Deflection Analysis for Spatially Propagated Web Sensors

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ABSTRACT

We experience or forecast various phenomena (e.g., rain, snow, and earthquake) in the physical world, while we carry out various actions (e.g., blogging, searching, and e-shopping) in the Web world. Many researches have tried to mine the Web for knowledge about various phenomena in the physical world, and also Web services with Web-mined knowledge have been made available for the public. However, there are not enough investigations on how accurately Web-mined data reflect physical-world data. It is socially-problematic to utilize Web-mined data in public Web services without ensuring their accuracy sufficiently. The previous work has introduced various kinds of "Web Sensors" with Temporal Shift and Spatio-Temporal Propagation to extract spatiotemporal numerical data about a targeted physical phenomenon from Web documents searched by linguistic keyword(s) representing the physical phenomenon, and compared them based on their correlation coefficients with Japan Meteorological Agency's physically-sensed spatiotemporal statistics. To analyze the deflection of Spatially-Propagated Web Sensors, this paper introduces their novel definition based on not only distance but also azimuthal angle between geographic spaces.

KEYWORDS

Deflection Analysis, Web Sensor, Web Mining, Web Credibility, Spatiotemporal Data Mining.

1 INTRODUCTION

We experience or forecast various phenomena (e.g., rainfall, snowfall, earthquake, influenza, and traffic accident) in the physical world, while we carry out various actions (e.g., blogging, searching, and e-shopping) in the Web world. Recently, there have been many researches to mine a huge amount of various documents in the exploding Web world, especially User Generated Content such as blogs, microblogs (e.g., Twitter), Word-of-Mouth sites, and Social Networking Services (e.g., Facebook), for knowledge about various phenomena and events in the physical world. For instance, opinion and reputation extraction [1], [2] of various products and services in the physical world, experience mining [3], [4] of various phenomena and events in the physical world, concept hierarchy (semantics) extraction [5–10] such as is-a/has-a relationships, and visual appearance (look and feel) extraction [10–15] of physical objects in the physical world. Meanwhile, Web services with Web-mined knowledge have been made available for the public, and more and more ordinary people actually utilize them as important information for choosing better products, services, and actions in the physical world.

However, there are not enough investigations [16–18] on how accurately Web-mined data about a targeted phenomenon or event in the physical world reflect physical-world data. It is not so difficult to mine the Web for some kind of potential knowledge data by using various text mining techniques, and it might not be problematic only to enjoy browsing the Web-mined knowledge data. But while choosing better products, services, and actions in the physical world, it must be socially-problematic to idolatrously/immoderately utilize the Web-mined data in public Web services without ensuring their accuracy sufficiently.

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The previous papers [19–26] have introduced "Web Sensors" that sense the Web to extract spatiotemporal numerical values about a target phenomenon in the physical world from various action-based data (e.g., blogs, search query logs, and e-shopping history) in the Web world, and investigated how correlated Web-sensed spatiotemporal data are with physically-sensed spatiotemporal data as shown in Figure 1.

Blog-based Web Sensors with "Temporal Shift" [20], [25] showed that

- The optimal temporal shift parameter δ of Web Sensors depends on physical phenomena: Not-Shifted Web Sensor whose temporal shift parameter δ is ± 0 gives the highest correlation coefficient (i.e., the Weblog runs parallel to the physical world) for rainfall, Shifted-to-Future Web Sensor whose temporal shift parameter δ is negative gives the highest correlation coefficient (i.e., the Weblog leads the physical world) for snowfall, and Shifted-to-Past Web Sensor whose temporal shift parameter δ is positive gives the highest correlation coefficient (i.e., the Weblog follows the physical world) for earthquake,
- The optimal temporal shift parameter δ and correlation coefficient for rainfall are not much dependent on geographical spaces (e.g., 47 prefectures in Japan) and time periods, while the optimal temporal shift parameter δ for snowfall and earthquake varies more widely, and
- More shaken geographical spaces and time periods are given higher correlation coefficient between Web-sensed data and physically-sensed data by the Great East Japan Earthquake (3.11).

