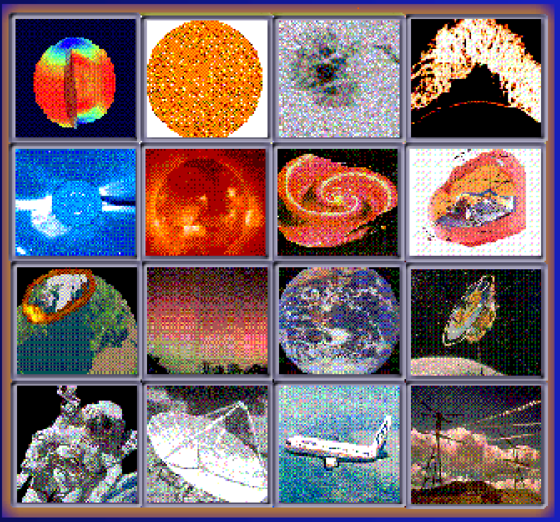
Space weather forecasting



Henrik Lundstedt

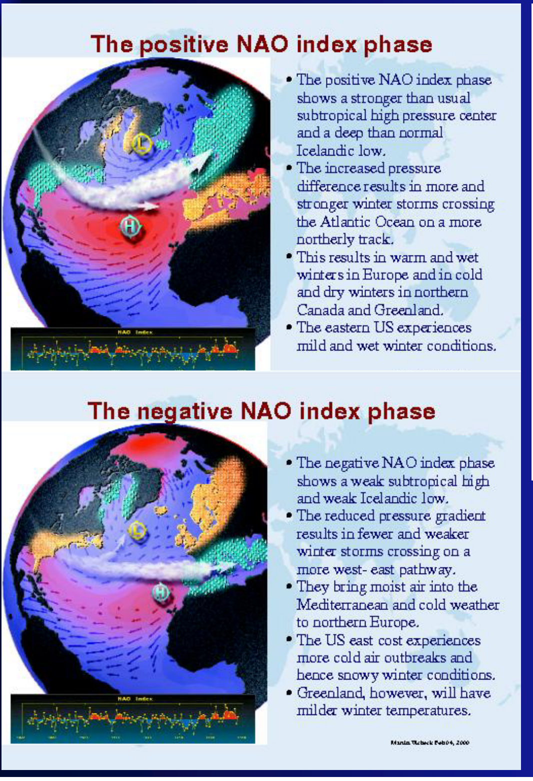
Swedish Institute of Space Physics, Lund, Sweden

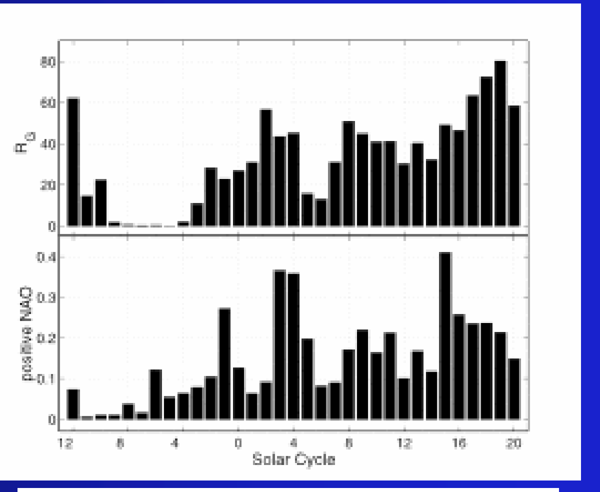
www.lund.irf.se

Contents

- Solar activity - the driver of space weather
- Forecast methods
- Applications
- Implementations for users
- Forecast centers (ISES/RWCs)

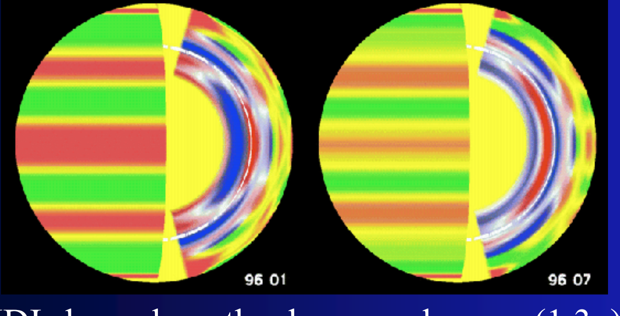
Solar activity, space weather and climate



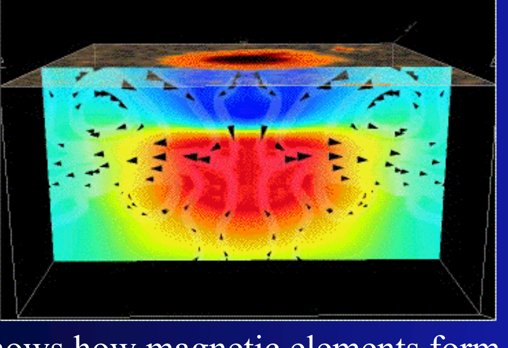


During the Little Ice Age, London's Thames River froze in winter, something that no longer happens. This 19th century engraving depicts the annual Frost Fair held on the ice-bound river, this one during the winter of 1683-84.

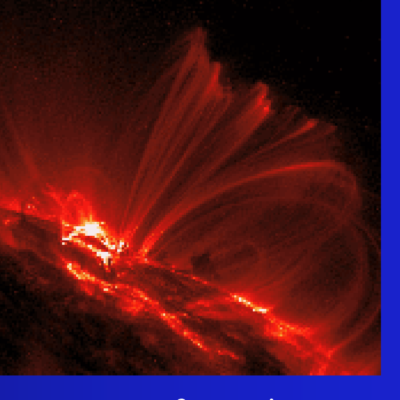
MDI/SOHO reveals the interior and explains surface activity



MDI shows how the dynamo changes (1.3y)



