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The quiet revolution of numerical weather prediction

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Advances in numerical weather prediction represent a quiet revolution because they have resulted from a steady accumulation of scientific knowledge and technological advances over many years that, with only a few exceptions, have not been associated with the aura of fundamental physics breakthroughs. Nonetheless, the impact of numerical weather prediction is among the greatest of any area of physical science. As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe, and it is performed every day at major operational centres across the world.

At the turn of the twentieth century, Abbe[1] and Bjerknes[2] proposed that the laws of physics could be used to forecast the weather; they recognized that predicting the state of the atmosphere could be treated as an initial value problem of mathematical physics, wherein future weather is determined by integrating the governing partial differential equations, starting from the observed current weather. This proposition, even with the most optimistic interpretation of Newtonian determinism, is all the more audacious given that, at that time, there were few routine observations of the state of the atmosphere, no computers, and little understanding of whether the weather possesses any significant degree of predictability. But today, more than 100 years later, this paradigm translates into solving daily a system of nonlinear differential equations at about half a billion points per time step between the initial time and weeks to months ahead, and accounting for dynamic, thermodynamic, radiative and chemical processes working on scales from hundreds of metres to thousands of kilometres and from seconds to weeks.

A touchstone of scientific knowledge and understanding is the ability to predict accurately the outcome of an experiment. In meteorology, this translates into the accuracy of the weather forecast. In addition, today's numerical weather predictions also enable the forecaster to assess quantitatively the degree of confidence users should have in any particular forecast. This is a story of profound and fundamental scientific success built upon the application of the classical laws of physics. Clearly the success has required technological acumen as well as scientific advances and vision.

Accurate forecasts save lives, support emergency management and mitigation of impacts and prevent economic losses from high-impact weather, and they create substantial financial revenue—for example, in energy, agriculture, transport and recreational sectors. Their substantial benefits far outweigh the costs of investing in the essential scientific research, super-computing facilities and satellite and other observational programmes that are needed to produce such forecasts[3].

These scientific and technological developments have led to increasing weather forecast skill over the past 40 years. Importantly, this skill can be objectively and quantitatively assessed, as every day we compare the forecast with what actually occurs. For example, forecast skill in the range from 3 to 10 days ahead has been increasing by about one day per decade: today's 6-day forecast is as accurate as the 5-day forecast ten years ago, as shown in Fig. 1. Predictive skill in the Northern and Southern hemispheres is almost equal today, thanks to the effective use of observational information from satellite data providing global coverage.

More visible to society, however, are extreme events. The unusual path and intensification of hurricane Sandy in October 2012 was predicted 8 days ahead, the 2010 Russian heat-wave and the 2013 US cold spell were forecast with 1–2 weeks lead time, and tropical sea surface temperature variability following the El Niño/Southern Oscillation phenomenon can be predicted 3–4 months ahead. Weather and climate prediction skill are intimately linked, because accurate climate prediction needs a good representation of weather phenomena and their statistics, as the underlying physical laws apply to all prediction time ranges.

This Review explains the fundamental scientific basis of numerical weather prediction (NWP) before highlighting three areas from which the largest benefit in predictive skill has been obtained in the past—physical process representation, ensemble forecasting and model initialization. These are also the areas that present the most challenging science questions in the next decade, but the vision of running

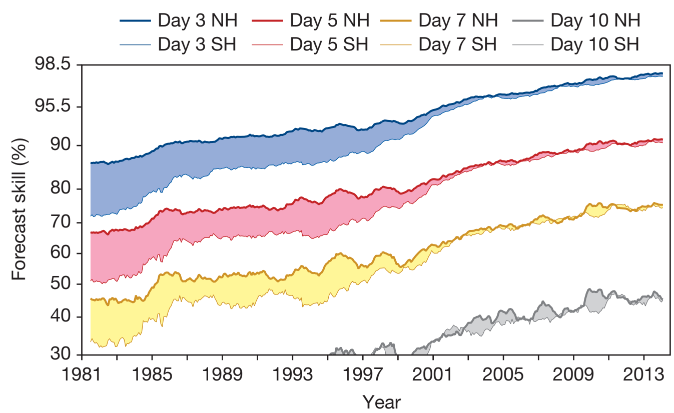

Figure 1 | A measure of forecast skill at three-, five-, seven- and ten-day ranges, computed over the extra-tropical northern and southern hemispheres. Forecast skill is the correlation between the forecasts and the verifying analysis of the height of the 500-hPa level, expressed as the anomaly with respect to the climatological height. Values greater than 60% indicate useful forecasts, while those greater than 80% represent a high degree of accuracy. The convergence of the curves for Northern Hemisphere (NH) and Southern Hemisphere (SH) after 1999 indicates the breakthrough in exploiting satellite data through the use of variational data[100].

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global models at 1 km horizontal resolution, thus with an order of magnitude greater resolution than today, has added a new dimension, as it requires significant investment in high-performance computing with as-yet unknown technology.