Query-based Web Sensor using Web search query logs [24] is superior to Blog-based Web Sensor using Web documents such as blogs for snowfall and earthquake, while Query-based Web Sensor is inferior to Blog-based Web Sensor for rainfall. In addition, the best combined Web Sensor using both Web search query logs and Web documents is superior to uncombined Web Sensors using only Web search query logs or Web documents.

Meanwhile, these Web Sensors are being integrated into Smart Spaces [27] and Secure Spaces [19], [20], [28–30] as shown in Figure 2. Secure Spaces assuredly enforce space entry control and information access control based on Web-sensed spatiotemporal data as their approximate characteristics and their changing contents such as visitors, physical information resources, and virtual information resources via their embedded output devices, to protect any visitor from her/his unwanted information resources and also to protect any information resource from its unauthorized visitors.

This paper introduces the novel definition of Spatially-Propagated Web Sensors based on not only distance but also azimuthal angle between geographical spaces in Section 2, and analyzes their deflection by using rainfall, snowfall, and earthquake statistics per day by region in Japan [31] as physically-sensed data in Section 3.

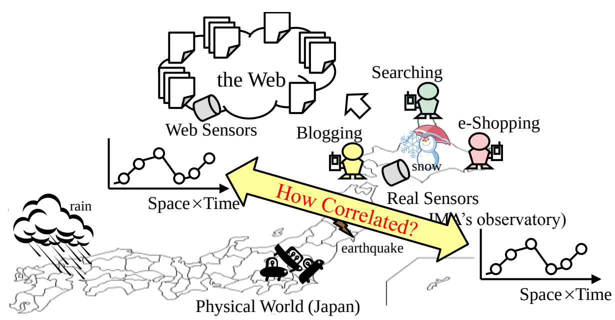

Figure 1. Web Sensors correlate with Real Sensors?

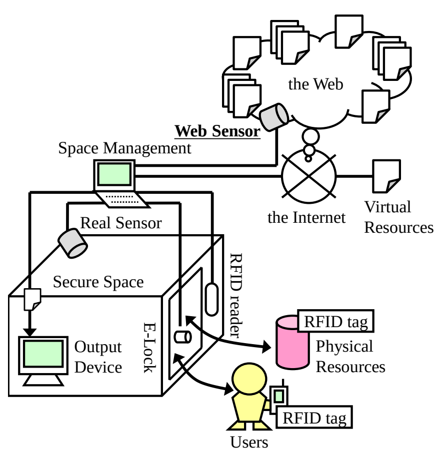

Figure 2. Web Sensors in Secure Spaces.

2 DEFINITION OF WEB SENSOR

This section introduces the novel definition of Spatially-Propagated Web Sensors based on not only distance but also azimuthal angle between geographic spaces that sense the Web for spatiotemporal numerical values dependent on a geographic space (e.g., one of 47 prefectures in Japan) and a time period (e.g., days and weeks in 2011) about a physical phenomenon (e.g., rainfall, snowfall, and earthquake).

First, the simplest and spatiotemporally-normalized Web Sensor [19] by using only Web documents (not Web search query logs [24]) with a linguistic name of a geographic space s, e.g., one of 47 prefectures in Japan such as "Hokkaido," a time period t, e.g., one of 52 weeks in 2011 such as from January 1st to 7th and from December 24th to 30th, and a linguistic keyword kw representing a targeted physical phenomenon, e.g., "rain," "snow," and "earthquake," is defined as

$$\text{ws}(kw, s, t) \coloneqq \frac{\text{df}_t([\,"kw"\ \&\ "s"\,])}{\text{df}_t([\,"s"\,])} \tag{1}$$

where $\text{df}_t([q])$ stands for the Frequency of Web Documents searched from the Web, especially the Weblog, by submitting the search query q with the custom time range t to Google Web Search. Note that the Weblog is superior to the whole Web, Twitter, Facebook, and News as a corpus of Web Sensors [22].

