Modeling and Synthesis of 3-D Water Vapor Fields for EM Wave Propagation Applications

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Abstract—SMOV (Stochastic MOdel of water Vapor), a methodology to generate realistic three-dimensional spatially correlated water vapor fields is presented, which is devised by investigating remote sensing observations acquired by the MODIS sensor (Aqua satellite). Synthetic water vapor fields are 200 km×200 km, with 1 km×1 km horizontal spatial resolution, while the water vapor content \( v \) extends up to 20 km with a vertical sampling of 100 m. The field synthesis relies on the stochastic approach proposed by Bell and requires as input the average integrated water vapor content provided with coarse spatial and temporal resolution by NWP products. The vertical profile of \( v \) is modelled as a simple exponential function decreasing with height, as observed from typical RAOPS and NWP data. Tests on the model’s accuracy show that both first-order (Complementary Cumulative Distribution Function - CCDF) and second-order (spatial distribution) statistics of the integrated water vapor content are closely reproduced in several European sites. Results corroborate the use of SMOV as part of a comprehensive simulator of atmospheric impairments, which aims at taking into account all the constituents affecting the propagation of millimeter-waves in different scenarios, including applications involving very low elevation links such as UAVs and LEO satellites.

Index Terms—Electromagnetic wave propagation, atmospheric effects, water vapor.

I. INTRODUCTION

The last decade has been characterized by a large diversification and increase in millimeter-wave communication systems. On the one hand, new high-data rate interactive services, e.g., those provided via satellite to offer global Internet connectivity [1], are pushing towards the employment of higher frequency bands giving access to wider bandwidths (Ka band nowadays, Q/V bands as the next step [2]); on the other hand, new applications involving very low elevation links are being increasingly employed (e.g., Unmanned Aerial Vehicle – UAVs) or are planned to be implemented in the near future (e.g., Ka-band links from ground stations to Low Earth Orbit – LEO – satellites [3] and deep-space probes [4]).

In this context, the system design task becomes more and more critical, not only because the higher is the frequency, the larger is the detrimental impact of the atmosphere on the link (induced by hydrometeors, clouds and gases), but also because for very low elevations links (say angles smaller than 10 degrees) specific modeling needs to be properly considered, such as the Earth’s curvature, the ray bending effect and the large-scale spatial distribution of the atmospheric constituents. In such scenarios, even in clear sky conditions (sole presence of gases in the atmosphere), the path attenuation might exceed several dBs (especially in tropical/equatorial sites) [5], such that taking in due account the modeling aspects mentioned above would definitely increase the accuracy of the estimated link performance. In order to meet these needs, the recent tendency in the theoretical research on millimeter-wave propagation is to move from empirical models, typically limited in their applicability to specific climatic regions, frequency ranges and/or scenarios, to highly sophisticated physically-based methodologies which inherently aim at being globally applicable and are sufficiently flexible to allow simulating with increased accuracy and reliability the impact of the atmosphere on several different millimeter-wave communication systems.

This contribution presents the development and assessment of SMOV (Stochastic MOdel of water Vapor), a methodology to synthesize statistically meaningful sets of three-dimensional (3-D) water vapor fields. SMOV represents a key element, which, together with MultiEXCELL (for precipitation) [6] and SMOC (for clouds) [7], contributes to the development of a comprehensive simulator of weather disturbances affecting the propagation of millimeter-waves [8]. SMOV reproduces the spatial distribution of the water vapor content \( v \) (this abbreviation – in place of the more common WVC – is used throughout this contribution in order to deal with more compact equations) with high resolution across large areas (200 km×200 km×20 km with 1 km×1 km horizontal detail and 100 m vertical sampling) starting from the generation of spatially correlated Gaussian fields, as explained in [9]. To this aim, the model relies on some key information on \( v \) extracted from the water vapor fields observed by the MODIS sensor onboard the Aqua satellite. Inputs to SMOV are the time series of the integrated water vapor content \( V \) (as for \( v \), this abbreviation is preferred here to the more customary – yet less compact – IWVC), part of Numerical Weather Prediction
(NWP) data provided e.g. by the European Centre for Medium-range Weather Forecast (ECMWF) over a low-resolution latitude×longitude grid (1.125°×1.125°) every 6 hours. The remainder of the paper is organized as follows: Sections II and III deals with the investigation and modeling of the horizontal and vertical distribution of water vapor, respectively, while Section IV describes in detail the procedure for the synthesis of realistic 3-D water vapor fields. Tests to evaluate the accuracy of SMOV in reproducing first- and second-order statistics of V are shown in Section V and, finally, Section VI draws some conclusions.