The physics of forecasting

The Navier–Stokes and mass continuity equations (including the effect of the Earth's rotation), together with the first law of thermodynamics and the ideal gas law, represent the full set of prognostic equations upon which the change in space and time of wind, pressure, density and temperature is described in the atmosphere[4]. These equations have to be solved numerically using spatial and temporal discretization because of the mathematical intractability of obtaining analytical solutions, and this approximation creates a distinction between so-called resolved and unresolved scales of motion. Physical processes that operate on unresolved scales down to the molecular enter the equations for the resolved scales through source terms for mass, momentum and heat originating from friction, moist processes such as condensation and evaporation, and radiative heating and cooling. Since these processes are typically unresolved they need to be 'parameterized' in terms of their interaction with the resolved scales. Simplifications can be applied that facilitate the numerical solution and reduce somewhat the complexity of the set of equations, as demonstrated for the first time—even though with limited success—by Richardson[5]. By introducing approximations that accurately describe the largest scales of motion in the atmosphere, the first attempt to use the first electronic computer for weather prediction was carried out in Princeton in 1950[6]. While the Princeton simulations were hindcasts, the first real-time forecasts were made in Stockholm in 1954[7].

Only with increasing availability of supercomputing power in the 1970s was it feasible to solve the full set of equations as proposed by Abbe and Bjerknes[8]. Consequently, various numerical methods of solution emerged that addressed numerical stability, accuracy, computational speed[9] and versatility to deal with more prognostic variables, and the interaction between resolved and unresolved scales[10]. The main components of these methods are: the representation of spatial variability by the choice of spatial discretization, the time stepping method, the treatment of boundaries, and the initialization approach[11]. This capability has founded what we refer to as NWP[12]. Today, a hierarchy of many models with different levels of complexity exists covering the full range between global climate projections[13], global weather prediction, and local-area modelling for high-impact weather[14] or air-quality prediction[15].

Major steps

The improvements in the representation of unresolved processes in global models, the advent of ensemble methods producing forecast uncertainty estimates, and the introduction of objective analysis techniques to determine the initial state have led to the predictive skill attained today. Representing physical processes, ensemble modelling and model initialization are also the key challenges for the future, combined with technological challenges associated with observations and computing, as we will discuss later.

Physical processes

Parameterizations capture radiative, convective and diffusive effects in the atmosphere and at the interface between the atmosphere and the surface, and are often determined by relatively small spatial scales[16,17]. Figure 2 provides an illustration of these processes and where they are relevant. Despite not being resolved, these processes drive heat and momentum budgets at the grid scale[18,19] and are crucial for achieving predictive skill. The degree of parameterization and therefore the representation of the basic physics varies significantly for different processes[20]. For example, the global model formulation for radiation and cloud microphysics processes is similar to that used in regional and high-resolution models because the formulation accounts for the basic small-scale physics, which is similar across these model spatial scales, even if they require added complexity going to higher spatial resolution. The formulations are mostly limited by our understanding of physical process detail needed for parametric representations that define the spatially averaged impact of the process on momentum and heat fluxes. On the other hand, deep convection and specific boundary layer processes require a higher degree of parametric formulation as they only occur in small fractions of the grid scale; consequently these parameterizations critically depend on which resolution is actually used.

Parameterizations play a fundamental role in determining predictive skill because they determine key aspects of the simulated weather, such as clouds and precipitation, as well as temperature and wind. In operational NWP models, essentially the same formulation for the parameterizations is used for scales of 10–100 km in short-to-medium range forecasts, minimization algorithms used for model initialization, and seasonal range forecasts. Achieving this element of 'grid-scale invariance' while including as much physical process detail as possible has been a fundamental breakthrough in the recent past.

Ensemble modelling

Early in the twentieth century, Poincaré[21] recognized that forecasts of nonlinear systems can vastly differ if small perturbations are applied to the initial conditions, and that this difficulty could be fundamental in limiting predictive skill. In the 1950s, Thompson performed one of the first quantitative estimates of initial errors growing during the forecast[22], while Lorenz[23] formulated this understanding more holistically and

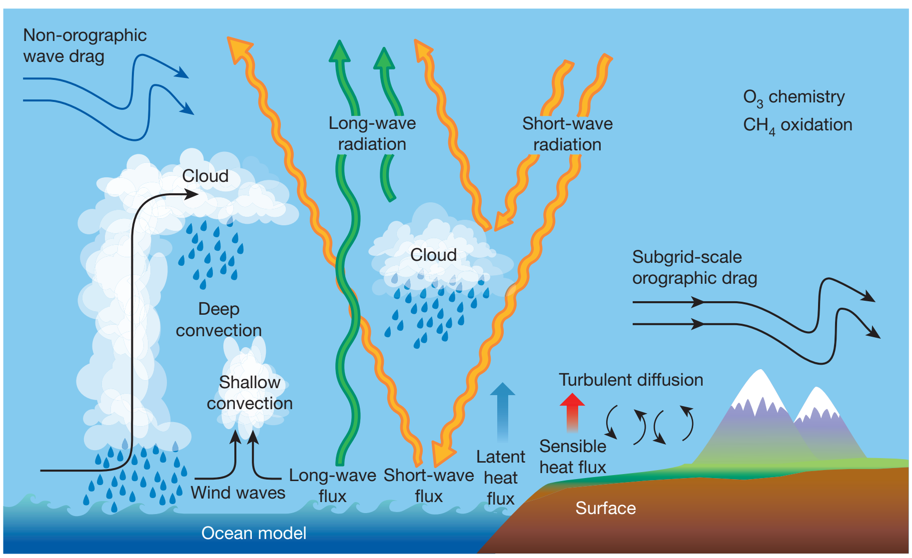


Figure 2 | Physical processes of importance to weather prediction. These are not explicitly resolved in current NWP models but they are represented via parameterizations describing their contributions to the resolved scales in terms of mass, momentum and heat transfers.

founded chaos theory as a result of his attempt to quantify atmospheric predictability. From his conclusion—that unstable systems have finite, state dependent limits of predictability—was born the need for encapsulating the growth of initial condition uncertainties, their evolution as a function of the atmospheric state, and errors introduced by imperfect models. The recognition of imperfect forecasts[24] and determining how to calculate analysis and forecast uncertainty using an ensemble approach[25] represent major and unique accomplishments in physical sciences. This is particularly true for the prediction of highly variable parameters like precipitation (Fig. 3), where ensemble spread quantifies forecast uncertainty of rainfall location and intensity and thus provides essential information to users.

