Integrated Geo-Sensing: a Case Study on the Relationships between Weather and Mobile Phone Usage in Northern Italy

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***Abstract*— Meteorological phenomena, in particular rapid events with local dynamics such as the onset of heavy rainfall, may have several instantaneous impacts on human behaviour. These impacts include, for example, the utilization of private or public transportation or on scheduling of personal and business activities. Given the increasing accuracy of weather forecasting at any scale, understanding the relationship between weather patterns and collective mobility behaviour or activity could, for instance, provide valuable insights into understanding urban dynamics and/or demand for public resources such as transportation. Scientific studies show that user-generated traffic in wireless communication networks can serve as a proxy for spatio-temporal patterns of human behaviour. In this paper we explore the relationship between weather and mobile phone usage and indirectly on human behaviour. We link the time-space pattern of meteorological measurements with that of mobile phone usage in the same large scale area (a region in Northern Italy). Taking the spatial context into account, we compare frequency-domain statistics correlations between weather and telecom activity and how they change between mountainous, urban, and coastal areas. The results indicate significant relationships between weather conditions, telecom activity, and area type.**

***Keywords*— sensor networks, user-generated network traffic, environmental monitoring, human behaviour, factor analysis, spectral analysis, squared spectral coherence estimation**

I. INTRODUCTION

Today, we witness an increasing use of user-generated traffic in wireless communication networks to analyse spatio-temporal patterns of human activities [1-3]. Several scientific studies link such patterns to other data in order to explore, for example, the structure of social networks [4], the physical environment [5], or city dynamics [6], [7]. Human's activity patterns of both individuals [8] and the communities [9] have been evaluated to disclose patterns that can assist urban planning and transportation analysis.

Within the environmental monitoring domain, the amount and the availability of digital information based on near real-time sensor measurements have been rapidly increasing over the last few years [10], [11]. These sensor measurements quantify rainfall, temperature, particulate matter, concentration of trace gases etc. Distributed geo-sensor networks in combination with GIS are indeed employed to automatically generate multi-dimensional information beyond point measurements through web-based geoprocessing routines [12] and geospatial cloud computing [13].

However, the consideration of "exogenous factors", specifically environmental phenomena mentioned above, has been primarily addressed for sensor network design purposes (e.g. [14]) rather than integrated into the analyses of human activity patterns. Such integration in combination with geo-spatial analysis and GIS enable novel capabilities to monitor the status of the environment in a more integrated and intelligent manner.

Bridging the gap between large-scale collective social sensing and environmental monitoring can potentially disclose useful insights into the instantaneous interactions between people and their environmental context factors. From an integrated geo-sensing perspective, such insights might have far-reaching impacts, for example on time-critical decision making.

Within this research, mobile phones are considered ubiquitous sensors capable of disclosing communication behaviour and whereabouts of their users. The traffic within a "large-scale sensor network" – the mobile network – thus reflects spatio-temporal communication characteristics and movement patterns of hundreds of thousands of subscribers.

Hence, the following research question arises: Can a significant relationship between weather and mobile phone activity – and indirectly human behaviour – be revealed by examining their digital measurements from geo-sensing technologies?

In this paper we link meteorological in-situ sensor measurements to collective mobile phone usage derived from user-generated cellular network traffic. Subsequent analyses include factor- and spectral analysis. Taking the regional context into account, we compare analyses results among mountainous, urban, and coastal landscapes in Northern Italy.

The next section explains the methodology. Section III describes the case study including test areas selected and data sets used. Section IV presents experimental results followed by a critical discussion in Section V. Finally, in Section VI, conclusion and future research interests are given.

II. METHODOLOGY

A. Data Acquisition and Information Retrieval

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We employ two inherently independent sensing technologies to monitor the current state of environmental and human dynamics: (1) in-situ multi-sensor nodes for measuring environmental parameter, and (2) mobile phone networks for sensing human behaviour indirectly.

