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INTERPRETATION OF ERS-1 WINDSCASTTEROMETER DATA: WIND FIELD
EXTRACTION

Abstract

This paper discusses the application of a "Bayesian Estimator"
(BE) to the problem of converting the backscatter coefficients
derived from radar scatterometer experiment back into the sea
surface wind vectors. To use a BE prior information on the sur-
face winds to be measured is necessary. This prior information
might be taken from meteorological forecast wind fields. If no
independent prior information is available a method generating
this information online within the wind field identification pro-
cess is reported. The procedure gives all ambiguous solutions.
But compared with order estimation routines the solution fitting
the BE best is the "true" solution, as long as the quality of the
data and the prior information is adequate.
The method proposed was tested using simulated measurement data
sets of the scatterometer experiment of the first experimental
Eurepean Radar Satellite (ERS-1).

Introduction

Radar satellites have flown (SEASAT) or will fly (ERS-1, NOSS)
scatterometer experiments which illuminate the sea surface by
active radar beams and measure the backscattered energy. This
energy is among other things dependent on the structure of the sea
surface mainly modeled by the surface winds. This dependency was
described by an empirically established relationship given by
Moore et all (Ref.1) or Long (Ref.2) for different measurement
characteristics. So the backscatter coefficient resulting from the
radar equation might be converted back to the surface wind vectors
fitting them to thuch a radar model using any estimation procedure
like Weighted Least Square (WLS) or Maximum Likelihood (MLE) as
done interpreting the SEASAT scatterometer experiment data or pro-
posed by different authors see par example (Ref.'s 3,4).
This conversion process is not unique. It gives for each measure-
ment depending on the measurement geometry in respect to the
orientation of the backscattering waves some ambiguous solutions.
To pick therefrom the "true" wind vector an ambiguity removal
strategy has to be developed.

This paper describes a method of sea surface wind vector cell by
cell extraction from radar backscatter measurements for a complete
swath using a "Bayesian Estimator" see (Ref.'s 5,6) partially de-
velopment from the author under ESA contract. So the scatterometer

experiment of the ERS-1 satellite was a natural choice to serve as an example to investigate the ability of the method. Therefore ESA had provided simulated data sets for the tests to the author (Ref.7).

The basic characteristic of this estimate is the additional use of prior information on the wind vectors to be determined. This prior information can be taken from any independent source. For the test cases ESA supplied meteorological forecast wind fields covering the swath (Ref. 7). If there is no independent source prior information available a method was tested to generate for each measurement cell a forecast wind vector from a neighboring cell of the swath where the wind vector is determined already.

The main resulte of the tests are given in this paper also.

The ERS-1 Scatterometer Experiment

The European Radar Satellite ERS-1 will fly a wind scatterometer experiment. Figure 1 shows an overall view of that satellite. During the active microwave instrumentation wind mode operation the sea surface is sequentially illuminated by RF-pulses for reflectivity measurements. Each measurement cell of the swath on the sea surface is seen by the three radar beams of ERS-1 under different geometrical conditions.

Figure 1 shows the scatterometer measurement geometry and the swath, figure 2 shows the antenna configuration. Hence for any resolution cell centered node three independent measurements of the backscattered power are allocated and expressed by the three backscatter coefficients σ^o's. The σ^o's are known to be a function of the surface wind speed v and direction φ, the beam polarisation POL and frequency f and the incidence angle θ.

$$\sigma^o = \sigma^o \ (v, \ \varphi, \ POL, \ f, \ \theta)$$

The mathematical formulation of this empirically derived relationship, ESA's C-band Long model, is given in Ref. (2), see figure 3. The polarisation is vertical (VV) and the carrier frequency is 5.3 GHz (C-band). The incidence angle is within the range of 20 to 60 degrees.

The Wind Field Estimation Process

The algorithm described in this paper converts the σ^o's back into the most likely wind vector as an average over each resolution cell using prior information if available or information extracted from the surface winds retrieved already from measurements at a neighboring cell of the swath. In addition all ambiguous wind vectors are determined also. This is important for any further processing in case the most likely wind vector given by BE at any measurement cell is recognized not to be the true one.

For that purpose the σ^o's are fitted onto the model equation using a 'Bayesian estimators'.

The posterior density $p^*(\nu)$ is given by Bayes'theorem as

$$p^*(\nu) = cL(\nu)\, p_0(\nu)$$

where $L(\nu)$ is the likelihood function and $p_0(\nu)$ the prior density.
The natural extension of the maximum likelihood method to Bayesian estimation problems consists of looking for those values of ν for which $p^*(\nu)$ is a maximum.

The Bayesian estimate has the following characteristics:

- The estimate is identical with the maximum likelihood estimate (MLE) if no prior information is available

- it coincides with the MLE in case of a uniform prior distribution

- it is affected only slightly when a slight amount of prior information is known.

- If the number of experiments is increased indefinitely the BE converges to MLE (von Mises).

- a Bayesian estimate can be obtained even in cases where $p^*(\nu)$ is no proper distribution.