The nonlinear complexity of the system means that purely statistical methods to assign an uncertainty to the forecast are inadequate. Instead, an ensemble of many complete, physical, nonlinear realizations of the system is needed[26,27], providing a seamless analysis and forecast ensemble in which observational information is used to reduce uncertainty. In practice, the ensemble members are created using perturbations, equivalent to analysis and model errors, added to the initial state and the model physical processes. Determining these perturbations consistently and seamlessly so that the ensemble provides a good estimate of uncertainty across a wide range of prediction scales is challenging, and the input of mathematics and statistical physics expertise was crucially important[28,29]. Weather forecasts today involve an ensemble of numerical weather predictions, providing an inherently probabilistic assessment.

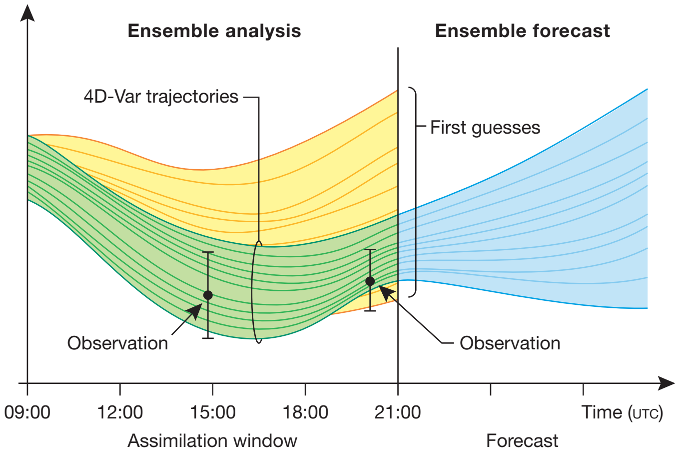


Figure 4 | Schematic of the ensemble analysis and forecast cycle. Global ensemble forecast trajectories, which have been initialized by a previous analysis ensemble, are produced over a time window (for example, 09:00–21:00 UTC). These provide estimates of the current weather (first guesses). The difference between these forecasts and available observations (shown as data points with error bars) is the short-range forecast error. By minimization in four dimensions employing variational techniques, improved estimates (4D-Var trajectories) are created with reduced distance to observations. The next cycle of ensemble forecasts is then initialized from these refined analyses. Image courtesy of M. Bonavita (ECMWF).

Model initialization

Early methods for the specification of initial conditions were based on the analysis of graphical and synoptic weather charts. Various forms of interpolation procedures were later replaced by data assimilation techniques based on optimum control theory[30]. The derivation of the current state (called the analysis) of the atmosphere and surface is treated as a Bayesian inversion problem using observations, prior information from short-range forecasts and their uncertainties as constraints as well as the forecast model[31,32]. These calculations, involving a global minimization, are performed in four dimensions to produce an analysis that is physically consistent in space and time and can deal with huge amounts of observational data that are heterogeneously distributed in space and time (such as the vast amount and diversity of satellite data used for Earth observation since the 1980s). Since initial state uncertainty estimation is also crucial for ensemble prediction and because data assimilation employs both imperfect observations and forecast model, ensemble methods have also become an integral part of data assimilation[33], as shown in Fig. 4.

The operational implementation of these four-dimensional variational (4D-Var) data assimilation techniques[34] marks a major milestone in operational global NWP. At the European Centre for Medium-Range Weather Forecasts (ECMWF) this occurred in 1997[35], followed by Météo-France in 2000[36], the Met Office in 2004[37], both the Japan Meteorological Agency[38] and Environment Canada in 2005[39], and the United States Naval Research Laboratory in 2009[40]. Development and first implementation of 4D-Var took more than 10 years, and further research has substantially refined the main ingredients. These were the increasing use of satellite radiance data by combining the forecast model with computationally efficient radiative transfer models[41,42], the much refined characterization of short-range forecast[43] and observation errors[44] using state dependent weights for each, and better use of observations arising from significant improvements of physical parameterizations[45].

