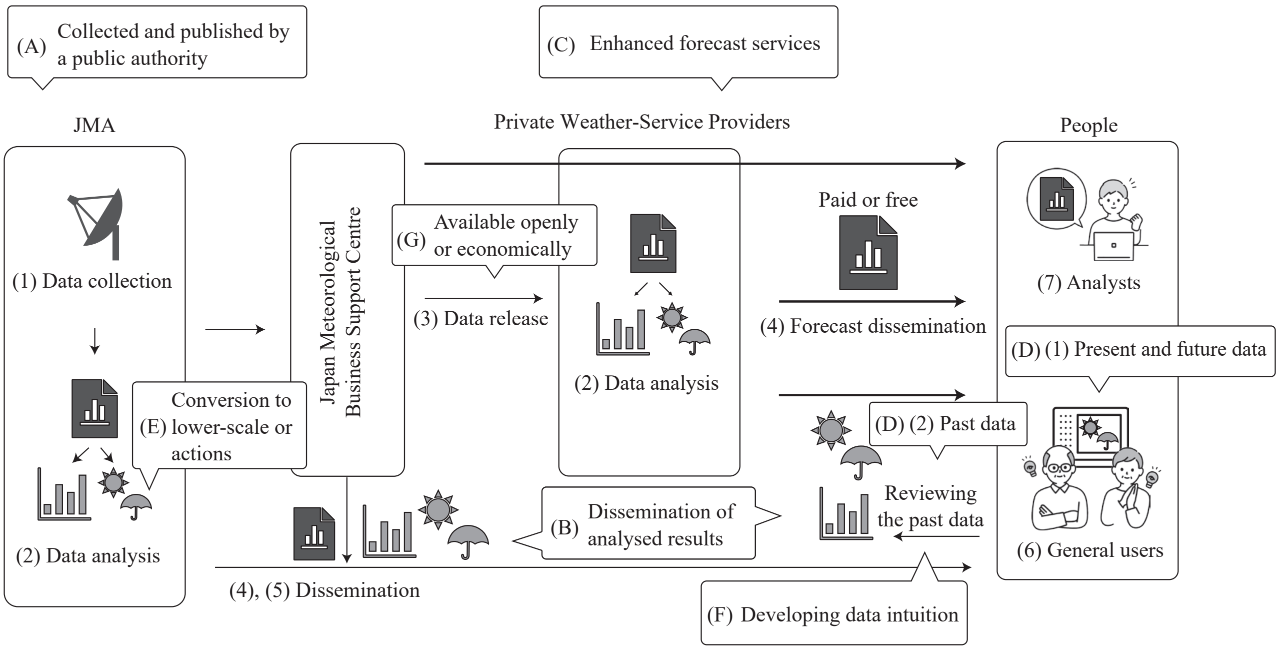

Figure 1: Meteorological data flow (Steps 1-7) and requirements (A-G), as discussed in Chapter 6

(4) Through the same centre, the JMA disseminates its analysis results as numerical weather predictions for private providers.
(5) It also disseminates index-based forecasts to private providers via the centre.
(6) General users consult these forecasts to inform decision-making.
(7) Advanced users, such as analysts and corporate stakeholders, may conduct further analyses to support more complex decision-making.

Step 6 can be illustrated by everyday users of "Yahoo! Weather", who consult meteorological information supplied by Weather Map Co., Ltd., a licensed forecasting service provider, to decide, for instance, whether to carry an umbrella [Weather Map, n.d.]. Step 7 is exemplified by Japanese convenience-store chains that analyse data delivered by Weathernews Inc. and use the results to optimise their ordering operations [Weathernews, 2023].

Here we identify several factors that are equally important for the utilisation of urban data in tourist destinations. Together, these factors lower the barriers to data utilisation for the large population of general users:

- Data are centrally collected by public institutions, relieving individuals from the burden of collection.
- In addition to releasing raw numerical data, the institution analyses the data and publishes the interpreted results in an accessible form.
- Private companies add further value, sometimes through paid services, by distributing forecasts that are even more convenient for end users.