II. HORIZONTAL DISTRIBUTION OF WATER VAPOR

A. The reference water vapor dataset

The reference water vapor database used in this work originates from the MODIS sensor onboard the Aqua satellite, which flies along Low Earth Orbit (LEO) orbit covering the whole Globe with a repetition period of approximately two days. The MODIS instrument, whose main aim is to observe large-scale global dynamics of oceanic and tropospheric processes, collects radiance data in 36 optical channels (wavelengths between 0.4 and 14.4 µm) with high spatial resolution (from 250 m to 5 km footprint, linear size) implementing automatic in-flight calibration procedures [10]. Raw data are processed by the MODIS Characterization Support Team (MCST) to provide high quality calibrated products for several Earth science applications [11]. Specifically, maps of V with dimensions of 200 km×2000 km and spatial resolution of 5 km×5 km, appropriate to adequately sample the spatial distribution of water vapor, are freely available on the web for research purposes. In particular, in this work, we have employed the maps derived from 3090 swaths over Europe (20° E ≤ latitude ≤ 62° E and 10° W ≤ longitude ≤ 37° E) in 2010. As an example, Fig. 1 depicts the integrated water vapor content as observed by MODIS along a swath over Africa and Europe. Furthermore Fig. 2 depicts the Complementary Cumulative Distribution Function (CCDF) of the integrated water vapor as obtained from an extensive dataset of radiosonde observations collected at Milano Linate airport between 1980 and 1989 and as extracted from MODIS data in the same area (100 km×100 km centered over the airport). The satisfactory agreement between the two curves gives a hint on the good quality of MODIS-derived water vapor data.

B. Characterization of water vapor horizontal distribution

As a first step to investigate the key properties of water vapor fields, we have partitioned the large swaths into 200 km×200 km maps to achieve dimensions typical of Numerical Weather Prediction (NWP) products such as 2°×2° latitude/longitude. The analysis of the horizontal distribution of the integrated water vapor content within each 200 km×200 km map showed that the values of V tend to follow the Weibull distribution:

\[ p(V) = \frac{B_W}{A_W} \left( \frac{V}{A_W} \right)^{B_W-1} \exp \left[ -\left( \frac{V}{A_W} \right)^{B_W} \right] \]

where \( A_W \) and \( B_W \) are the scale and shape parameters, respectively, regulating the expression in (1). This finding confirms what is discussed in [12] and is clearly exemplified in Fig. 3, where a sample water vapor field observed by MODIS (top) and the associated statistical characterization of V (bottom) is provided in terms of Cumulative Distribution Function (CDF). The bottom figure title reports \( E_\varepsilon \), the value of V averaged over the whole area, as well as \( A_W \) and \( B_W \) of the Weibull distribution fitting data with good accuracy (maximum likelihood estimation - MLE). This is quantified by \( E_\varepsilon \) and \( RMS_\varepsilon \) in the figure legend, i.e. the average and root mean square values, respectively, of the error figure \( \varepsilon \) defined.
as:

\[ \varepsilon(P) = 100 \left( \frac{V_m(P) - V_f(P)}{V_m(P)} \right) \]  (2)

In (2), \( V_m(P) \) and \( V_f(P) \) are the \( V \) values (mm) associated to the reference (MODIS) and MLE CDFs, respectively, at probability levels \( P \) ranging from 0 to 1 with step of 0.001.