1) In-Situ Sensors: In-situ multi-sensor nodes measure a diversity of environmental parameter relating weather (temperature, precipitation etc.), air quality (trace gases, particulate matter etc.), hydrological conditions (river gauges, surface runoff etc.) and so on. Such sensor nodes include highly mobile and intelligent sensor pods [15] as well as fixed sensor stations [16]. By requesting measurements from such sensor nodes, we are capable of monitoring and analysing environmental dynamics near real-time.

2) Mobile Phone Networks: User-generated traffic in such "large-scale sensor networks" reflects spatio-temporal behavioural patterns of their users. Moreover, depending on a provider's market share and mobile penetration rate, these patterns reflects to some degree the dynamics of the larger population. In order to derive spatio-temporal information from a huge volume of raw mobile network traffic data a semi-automated (geo-)processing workflow has been developed (not further described in this paper).

B. Analysis Methods

In contrast to techniques applied in previous mobile network traffic research such as eigen-decomposition [17] or multi-level regression analysis [9], we integrate weather data and focus on potential temporal relationships between weather and telecom data.

1) Factor Analysis: An exploratory factor analysis (EFA) has been undertaken to reduce dimensionality and redundancy in a number of meteorological variables. EFA is utilized to extract underlying and interrelating structure in the data. Resulting factors should account for simple weather conditions such as favourable/non-favourable and positive/negative respectively.

2) Spectral Analysis: A spectral analysis (SA) has been performed to unveil significant periodical components in the time series of the remaining factors (output of EFA) and mobile telecom traffic intensity. The squared spectral coherence – the spectral equivalent of the R^2 in regression analysis [18] – is computed to evaluate the relationships between weather and mobile phone traffic.

C. Limits and Constraints

A variety of different factors influence the status of the environment and of human behaviour. This includes for example (heavy) industry, large public events, construction areas, traffic jams etc. Most of them are hardly detectable; many of them are too complex to sense. Here we consider "only one" context factor that might influence mobile phone usage, namely weather.

III. CASE STUDY

To answer our research question stated above we performed a case study in Northern Italy. Emphasis is put on small-scale (spatial dimension: ~30 km^2) and short-term (temporal dimension: 1 day) dynamics of weather, and mobile phone usage.

A. Study Areas

To take into account the environmental and land-use context we study three different areas:

- Urban area: a small city – around 100,000 inhabitants;
- Mountainous area: a sparsely populated area characterized by an economy that depends on low-scale farming and tourism (e.g. outdoors, skiing, or hiking);
- Coastal area: a popular beach holiday area, populated mainly in the summer season;

B. Datasets used

We used data for the period between September 10th and September 20th 2009 for the Region Friuli Venezia Giulia, Italy.

1) Meteorological Data. We used the following five parameters: rainfall, air temperture, relative humidity, air pressure, and solar radiation. All measurements are hourly averages and are measured by accurately calibrated weather stations used for regional weather forecasting by the Regional Environmental Agency.

2) *Mobile Network Traffic Data.* Anonymized and aggregated volumes of traffic data were provided by a network operator in raster and vector formats at 15-minute intervals. Traffic intensity measured in Erlang[1] is represented as a regular 250m x 250m regular raster.

The datasets have been consolidated on a GIS platform and associated to the same underlying time-space basis.

IV. EXPERIMENTAL RESULTS

In this section we describe the analysis for the urban area. The analysis for the other two areas follows the same methodology.

A. Preparation for Exploratory Factor Analysis of Meteorological Variables

As stated above we consider five meteorological variables, namely rainfall R, air temperature AT, relative humidity RH, air pressure AP, and solar radiation SR. For an exploratory factor analysis a sufficient number of significant correlations among the five variables are needed [19]. We therefore apply the Bartlett's test of sphericity [20], and the Kaiser-Meyer-Olkin (KMO) test [21]. Regarding the former test, the expected χ^2 with ten degrees of freedom (df) and a significance level $\alpha < 0.001$ is equal to 29.5880 (according to the standard table for critical values of the χ^2 distribution).