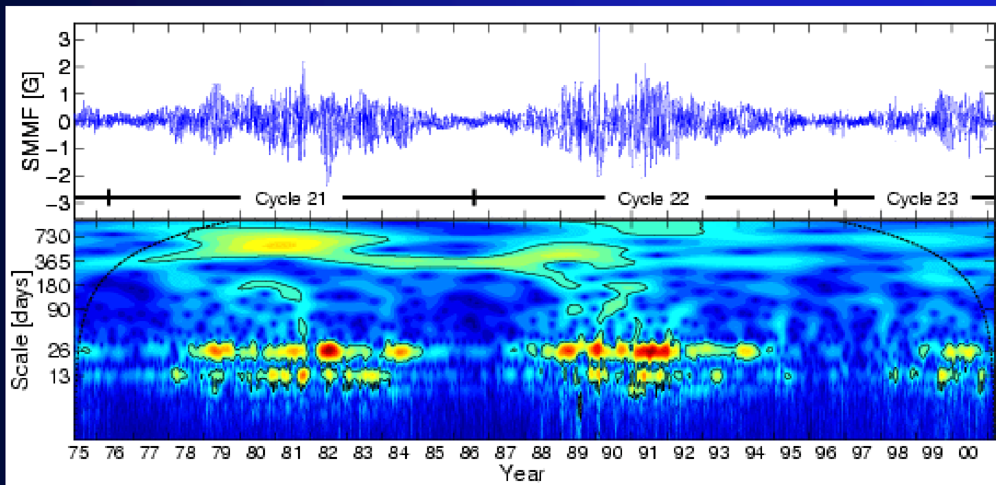
MDI shows how magnetic elements form sunspots



Sunspots are footpoints of emerging magnetic flux tubes

Wavelet power spectra reveals solar activity periodicities

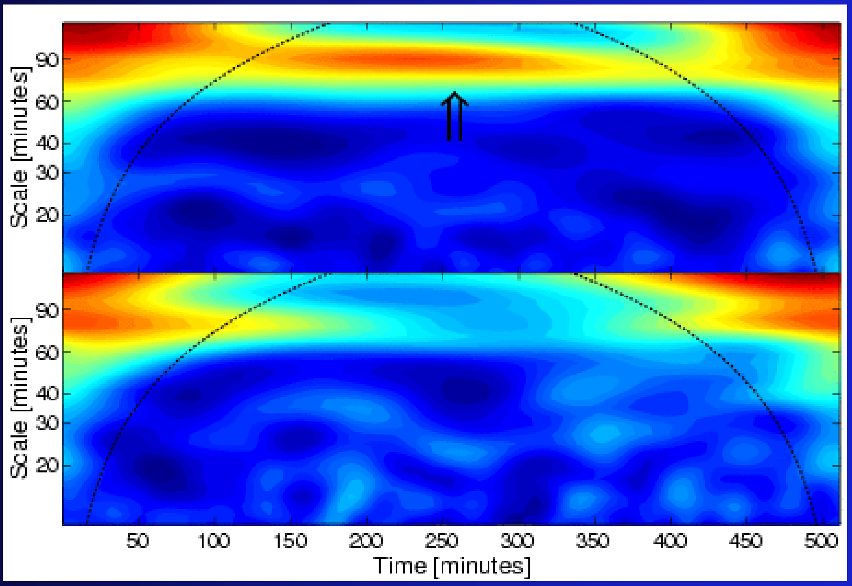
WSO solar mean field May 16, 1975 - March 13, 2001



Wavelet power spectra shows 13,5, days 27 days, 154 days, 1.3 years periodicities

The solar magnetic field further expand and CMEs occur

Wavelet power spectra of MDI magnetic mean field



Upper panel shows for 53 CME events.
Lower panel shows for times without CMEs.

Forecast Methods

- First principles (MHD models)

  (MHD models of the whole Sun-Earth Connection are good at explaining and good for education, but not so good at forecasting.)

- Linear and nonlinear filters (MA, ARMA, NARMA)

$$AL(t+\Delta t)=\sum_{j=0}^{T}H(j\Delta t)[VB_s](t-j\Delta t)$$

$$D_{st}(t+\Delta t)=\sum_{i=0}^{m-1}a_i\cdot D_{st}(t-i\Delta t)+\sum_{j=0}^{l-1}b_j VB_s(t-j\Delta t)$$

MA filter applied as linear filter of AL.The impulse response function H of the magnetospheric system is convolved with a sequence of solar wind inputs

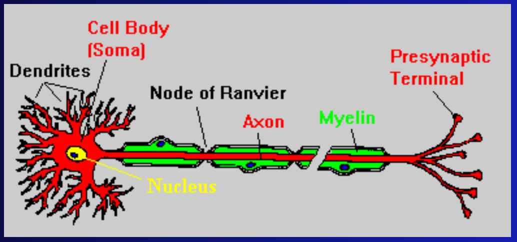
Dst is predicted with an ARMA filter.

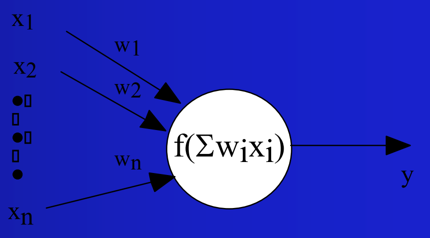
(Problems: Linearity, nonstationary systems, high dimensions)

- Knowledge-Based Neural Models (KBNM) i.e.

  Knowledge (Diff.eqs of physics, dynamical system analysis, filters

Artificial Neural networks



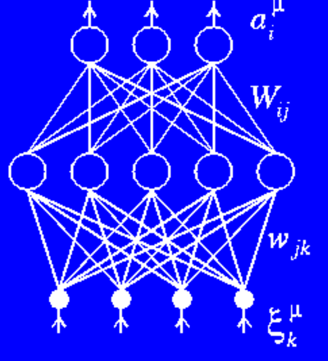


The basic element of every ANN is an artificial neuron or simply a neuron (which is an abstract model of a biological neuron (nerve cell)).

The neuron receives signals (information) from other nerve cells thru the dendrites. The axons take information away from the neuron. The output of the neuron is $y=f(\Sigma w_i x_i)$, with x as input vector.The value y is the state of the neuron. If f=sgn then the state of the neuron is (+1,-1).

Neural networks

Multi-layer error-back-propagation (MLBP)



$$a_i^\mu = g_i\left(\sum_j W_{ij}\, g_j\left(\sum_k w_{jk}\xi_k^\mu\right)\right)$$

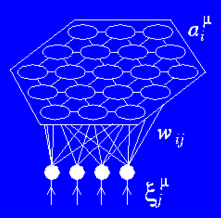
Back-propagation learning : $\Delta W_{ij}(t+1) = -\eta \dfrac{\partial E}{\partial W_{ij}} + \alpha \Delta W_{ij}(t)$

Error measure : $E = \frac{1}{2}\sum_{i\mu}(d_i^\mu - a_i^\mu)^2$

A time-delay network is essentially a nonlinear generalization of linear moving-average (MA) filter.