Considering the whole MODIS dataset, Fig. 4 depicts the trend of the average \( E_\varepsilon \) (solid line with triangles) and \( \text{RMS}_\varepsilon \) (dashed line with stars) as a function of the average integrated water vapor content \( E_V \), together with the percentage number of MODIS fields considered in each \( E_V \) class (blue bars).

All the MODIS-derived 200 km×200 km maps were afterwards processed to identify possible relationships of \( E_V \) with \( A_W \) and \( B_W \). As for the former, \( A_W \) was found to be proportional to \( E_V \), with the very high linear correlation shown in Fig. 5 (see the inset in the figure for more details):

\[ A_W = 1.044 E_V \]  (3)

Concerning the second parameter of the Weibull distribution, as shown in Fig. 6, the scatterplot between \( E_V \) and \( B_W \) turned out to be rather spread, which prevents from defining a simple analytical expression relating the two quantities. On the other hand, the conditional lognormal probability density function \( p(B_W | E_V) \) in (4) was found to be well suited for modeling the statistical relationship between \( B_W \) and \( E_V \):

\[ p(B_w | E_V) = \frac{1}{B_w \sigma(E_V) \sqrt{2\pi}} \exp \left[ -\frac{(\ln B_w - \mu(E_V))^2}{2\sigma(E_V)^2} \right] \]  (4)
where $\mu$ and $\sigma$, which are both function of $E_V$, are the mean and standard deviation values of the natural logarithm of $B_W$, respectively. A hint of the modeling accuracy of (4) is given by Fig. 7, which depicts $p(B_W|E_V)$ for two classes of $E_V$ (low values on the top and high values on the bottom), including $\mu$ and $\sigma$ of the fitting MLE lognormal distribution.

For the complete characterization of $p(B_W|E_V)$, we have defined eight $E_V$ bins of different width but containing roughly the same number of samples ($NS \approx 3000$). The maximum error in fitting the empirical $p(B_W|E_V)$ with the MLE lognormal distributions (specifically, root mean square values of the percentage relative difference error) is 8%. In addition, as can be inferred from Fig. 8 and Fig. 9, both $\mu$ and $\sigma$ show quite a regular trend with $E_V$ (blue squares indicate the center values of each class), which can be closely approximated by the following analytical expressions:

$$\mu(E_V) = -1.408 E_V^{0.239} + 6.885 E_V^{0.156} - 3.725$$
$$\sigma(E_V) = -2.228 E_V^{0.156} + 6.66 E_V^{0.107} - 3.962$$

(5)

The additional information needed to generate synthetic water vapor fields concerns the spatial variability of $V$, which was studied by resorting to the correlation index $\rho$ [13]:

$$\rho(x,y) = \frac{E[V(x)\cdot V(y)] - E[V(x)]E[V(y)]}{\sigma[V(x)]\sigma[V(y)]}$$

(6)

$E[\cdot]$ and $\sigma[\cdot]$ in (6) indicate the mean and standard deviation, whereas $V(x)$ and $V(y)$ represent the integrated water vapor content time series, respectively associated to pixels $x$ and $y$ in each 200 km x 200 km water vapor map. An underlying assumption in the calculation of $\rho$ is the spatial stationarity of the water vapor (also valid for precipitation [13]); this entails that the spatial correlation between two points depends (mostly) on their distance and only marginally on their position, i.e.:
\[ \rho(x, y) = \rho(d = |x - y|) \]  
(7)

Fig. 10 shows the spatial correlation of \( V \) calculated by averaging \( \rho \) values associated to pairs of pixels at the same distance \( d \) (red line): besides showing that the water vapor decorrelates slowly with distance, the limited spread of \( \rho \) around its average value (density scatter plot, higher concentration in darker areas) definitely validates the spatial stationarity assumption mentioned above.