[1] Dimensionless basic unit of telecom traffic intensity, named after A. K. Erlang: 1erlang=1person calling 1hour, or 2 persons calling 0.5hour each…

Since the calculated χ^2 value of 697.042 – shown in Fig. 1 – is considerably higher than the expected χ^2 value (697.042 >> 29.5880), the null hypothesis (H_o: the correlation matrix is the identity matrix) is rejected. This in turn means that there is significant correlation among the five variables. With respect to the KMO test, Fig. 1 shows that the overall KMO Measure of Sampling Adequacy (MSA) of 0.710 indicate a "middling" relative relationship between Pearson's correlation and partial correlation among all variables [21]. This value is, nevertheless, sufficient to perform a factor analysis.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		,710
Bartlett's Test of Sphericity	Approx. Chi-Square	697,042
	df	10
	Sig.	,000

Fig. 1: KMO and Bartlett's Test results of five meteorological parameters for the urban environment

In addition to the overall KMO MSA, the individual MSA indicates how strongly each meteorological parameter is correlated with all the others. All individual MSAs, as shown in the main diagonal in the Anti-Image Correlation Matrix (Fig. 2) are > 0.6. These confirm the overall KMO test and indeed approve the involvement of all items. The correlation matrix is therefore factorable.

	R	AT	RH	AP	SR
R	,774[a]	-,011	-,076	,267	,023
AT	-,011	,669[a]	,656	,034	-,544
RH	-,076	,656	,720[a]	,342	,079
AP	,267	,034	,342	,645[a]	,181
SR	,023	-,544	,079	,181	,770[a]

a. Measures of Sampling Adequacy (MSA)

Fig. 2: Anti-Image Correlation Matrix of five meteorological variables for the urban environment

Similar results have been achieved for both the mountainous and the coastal environment as summarized hereafter.

- Mountainous: calculated χ^2 = 611.970 (df = 10, α < 0.001); overall KMO MSA = 0.661; all individual KMO MSA values > 0.6
- Coastal: calculated χ^2 = 476.612 (df = 10, α < 0.001); overall KMO MSA = 0.646; all individual KMO MSA values > 0.6

We conclude from these results that there are a sufficient number of significant correlations among the five items. This is a proper basis for performing an exploratory factor analysis of the five meteorological measurements (R, AT, RH, AP, and SR) for the urban, mountainous, as well as the coastal landscape.

B. Exploratory Factor Analysis of Meteorological Variables

The next step is to determine the factor extraction method. Our intention is to find, in a descriptive way, the underlying uncorrelated constituents in the data. For this we select the Principal Component Analysis (PCA) method.

As shown in Fig. 5 78.955 % of the total variance (i.e. specific, common, and error variance) is explained by two principal components with eigenvalues greater than one. The number of two principal components is indeed confirmed by scree plot evaluation (according to [22]). The rotated component matrix shown in Fig. 3 summarizes the final loadings of the five meteorological variables for the two orthogonal principal components extracted.

	Principal Component	
	1	2
R	-,076	,808
AT	,942	-,165
RH	-,864	,334
AP	,174	-,810
SR	,911	,003

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Fig. 3: Loadings of the five meteorological parameters on the two orthogonal principal components (urban environment)

Principal component 1 is heavily positively loaded by air temperature and solar radiation, and heavily negatively loaded by relative humidity – which correspond to nice weather conditions. We, therefore, term the first component "Nice Weather". In contrast, principal component 2 is heavily positively loaded by rain; moderately positively by relative humidity; strongly negatively by air pressure. Since these loadings indicate adverse weather conditions, we term this second component "Bad Weather".

The presence of periodic elements in the three remaining time series "Nice Weather" (PC 1), "Bad Weather" (PC 2), and "Mobile Telecom Traffic" are obvious in the time domain (Fig. 4 shows the three time series for the urban area). To explore such periodic patterns and their potential relationships within these time series, they are input for frequency domain analysis.