Neural networks

Self Organized Map (SOM)



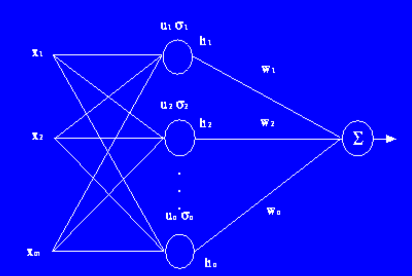
$$a_i^\mu = \begin{cases} 1 & \text{if } i = i^* \\ 0 & \text{if } i \neq i^* \end{cases}$$

$$h_i^\mu = \sum_j w_{ij} \xi_j \qquad h_{i^*}^\mu > h_i^\mu \text{ for all } i$$

Kohonen learning : $\Delta w_{ij} = \eta \Lambda(i,i^*)(\xi_j^\mu - w_{ij})$

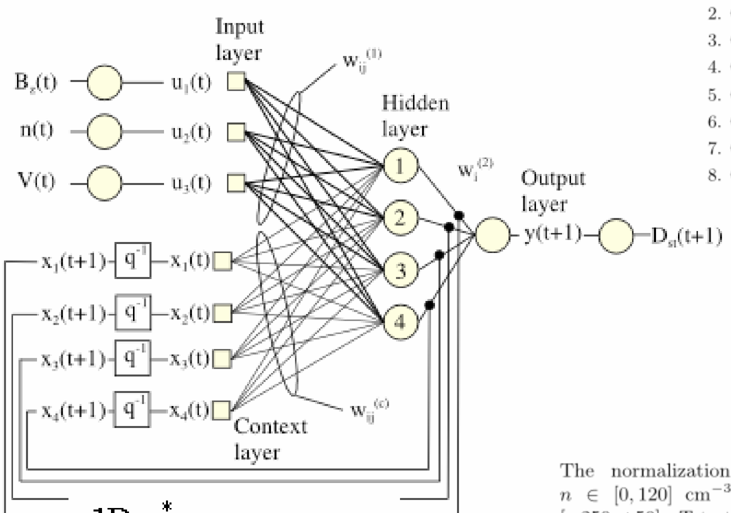
Neighborhood function : $\Lambda(i,i^*) = e^{-\frac{|\mathbf{r}_i - \mathbf{r}_{i^*}|^2}{2\sigma^2}}$

Radial Basis Function Network



$$h_i = exp[-\frac{(\mathbf{x} - \mathbf{u}_i)^{\mathbf{T}}(\mathbf{x} - \mathbf{u}_i)}{2\sigma^2}], \ \mathrm{y} = \sum_{\mathrm{i}} \mathrm{h_i w_i}$$

Download Lund Dst model in Java and Matlab (www.lund.irf.se/dst/models)



$$\frac{dDst^*}{dt} = Q - \lambda Dst^*$$

The ARMA filter is obtained by adding auto-regressive terms to a MA filter.The partial recurrent network (Elman) becomes identical to a linear ARMA filter if it is assigned linear activations functions

1. Set $\mathbf{x} = (0.39, 0.22, -0.83, 0.14)^T$.
2. Get the first observation of B_z, n, and V.
3. Compute $\mathbf{u} = (u_1, u_2, u_3)^T$ from Eq. 7.
4. Compute $\mathbf{x} \leftarrow \tanh\left(\mathbf{W}^{(1)}\mathbf{u} + \mathbf{W}^{(c)}\mathbf{x} + \mathbf{b}^{(1)}\right)$.
5. Compute $y \leftarrow \mathbf{w}^{(2)}\mathbf{x} + b^{(2)}$.
6. Compute Dst from Eq. 8.
7. Get the next observation of B_z, n, and V.
8. Go back to step 3.

The weights and biases are

$$\mathbf{W}^{(1)} = \begin{pmatrix} -0.5946 & 0.0904 & 0.0428 \\ 0.6215 & 0.4485 & 0.2516 \\ -1.4217 & 0.4988 & 0.1409 \\ 0.3372 & -0.5065 & 0.7190 \end{pmatrix}$$

$$\mathbf{W}^{(c)} = \begin{pmatrix} 0.6099 & 0.2223 & -0.4379 & 0.0053 \\ 0.7935 & 0.5000 & -1.2654 & -0.0428 \\ -0.3496 & 0.1024 & 0.3605 & 0.1790 \\ -0.2067 & 0.2270 & 0.5446 & 0.1019 \end{pmatrix}$$

$$\mathbf{b}^{(1)} = \begin{pmatrix} -0.1081 \\ -0.7252 \\ -0.2307 \\ 0.5406 \end{pmatrix}$$

$$\mathbf{w}^{(2)} = \begin{pmatrix} 0.2535 & 0.3172 & -0.4860 & -0.2346 \end{pmatrix}$$

$$b^{(2)} = 0.0712$$

$$Dst = 150y - 100. \tag{8}$$

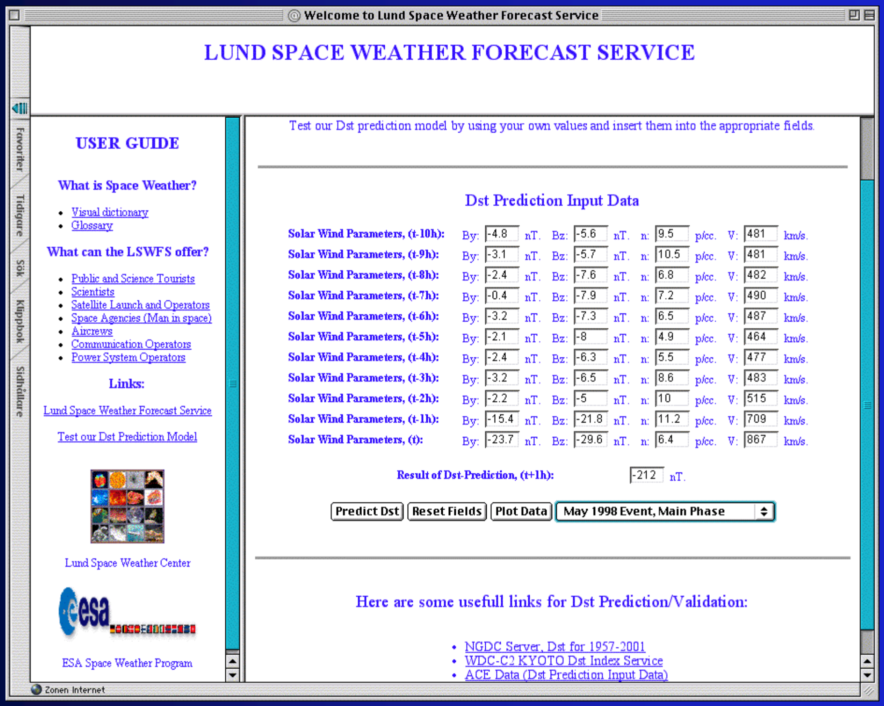
The normalization transforms $B_z \in [-30, +30]$ nT, $n \in [0, 120]$ cm^{-3}, $V \in [200, 1000]$ km/s, and $Dst \in [-250, +50]$ nT to the $[-1, +1]$ interval.