In order to synthesize realistic water vapor fields according to [9], random Gaussian fields with spatial correlation \( \rho_0(d) \), to be known a priori, need to be first generated. The mean \( \rho_0(d) \) can be estimated by first converting each MODIS water vapor field into a Gaussian field, which, under the assumption of Weibull distribution for \( \rho \), corresponds to employing (14) and (15) reported in Section III below. Afterwards the spatial correlation of the random Gaussian process was evaluated from converted maps using the same definition of \( \rho \) as in (6) and assuming again spatial stationarity. The resulting average \( \rho_0(d) \) is well fitted by the following analytical expression:

\[ \rho_0(d) = 1.656e^{-\frac{d}{20 km}} - 0.337e^{-\frac{d}{4 km}} - 0.319 \]  
(8)

where \( d \) is expressed in km.

III. VERTICAL DEVELOPMENT OF WATER VAPOR

As can be inferred from RAOBS and NWP data [14], the vertical profile of water vapor density \( \nu \) follows a fairly regular trend, which is typically modeled using the following exponential profile:

\[ \nu(h) = \nu_G e^{-\frac{h}{h_v}} \]  
(9)

In (9), \( \nu_G \) is the water vapor content at sea level (g/m\(^3\)) and \( h_v \) is the exponential decay rate, also known as water vapor scale height. An example of a typical vertical profile of the water vapor density is shown in Fig. 11: the black curve comes from the data measured by the radiosonde launched in Milano Linate airport, Italy, while the red line is obtained from fitting (9) to such data (in this case \( \nu_G = 2.6 \text{g/m}^3 \) and \( h_v = 1.48 \text{km} \)).

Based on (9), if the integrated water vapor content \( V \) and the water vapor scale height \( h_v \) are known, \( \nu_G \) can be derived by imposing:

\[ V = \int_{0 \text{ km}}^{20 \text{ km}} \nu_G e^{-\frac{h}{h_v}} dh \]  
(10)

which, inverted after simple passages, leads to:

\[ \nu_G = \frac{V}{h_v \left( 1 - e^{-\frac{h_{20 \text{ km}}}{h_v}} \right)} \approx \frac{V}{h_v} \]  
(11)

The integral in (10) is calculated up to 20 km, which is approximately the upper limit of the troposphere; the approximation on the right hand side of (11) is justified by common values of \( h_v \), which are typically comprised roughly between 0.5 km and 4 km.

As a result, starting from a \( V \) field generated by SMOV and knowing \( h_v \), the full three-dimensional distribution of the water vapor content \( \nu \) is given by:

\[ \nu(x, y, h) = \frac{V(x, y)}{h_v} e^{-\frac{h}{h_v}} \]  
(12)

IV. FULL PROCEDURE FOR WATER VAPOR FIELD SYNTHESIS

On the basis of the analysis reported in previous sections, the horizontal synthesis of \( V \) over the target area can be obtained starting from \( \rho_0(d) \) in (8), and from \( E_v \) and \( h_v \). As for \( E_v \), this information can be derived from NWP products, such as the ECMWF (European Centre for Medium-range Weather Forecast) ERA-40 dataset: in this work, we have taken advantage of the area-averaged integrated water vapor content.
V_{ERA} sampled every 6 hours and characterized by spatial resolution of $2^\circ \times 2^\circ$ (latitude-longitude), i.e. roughly 200 km×200 km in Europe. As for $h_v$, time series are not directly available in the ERA-40 database, but statistics and monthly average values are included in recommendation ITU-R P.836-5 [15]. Based on these inputs, the procedure involves the following steps:

1. Given the site of interest with coordinates (lat,lon), extract from the ERA-40 database times series of the average integrated water vapor content ($V_{ERA}$) and derive from recommendation ITU-R P.836-5 monthly mean values of the water vapor scale height ($h_{V,m}$) associated to values relative to the four surrounding grid pixels.

\[
V_{ERA,sea} = V_{ERA} \exp \left( -\frac{h_{sea} - h_{ERA}}{h_{V,m}} \right) = V_{ERA} \exp \left( \frac{h_{ERA}}{h_{V,m}} \right) \tag{13}
\]