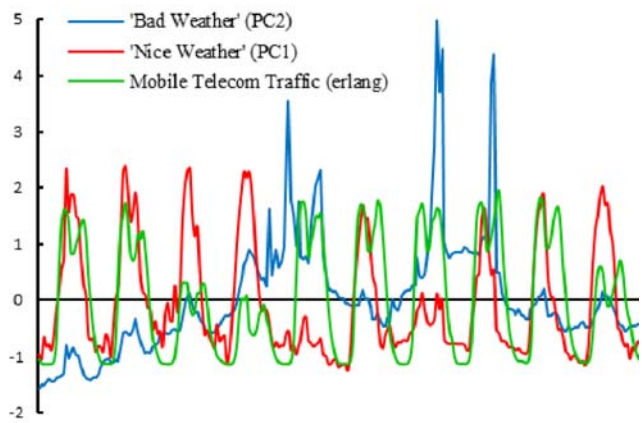

Fig. 4: Periodic patterns in the time domain: 10 days of three standardized variables for the urban environment

Similar underlying principal components have been extracted for the mountainous (Fig. 6) and the coastal area (Fig. 7).

Thus, for all three environments – urban, mountainous, and coastal – we term the first principal component as "Nice Weather" and the second as "Bad Weather". The respective component scores used for further analyses have been estimated using the Anderson-Rubin approach [23]. The resulting new variables are therefore standardized.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,805	56,095	56,095	2,805	56,095	56,095	2,500	50,008	50,008
2	1,143	22,860	78,955	1,143	22,860	78,955	1,447	28,947	78,955
3	,666	13,316	92,271						
4	,265	5,290	97,561						
5	,122	2,439	100,000						

Extraction Method: Principal Component Analysis.

Fig. 5: Explanation of total variance in five meteorological variables (R, AT, RH, AP, and SR) using Principal Component Analysis: Components 1 and 2 having a eigenvalue > 1and account for 78.955 % of the total variance (urban environment)

	Principal Component	
	1	2
R	-,262	,733
AT	,909	-,201
RH	-,778	,395
AP	,001	-,898
SR	,939	,054

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Fig. 6: Mountainous environment: Loadings of the five meteorological parameters on the two orthogonal principal components

	Principal Component	
	1	2
R	,006	,730
AT	,885	-,216
RH	-,801	,445
AP	,222	-,758
SR	,842	,110

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Fig. 7: Coastal environment: Loadings of the five meteorological parameters on the two orthogonal principal components

C. *Spectral Analysis of Weather and Mobile Telecom Traffic*[2]

For each environment – urban, mountainous, and coastal – the periodogram of "Mobile Telecom Traffic" shows the main and first peak at a frequency f1 = 0.0417/h, thus a period T1 = 1/f1 = 24 hours. This first harmonic indicates, intuitively, the predominance of the day-night pattern. The second (f2 = 0.0833/h → T2 = 12h) and third harmonic (f3 = 0.125/h → T3 = 8h) contribute with ~6% and ~12%, respectively, of the first harmonic's magnitude. Depending on their phasing, these two harmonics affect – per day for the graph in the time domain – the double-peak at noon and signifies working/non-working hours [9], [14] (see Fig. 4 Mobile Telecom Traffic).

In the bivariate spectral analysis, "Mobile Telecom Traffic" is considered the dependent variable and "Nice/Bad Weather" is considered the independent one. Cospectral density plots do not expose much new information due to the power of day/night pattern. In contrast, additional periodic components arise when emphasis is put on the squared spectral coherence γ^2 – the squared magnitude of the cross-spectrum – of the aforementioned variables and, indeed, taking the different scenic context into account. "Within each frequency band, the squared coherence (like an R^2 in regression analysis) estimates the percentage of the variance in time series X that is predictable from time series Y, within this particular frequency band" [18] (p138). The results below illustrate the squared coherence of mobile network traffic and weather – this corresponds to the time series X and Y respectively cited above. We elaborate on dominant sinusoidal components with $8h \geq T \geq 24h$ because of the presence of the three harmonics and the total time interval covered by the data (10 days). For all these components, the hypothesis of zero coherence is rejected [24]. Numbers (1, 2, and 3) within the figures correspond to the number of the harmonic.