Secondly, the temporally-shifted Web Sensor [20], [25] with a "Temporal Shift" parameter δ [day], a geographic space s, a time period t, and a linguistic keyword kw representing a targeted physical phenomenon is defined as

$$\text{ws-ts}_\delta(kw, s, t) \coloneqq \text{ws}(kw, s, t + \delta) \tag{2}$$

As shown in Figure 3, Shifted-to-Past Web Sensor for a targeted physical phenomenon (e.g., earthquake) when its Temporal Shift parameter δ is positive (e.g., $+14$) calculates a numerical value dependent on a geographic space s (e.g., "Hokkaido" prefecture in Japan) and a time period t (e.g., one of 52 weeks in 2011) by using Web documents uploaded δ day(s) after the time period t (i.e., infers the past from the future), while Shifted-to-Future Web Sensor when its Temporal Shift parameter δ is negative (e.g., -14) calculates a numerical value dependent on a geographic space s and a time period t by using Web documents uploaded $|\delta|$ day(s) before the time period t (i.e., infers the future from the past).

Thirdly, the temporally-propagated Web Sensor [20] with a "Temporal Propagation" parameter σ_t^2, a geographic space s, a time period t, and a linguistic keyword kw representing a physical phenomenon is defined by integrating the surrounding time periods as

$$\text{ws-tp}^{\sigma_t^2}(kw, s, t) \coloneqq \sum_{\forall\delta} \text{ws-ts}_\delta(kw, s, t) \cdot p^{\sigma_t^2}(\delta) \tag{3}$$

$$p^{\sigma_t^2}(\delta) \coloneqq N(0, \sigma_t^2, \delta) \tag{4}$$

$$N(\mu, \sigma_t^2, \delta) \coloneqq \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{(\delta-\mu)^2}{2\sigma_t^2}\right) \tag{5}$$

where $N(\mu, \sigma_t^2, \delta)$ stands for a Normal Distribution with a mean μ and a variance σ_t^2. In the experiment, $\forall\delta$ is restricted to $[-30, 30]$.

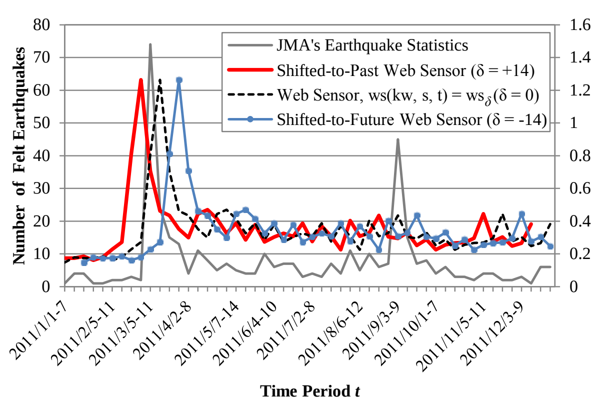

Figure 3. Three kinds of Temporally-Shifted Web Sensors for earthquake and JMA's weekly earthquake statistics in Hokkaido prefecture, 2011.

Next, the spatially-propagated Web Sensor [26] with a "Spatial Propagation" parameter σ_s^2, a geographic space s, a time period t, and a linguistic keyword kw representing a targeted physical phenomenon is defined by integrating the surrounding geographic spaces as

$$\text{ws-sp}^{\sigma_s^2}(kw, s, t) \coloneqq \sum_{\forall s_i} \text{ws}(kw, s_i, t) \cdot p^{\sigma_s^2}(\text{distance}(s, s_i)) \quad (6)$$

$$p^{\sigma_s^2}(d) \coloneqq N(0, \sigma_s^2, d) \quad (7)$$

$$N(\mu, \sigma_s^2, d) \coloneqq \frac{1}{\sqrt{2\pi\sigma_s^2}} \exp\left(-\frac{(d-\mu)^2}{2\sigma_s^2}\right) \quad (8)$$

where $\text{distance}(s, s_i)$ stands for the geographic distance [km] between geographic spaces s and s_i and is calculated based on their latitude and longitude. In the experiment, $\forall s_i$ is restricted to 47 prefectures in Japan, and the latitude and longitude of its prefectural capital are used for calculating $\text{distance}(s, s_i)$ by using the Survey Calculation API of Geospatial Information Authority of Japan (GSI) [32]. In pairs of 47 prefectures in Japan, the pair of Hokkaido pref. (Sapporo city) and Okinawa pref. (Naha city) has the longest distance, 2243.9 [km], while the pair of Shiga pref. (Otsu city) and Kyoto pref. (Kyoto city) has the shortest distance, 10.5 [km], as shown in Figure 4.