If the prior information does not vanish anywhere we maximize

$$BE = \log L(\nu) + \log p_0(\nu)$$

The same ideas as used for MLE can be applied here.
In case of a single equation and considering for the measurement error Gaussian noise only, the BE can be written as (see Ref.5)

$$BE = WLS + TPI$$

where

WLS: the $\underline{W}$eighted $\underline{L}$east $\underline{S}$quare estimator

$$WLS = \sum_{i=1}^{3} \frac{(\sigma_i^o - f_i(v,\varphi))^2}{VAR_i}$$

$$i: \ = \text{measurements}, \ i=1,2,3$$

$$f_i(v,\varphi): \ = \text{model function evaluations}, \ i=1,2,3$$

$$v: \ = \text{wind speed}$$

$$\varphi: \ = \text{wind direction}$$

$$VAR_i: \ = Kp_i \ f_i \ (v,\varphi))^2 \ i=1,2,3; \ \text{Variance}$$

$$Kp: \ = \text{the radiometric resolution is given by}$$

$$Kp = \left\{ \frac{1}{B\tau_{SN}} \left[1 + \frac{2}{SNR} + \left(\frac{1}{SNR}\right)^2 \left(1 + \frac{\tau_{SN}}{\tau_N}\right) \right] \right\}^{1/2}$$

where

B   = system bandwith

τ_N = noise only integration time

τ_{SN} = signal plus noise integration time

$SNR = \sigma^{\circ}/\sigma_R$ = signal to noise ratio

The Kp values for the tests are taken from a noise model simulating the ERS-1 scatterometer charcteristics, Ref. (4).

TPI: <u>T</u>erm summarizing <u>P</u>rior <u>I</u>nformation

$$TPI = TPI \ (N \ (VPI, VAR_v) + N \ (PhIPI, VAR_{\varphi}))$$

VPI   : = wind speed taken from prior information

PHIPI   : = wind direction taken from prior information

$VAR_{v,\varphi}$: = variance of wind speed or wind direction taken from prior information

N(x,y)   : = normal distribution with mean x, variance y

Minimizing BE with respect to the unknown wind speed v and wind direction φ for each set of σ_i° of the measurement gives the most likely wind vector related to the "best fit". For more than one lokal minima of the function BE the value of BE serves as a measure for a "ranking" of the corresponding solutions.

Discussion of the Method

Extremizing BE is a nonlinear optimization process. It can be performed by standard parameter optimization software. The algorithm allows a simple modular structure. Therefore the change of the model equation is a straight forward task. Some care must be taken in programming to met real time requirements if requested. As is

well known we would expect two to four local minima each of it corresponding to an ambiguous wind vector solution. The solutions are ranked following the quality of fit.
The process can be applied to any number of measurements greater than one. Two beam cases have to be evaluated with care for some special wind directions they may degenerate to one beam cases. That happens for a measurement geometry where the orientation of the backscattering waves is identical with the looking direction of one of the antennas because the signal to noise level will than drop to one.

The main difference to other estimation methods proposed by different authors is the necessity to have prior knowledge on the wind vector field to be determined.

There might be two different modes of providing such forecast values:

1) The method recommends itself for usage within a meteorological data processing environment, there might be available a forecast wind field from other sources covering the swath of the ERS-1 measurements. An interpolated forecast wind vector for each cell of the swath can serve as the mean of the normal distribution in the BE function. The variance might be taken from this forecast field too.

If there is no meteorological forecast wind field known in the region of interest a second method proved itself as very effective in the tests performed by the author.

2) Generating the forecast wind vectors for each cell of the swath using results of the running identification process will create the prior information necessary. In a simple case the wind vector just derived at the preceeding cell can be taken as mean of the normal distribution within the BE function. The variance once extracted from test data sets can be kept constant or iterativebly improved with aid of the growing knowledge of the wind field.

The second method leaves us with the difficulty to start the identification procedure if there is not a forecast wind vector available at least at one single cell of the swath.
A possible starting procedure might be to suppress the term TPI within the function BE. BE serves than as a WLS estimator. When for a sufficient part of the wind field the ambiguous solutions are determined therefrom a guess of the wind vector for the next cell of the swath may start the BE fitting.

Large disturbances of the measurements or an inconsistent forecast wind vector can cause a wrong ranking of the ambiguous solutions. If there is a forecast wind field available the method proposed is a cell by cell independent identification process. A wrong wind vector identified at one cell of the swath will not have any influence on the identification of the wind vector at an other cell.

Generating the forecast wind using information at any neighbouring
cell of the swath produces a dependency of the identification
procedure. A wrong ranking of the ambiguous solutions at one cell
of a row brings typically first the solution which is about 180
degrees apart of the true one. Working than in rows through the
swath leads typically to a continuous skipping of the rest of the
row to this wrong solutiion.
On a first glance this characteristic might be considered as dis-
advantageous but in fact it makes simple to discover a wrong
ranking in any second iteration to get the true wind field iden-
tified (see the example presented within the next part of this pa-
per).