Predictability and predictive skill

A continuing and important area of research focuses on the sources of predictability in the Earth system. Forecasting future weather is like a battleground, with the forces of predictability pitched against those of unpredictability. The sources of predictability include large-scale forcing of smaller-scale weather, teleconnections or the chain of predictability across different geographical areas[46], and the interactions between atmosphere, land surfaces and vegetation, sea-ice and ocean acting on longer timescales. The sources of unpredictability include

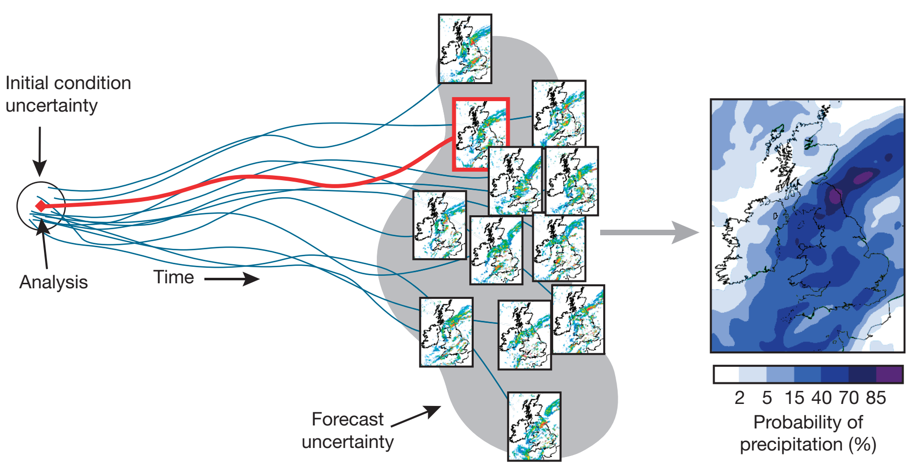


Figure 3 | Schematic diagram of 36-h ensemble forecasts used to estimate the probability of precipitation over the UK. A single forecast (red frame, centre) is generated by integrating the model forward in time from the analysis of initial atmospheric state (left). Small perturbations to the analysis, within known analysis uncertainty, provide an ensemble of forecast solutions, which sample the forecast uncertainty (multiple frames). These solutions are combined, including some spatial neighbourhood sampling, to provide a smooth estimate of probability of precipitation (right). Image courtesy of K. Mylne (Met Office).

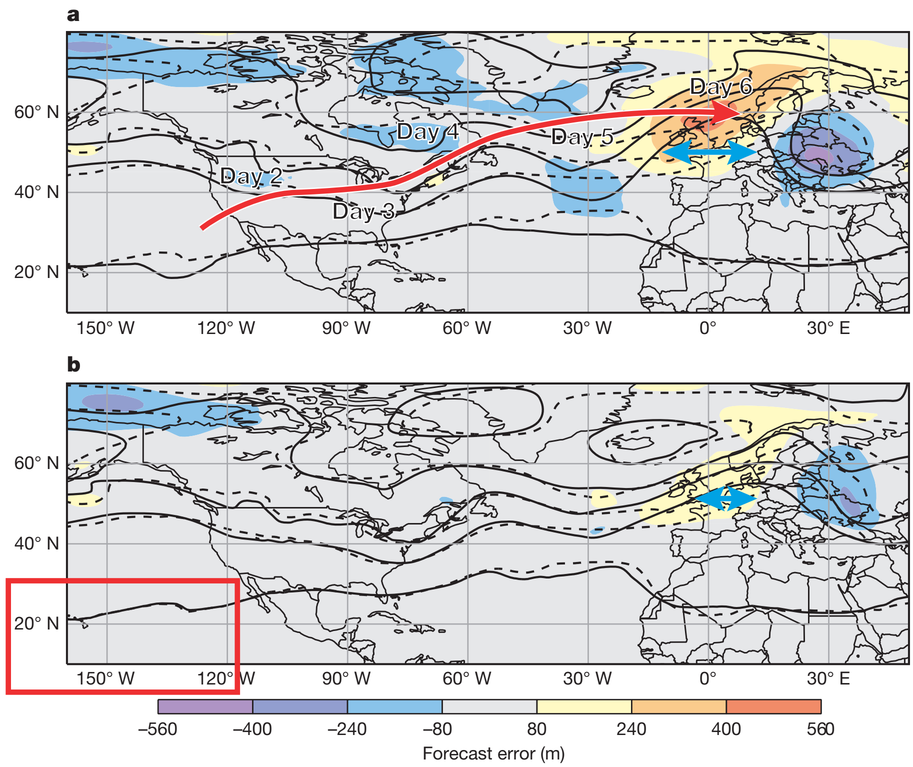
instabilities injecting chaotic 'noise' at small scales and the upscale propagation of their energy, the errors associated with numerical and physical approximations, as well as the insufficient number and poor use of observations. Box 1 provides an example of such teleconnections and the sources of poor forecast performance over Europe in the medium range.

The outcome of this 'battle' can be described as noise growing nonlinearly during the forecast and thereby leading to fundamental limits of how far into the future certain structures can be predicted. The limit for small-scale events is between hours and days, for accurate and reliable prediction of high-impact weather events about 1–2 weeks, for prediction of large-scale weather patterns and regime transitions about a month, and for global circulation anomalies about a season[47]. The longer the forecast range the more the predictive skill relates only to anomalies, that is, the difference between the state and its modelled climatological mean, and the more important space-time averaging becomes to identification of the signal. In the short range predictive skill exists for the details, while in the long range skill relates to larger-scale structures. Predictive capability that is seamless across this wide range of forecast horizons is therefore about capturing processes acting on very different time and space scales.