Figure 4. The longest distance between Hokkaido (Sapporo) and Okinawa (Naha), and the shortest distance between Shiga (Otsu) and Kyoto (Kyoto).

Subsequently, the generalized definition of Spatially-Propagated Web Sensors is shown as

$$\text{ws-sp}(kw, s, t) \coloneqq \sum_{\forall s_i} \text{ws}(kw, s_i, t) \cdot f(s, s_i) \quad (9)$$

where $f(s, s_i)$ stands for a function of some kind of relationship (e.g., distance in [26]) between geographic spaces s.

Last, to analyze the deflection of Spatially-Propagated Web Sensors, their novel definition is based on not only distance but also azimuthal angle between geographical spaces:

$$\text{ws-sp}_{\theta,b}^{\sigma_s^2}(kw, s, t) \coloneqq \sum_{\forall s_i} \text{ws}(kw, s_i, t) \cdot f_{\theta,b}^{\sigma_s^2}(s, s_i) \quad (10)$$

$$f_{\theta,b}^{\sigma_s^2}(s, s_i) \coloneqq p^{\sigma_s^2}(\text{distance}(s, s_i)) \cdot \text{oval}_{\theta,b}(\text{angle}(s, s_i)) \quad (11)$$

where $\text{angle}(s, s_i)$ stands for the azimuthal angle between geographic spaces s and s_i, and $\text{oval}_{\theta,b}(a) \in [b, 1.0]$ is calculated based on the θ-rotated ellipse with major radius 1.0 and minor radius $b \in [0.0, 1.0]$ as shown in Figure 5.

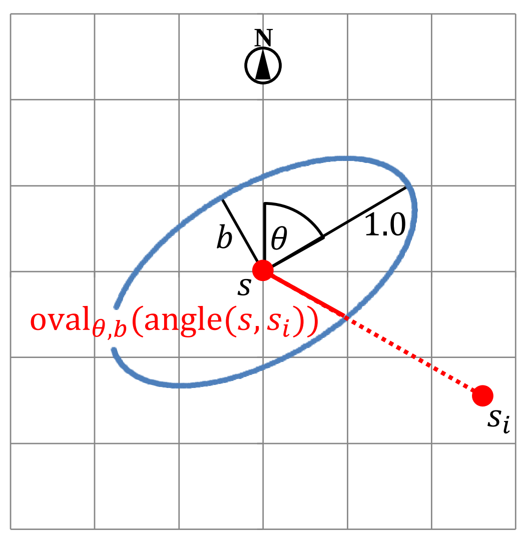

Figure 5. The oval function $\text{oval}_{\theta,b}(\text{angle}(s, s_i))$ based on the AZ angle between geographical spaces s and s_i.

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3 EXPERIMENT

This section compares the Spatially-Propagated Web Sensors based on distance and/or azimuthal angle between geographical spaces, and the Temporally-Propagated Web Sensors, by calculating correlation coefficients between their Web-sensed spatiotemporal data and Japan's rainfall, snowfall, and earthquake statistics [31] per day by region of Japan Meteorological Agency (JMA) as physically-sensed spatiotemporal data.

Figures 5 to 7 show the dependency on Temporal Propagation parameter σ_t^2 of the average of correlation coefficients of the Temporally-Propagated Web Sensors with JMA's daily stats in 2011 for rainfall, snowfall, and earthquake, respectively. As a result, the optimized Temporally-Propagated Web Sensor, which integrates the very near surrounding time periods (i.e., its optimal Temporal Propagation parameter σ_t^2 is small), is slightly superior to the simplest Web Sensor (baseline).

Figures 8 to 10 show the dependency on Spatial Propagation parameter σ_s^2 of the average of correlation coefficients of the Spatially-Propagated Web Sensors based on only distance (not azimuthal angle) for rainfall, snowfall, and earthquake, respectively. As a result, the optimized Spatially-Propagated Web Sensor is significantly superior to both the simplest Web Sensor (baseline) and the optimized Temporally-Propagated Web Sensor.

For rainfall and snowfall, the Spatially-Propagated Web Sensor based on only distance draws very similar curves of the average of correlation coefficients with JMA's daily stats and also its optimal Spatial Propagation parameter σ_s^2 is similar. Meanwhile, the Spatially-Propagated Web Sensor based on only distance draws quite a different curve and its optimal Spatial Propagation parameter σ_s^2 is much huger for earthquake. This is caused by the difference between more local physical phenomena (e.g., rainfall and snowfall) and more global ones (e.g., earthquake).