To demonstrate the working mechanism of BE in case of multiple
(ambiguous) solutions let us consider a simplified example. Sup-
pose the wind speed v is known at cell "n" of the swath and the
wind direction φ_n has to be identified by BE. The graph of the
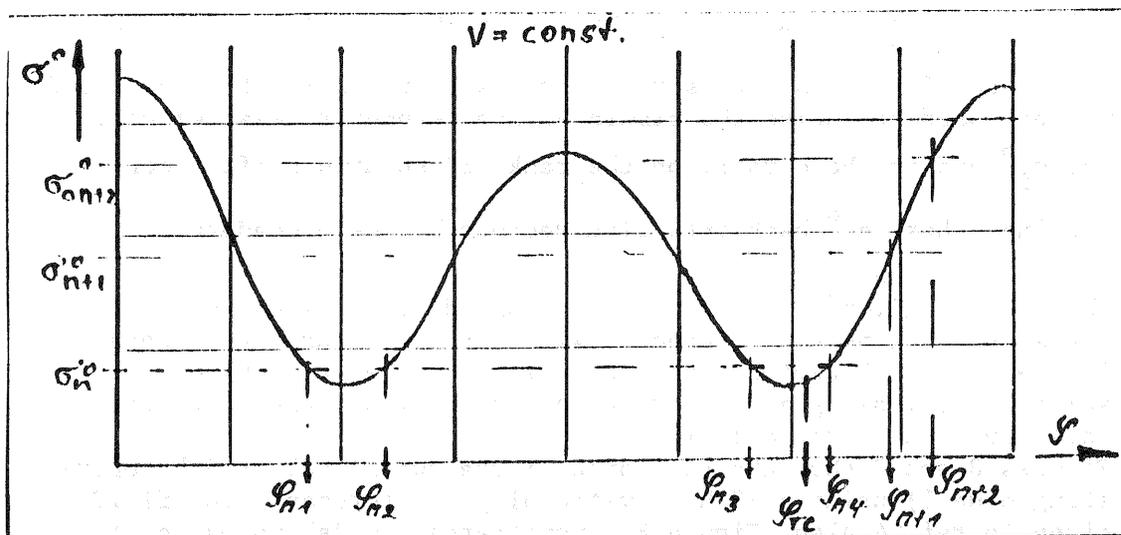model function might look as given in figure 4.

Figure 4 A simple example to demonstrate BE using the model with
v=const.

Than one measurement at cell "n", σ_n^o, is sufficient to determine
as shown all ambiguous solutions of the unknown wind direction
φ_{n1}, φ_{n2}, φ_{n3}, φ_{n4}. Using the MLE or a WLS estimator it is com-
pletely arbitrary to use the residual, the measure of the quality
of fit, to prefer any of those solutions.
Using prior information φ_{FC} in connection with BE gives a weighted
residual which typically puts the solution nearest to the forecast
φ_{n4} on rank "1" position, see figure 4.
If there is no forecast wind available except at the starting cell
of the swath BE allows, advancing in rows cell by cell given by the
swath through a wind field, to track this solution as shown in
figure 4 considering the next measurements φ_{n+1}^o and φ_{n+2}^o at the

cells "n+1", "n+2", which gives the rank "1" solutions φ_{n+1}, φ_{n+2} etc.

Some Results

This method has proven itself as very effective when tests where performed using simulated wind field measurement data provided by ESA, Ref. (7).
For more than 94% of all test cases the rank "1" solution given by BE was closest to the known wind vectors.
This happens to be true for both operating modes 1) using a meteorological forecast wind field provided by ESA also or 2) using only a forecast wind vector at the starting point. No effort was made to improve this result by applying any second step identification strategy.

Figures 5 to 9 are added to demonstrate the ability of the method proposed. Figure 5 shows one of the test wind fields taken from ref. 7 with the outcuts (shown by figures 6 to 7 and 8 to 9 respectively) marked.
In figures 6 to 9 the two sets of arrows representing to known wind vectors used to derive the simulated scatterometer measurements,

the $\sigma_i^{\,o}$ and in the comparison the rank "1" solutions after con-

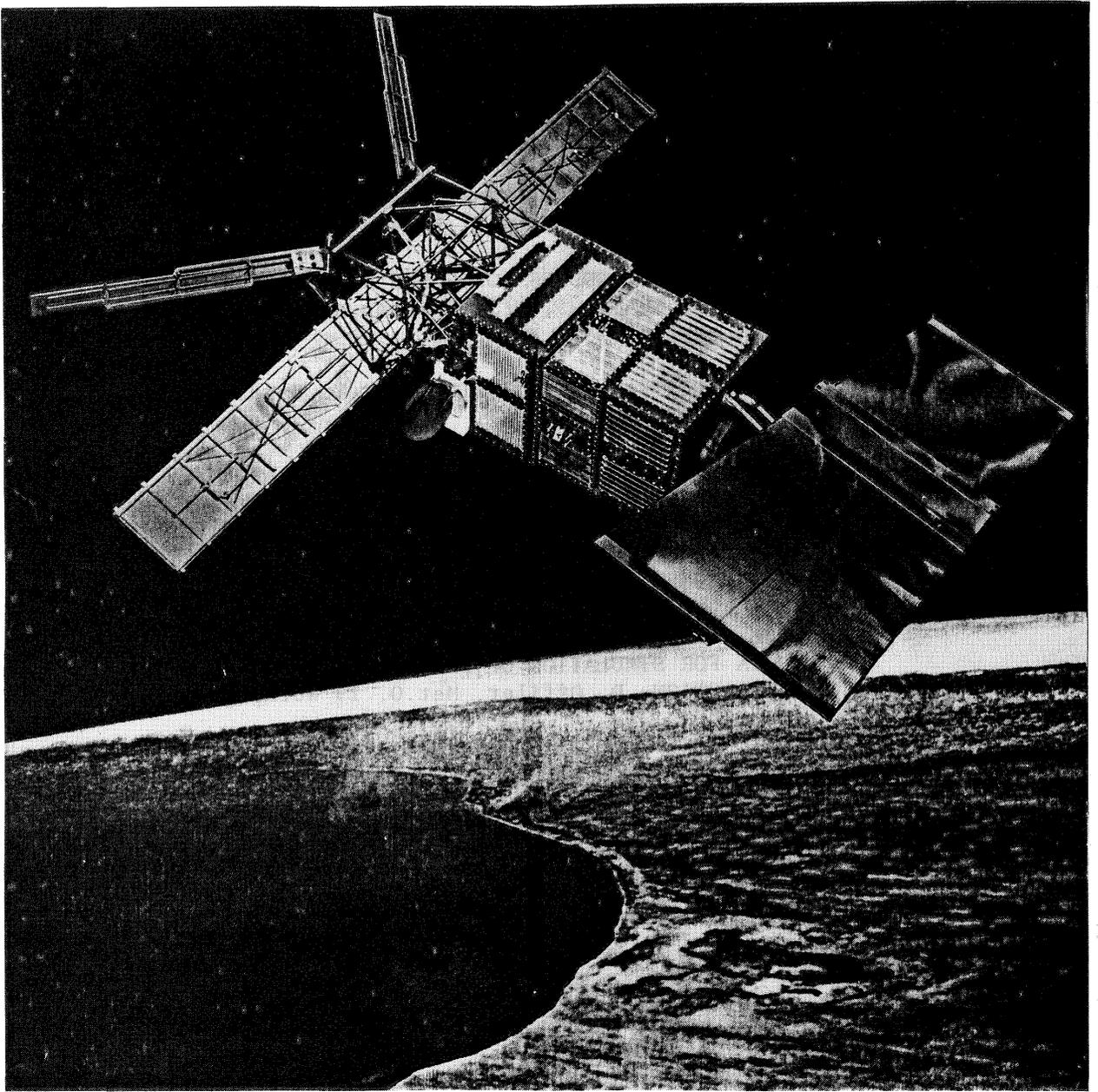verting these $\sigma_1^{\,o}$ back into wind vectors by the procedure