5.2 Temporal dimension of data

This section organises meteorological information according to its temporal context. Weather forecasting relies on three distinct categories of data: past, present, and future. Past data comprise retrospective summaries such as the review of the day's weather broadcast in evening news programmes. Although seemingly less critical, these historical observations play a key role in data utilisation, as explained in the next section. Present data capture imminent, rapid changes in conditions. An example is Weathernews Inc.'s "Guerrilla Thunderstorm Alarm," which sends smartphone alerts up to 30 minutes before a sudden cloudburst. Future data span short-lead products such as the Japan Meteorological Agency's Nowcasts that display precipitation distributions up to one hour ahead, as well as conventional forecasts for tomorrow, the coming week, and beyond.

Users primarily consult weather forecasts for present and future data, using these time frames to guide decisions in the next few hours, the same day, or the days ahead. This emphasis underscores the high value placed on present and future information; the minimal broadcasting time or column space devoted to historical observations in forecast media further confirms the lower priority of past data. In tourist destinations, therefore, ordinary people will likewise need to provide real-time and forward-looking information. For instance, a restaurant serving visitors could use present data to detect an impending influx of customers and accelerate table bussing, while future projections would enable managers to adjust staff rosters in advance.

Conversely, historical records play an even more critical role in the utilisation of urban data than they do in weather forecasting. Many destination managers possess a rough, experience-based sense of situation in their locales, yet some wish to replace these hunches with objective, data-driven judgements [Hori et al., 2024]. Doing so requires linking already available past data to the intuitive cues underpinning their decisions, a task that can be achieved only through systematic analysis of past data. By exploiting such records, managers can corroborate their intuition, correct misconceptions, quantify vague impressions, and uncover patterns that previously escaped notice [Hori et al., 2023]. In this way, analysing historical data and establishing a shared, objective, and quantitative view is important. Unlike meteorology, whose forecasting methods rest on knowledge accrued since the 19th century [Japan Meteorological Agency, n.d.a], routine urban data collection began only recently with advances in AI. As a result, data accumulation is insufficient, and robust predictive techniques have yet to emerge. Even in today's technology-rich environment, developing mature forecasting tools for urban data will take time. In the interim, analysing historical records can yield information far more precise than intuition alone and can serve as a practical substitute for real-time or forward-looking data in decision-making.

This analogy underscores two requirements for data utilisation in tourist destinations:

- Continual forecasting of the present and near future, updated daily to match users' principal interests.
- Analysis, publication, and use of past data.

5.3 Data scales

This section organises weather forecast information according to its measurement scale. The data supplied to end users can be grouped into three classes: numerical values, indices, and categories.

- Numerical values—e.g., precipitation (mm) or air temperature (°C), belong to the ratio or interval scale in statistical terms.
- Indices—e.g., the five-point "laundry index," indicating how well clothes will dry, constitute an ordinal scale.
- Categories—e.g., sunny, cloudy, or rainy, are measured on a nominal scale.

In statistics, the ratio scale occupies the higher-level scale, followed sequentially by the interval, ordinal, and nominal scales. Higher-level scales contain more detailed information and can be collapsed into any lower-level scale; conversely, lower-level scales cannot be expanded without additional data. Put differently, higher scales provide finer data granularity. Within weather forecasting, numerical data are processed to derive indices and categories. Therefore, numerical values represent the highest-level scale, whereas indices and categories constitute lower-level scales derived from them. Data that have been converted to a lower-level scale are easier for general users to handle because their meaning is unambiguous and the implied action is obvious. The trade-off, however, is a loss of informational richness that limits statistical analysis and advanced applications.