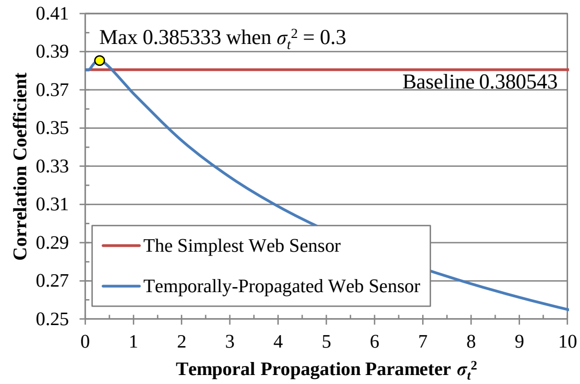

Figure 5. Temporally-Propagated Web Sensor with σ_t^2 vs. the simplest Web Sensor (baseline) for rainfall.

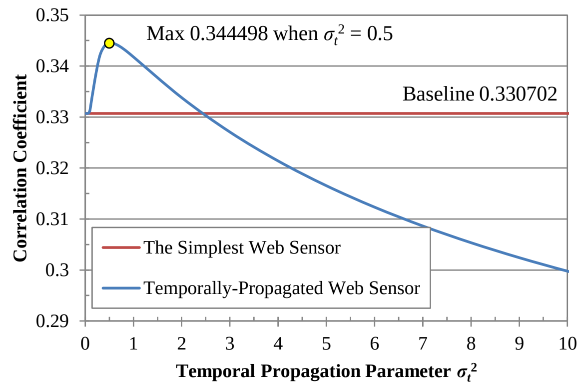

Figure 6. Temporally-Propagated Web Sensor with σ_t^2 vs. the simplest Web Sensor (baseline) for snowfall.

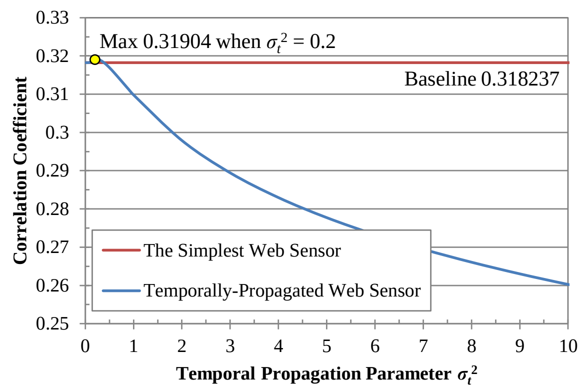

Figure 7. Temporally-Propagated Web Sensor with σ_t^2 vs. the simplest Web Sensor (baseline) for earthquake.

Figures 11 to 13 and Figures 14 to 16 show the dependency on oval's rotation angle θ and minor radius b (which the newly-introduced oval function $\text{oval}_{\theta,b}(\text{angle}(s, s_i))$ has) of the average of correlation coefficients of the novel

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Spatially-Propagated Web Sensors based on not only distance but also azimuthal angle between geographical spaces with JMA's daily stats in 2011 for rainfall, snowfall, and earthquake, respectively.

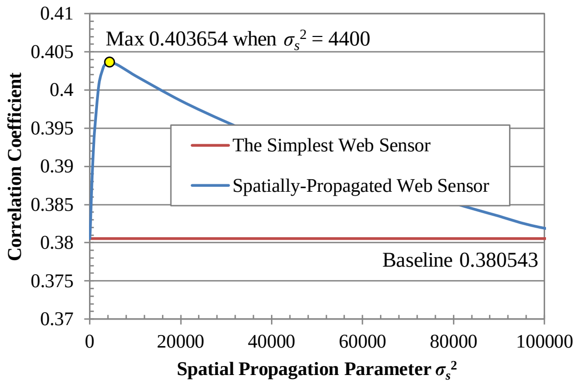

Figure 8. Spatially-Propagated Web Sensor based on only distance (not AZ angle) with σ_s^2 for rainfall.