described above.
The results given in figures 6 and 7 are derived using the operating mode 2), generating forecast winds from the running process.
Figure 6 line 25 demonstrates the effect of the skipping of the solutions following a wrong ranking caused by an inadequate forecast wind vector for cell 12.
Figures 8 and 9 show the same area of the swath evaluated by operating mode 1) using a 12 hour meteorological forecast wind field given in ref. 4 also. Figure 8 demonstrates the "skipping" of the rank "1" solution in some areas by about 180 degrees using inconsistent forecast winds. The "correct" solution appears than typically as rank "2" solution within the set of ambiguous solutions derived by the estimation process.

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   DATA FOR SIMULATION OF ERS-1 SCATTEROMETER WIND
   EXTRACTION, D. Offiler, Met.O. 19 Working Paper
   No. 35

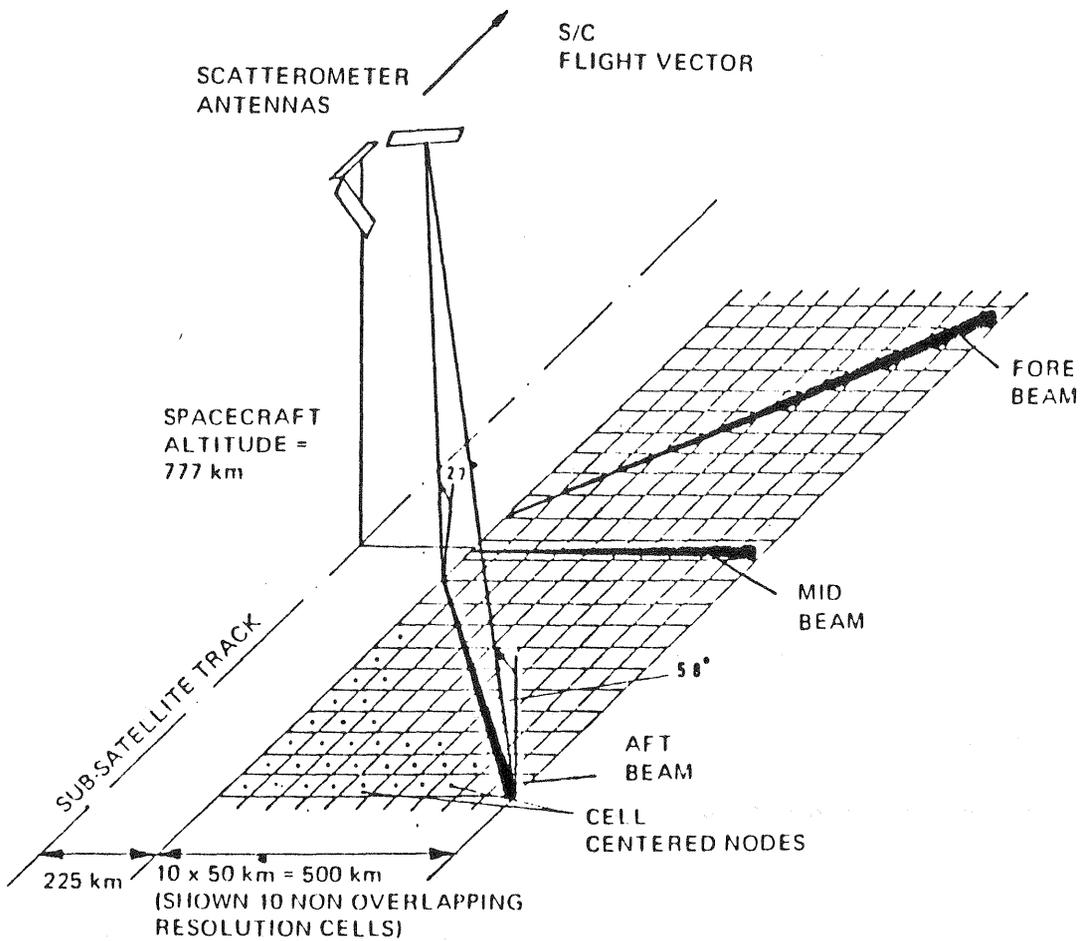*Bild 1   Overall view of the ERS-1   satellite,   an   artist picture*