The output from the network is described by the following equations

$$x_i(t+1) = \tanh\left(\sum_{j=1}^{n_1} w_{ij}^{(1)} u_j(t) + \sum_{j=1}^{n_c} w_{ij}^{(c)} x_j(t) + b_i^{(1)}\right) \tag{9}$$

$$y(t+1) = \sum_{j=1}^{n_2} w_i^{(2)} x_i(t+1) + b^{(2)}. \tag{10}$$

Test Dst forecasts



Knowledge-Based Neural Models

The basis of using neural networks as mathematical models is "mapping". Given a dynamic system, a neural network can model it on the basis of a set of examples encoding the input/output behavior of the system. It can learn the mathematical function underlying the system operation (i.e. generalize not just fit a curve), if the network is designed (architechure, weights) and trained properly (learning algorithm).

Both architechure and weights can be determined from differential equations which describe the causal relations between the physical variables (solution of diff eq is approximized by a RBF). The network (KBN) is then trained with observations.

The architechure (number of input and hidden nodes) can also be determined from dynamic system analysis (reconstruction of state space from time series gives dimension).

Neural networks can discover laws from regularities in data (Newton's law e.g.). If one construct a hierachy of neural networks where networks at each level can learn knowledge at some level of abstraction, even more advanced laws can be discovered.

Workshops arranged by us

Workshops on ”Artificial Intelligence Applications in Solar-Terrestrial Physics” were held in Lund 1993 and 1997.

Applications

- Forecasting solar wind velocity
- Forecasting Geomagnetic activity
- Tables summarizing forecasts based on KBNM

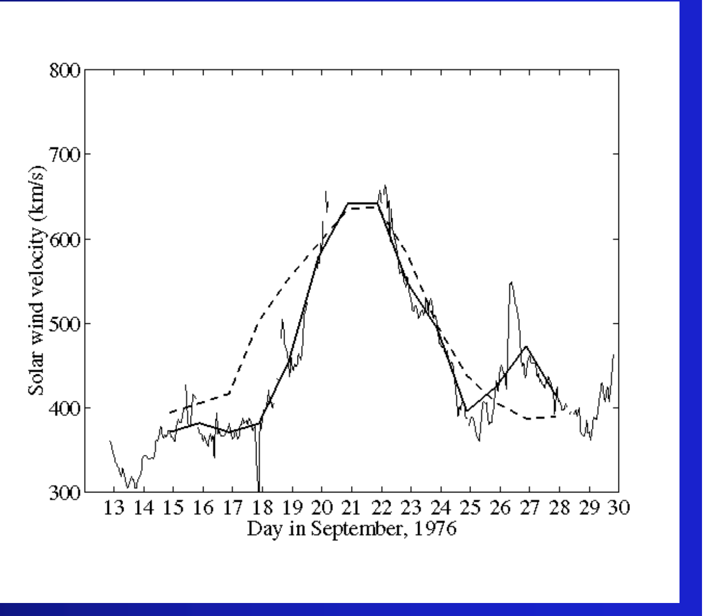
Forecasts of solar wind velocity from daily solar WSO magnetograms

Input

A time-series
$f_s(t - 4),..f_s(t)$ of
the expansion factor
$f_s(t)$,
$f_s = (R_{ps}/R_{ss})^2$
B_{ps}/B_{ss}.

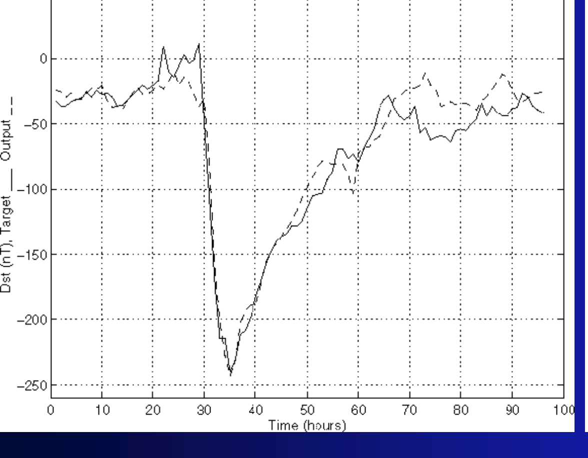
Output

Daily solar wind
velocity $V(t + 2)$
(---)

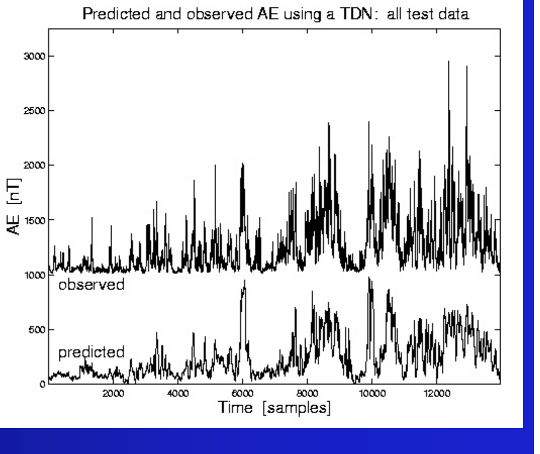


With the use of MDI data (short-term solar activity)
we will try to forecast hourly V

Forecasting global Dst and AE indices

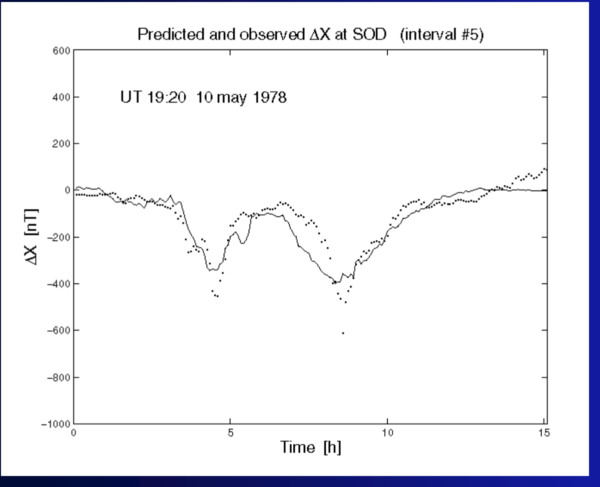


Forecasts of Dst index
Two hours ahead from only
solar wind data based on an
Elman recurrent neural
network.