Numerical variables such as air temperature are a higher-level scale. To make practical use of these figures, users must link them to lived experience—for example, by learning what clothing feels comfortable at a given maximum temperature through repeated evening forecasts. Because such tacit knowledge takes time to accumulate, purely numerical data are relatively difficult to exploit, and the historical records discussed in the previous chapter become indispensable. Indicator variables such as the laundry index or the outing index combine objective meteorological measurements with an explicit behavioural recommendation for forecast users. These behavioural indices are therefore highly user-friendly: although they limit analytical freedom and the range of possible applications, they translate directly into action and are easy for the general public to grasp. By contrast, not every index specifies what users should do. Measures such as the discomfort index or the sleep index leave the choice of action to the individual and are consequently less immediately actionable and somewhat harder to exploit than behavioural indices. Non-behavioural indices can be divided into two types. Analytical indices, for example, the discomfort or sleep index, are derived from statistical analysis of meteorological data. Classified indices, such as five-level temperature or rainfall scales, are created by partitioning higher-level numerical variables into fixed intervals to enhance readability. Finally, categorical data like sunny, cloudy, and rainy have a coarser granularity than continuous values; the stark differences between categories make them even simpler and, for many users, easier to apply than raw numerical data.

Another approach represents rainfall intensity with onomatopoeia (hereafter, the onomatopoeic index). Onomatopoeia is defined as “the formation of a word from a sound associated with the thing or action being named; the formation of words imitative of sounds. Occasionally, the fact or quality of being onomatopoeic” [Oxford English Dictionary, 2025]. Although Japanese is one of the languages richest in onomatopoeic expressions [Akita and Dingemanse, 2019], other languages also use them, for example, “meow” in English or “ouah” in French. Native speakers intuitively link an onomatopoeic word to the phenomenon it denotes, enabling instantaneous understanding [Hamano, 1998]. By exploiting this property, onomatopoeia anchors data to sensory impressions, making the information highly intuitive. Weathernews, a major Japanese forecasting website, illustrates rainfall amounts using the terms listed in Table 1. Through this onomatopoeic index, forecast users perceive rainfall strength as an ordered sequence, placing the index on the ordinal scale. Comparable onomatopoeic schemes are also employed to describe snow intensity.

Based on the analysis thus far, categorical data, behavioural indices, and onomatopoeic indices are the easiest for individuals without prior knowledge of weather forecasting to use effectively. This ease stems from their intuitive clarity about appropriate actions (hereafter referred to as Type-1 data). These data types are particularly user friendly because categorical data, such as whether it rains or not, significantly influence the actions people take. Behavioural indices explicitly recommend specific actions, and onomatopoeic indices leverage intuitive, naturally acquired sensory impressions. The next-most accessible data are numerical values and classified indices, which require users to undergo some degree of training to link numerical values with real-world conditions. Thus, while somewhat less intuitive than Type-1 data, these remain relatively easy to grasp because they consist of single, clearly defined measurements. Users can effectively employ these data by developing familiarity through experience that associates numerical values with sensations or actions (hereafter referred to as Type-2 data). Finally, the analytical indices, which involve more complex calculations, represent the least intuitive data type (hereafter referred to as Type-3 data). For instance, the discomfort index is calculated using the following formula:

Discomfort Index = 0.81 × Temperature + 0.01 × Humidity ×

Table 1: Onomatopoeic index corresponding to rainfall amounts

Rainfall	Onomatopoeic Index	Explanation
Less than 1 mm	*potsu-potsu*	No umbrella needed
1-2 mm	*para-para*	Umbrella needed; Short dash to nearby shelter
2-4 mm	*sā*	Moderate rainfall
4-10 mm	*zā-zā*	Large umbrella essential; Going out unpleasant
Over 10 mm	*gōō*	Downpour; Going out difficult

Source: Created based on Weathernews [n.d.].