S/C
FLIGHT VECTOR

SCATTEROMETER
ANTENNAS

SPACECRAFT
ALTITUDE =
777 km

27°

FORE
BEAM

MID
BEAM

58°

AFT
BEAM

CELL
CENTERED NODES

SUB-SATELLITE TRACK

225 km / 10 x 50 km = 500 km
(SHOWN 10 NON OVERLAPPING
RESOLUTION CELLS)

Figure 1 ERS-1 scatterometer measurement geometry

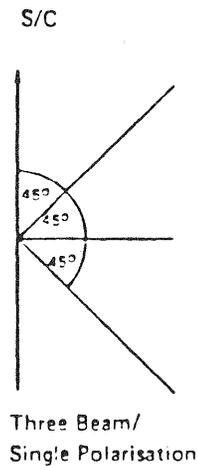S/C

45°
45°
45°

Three Beam/
Single Polarisation

Figure 2   ERS-1 scatterometer antenna geometry

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FIGURE 3   THE LONG C-BAND MODEL

$$\sigma^0 = U*(1 + b_1 * \cos(\phi) + b_2 * \cos(2*\phi))/(1 + b_1 + b_2)$$

where

$$\log_{10} U = 1.877 - 0.1466 * \theta + 0.00105 * \theta^2 + \gamma * \log_{10} v$$

$$b_1 = 2 - 4 * (1 + UC/UD)/(2 + UC/UD + UC)$$

$$b_2 = 1 - 4/(2 + UC/UD + UC)$$

$$\gamma = -0.09885 + 0.0506 * \theta - =.000406 * \theta^2$$

$$UC = \quad 1.058 + 0.02835 * \theta - 0.000002 * \theta^2$$
$$+ (-0.114 + 0.00714 * \theta - 0.000055 * \theta^2) * v$$

$$UD = \quad 0.637 + 0.02507 * \theta - 0.000295 * \theta^2$$
$$+ (.00737 - 0.00094 * \theta + 0.000026 * \theta^2) * v$$

with the specifications

θ = incidence angle (degree)

v = wind speed at 10 metres, neutral stability

ϕ = azimuth angle (degree) between radar
beam and approaching wind direction

U = upwind

UC = upwind/crosswind ratio (linear)

UD = upwind/downwind ratio (linear)

γ = exponent of wind speed v, upwind direction

Figure 5 Example test wind field, outcuts shown by figures 6
         to 9 marked

Figure 6 Rank "1" solution compared to known wind vectors, no meteorological forecast (outcut 1, see fig. 5)