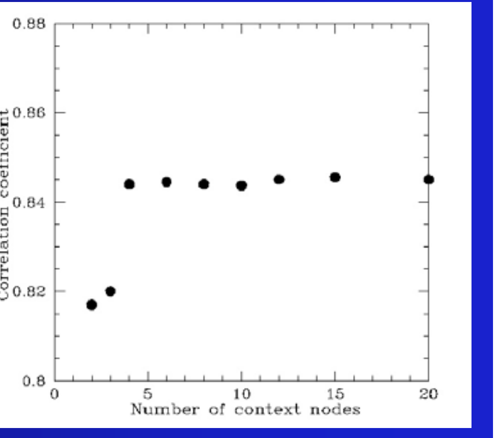


Forecasts of AE index one
hour ahead from only solar
wind data based on a Time
Delay Network.

Forecasting local geomagnetic activity and interpretation



A hybrid (MLP, RBF) neural network was applied to data from Sodankylä Geomagnetic Observatory. It was shown that 73% of the ΔX variance is predicted from solar and solar wind data as input.



Number of context nodes gives the dimension of magnetospheric dynamic system. Weights give decay time τ .

Applications

Input parameters	Output	KBNM method	Reference
Daily sunspot number	Daily sunspot number	SOM and MLP	Liszka 93;97
Monthly sunspot number	Date of solar cycle max and amplitude	MLP and Elman	Macpherson et al., 95, Conway et al, 98
Monthly sunspot number and aa	Date of solar cycle max and amplitude	Elman	Ashmall and Moore, 98
Yearly sunspot number	Date of solar cycle max and amplitude	MLP	Calvo et al., 95
McIntosh sunspot class & MW magn complex.	X class solar flare	MLP expert system	Bradshaw et al., 89
Flare location, duration X-ray and radio flux	Proton events	MLP	Xue et al., 97
X-ray flux	Proton events	Neuro- fuzzy system	Gabriel et al., 00
Photospheric magnetic field expansion factor	Solar wind velocity 1-3 days ahead	RBF & PF MHD	Wintoft and Lundstedt 97;99

Applications

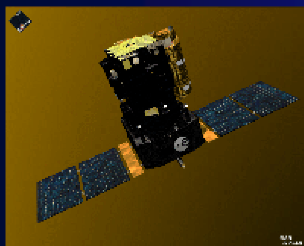
Input parameters	**Output**	**KBNM method**	**Reference**
Solar wind n, V, Bz	Relativistic electrons in Earth magnetosphere hour ahead	MLP	Wintoft and Lundstedt, 00
Solar wind n,V, Bz, Dst	Relativistic electrons hour ahead	MLP, MHD, MSFM	Freeman et al., 93
ΣKp	Relativistic electrons day ahead	MLP	Stringer and McPherron, 93
Solar wind V from photospheric B	Daily geomagnetic Ap index	MLP	Detman et al., 00
Ap index	Ap index	MLP	Thompson, 93
Solar wind n, V, Bz	Kp index 3 hours ahead	MLP	Boberg et al., 00
Solar wind n, V, B,Bz	Dst 1-8 hours ahead	MLP, Elman	Lundstedt, 91; Wu and Lundstedt, 97
Solar wind n, V, B,Bz	AE 1 hour ahead	Elman	Gleisner and Lundstedt, 00

Applications

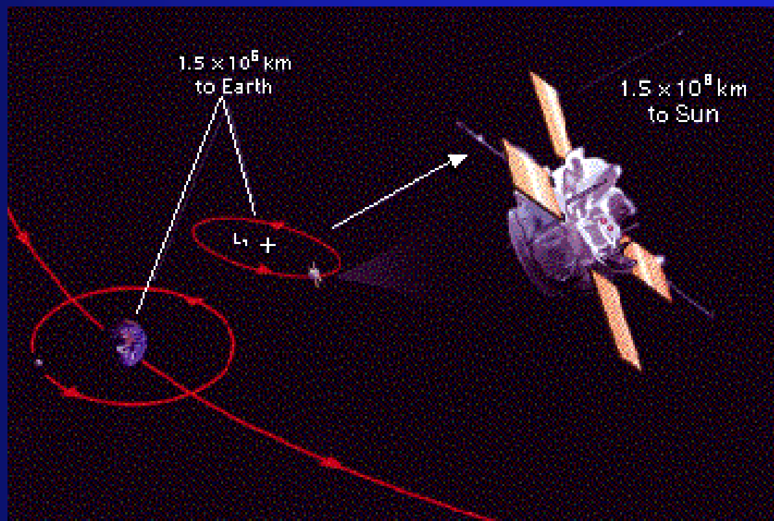
Input parametrs	**Output**	**KBNM method**	**References**
Solar wind V^2B_s, $(nV^2)^{1/2}$, LT, local geomag Δx^e, ΔY^w	Local geomagnetic field ΔX, ΔY	MLP and RBF	Gleisner and Lundstedt 00
Solar wind n,V, Bz	None, weak or strong aurora	MLP	Lundstedt et al., 00
foF2	foF2 1 hour ahead	MLP	Wintoft and Lundstedt, 99
AE, local time, seasonal information	foF2 1-24 hours ahead	MLP	Wintoft and Cander, 00
foF2, Ap, F10.7 cm	24 hours ahead	MLP	Wintoft and Cander, 99
ΣKp	Satellite anomalies	MLP	Wintoft and Lundstedt 00
Solar wind n, V, Bz	GIC	Elman, MLP	Kronfeldt et al., 01

Real-time forecasts and warnings based on KBN

Solar input data

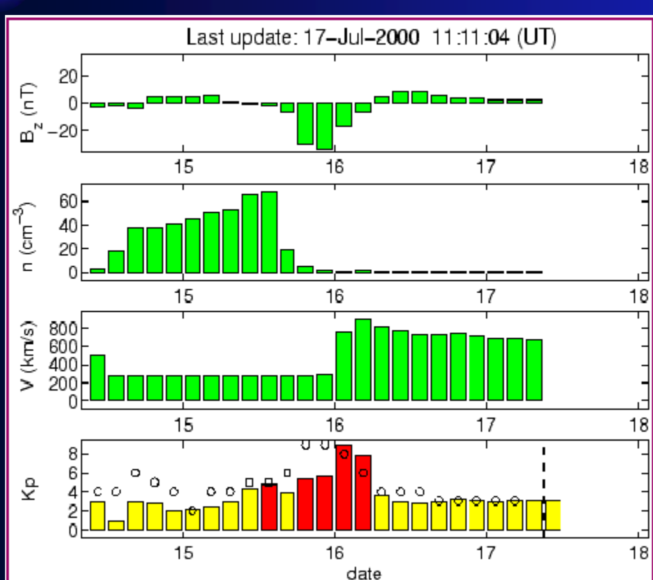


Solar observations with SOHO make warnings 1-3 days ahead possible.