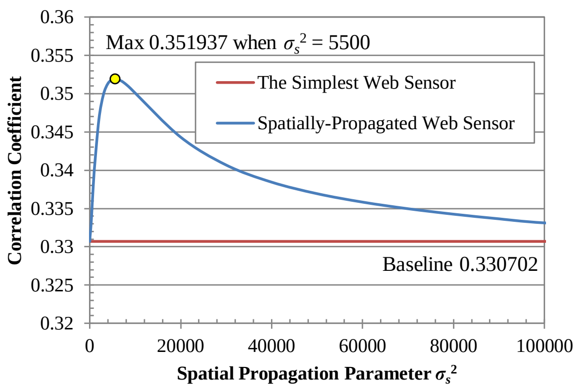

Figure 9. Spatially-Propagated Web Sensor based on only distance (not AZ angle) with σ_s^2 for snowfall.

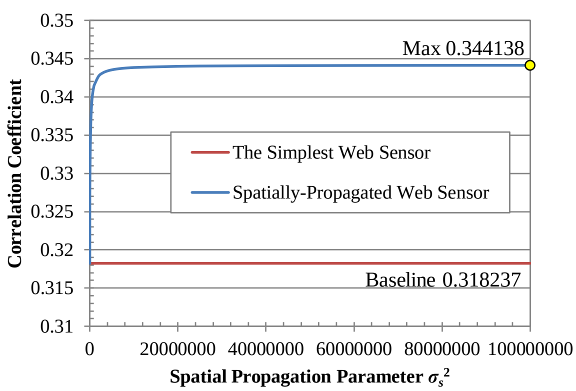

Figure 10. Spatially-Propagated Web Sensor based on only distance (not AZ angle) with σ_s^2 for earthquake.

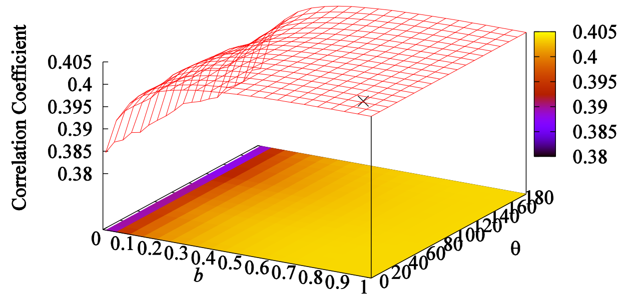

Figure 11. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, b, and $\sigma_s^2 = 4400$ for rainfall.

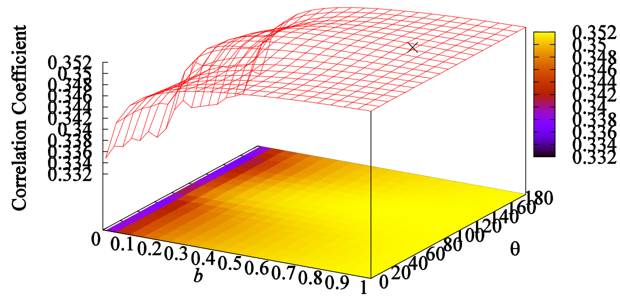

Figure 12. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, b, and $\sigma_s^2 = 5500$ for snowfall.

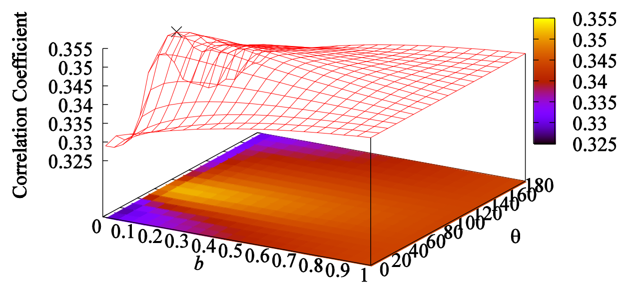

Figure 13. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, b, and $\sigma_s^2 = 1.0 \cdot 10^8$ for earthquake.

The Spatially-Propagated Web Sensor based on not only distance and but also azimuthal angle draws similar curves and color maps of the average of correlation coefficients with JMA's daily stats for rainfall and snowfall, while it draws a different curve and color map for earthquake. And the optimal azimuthal angle θ varies depending on the kind of a targeted physical phenomenon.