NWP has a fundamental advantage over many other scientific disciplines in that its skill is objectively evaluated daily and globally, so that success and failure of forecasts is accurately known and pathways to improve predictive skill can be effectively tested[48,49]. To evaluate forecast skill, metrics such as mean and root-mean-square errors, and the correlation of the forecast with analysis anomalies of upper-air and surface forecast fields are used. In addition, scores targeting more variable parameters such as precipitation[50] exist. Model biases become significant further into the forecast range. While biases can be reduced through calibration using past forecasts[51], the identification of their sources in complex models remains one of the dominating challenges for NWP and even more so for climate prediction[52]. Diagnostic methodologies employing data assimilation statistics[53] can help since the signature of most biases is already evident in the analysis and early in the forecast, even though their magnitude is small. This approach offers benefits for weather and climate science alike.

BOX 1

Sensitivity of forecasts to initial conditions and error propagation



Box 1 Figure | Maps showing the long-range impact of model initialization on the European forecast. Panel **a** shows the day-6 mean forecast error (the height of the 500 hPa pressure level in metres) of the flow at around 5 km height (colour-coded shading), the forecast itself (solid isolines) and the verifying analysis (dashed isolines) valid on 15 February 2014. Over the western US, the jet stream extended far to the south, aligned with a lower level trough. The long red arrow indicates the travel path of an atmospheric wave disturbance guided by the westerly flow. The presence of a large-scale dipole error pattern highlights the lag between forecast and analysed state (blue double-headed arrow). The large forecast errors over Europe were mostly produced by a phase-shift of the wave that increased with time. Back-tracking the wave propagation path identifies the tropical East Pacific (boxed in **b**) as a likely location of a possible forecast error source. This area was characterized by very large 24-h forecast errors of upper-level winds because of the paucity of wind observations there. When running an experiment where the area in the box in **b** is relaxed towards the analysis rather than evolving in the forecast, the strong initial growth of forecast errors is reduced and, six days later, the lag of the wave patterns between forecast and analysis is reduced over Europe (blue double-headed arrow), producing about half of the original forecast errors. This experiment demonstrates the long-range impact of model initialization, the linkage between tropics and mid-latitudes, and thus shows an example of how predictive skill in the one-week time range can be increased.

As NWP involves an ensemble of forecasts, evaluation metrics need to assess the moments of probability distributions such as ensemble mean error and the sharpness of the distributions. Forecast reliability is determined by comparing forecast distributions with the observed frequency of occurrence. Since ensembles are designed to provide valuable information on the probability of weather extremes[54], scores targeting the tails of probability distributions are being developed accounting for sparse statistics[55].

In addition, comprehensive feature-based evaluation is available for tropical cyclones[56] or weather regimes[57], and for the evaluation of how well models represent the links between lower and higher latitudes[58,59], troposphere and stratosphere[60,61], planetary wave activity driving synoptic scale features[62], and synoptic scales interacting with small-scale convection[63,64] and the surface[65,66].

An effective way to verify predictive skill also arises from combining weather with hydrological modelling, whereby predicted river streamflow and discharge help to evaluate predictions of precipitation, run-off and storage in NWP models, both for single realization and ensemble forecasts[67,68]. The enhancement of weather models with variables describing atmospheric composition such as aerosols and trace gases also introduces new ways to evaluate atmospheric evolution by considering tracer advection and model chemistry parameterizations[69].

Where we are today

Operational NWP centres provide predictions from the very short range at kilometre scale multiple times per day up to global seasonal forecasts at tens of kilometres horizontal resolution once per month. These forecasts relate to the weather but are also extending to air-quality[70] and hydrological[71] applications.

Data assimilation algorithms employ the forecast model and of the order of 10^7 observations per day to derive initial conditions that are physically consistent in four dimensions: over the globe, from surface up to mesosphere (~80 km) and along time windows from hours to days. Operational models are updated frequently to incorporate new science that enables improvements in the representation of model physics and model uncertainty, in numerical algorithms and observational data usage, and to enhance computational efficiency.

Gauging the relative contributions to success and progress from model development, data assimilation algorithms and observational data usage is difficult because they are interdependent. More accurate model physics means that forecasts compare better with observations and facilitate improved data assimilation; in turn this permits ingestion of more observations thereby further improving forecasts.

NWP has also benefited enormously from computing advances. In terms of floating point operations, computing power has increased by about one order of magnitude every five years since the 1980s. This is the result of processor technology advances and more processors being used. Intel co-founder Gordon Moore's law states that computing power doubles every 18 months owing to increased transistor density per chip and clock speeds. This growth has gone hand-in-hand with the increasing size of the analysis and forecast computational task in NWP. At ECMWF, the data assimilation performs model integrations in multiple stages totalling of the order of 100 iterations across a 12-h window for a total of 650 million grid-point calculations. In parallel, about 10 million radiance calculations are performed to compare the forecast model with satellite observations from more than 60 instruments. Today, the ECMWF 16-km highest-resolution model performs calculations on two million grid columns with 10-min time stepping over a 10-day period, that is, 1,440 time steps. The corresponding ensemble produces 15–30 day forecasts with 50 members with a horizontal resolution of 30–60 km and 30-min time steps. Thus twice per day about 40 billion grid-column calculations are performed in about 2.5 h real time. This computing task demands some of the largest supercomputing facilities available.

The time series describing the improving skill of global NWPs is impressive (Fig. 1), revealing that while there is some year-to-year variability, for more than three decades forecast skill has been advancing continuously[72,73]. Predictive skill improves at a rate such that useful skill is retained one more day into the forecast range for every decade of research and development. This steady progress has been the result of advances in the science, in the utilization of observations and in supercomputing capacity. Some of the fluctuations in skill are a result of periods when the atmosphere exhibits more or less potential predictability. This means that certain weather regimes appear to be easier to predict accurately further into the future than others. Our understanding of these regimes of flow is developing and enabling a more discerning quantification of predictive skill to be developed.