Solar wind observations with ACE make accurate forecasts 1-3 hours ahead possible.

Satellite anomalies of July 14-16, 2000 event



The proton event caused problems for ACE, SOHO, Ørsted, Japanese X-ray satellite, star trackers on board commercial satellites.

Proton flux (pfu) > 10 MeV, 24000 pfu (July 15, 12.30 UT). Third largest!

Largest 43 000 pfu, (March 24, 1991). Second 40 000 pfu (October 20, 1989).

Today IRF-Lund has real-time neural networks forecasts of satellite anomalies one day in advance (ESA project SAAPS). The work has been in collaboration with Swedish satellite operators (ESRANGE).

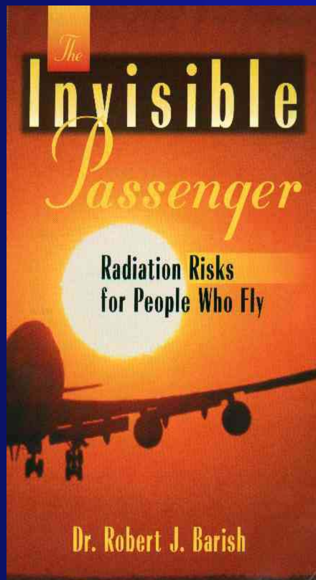
Radiation risks and aviation

The radiation exposure is doubled every 2.2 km.

Solar flares can increase the radiation by 20-30 times.

Pilots get cancer more often than average.

New EU law: Pregnant (aircrew) should not be exposed to more than 1 (1-6) millisievert/year

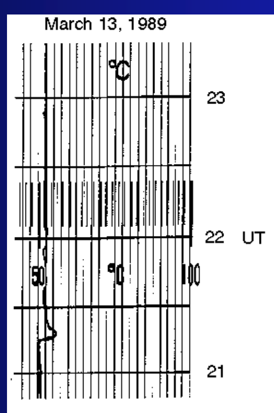


The intensive solar flare of April 2, 2001, which caused major communication problems also made Continental Airlines to change their route between Hong Kong and New York.

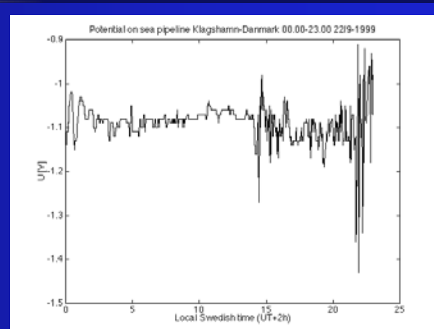
IRF-Lund collaborates with the Swedish Radiation Protection Institute and Medical University in Stockholm to develop forecasts of radiation doses for Aviation Industry.

Power systems and pipeline systems are effected at times of geomagnetic storms

This severe electrojet caused the failure of Quebec's power system March 13-14, 1989.



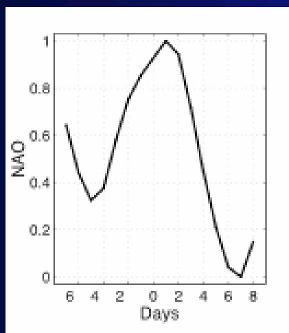
One of the generators of OKG's (Sydkraft's) nuclear plants was heated due to the geomagnetically induced current in March 13-14 1989.



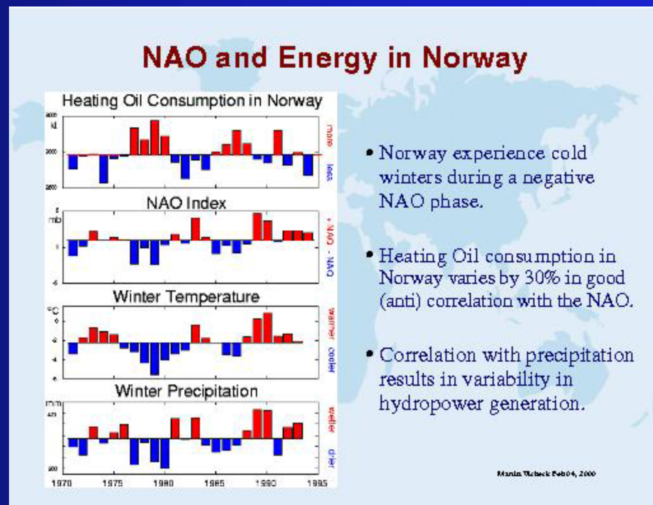
Measured (SydGas) geomagnetically induced disturbance at time of the Nordic GIC meeting in Lund September 23-24, 1999.

We in Lund have collaborated with the Swedish power industry during more than twenty years. Today we have real-time neural network forecasts of local GICs, based on ACE solar wind and warnings based on SOHO (LASCO and MDI) data.

User of NAO forecasts

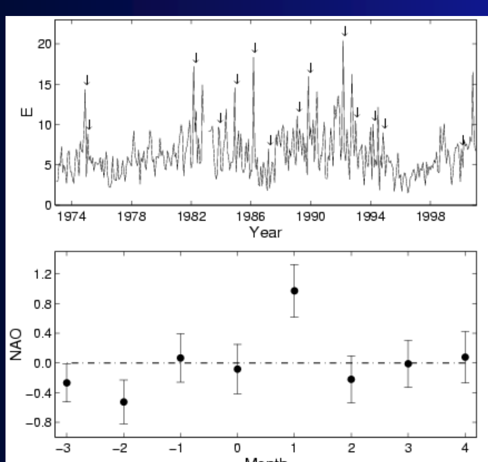


Proton events give positiv NAO within days!