FILE: WINTST15.PLT

FILE: WINRKS15.DAT
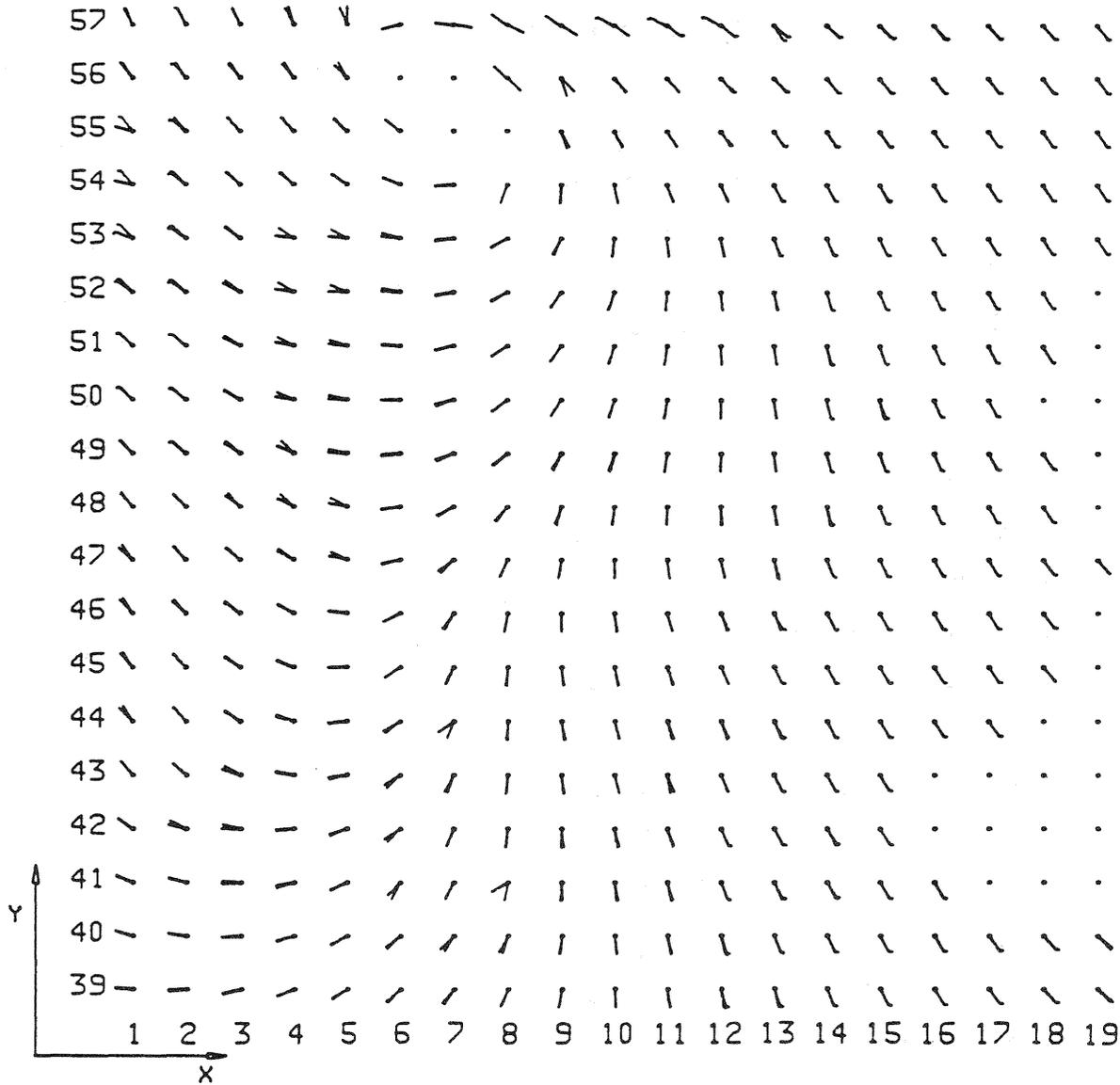
KEY:
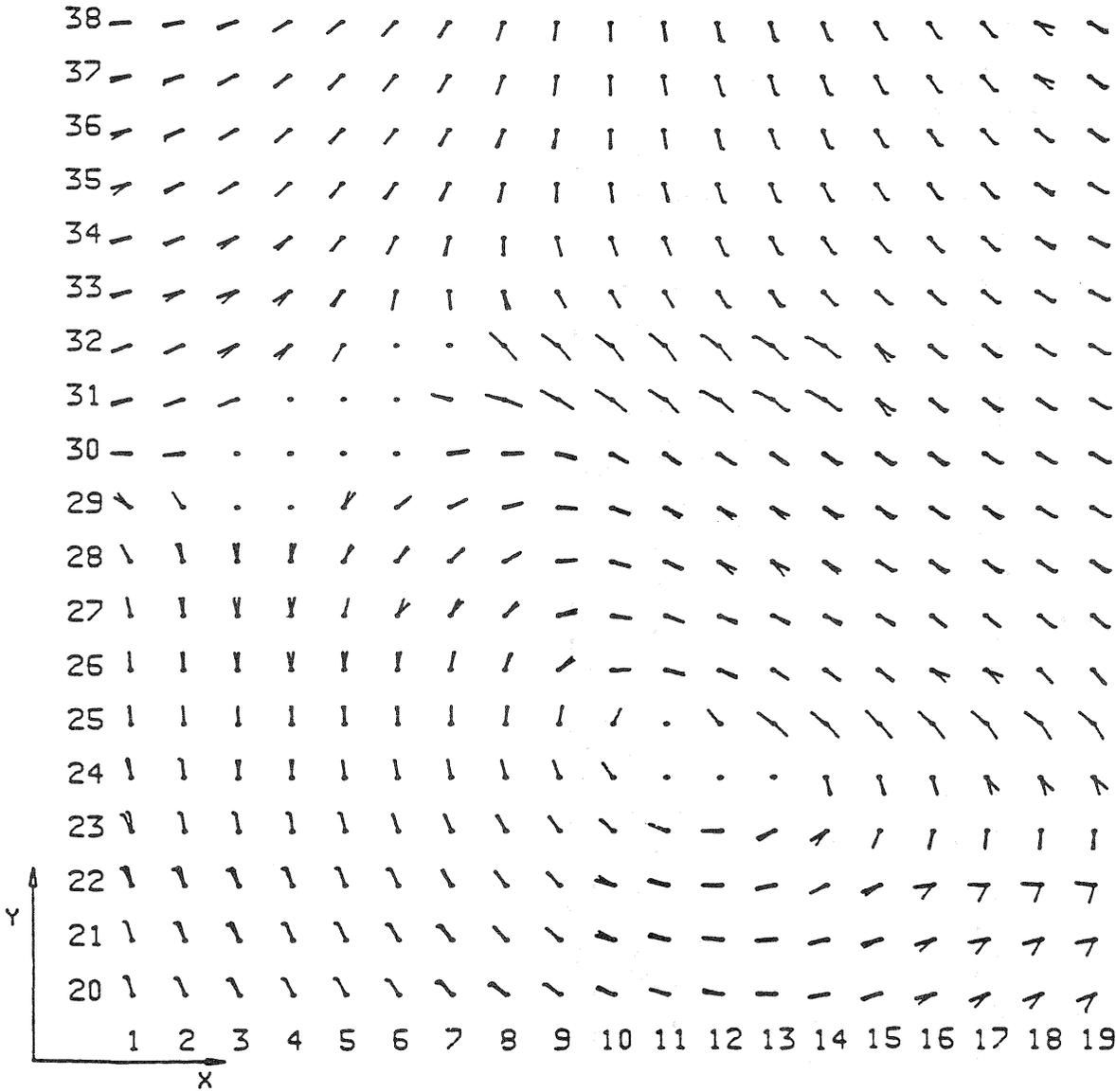
·	0,0... 1,0 m/s
—	1,1... 4,0 m/s
—	4,1... 7,0 m/s
—	7,1...10,0 m/s
—	10,1...13,0 m/s
—	13,1...16,0 m/s
—	16,1...19,0 m/s
—	19,1...22,0 m/s
—	22,1...25,0 m/s
—	25,1...28,0 m/s
—	28,1...31,0 m/s
—	31,1...34,0 m/s
—	34,1...37,0 m/s
—	37,1...40,0 m/s
—	40,1...43,0 m/s
—	=> 43,1 m/s