The future is bright

The evolution of weather science as well as of high-performance computing and observing systems in the future is crucial for continuing the progress in NWP. Critical scientific and technological cross-roads have been reached or are very likely to be reached in the near future. Consequently, the present period is of fundamental importance for how weather forecasting and also climate science will evolve. Building on anticipated advances in the understanding of physical processes, in numerical model development, in observation technology and high-performance computing, the vision for global weather and climate modelling a decade or more in the future is as follows: in terms of resolution to be able to perform global convection-resolving simulations at a horizontal resolution of the order of 1 km; in terms of complexity to be able to run fully coupled atmosphere–land–ocean–sea-ice models. Ensembles at this resolution and complexity will predict probabilities of dynamics, physics, chemistry and probably selected bio-chemical processes into the multi-seasonal range for weather, and into the multi-decadal range for climate. These global predictions provide essential initial and boundary information for finer-scale limited-geographical-domain simulations of short-range detailed weather development.

The scientific challenges

The main scientific challenges for future global NWP relate to the main themes that have produced key advances in the recent past and that have brought weather forecasting to the level where it is today: physical process parameterization, analysis and forecast uncertainty formulation through ensembles, and the provision of physically consistent initial conditions for forecasts using observations. There are a number of key areas in which substantial progress can be expected in the future that also require significant advances compared to current thinking.

Regarding physical parameterizations, one might anticipate that with increasing resolution the need for parameterization would be gradually reduced. For radiation and cloud processes and land surface models this is a matter of moving current schemes towards fully explicit models already used in regional and local applications at the kilometre scale. For convection, the situation is more complex because large tropical convective clouds or organized convection occur even at currently resolved scales (15 km) while embedded small-scale convective plumes may not be resolved even at 1 km and will still require parameterization. This range of model resolutions with partly resolved convection is also referred to as the grey zone, since resolved and parameterized contributions to fluxes need to be quantified and combined. Existing schemes assume that convection is entirely unresolved and so they are not able to adequately represent the impact of both resolved and unresolved process components on heat and momentum at resolved scales in the grey zone.

High-resolution limited-area cloud models have demonstrated that the dynamic modes of organized convection can be captured and that the modelling of the lifecycle of convection, cloud organization or its interaction with large-scale circulation can be improved[74]. Whether running global models at scales of the order of 1 km also eliminates all convection-related uncertainties and produces a fundamental stepping stone for reduced model biases and enhanced predictive skill at all forecast ranges is not clear at present[75]. As these high resolutions are not yet in reach, convection parameterizations will remain crucial for global weather and climate modelling for the next decade[76] and progress in this area will require joint efforts in the weather and climate communities[77,78].

There are two other areas that need much more attention in the future and promise significant boosts of skill, but also involve substantial investments in scientific development and computing.

First, the uncertainties inherent to physical parameterizations, either from incomplete process understanding or the dilemma of representing the impact of unresolved processes on the resolved scales, may require a fundamentally different approach. Elements of parameterizations or entire schemes are likely to require components that appear statistical to the large scales because they are not fully determined by the resolved scales[79]. Examples are stochastic sampling of parameter probability distribution functions, stochastically driven sub-cell models, or super-parameterizations[80] through embedding entire convection-resolving simulations at sub-grid scale. How radical this approach needs to be is currently not clear.

Second, more physical as well as chemical processes will be added. More physical processes will be needed because of the modelled coupling of the atmosphere with ocean, land surface and sea-ice models, some of which are already in operational use today[81,82]. Each coupling has its own characteristic space and time scales and the coupling *per se* provides most benefit beyond the 3–7 day range since ocean, sea-ice and land surface processes are relatively slow and mostly affect longer-term system memory. However, there are examples where coupling also affects the short range: for example, when oceanic upwelling in the wake of slowly moving tropical cyclones affects their intensity, or where rainfall over land is strongly constrained by surface evaporation and thus soil moisture.

The greatest scientific challenge for coupling is associated with matching fluxes at the interfaces where systematic errors in each component interact[83] and can produce model shocks and compensating changes of mean state at every coupling time step and through feedbacks in longer integrations.

Atmospheric constituents such as trace gases and aerosols directly affect radiative heating, but aerosols can also act as condensation nuclei in cloud formation and heterogeneous chemistry occurs at the surface of polar stratospheric clouds, accelerating ozone destruction. Nevertheless, aerosols and trace gases are important to forecast in their own right because of their impacts on air quality. An associated challenge from adding more physical and chemical processes is that initial conditions for these constituents are also required and thus more and complex observations need to be assimilated. Ensemble prediction reliability beyond the medium range will therefore be enhanced by representing the uncertainty of much more complex processes in models and by being able to initialize coupled models using much more diverse observations.