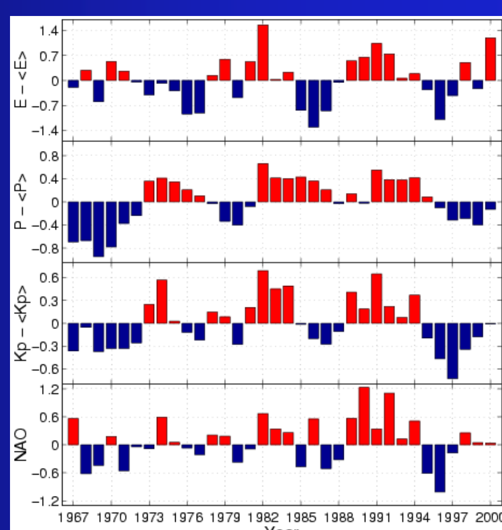


A User: Power sytem operators

North Atlantic Oscillation and solar wind activity

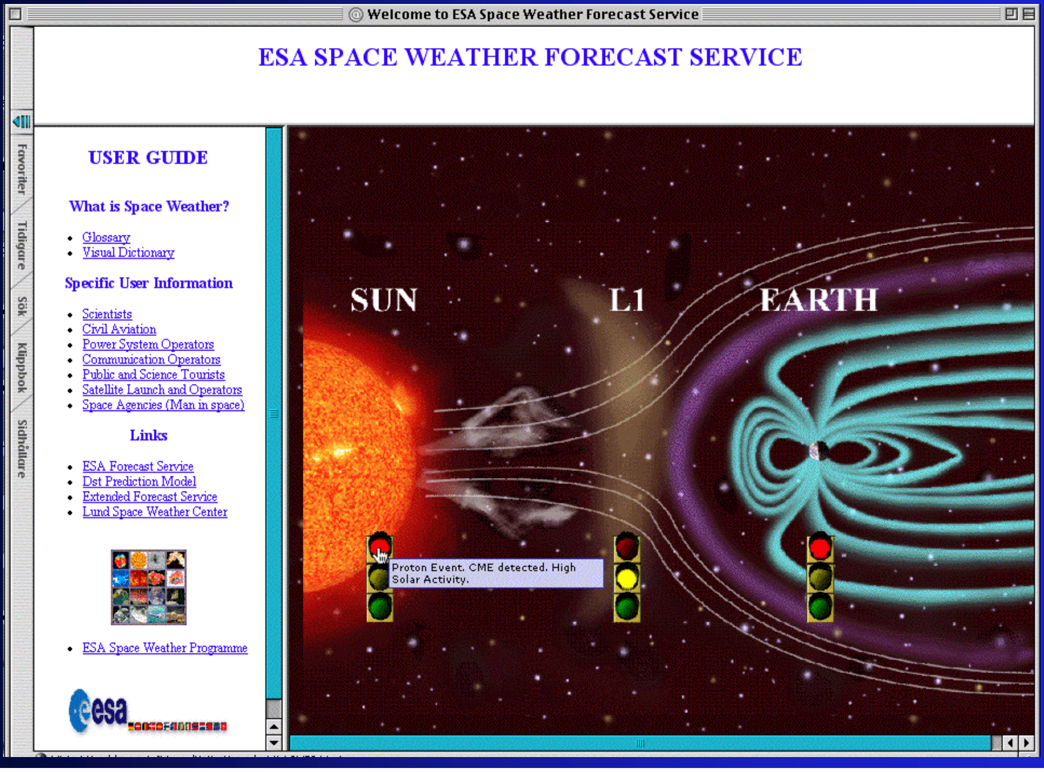


The NAO response on increased solar wind E, one month later! That makes forecasts one month ahead possible.

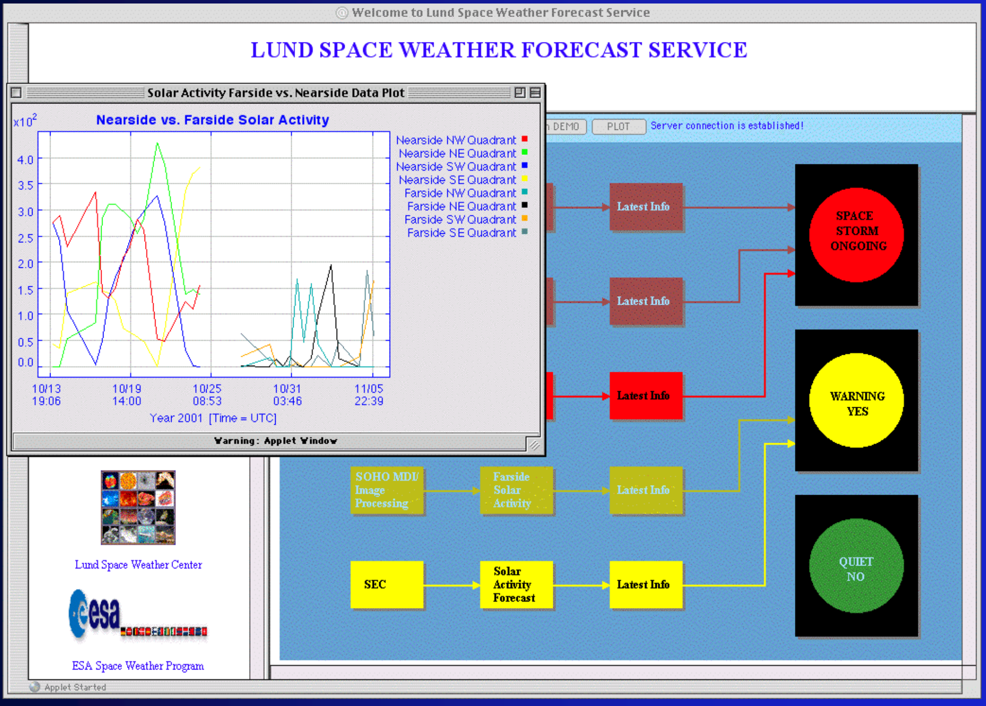


11 års, 1.3 variations are seen both in solar wind and NAO.