Figure 7 Rank "1" solution compared to known wind vectors, no meteorological forecast (outcut 2, see fig. 5)
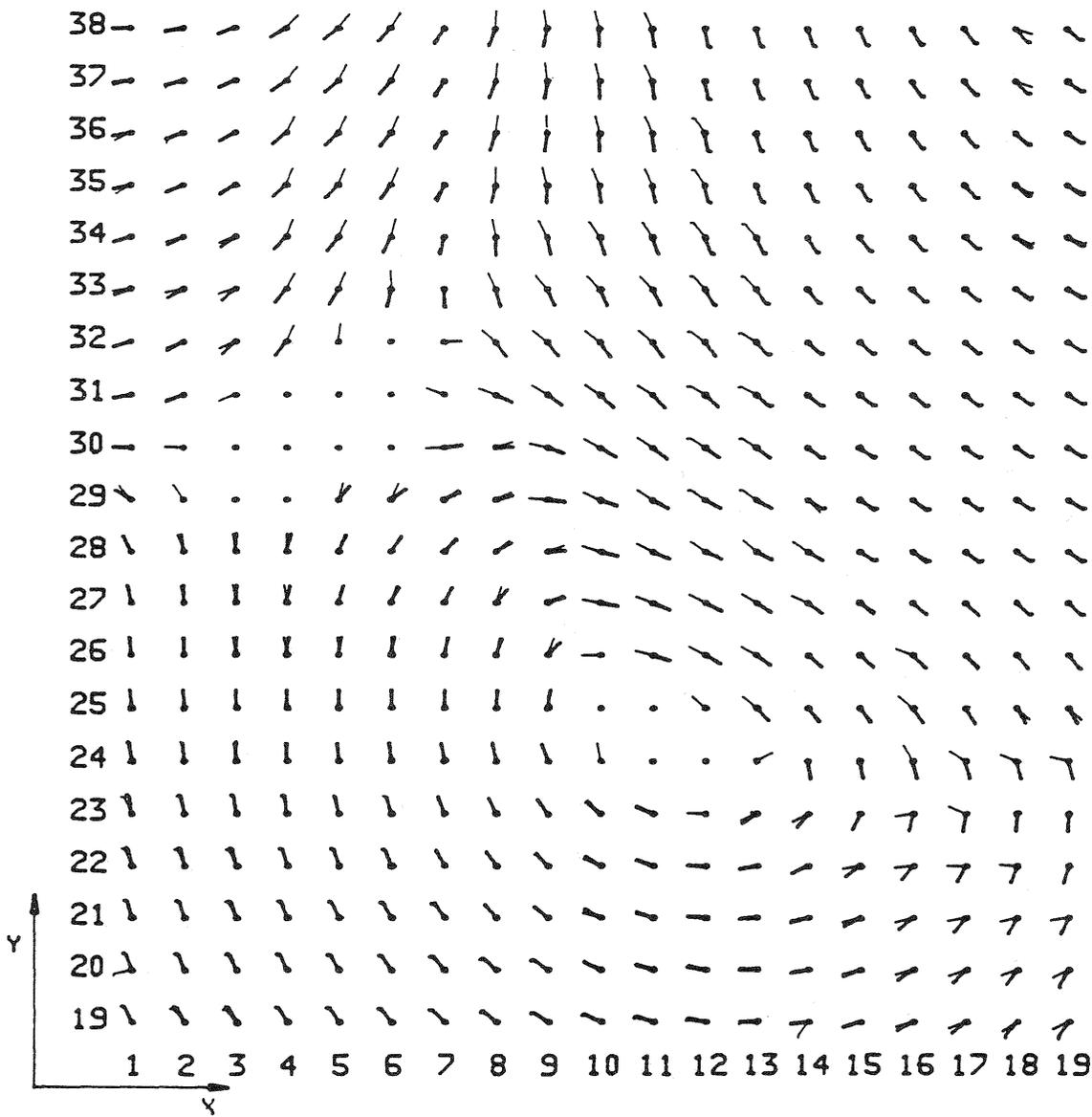
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FILE: WINTST15.PLT

FILE: WINRKS15.DAT

KEY:

.	0,0... 1,0 m/s
—	1,1... 4,0 m/s
—	4,1... 7,0 m/s
—	7,1...10,0 m/s
—	10,1...13,0 m/s
—	13,1...16,0 m/s
—	16,1...19,0 m/s
—	19,1...22,0 m/s
—	22,1...25,0 m/s
—	25,1...28,0 m/s
—	28,1...31,0 m/s
—	31,1...34,0 m/s
—	34,1...37,0 m/s
—	37,1...40,0 m/s
—	40,1...43,0 m/s
—	=> 43,1 m/s