(0.99 × Temperature − 14.3) + 46.3

This formula clearly indicates that lowering either temperature or humidity will reduce discomfort. However, the name discomfort index itself does not directly imply specific actions, making it difficult for general users to translate this data into immediate behaviour without further analysis. Similarly, the sleep index, developed in 2018 by the Japan Weather Association and Tohoku Fukushi University, describes the relationship between thermal conditions in bedrooms and sleep quality [Japan Weather Association, 2018]. This index has separate scales for the cold season (October 1 to March 31) and the warm season (April 1 to September 30). For the warm season, it is divided into five scales: slightly cold night, comfortable for sleep, slightly hot, somewhat humid, and uncomfortable night. For the cold season, the scales are: good sleep conditions, slightly cold the next morning, heating needed before bedtime, heating needed both night and morning, and heating absolutely necessary! Of these scales, expressions like heating needed before bedtime, heating needed both night and morning, and heating absolutely necessary! clearly incorporate recommended actions and thus correspond to Type-1 data (behavioural indices). Scales such as slightly cold, slightly hot, somewhat humid, and slightly cold the next morning align with Type-2 data, as users typically understand these sensations through personal experience and can intuitively determine appropriate actions. However, the scale uncomfortable night lacks explicit references to temperature conditions, making it less clear what specific action should be taken. This places it into Type-3 data, as it requires further interpretation and analysis. Thus, while the sleep index combines elements of all three data types, the overall mixture and the presence of specialized terminology in Type-2 segments render it relatively complex, justifying its classification predominantly as Type-3 data.

Thus far, we have argued that lower-scale indicators (such as behavioural indices, categorical data, or onomatopoeic index) are easier to understand intuitively. However, some users may find numerical measures of temperature or rainfall, examples of higher-scale data, more practical than lower-scale behavioural indices or categorical data. This preference arises from extensive personal experience that closely links numerical data to intuitive sensations and everyday decisions. For instance, many residents of Japan easily recognise the clothing differences required for temperatures of 15 °C versus 5 °C, yet would struggle to distinguish the necessary attire at –15 °C versus –25 °C. While lower-scale indices are intrinsically simpler for users who lack experiential training to connect data directly to sensations or actions, sustained exposure and experience with numerical data can gradually enable effective use of even higher-scale measures.

We have identified key requirements that make weather forecasts intuitive and easily accessible for everyday users. Similarly, for ordinary people to effectively utilise urban data in tourist destinations, data providers must strive to present information on the lowest practical measurement scales. Specifically, data should be provided at scales that directly inform and influence users' actions—such as clearly defined categories (e.g., sunny/cloudy/rainy). Furthermore, integrating actionable insights or familiar experiential cues alongside objective urban data significantly enhances data usability. This approach aligns with feedback from tourism-related businesses in Takayama City, which explicitly requested practical guidance on how best to utilise local data [Hori et al., 2024]. Additionally, employing onomatopoeia could further bridge the gap between data and intuitive understanding. Ordinary users of weather forecasts typically do not engage in analysing meteorological data. They are primarily consumers rather than analysts. To achieve the same user-friendly state for urban data utilisation, merely providing open data (such as comma separated values, CSV) is insufficient. Instead, data publishers must thoroughly analyse raw data and present distilled, simplified insights directly to the community. At the same time, users gradually develop intuitive connections to higher-scale numerical data through exposure to past data. It is crucial for data users to recognise that effective data utilisation skills cannot be acquired instantly; rather, regular interactions with data are necessary to refine their intuitive understanding. In summary, while data providers should proactively simplify data presentation to reach general users, data users must also actively engage with data to enhance their intuitive interpretation skills.

5.4 Collaboration with private-sector providers

This section outlines the roles played by licensed private forecasting businesses and other private-sector organisations that leverage weather forecasts, separate from public institutions such as the JMA and the ordinary public users of forecasts.

Licensed private forecasting businesses are entities authorised by the Director-General of the JMA, in accordance with Article 17 of Japan's Meteorological Service Act, to deliver weather or wave forecasts independently from the JMA. As of March 31, 2025, 86 entities have obtained permission to conduct weather forecasting [Japan Meteorological Agency, n.d.b]. These licensees include specialised weather-service companies such as Weather Map Co., Ltd., media organisations such as TV Tokyo Corporation, and even municipal governments such as Hiroshima City. Notably, the licensees are not necessarily corporations—there are cases of individuals also obtaining permission [Tabira, n.d.]. These licensed providers deliver forecasts enriched with additional value by combining publicly available JMA datasets with their own independently collected data. For example, the Japan Weather Association offers data analysis and consulting services, analysing meteorological information to forecast product demand for manufacturers, apparel businesses, and retail enterprises [Japan Weather Association, n.d.]. The JMA openly distributes its collected data, charging only a modest fee (typically a few thousand yen) solely to offset distribution costs, not as payment for the data itself.