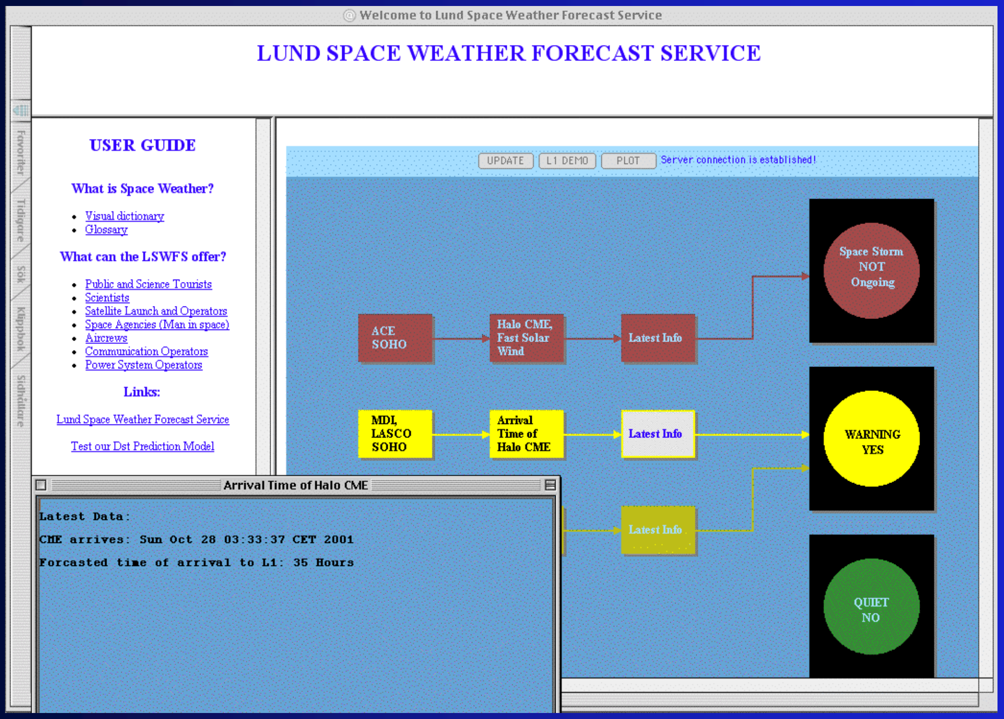
ESA/Lund Space Weather Forecast Service



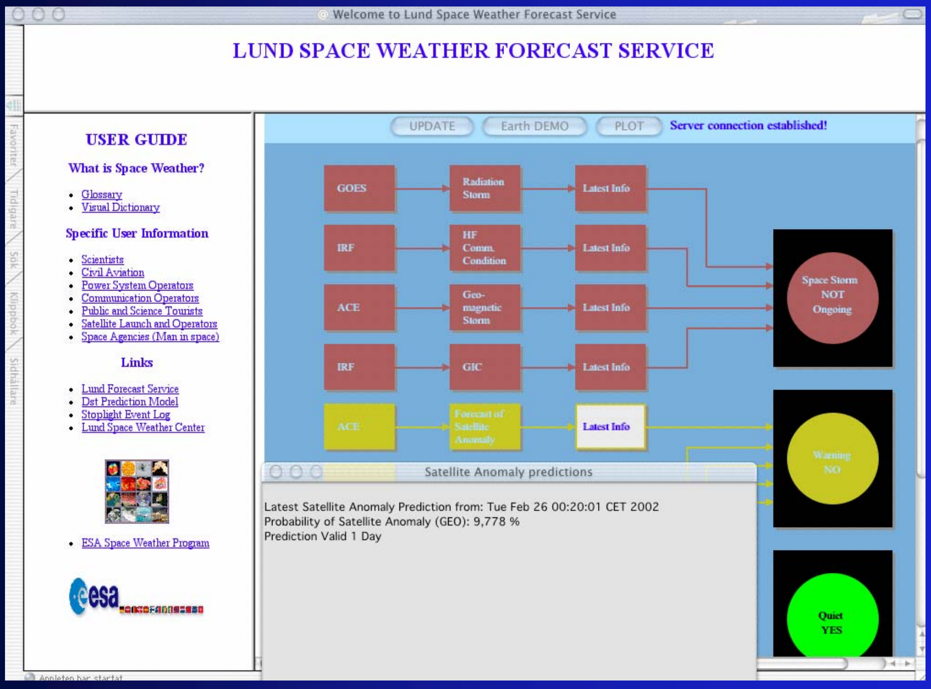
Near and farside solar activity from MDI/SOHO observations



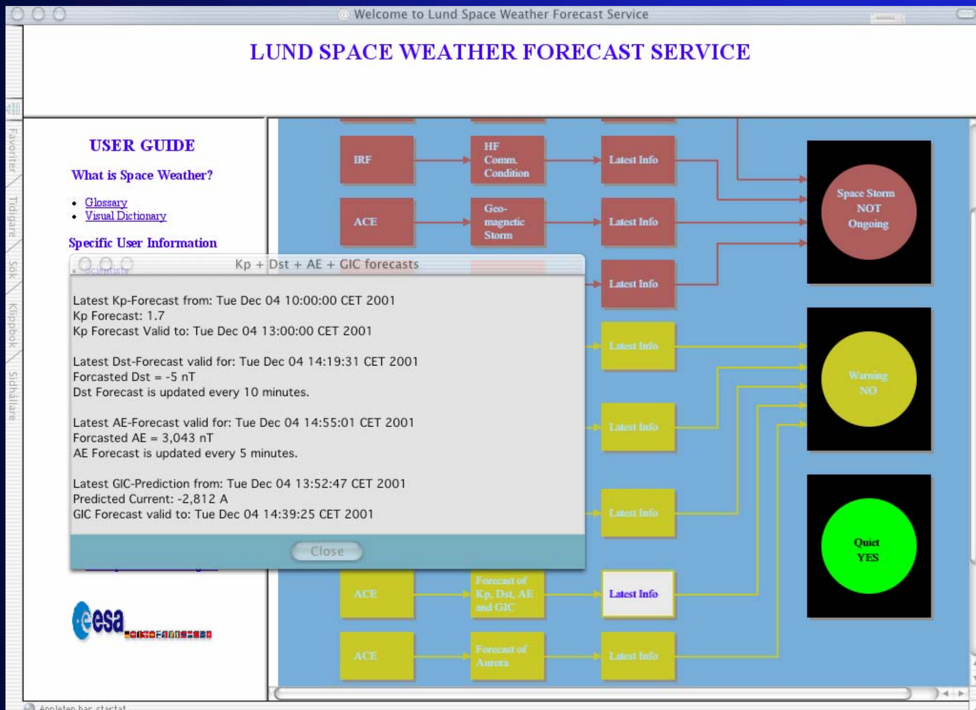
Latest information on arrival of halo CME at L1



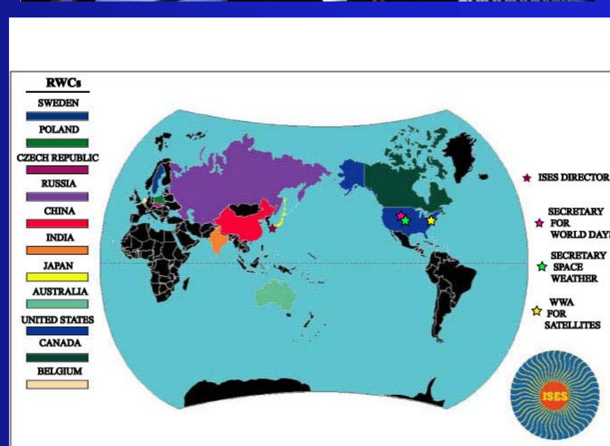
Latest info on forecasts of satellite anomalies (SAAPS)



Latest information on forecasts of Kp, Dst, AE and GIC



Forecast Centers (ISES/RWC)



Forecasts of aurora as SMS, voice messages or WAP service

Where to learn more?