[2] *Note:* each of the data points in the time series represents one hour, thus the sampling frequency is 1/hour.

1) *Urban Context:* Addressing "Nice-Weather", the three most significant peaks (1-3) are at harmonic frequencies with T = 24h, 12h, 8h (Fig. 8).

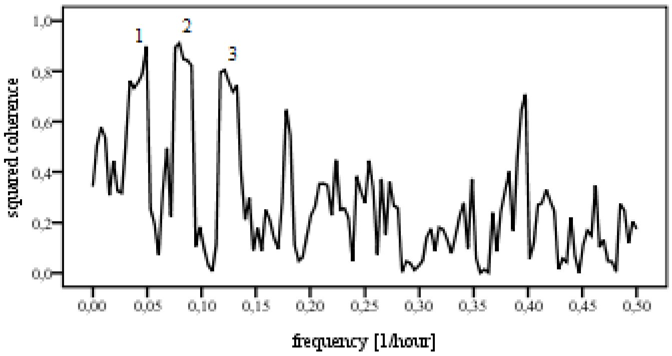

Fig. 8: Urban: spectral correlation of "Nice Weather" and z-erlang

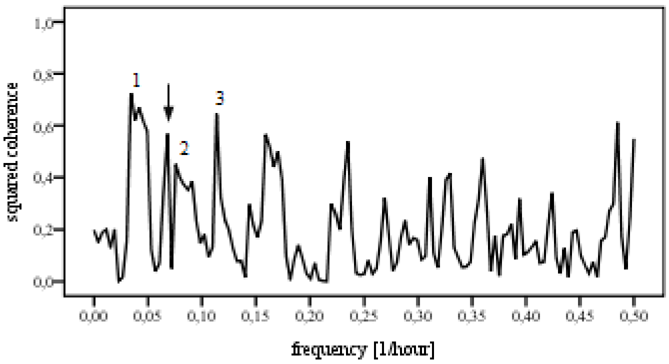

Fig. 9: Urban: spectral correlation of "Bad Weather" and z-erlang

At "Bad Weather" conditions, Fig. 9 shows less significant coherence at harmonic frequencies in general and at the second harmonic in particular – in comparison with Fig. 8. Furthermore, peak 3 has a considerably smaller peak-width.

2) *Mountainous Context:* The first two peaks in Fig. 10 (1-2) are as dominant as is Fig. 8 (T_1 = ~24h, T_2 = ~12h). When including peak 3 (T_3=~8h), the squared coherence does not drop below 0.22 (dashed line) within the spectrum of the

harmonics. Fig. 11 shows significant peaks at f = 0.015/h (T = 66h = 2.7d), T = ~24h (1), and T = ~12h (2).