Using more of the existing and new observations, and advances in data assimilation pose more science challenges for NWP. Currently, each global forecast uses about 5–10% of the total satellite data volume; this fraction contains most of the information content for that particular forecast. This approach is of fundamental importance to optimally manage the substantial global investment in Earth observation, especially from satellites[84]. However, NWP is limited by insufficient observational data. Beyond the maintenance of the backbone satellite and ground-based observing systems that measure vertical profiles of temperature, moisture, clouds and near-surface weather, fundamental observables are missing. An example is the direct observation of upper-level wind with Doppler-radar technology[85], but this technology is not yet available in operational satellite programmes. Wind information is primarily needed in the tropics, an area covering around 50% of the Earth and where sparse observations are a serious impediment to increased analysis accuracy. However, the existing backbone observations also need to be provided by a robust and resilient observing system, which requires substantial international investment and coordination. A similar level of coordination is required for satellite and ground-based observations.

Notwithstanding the complexity of current data assimilation there are many challenges for the future, most of all regarding improved solution algorithms; such algorithms will be targeted at enhancing the exploitation of new observational data, but will also be able to handle improved models. Computational affordability will continue to be a constraint, given that a sizeable proportion of the cost of producing a forecast is associated with data assimilation. Next-generation data assimilation methods will probably employ fundamentally new mathematics, but assimilation methods in the near future will probably be based on a combination of existing concepts.

Current algorithms commonly rely on linear principles and variational methods, whereas certain components, such as error statistics, are obtained from ensembles. The variational principle has been implemented in different ‘flavours’ and the next decade is likely to be dominated by either choosing the most effective combination of variational and ensemble elements[86] or by using purely ensemble based methods like ensemble Kalman filters[87]. Smaller-scale effects operating on shorter time scales (for example, convection) may require nonlinear data assimilation methods for which only limited experimentation with idealized models exists[88]. These are currently difficult to generalize for global operational applications.

Coupled data assimilation will become critical for the initialization of the future coupled models[89]. This assimilation will need to include atmospheric composition (aerosols, trace gases) as well as ocean, land surfaces and sea-ice. Each Earth-system component has particular process characteristics and space–time scales, and dealing with those in a fully unified data assimilation framework will be extremely challenging.

Technological challenges

Today’s highest-performance computers employed in NWP rank in the top 20 of the 500 most powerful systems and execute computations at petaflop (10^{15} floating point operations) per second rates, ingesting of the order of 100 Mbytes of observational data and producing of the order of 10 Tbytes (that is, 10×10^{12} bytes) of model output per day. Future generations of global NWP models with kilometre scales in the horizontal will integrate of the order of 100 prognostic variables over about 5×10^8 grid points for of the order of 100 ensemble members with time steps of seconds in an atmosphere with about 100 levels, coupled to surface models of somewhat smaller dimensions. Observational data usage will also increase by an order of magnitude owing to the internationally coordinated availability of high-resolution spectrometers in low-Earth and geostationary orbits with thousands of spectral channels.

However, the expected future high-performance computing technology development will impose new constraints on how to address the science challenges. In the past, processor performance has evolved according to Moore’s law[90], as has memory capacity and processor clock-speeds. This trend cannot be expected to continue in the future as energy cost has to be reduced. In the future, much more emphasis will be placed on parallel computing and this is where the ‘scalability’ of an application becomes important, providing time-to-solution gains when the model is run on more (and combinations of different types of) processors. The gain from the parallel execution of parts of the code is limited by the sequentially run elements, which fundamentally limits scalability, as does the need to exchange large amounts of data between processors. Making NWP codes more scalable is among the top priorities in NWP for the next 10 years.

For NWP centres such as ECMWF, the upper limit for affordable power usage may be about 20 MVA (ref. 91). The likely future NWP system will be of the order of 100–1,000 times larger as a computational task than today’s systems, and would require about 10 times more power. Figure 5 illustrates the increase in compute cores and electric power supply if model resolution is increased for a single forecast and a 50-member ensemble, assuming today’s model design and available technology. To approach the resolutions of 1–5 km that are considered crucial for resolving convection, high-performance computers of unprecedented dimension and cost (assuming the use of conventional technology) would be required.

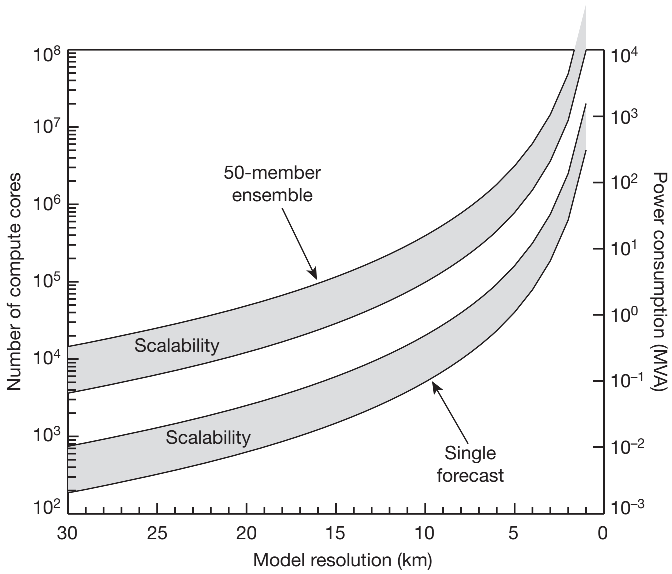


Figure 5 | CPU and power requirements as a function of NWP model resolution. Simplified illustration of the number of compute cores (left *y*-axis) and power (in units of megavolt amps, MVA, right *y* axis) required for single 10-day model forecast (lower curves) and 50-member ensemble forecast (upper curves) as a function of model resolution, given today's model code and compute technology. The shaded area indicates the range covered when assuming perfect scaling (bottom curve) and inefficient scaling (top curve), respectively. Today's single global forecasts operate at around 15 km while ensembles have around 30 km resolution.