2. Scale the $V_{ERA}$ values, each of which is associated to the reference height $h_{ERA}$ of the ERA-40 pixel (ground), to derive the integrated water vapor content at the sea level $V_{ERA,sea}$. As recommended by ITU-R in P.836-5, this is achieved again by considering that the integrated water vapor decays exponentially with height, i.e.:

\[
V_{ERA,sea} = V_{ERA} \exp \left( -\frac{h_{sea} - h_{ERA}}{h_{V,m}} \right) = V_{ERA} \exp \left( \frac{h_{ERA}}{h_{V,m}} \right) \tag{13}
\]

3. As recommended in P.836-5, bilinearly interpolate the values of $V_{ERA,sea}$ and $h_{V,m}$ on the site of interest with coordinates (lat,lon), thus obtaining $V'_{ERA,sea}$ and $h'_{V,m}$. Finally $E_V = V'_{ERA,sea}$ and $h_V = h'_{V,m}$.

4. Using $E_V$, calculate $\mu$ and $\sigma$ as from the expressions in (5), which define $p(B_V|E_V)$ in (4).

5. Calculate $A_W$ from $E_V$ using the linear relationship in (3).

6. Randomly extract $B_W$ as a random draw from the lognormal distribution $p(B_V|E_V)$ derived at step 4.

7. Generate a random Gaussian field $g(x,y)$ (zero mean and unit variance) with the spatial correlation $\rho_G$ in (8) according to [9].

8. Convert the Gaussian field $g(x,y)$ into a water vapor field (Weibull distribution) $V(x,y)$ according to:

\[
U(x, y) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{g(x, y)}{\sqrt{2}} \right) \right] \quad (14)
\]

\[
V(x, y) = A_W \left[ -\ln(1-U(x, y)) \right]^{1/\sigma} \quad (15)
\]

Equation (14) turns the Gaussian field into a random field with values uniformly distributed between 0 and 1 ($U$), while equation (15) converts the uniform field into the target water vapor field characterized by the Weibull distribution with parameters $A_W$ and $B_W$ (erf is the error function).

9. Derive the full spatial distribution of the water vapor density $v$ using (12), which extends vertically from the sea level up to 20 km.

10. Truncate the $v$ field according to the height of the site of interest $h_{stat}$ by discarding $v$ values for which $h < h_{stat}$.

Fig. 12 shows a sample field ($V$ in mm) reflecting the input values extracted from the ERA-40 database ($E_V = 18.9$ mm), while Fig. 13 depicts the spatial distribution of $v$ calculated by means of (12) starting from the synthetic field shown in Fig. 12; the bottom graph reports $v$ on the $y/h$ plane for $x = 120$ km, while the top graph shows the associated integrated water vapor content $V$ as a function of $y$.

**V. VALIDATION OF SMOV**

A. Accuracy in reproducing realistic water vapor fields

In order to test SMOV, using as input the ERA-40 time series of $V_{ERA}$ in the period 1996-2000, we have calculated first- and second-order statistics of $V$ starting from 7308 synthetic water vapor fields (200 km×200 km×20 km with 1 km×1 km horizontal detail and 100 m vertical sampling).
series of $V_{ERA}$ in the period 1996-2000). The reference statistics of $V$ used to assess the performance of SMOV were derived for 14 European sites where extensive RAOBs data were collected (and whose accuracy was duly checked) for 10 years (1980-1989); specifically the sites span very different climatic regions, from Sodankyla in Finland to Trapani in Southern Italy [16].

As an example, Fig. 14 compares the CCDF of $V$ estimated from SMOV with the one obtained from the RAOBs data collected in De Bilt, The Netherlands.

![De Bilt (NL), latitude = 52.06° N, longitude = 5.11° E](image)

Fig. 14. Validation of SMOV against RAOBs data collected in De Bilt, The Netherlands (1980-1989). Input values to SMOV are $V_{ERA}$ values extracted from the ERA-40 database in the period 1996-2000.