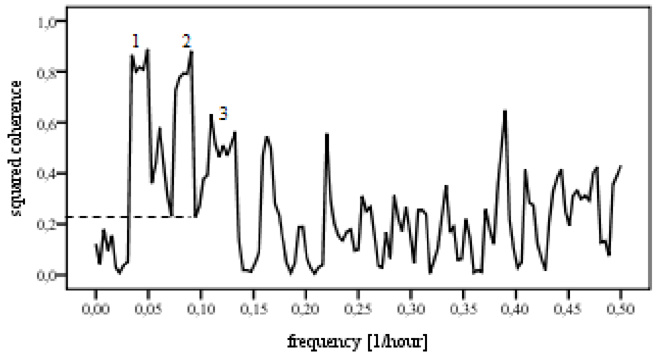

Fig. 10: Mountainous: spectral correlation of "Nice Weather" and z-erlang

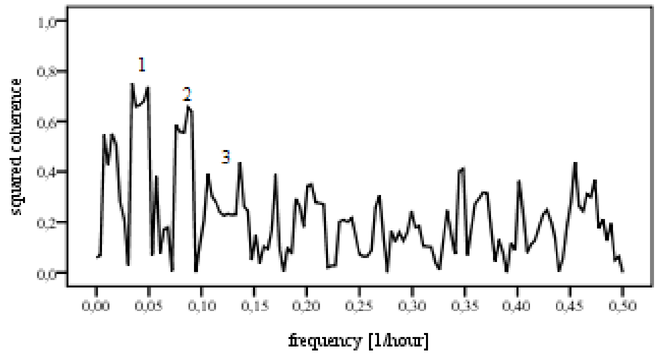

Fig. 11: Mountainous: spectral correlation of "Bad Weather" and z-erlang

3) *Coastal Context:* The coherence between "Nice Weather" and "Mobile Telecom Traffic" show dominant peaks (1, and 2) at T = ~24h, and ~12h, respectively (Fig. 12).

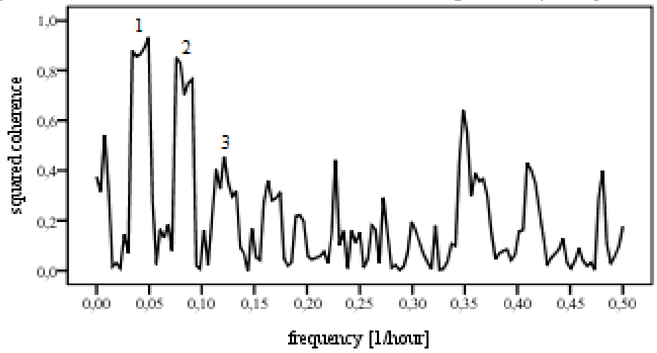

Fig. 12: Coastal: spectral correlation of Nice Weather" and z-erlang

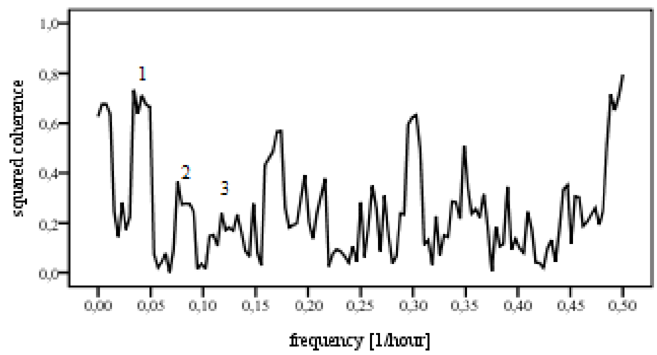

Fig. 13: Coastal: spectral correlation of "Bad Weather" and z-erlang

Focusing on "Bad Weather" condition in the costal test area the first harmonic's peak has a magnitude of 0.7, whereas peak 2 (T = ~12h) has a half of it (0.35).

V. Discussion

Most of the power of the relationship between weather and mobile telecom traffic is, as expected, centred on their harmonics. This reflects the predominant day/night pattern of all variables considered in general (T = 24h) and mobile telecom traffic in particular in particular (plus T = 12h, and 8h) as this signifies working/non-working hours within the daily circle [9].

In the urban context "Nice weather" ($\gamma^2 \leq 88\%$) rather than "Bad Weather" ($\gamma^2 \leq 75\%$) spectrally correlates with mobile telecom traffic at harmonics (Fig. 8 and Fig. 9). At the second harmonic (peak 2: T = 12h), γ^2 is significantly lower at "Bad Weather" as compared to "Nice weather" conditions (38% << 88%). This indicates that nice weather conditions explain more of the variance in mobile telecom traffic data, in particular during working hours.

Nice weather conditions in the mountainous area lead to an overall "high energy level" between peak 1 and peak 3 since this explains more than 22% of the variance in mobile telecom traffic within the entire spectrum of the three harmonics. Although this indicates a strong spectral relationship, it also indicates higher daily variation of both "Nice Weather" and "Mobile Telecom Traffic" (Fig. 10) compared to bad weather conditions (Fig. 11).