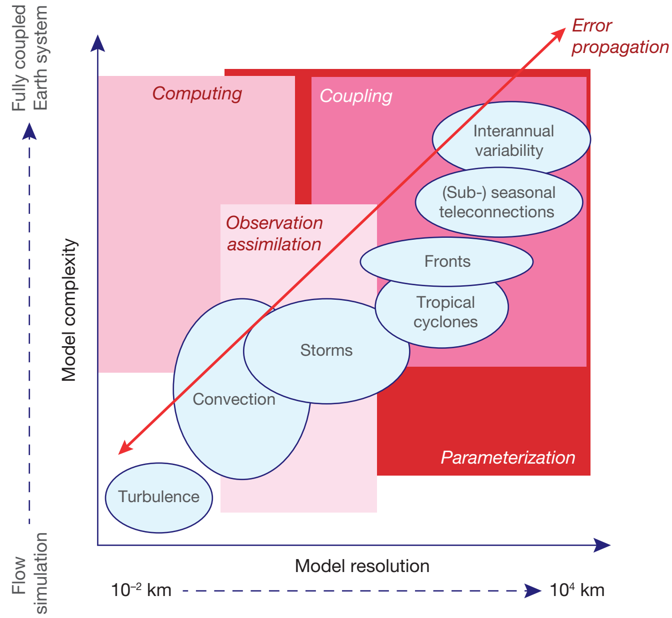


Figure 6 | Key challenge areas for NWP in the future. Advances in forecast skill will come from scientific and technological innovation in computing, the representation of physical processes in parameterizations, coupling of Earth-system components, the use of observations with advanced data assimilation algorithms, and the consistent description of uncertainties through ensemble methods and how they interact across scales. The ellipses show key phenomena relevant for NWP as a function of scales between 10^{-2} and 10^4 km resolved in numerical models and the modelled complexity of processes characterizing the small-scale flow up to the fully coupled Earth system. The boxes represent scale-complexity regions where the most significant challenges for future predictive skill improvement exist. The arrow highlights the importance of error propagation across resolution range and Earth-system components.

A change of paradigm is therefore needed regarding hardware, design of codes, and numerical methods[92]. New technologies will combine and integrate low-power processors with the successors of today's CPUs to give the best of both worlds—namely, highly parallel compute performance with little data communication at lower clock rates, and CPU-type performance with large memory, a fast data interface and higher clock rates. Code design and algorithm choice must be adapted to this technology by optimizing floating point operation counts and memory usage, which is a fundamental challenge given that we are dealing with vast heritage codes with millions of lines of instructions. In 10 years, global ensemble forecasts will be run on of the order of 10^5–10^6 processors. Fault awareness and resilience management will be crucial, given the certainty of processor failures and the advent of inexact low-energy hardware[93].

This computing challenge is enhanced by the requirements for data distribution and archiving. While data growth appears slower than compute growth, exabyte (10^{18} bytes) data production may be reached earlier than exaflop computing. Re-computing is even more costly than archiving, and thus it is inevitable that the data challenge will need to be tackled with high priority[94]. As for future processor technology, hardware will limit data transfer bandwidth. Occasional hardware failure needs to be actively accounted for by designing resilient storage systems. Such failures also have fundamental implications for the design of future work flows. Advanced data compression methods need to be implemented, and standardized and supported by the weather and climate community.

Many technological opportunities and challenges will arise from future Earth observing systems. At the high end, new satellite instrument technology will increasingly move towards hyper-spectral radiometers, with thousands of spectral channels sounding the atmospheric thermodynamical state and composition, together with active instruments (such as high-resolution radars and lasers) sounding surface characteristics, aerosols, wind, water vapour, clouds and precipitation. Both instrument categories can produce data rates of the order of 100 Gbytes per day that require downlinks, pre-processing, data dissemination within a few hours and ingestion in forecasting systems. The distribution and archiving of these data volumes will need to be managed with a similar parallelized approach as the model output. Data dissemination will only be feasible if compression techniques are applied, potentially accepting 'information loss'[95]. At the low end, the use of commodity devices, such as mobile phones, with good sampling but less accuracy for gathering meteorological observations is only starting now, but offers potential for high-density observational networks in certain areas[96,97].

It is clear that scientific and technological challenges are interdependent in many areas. The efficiency of computing and data handling imposes hard limits on model complexity in weather and climate models that are run within tight production schedules, and it will be challenging to run globally at 1 km convection-resolving scales. This trade-off between scientific and compute performance is not new, but 'scalability' issues add a new dimension[98].

The quiet revolution of numerical weather prediction has required combined scientific, observing and computational technology advances to be made. This combination is common to all natural sciences that necessitate the solution to large problems, such as simulating the neurological connectivity of the human brain or the evolution of the galaxies in the cosmos. Further advances require more interdisciplinary research at the science–technology interface. As society's requirement for more accurate and reliable information regarding weather and climate grows ever more pressing, global numerical models will need to increase in both resolution and complexity. This further progress in global NWP can be made but will require combined investment in all the elements reviewed in this paper[99], as summarized schematically in Fig. 6.

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