The good agreement between the two curves in Fig. 14 is quantified in the figure legend, which includes the average ($E_\psi$) and root mean square ($RMS_\psi$) values of the error $\psi$ ($P \geq 5 \times 10^{-3}$), defined as:

$$\psi(P) = V_L(P) - V_R(P)$$

(16)

In (16), $V_L(P)$ and $V_R(P)$ are the predicted and reference integrated water vapor contents, respectively, associated to the same probability level $P$.

Fig. 15 extends the prediction accuracy assessment to the whole set of 14 sites (as in Fig. 14, for the calculation of $E_\psi$ and $RMS_\psi$, $P$ ranges between $5 \times 10^{-3}$ and 1). Results in Fig. 15 show that SMOV achieves an overall very good accuracy in modeling first-order statistics of $V$.

The ability of SMOV in reproducing the spatial distribution of $V$ was evaluated against the average decorrelation trend ($\rho$ as defined in (6)) extracted from MODIS data. Fig. 16 compares this curve (large black dashed line) with all the ones associated to the synthetic water vapor fields generated by SMOV for the above 14 European sites (thin lines). The discrepancies in $\rho$ from site to site (at 150 km the correlation index varies from 0.85 to 0.95, i.e. approximately 10%) reflect the different climate which the 14 locations are subject to (typically drier in the North and more humid in the South). Overall, the agreement between the average decorrelation trend obtained from SMOV (dashed red line) and the MODIS curve is very good (the root mean square value of the relative difference between the two curves is 0.7%).

![Error $\psi$](image)

Fig. 15. Validation of SMOV against all RAOBs data available: first-order statistics. Input values to SMOV are $V_{ERA}$ values extracted from the ERA-40 database (1996-2000).

![Distance vs. $\rho$ index](image)

Fig. 16. Validation of SMOV against MODIS data: second-order statistics. Input values to SMOV are $V_{ERA}$ values extracted from the ERA-40 database (1996-2000).

VI. ATTENUATION INDUCED BY WATER VAPOR ON EARTH-SPACE LINKS

This section presents some examples of the use of SMOV to estimate the attenuation induced by water vapor ($A_V$) on Earth-space links.

Fig. 17 shows the CCDF of $A_V$ calculated for a hypothetical Earth-space link between an Earth Observation (EO) satellite flying along a near-polar Low Earth Orbit (LEO) and a ground station, set in Svalbard Islands, Norway (latitude 78.75° N, longitude 16° E, 10 m a.m.s.l.), from which the satellite is often visible. The elevation angle is $\theta = 10^\circ$, assumed here as a possible minimum elevation for which the satellite is tracked, and the link frequency is 26 GHz, a band allocated for data downlink in future EO missions. The path attenuation is calculated by first integrating $V$ along the link to obtain the slant integrated water vapor content $V_S$, and afterwards by employing the methodology presented in [17], according to which $A_V$ can be calculated from the simple knowledge of $V_S$ by exploiting the concept of mass absorption coefficient (specifically, refer to equation (7) in [17]). It is worth pointing out that, in order to improve the prediction accuracy and by taking advantage of the full 3-D spatial distribution of $V$, in calculating $A_V$, the Earth’s curvature has been taken into
account (calculation according to section 2.2 of recommendation ITU-R P.676-10 [18]), as well as the ray bending effect associated to the standard atmospheric profile for which the gradient of the refractive index with height close to the ground, $dn/dh$, is assumed to be $-40 \times 10^{-6}$ km$^{-1}$ [19]. Depicted in the same picture are the CCDFs of the attenuation due to rain ($A_R$) and clouds ($A_C$) as calculated according to ITU-R recommendation (e.g. P.840-6 for the latter [20]). For the selected site, results indicate that the contribution of water vapor is dominant for outage probabilities $P$ higher than 3%, and that $A_V$ is anyway larger than $A_R$ for $P \geq 0.5\%$.