For the coastal place, "Nice Weather" explains twice the variance in mobile telecom traffic at the 12h peak ($\gamma^2 = 70\%$) compared to "Bad Weather" ($\gamma^2 = 35\%$). The same proportion is available for the 8h peak (3). This indicates that nice weather conditions better explain the working/non-working pattern within the underlying daily circle than bad weather conditions.

A common noteworthy spike at f~0.06/h (T ~ 16h), marked with an arrow in Fig. 9, can be identified in the urban and mountainous but not in the coastal context. This spike is difficult to interpret and needs further investigation. Additionally, the very first peak in Fig. 8, and Fig. 11 to Fig. 13 at f ~ 0.0075/hour (T = ~ 5.5 days) might designate another periodic component, possibly the weekdays/weekend patterns as argued in [9].

Hence, for all three spatial environments – urban, mountainous, and coastal – "Nice Weather" rather than "Bad Weather" strongly covary with mobile telecom traffic in the frequency domain. The squared spectral coherence estimation indeed identified significant individual sinusoidal components with T = 24h, 12h, and 8h. These components together signify the predominant day/night pattern (24h) and particularly the working/non-working pattern (12h and 8h). Transferred back to the time-domain, this means a stronger temporal correlation of nice weather conditions with telecom traffic as compared to bad weather and telecom traffic.

VI. Conclusion and Outlook

In this paper we illustrated a novel approach to explore the relationships between weather on mobile phone usage. Meteorological measurements of rainfall, air temperture, relative humidity, air pressure, and solar radiation as well as user-generated mobile network traffic have been correlated and analysed on a common space-time basis for three different spatial environments in Northern Italy. Factor analysis of meteorological variables resulted in two principal components, termed „Nice weather“, and „Bad Weather“. Spectral analysis of the remaining datasets revealed underlying periodic relationships between weather conditions and mobile phone traffic within and across the respective spatial environments. Results show that "Nice Weather" conditions manifest significant relationships – expressed by their squared spectral coherence – with mobile telecom activity.

From a methodological point of view we conclude that explanatory factor analysis and squared spectral coherence estimation can be fruitfully utilized in the geo-sensing domain.

We also verified significant relationships between "exogenous factors", i.e. quantifiable environmental phenomena, and large-scale collective social behaviour indirectly measured through mobile phone usage.

However, it is important to underline that the assumption of linearity between weather and mobile phone usage is at best an approximation of the complex relationship between these variables (see also section II.C).

This research is, to our best knowledge, the first case study in the geo-sensing domain that consolidates and examines digital measurements of environmental and human related phenomena by utilizing factor analysis and spectral analysis.

Further research will first of all assess the validity of the results obtained when applied to a larger data sample (for instance a one-year time series of environmental and telecom data) and to other area types. The expectation is that time patterns with a longer period (seasonal variations, work-holiday patterns, generic weather patterns) will provide additional insights in the relationship between weather and human activities, and that this relationship could structurally depend on certain land-use factors.

Another angle of investigation is the elaboration of „pink noise" – e.g. exposed by filtering out harmonics – hidden in mobile network traffic's periodic components. Of particular interest is the potential interrelationship of that pink noise with small fluctuations of environmental conditions.

Acknowledgment

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References

[1] M. C. González, *et al.*, Understanding individual human mobility patterns, *Nature,* vol. 453, (2008), pp. 779-782.

[2] J. Candia, *et al.*, Uncovering individual and collective human dynamics from mobile phone records, *Journal of Physics A: Mathematical and Theoretical,* vol. 41, (2008), p. 224015.

[3] J. P. Onnela, *et al.*, Structure and tie strengths in mobile communication networks, *Proceedings of the National Academy of Sciences,* vol. 104, (2007), pp. 7332-7336.

[4] F. Calabrese, *et al.*, "The geography of taste: analyzing cell-phone mobility and social events," in *Pervasive Computing (Lecture Notes in Computer Science)*. vol. 6030/2010, ed Berlin / Heidelberg: Springer, 2010, pp. 22-37.