This economical and open approach facilitates data utilisation across a diverse range of organisations [Koshizuka, 2018].

The open and affordable dissemination of urban data in tourist destinations can likewise stimulate value-added data utilisation. Unlike proprietary store-level data, urban data are inherently suitable for sharing and collaborative use across multiple organisations within a community. Typically, such data lend themselves well to publication as open or low-cost data, accessible for analysis and application by a broad range of users. Moreover, this openness allows private-sector entities to create additional value-added services and business opportunities based on the original data.

In Japan, the Meteorological Service Act mandates that organisations providing independent forecasts to the public must obtain official authorisation from the JMA. This requirement reflects the critical role that weather forecasts play in public safety and business operations. Unverified forecasts, if widely disseminated, could cause confusion or damage to those acting upon them, posing risks to social stability [Japan Meteorological Agency Information Infrastructure Department, 2024]. As noted in Chapter 4, Japan's approach to weather forecasting, historically rooted in storm warnings, underscores its potential life-and-death significance—an ethos reflected in the existence of national certifications such as the Licensed Weather Forecaster. In contrast, the U.S.A., the U.K., and countries within the EU do not require official registration for providing weather forecasts. Urban data in tourist destinations rarely have direct life-threatening implications. Although inappropriate data use might incur financial losses under certain conditions, modern data-utilisation practices commonly adopt a "Proof of Concept" (PoC) step, allowing organisations to test data applications thoroughly before integrating them into operational processes. Consequently, imposing certification or licensing requirements would likely hinder, rather than enhance, data utilisation. It is therefore preferable to encourage the operational use of urban data without introducing formal licensing schemes, thereby facilitating greater data adoption and innovation.

6. Requirements for effective use of time-series data in tourist destination management

By examining weather forecasting from a data-utilisation perspective, this study has identified the necessary requirements for effectively leveraging time-series data in managing tourist destinations (Figure 1).

From the perspective of data collection, analysis, forecasting, and dissemination, the essential requirements are:

(A) Data should be collected centrally by a public authority rather than by individual users.
(B) The authority should not only publish numerical data but also analyse these data and release processed results for users.
(C) Private-sector entities should be encouraged, where necessary, to provide additional forecasts with higher utility—potentially as paid services.

From the perspective of the temporal dimension of data, the essential requirements are:

(D-1) Providing daily updated forecasts of current and future data is most important for users.
(D-2) Historical data should also be systematically analysed, published, and utilised.

From the perspective of data measurement scales, the essential requirements are:

(E) Data providers should simplify information by converting it to the lowest feasible measurement scale.
(E-1) Data should be categorised using clear distinctions (such as sunny/cloudy/rainy) that decisively influence user actions.
(E-2) Data provision should incorporate not only objective urban data but also recommended actions for users.
(E-3) Data provision should link objective urban data to familiar sensations or experiences already intuitive to users.
(F) Users should develop intuitive understandings of higher-scale data through repeated exposure to past data.

From the perspective of collaboration with private-sector providers, the essential requirement is:

(G) Data should be made openly or affordably available to encourage private-sector innovation and value-added applications.

Collectively, these 11 requirements constitute the necessary requirements for realising the local production and consumption of time-series data, crucial to sustainable destination development. By clearly defining the conditions for effective data utilisation by non-expert tourism stakeholders, this study provides concrete insights and practical guidelines toward the implementation of a smart tourism ecosystem.

7. Conclusion

By systematically analysing weather forecasting from the viewpoint of data utilisation, this study identified 11 essential requirements for effectively utilising urban time-series data by non-experts in tourist destination management.

The discussion presented here addresses general principles for the utilisation of time-series data. To ensure applicability in real-world contexts, future research should engage more concretely with specific local cases. This may include determining which lower-scale data presentations non-experts in tourist destinations find most intuitive or developing forecasting methods that integrate appropriate algorithms and features.

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