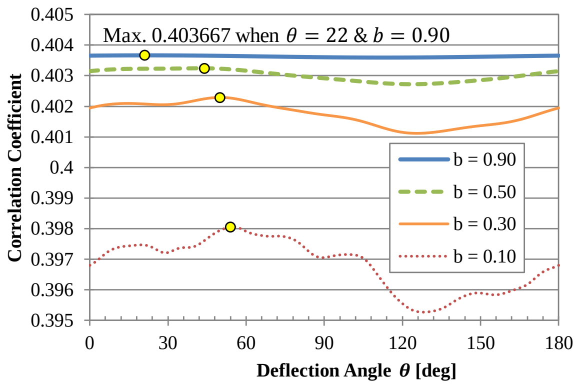

Figure 14. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, four kinds of b, and $\sigma_s^2 = 4400$ for rainfall.

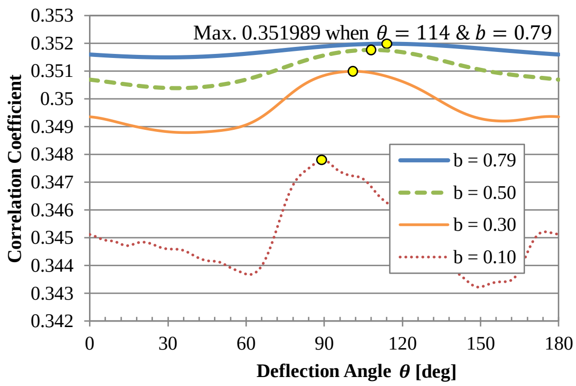

Figure 15. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, four kinds of b, and $\sigma_s^2 = 5500$ for snowfall.

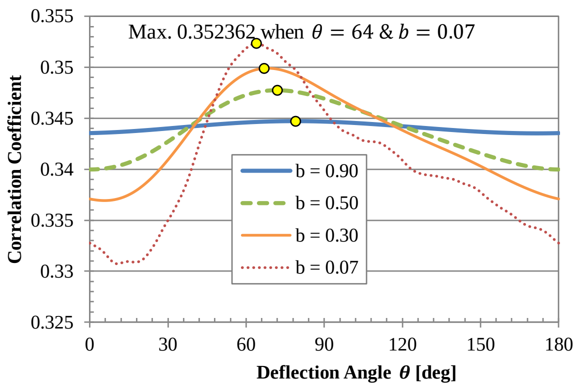

Figure 16. Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle with θ, four kinds of b, and $\sigma_s^2 = 1.0 \cdot 10^8$ for earthquake.

4 CONCLUSION

To analyze the deflection of Spatially-Propagated Web Sensors that extract spatiotemporal numerical values dependent on a geographic space (e.g., “Hokkaido” as one of 47 prefectures in Japan) and a time period about a targeted physical phenomenon from the Web, especially the Weblog, by integrating the effects from the surrounding geographic spaces (e.g., mainly “Aomori” and “Iwate” for “Hokkaido”), this paper has generalized their definitions, introduced their novel definition based on not only distance but also azimuthal angle between geographical spaces, and calculated correlation coefficients between their Web-sensed spatiotemporal data and Japan’s rainfall, snowfall, and earthquake statistics as physically-sensed spatiotemporal data.

The deflection analysis shows that the optimized Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle is superior to the one based on only distance for earthquake, while the optimized Spatially-Propagated Web Sensor based on not only distance but also azimuthal angle is almost equal to the one on only distance for rainfall and snowfall. It also shows that the optimal azimuthal angle θ (i.e., oval’s rotation angle θ which the newly-introduced oval function $\mathrm{oval}_{\theta,b}(\mathrm{angle}(s, s_i))$ has) varies depending on the kind of a targeted physical phenomenon, and that the optimal oval’s minor radius b is similar for rainfall and snowfall, but quite different from the one for earthquake.

The future work will try to apply the other physical phenomena to Web Sensors with Temporal Shift, Temporal Propagation, and Spatial Propagation, and to combine various Web actions, e.g., not only blogging and searching but also e-shopping to construct more high-sensitive Web Sensors. In addition, Web Sensors will be able to forecast future data about a targeted physical phenomenon, to interpolate lost data of real statistics, and to alert falsified data of real statistics.

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