Figure 8 Rank "1" solution compared to known wind vectors, with 12h meteorological forecast (outcut 1, see fig. 5)
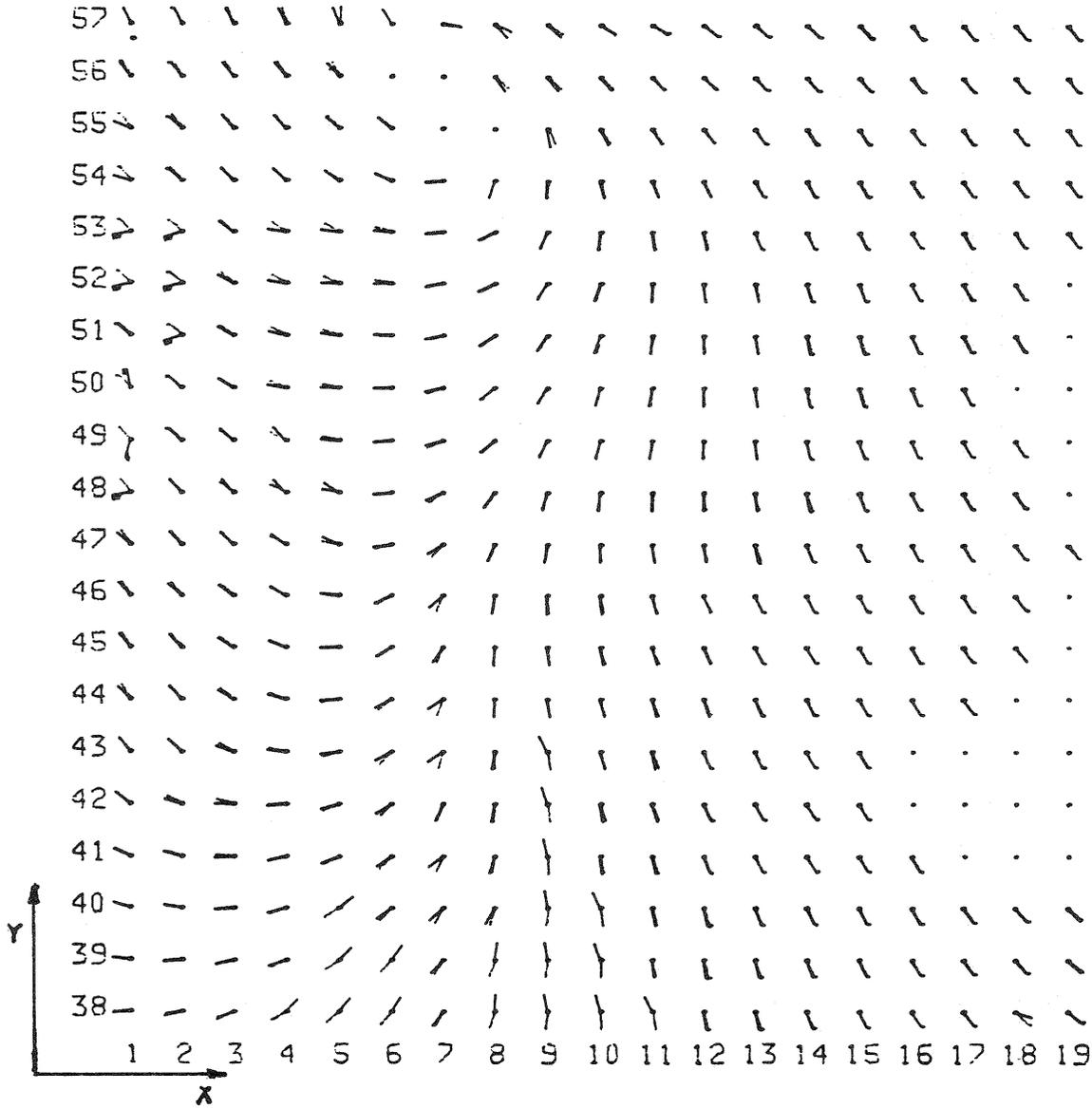
496

FILE: WINTST15.PLT

FILE: WINRKS .PLT

KEY:

.	0,0... 1,0 m/s
—	1,1... 4,0 m/s
—	4,1... 7,0 m/s
—	7,1...10,0 m/s
—	10,1...13,0 m/s
—	13,1...16,0 m/s
—	16,1...19,0 m/s
—	19,1...22,0 m/s
—	22,1...25,0 m/s
—	25,1...28,0 m/s
—	28,1...31,0 m/s
—	31,1...34,0 m/s
—	34,1...37,0 m/s
—	37,1...40,0 m/s
—	40,1...43,0 m/s
—	=) 43,1 m/s

Figure 9 Rank "1" solution compared to known wind vectors,
with 12h meteorological forecast (outcut 2, see fig. 5)

FILE: WINTST15.PLT

FILE: WINRKS .PLT

KEY:

.	0,0... 1,0 m/s
— —	1,1... 4,0 m/s
—	4,1... 7,0 m/s
—	7,1...10,0 m/s
—	10,1...13,0 m/s
—	13,1...16,0 m/s
—	16,1...19,0 m/s
—	19,1...22,0 m/s
—	22,1...25,0 m/s
—	25,1...28,0 m/s
—	28,1...31,0 m/s
—	31,1...34,0 m/s
—	34,1...37,0 m/s
—	37,1...40,0 m/s
—	40,1...43,0 m/s
—	=> 43,1 m/s