[5] F. Calabrese, *et al.*, Eigenplaces: Segmenting Space Through Digital Signatures, *IEEE Pervasive Computing,* vol. 9, (2010), pp. 78-84.

[6] F. Calabrese, *et al.*, Real-Time Urban Monitoring Using Cell Phones: A Case Study in Rome, *IEEE Transactions on Intelligent Transportation Systems,* vol. PP, (2010), pp. 1 - 11.

[7] C. Ratti, *et al.*, Mobile Landscapes: using location data from cell phones for urban analysis, *Environment and Planning B: Planning and Design,* vol. 33, (2006), pp. 727-748.

[8] S. Phithakkitnukoon, *et al.*, "Activity-Aware Map: Identifying Human Daily Activity Pattern Using Mobile Phone Data," in *Human Behavior Understanding*. vol. 6219, A. Salah, *et al.*, Eds., ed: Springer Berlin / Heidelberg, 2010, pp. 14-25.

[9] A. Sevtsuk and C. Ratti, Does Urban Mobility Have a Daily Routine? Learning from the Aggregate Data of Mobile Networks, *Journal of Urban Technology,* 2010), pp. 41 - 60.

[10] I. F. Akyildiz, *et al.*, A survey on sensor networks, *IEEE Communications Magazine,* vol. 40, (2002), pp. 102 - 114.

[11] J. K. Hart and K. Martinez, Environmental Sensor Networks: A revolution in the earth system science?, *Earth-Science Reviews,* vol. 78, (2006), pp. 177-191.

[12] A. Friis-Christensen, *et al.*, Service chaining architectures for applications implementing distributed geographic information processing, *International Journal of Geographical Information Science,* vol. 23, (2009), pp. 561 - 580.

[13] C. Yang, *et al.*, Geospatial Cyberinfrastructure: Past, present and future, *Computers, Environment and Urban Systems,* vol. 34, (2010), pp. 264-277.

[14] Y. Akinaga, *et al.*, "A proposal for a mobile communication traffic forecasting method using time-series analysis for multi-variate data," presented at the IEEE Global Telecommunications Conference, 2005. GLOBECOM '05, St. Louis, Missouri (USA), 2005.

[15] B. Resch, *et al.*, Pervasive Monitoring—An Intelligent Sensor Pod Approach for Standardised Measurement Infrastructures, *Sensors,* vol. 10, (2010), pp. 11440-11467.

[16] A. A. Alesheikh, *et al.*, Providing interoperability for air quality in-situ sensors observations using GML technology, *International Journal of Environment Science and Technology,* vol. 2, (2005), pp. 133-140.

[17] J. Reades, *et al.*, Eigenplaces: analysing cities using the space-time structure of the mobile phone network, *Environment and Planning B: Planning and Design,* vol. 36, (2009), pp. 824-836.

[18] R. M. Warner, *Spectral Analysis of Time-Series Data*. New York: The Guildford Press, 1998.

[19] M. A. Pett, *et al.*, *Making Sense of Factor Analysis: the use of factor analysis for instrument development in health care research*. Thousand Oaks, California: Sage Publications, Inc., 2003.

[20] M. S. Bartlett, Test of significance in factor analysis, *Britisch Journal of Psychology,* vol. 3, (1950), pp. 77-85.

[21] H. F. Kaiser, An index of factorial simplicity, *Psychometrika,* vol. 39, (1974), pp. 32-36.

[22] R. B. Cattell, The Scree Test For The Number Of Factors, *Multivariate Behavioral Research,* vol. 1, (1966), pp. 245 - 276.

[23] Anderson T.W. and Rubin H., Statistical inference in facor analysis, *Proceedings of the 3rd Berkeley Symposium on Mathematical Statistics and Propability,* vol. 5, (1956), pp. 111-150.

[24] L. H. Koopmans, *The Spectral Analysis of Time Series* vol. 22. San Diego, California: Academic Press, Inc., 1995.