This second example refers to Lurin, Peru (latitude $-12.2^\circ$ N, longitude $76.9^\circ$ W, 9 m a.m.s.l.), where an O3b gateway operates to upload contents to the 12 Medium Earth Orbit (MEO) telecommunications satellite of the company [21]. The frequency of the link is 29 GHz, used by O3b for the uplink, and the elevation angle is again 10°. The gateway site is characterized by a rather dry climate (according to recommendation ITU-R P.837-6, the probability to have rain is 1.5% and the rain rate exceeded for 0.01% of the time is approximately 14 mm/h) and by fairly limited cloud coverage (according to recommendation ITU-R P.840-6, the probability to have clouds is roughly 50%), whereas, as clearly visible in Fig. 18, the impact of water vapor is definitely significant due to the tropical climate affecting the site: the water vapor attenuation exceeded for 0.5% of the time is around 12 dB, in the same order of $A_R$.

As a final example, Fig. 19 reports the attenuation statistics for a link operating at 50 GHz between the geostationary satellite KA-SAT (orbital position 9° E) with the EUTELSAT gateway installed in a site close to Turin, Italy (latitude $45.1^\circ$ N, longitude $7.6^\circ$ E, 290 m a.m.s.l.). In this case the elevation angle is fixed to 38.1° and $A_V$ has a much more limited contribution to the total attenuation.

VII. CONCLUSIONS

This contribution presents SMOV (Stochastic Model Of water Vapor), a method for the synthesis of three-dimensional spatially correlated water vapor fields (200 km x 200 km x 20 km with 1 km x 1 km horizontal detail and 100 m vertical sampling) from Numerical Weather Prediction (NWP) products (reanalysis or forecasts) with coarse spatial (e.g. 1.125° x 1.125° latitude x longitude grid) and temporal resolution (6 hours). Fields of integrated water vapor content $V$ are generated by taking advantage of the stochastic approach developed by Bell and SMOV main parameters were determined from high-resolution MODIS-derived water vapor fields. The data investigation pointed out that $V$ values in each
map tend to follow the Weibull distribution, whose parameters turn out to depend on $E_v$, the V value averaged over the target area. As expected the spatial correlation of $V$ was found to decrease very slowly with distance (at 200 km distance, the spatial correlation index $\rho$ is roughly 0.87). Moreover, the vertical development of the water vapor content $v$ is modeled as a simple exponential function decreasing with height, as typically observed from RAOBS and NWP data.

The model's accuracy was tested against radiosonde data collected in 14 sites ranging from Northern (Sodankyla, Finland) to Southern (Trapani, Italy) Europe using as input to SMOV five years of $E_v$ time series extracted from the ERA-40 database: predicted CCDFs of $V$ closely reproduce the ones estimated from RAOBS data (overall, for all sites, the root mean square of the error on the CCDF of $V$ equal to 1.4 mm). Moreover, the average spatial correlation characterizing synthetic $V$ fields is in very good accordance with the one derived from the MODIS database. Finally, SMOV has been applied to estimate the impact of water vapor attenuation in three sites affected by different climates (cold, tropical and temperate). These-All the results shown in this contribution corroborate the use of SMOV as part of a comprehensive simulator of atmospheric impairments, which aims at taking into account all the constituents affecting the propagation of millimeter-waves in different scenarios, including applications involving very low elevation links such as UAVs and LEO satellites.

ACKNOWLEDGMENT

This effort was sponsored by the Air Force Office of Scientific Research, Air Force Material Command, USAF, under grant number FA8655-13-1-3081. The U.S Government is authorized to reproduce and distribute reprints for Governmental purpose notwithstanding any copyright notation thereon. The authors would also like to acknowledge: the MODIS scientists and associated NASA personnel for the production of the data used in this work; the ECMWF for granting access to the water vapor dataset included in the ERA-40 database; Dr. Martellucci from the European Space Agency for the provision of radiosonde data.

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