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There was a minor north/northwest shift noted in theQPF of the latest CAMs, particularly over portions of easternKansas, southeast Nebraska and northwest Missouri. To reflect thistrend very minor reshaping of the Slight and Moderate Risks weremade for this update. Campbell Deep moisture and a front extending from the Plains to New Englandis the main focus for potentially excessive rainfall today andtonight...especially across the plains where surface low pressurehelps focus convection along the front. However...plenty ofuncertainty lingers with the evolution/progression of the low...anyMCV or outflow boundary that could disrupt placement/magnitude ofany forcing in the low levels...and a mid- and upper- leveldisturbance hugging the Gulf coast. Despite that uncertainty...andin deference to the convective evolution Thursday night/earlyFriday morning prior to the start of the Day 1 period combined withthe amounts still expected to fall being in largely the samegeographic placement...warrantied a the upgrade to a Moderate riskin the Plains. Local 1.5 to 3 inch per hour rainfall rates and 2to 4 inch rainfall totals along with isolated higher maximumamounts remain in the realm of possibilities. A Slight risk areaextended into portions of the Ohio Valley along the best moisturetransport vectors. Downstream from there...across portions of the Great Lakes into NewEngland...maintained a Marginal Risk area along a corridor of 2inch precipitable water values which should be aligned along andahead of the cold front. The front should continue to provide afocus for showers and thunderstorms. Even though it is anenvironment which supports isolated convection capable ofproducing torrential downpours...the coverage of storms should bemuch less than areas upstream and the progressive nature ofindividual storms should be enough to mitigate concerns over awidespread area. ...Northern Plains... A quick moving shortwave ejecting out of the Rockies will sweepacross the Northern Plains later tonight/early Saturday morningwith scattered thunderstorms likely to roll through the Dakotasafter sunset. With precipitable water values climbing upwards of+2 deviations along with ample mid-level forcing...a period ofenhanced heavy rainfall prospects during the time frame of impact.Deterministic output remains chaotic in terms of placement andgenerally low in magnitude...but 1-3" of rainfall in a shortperiod of time would be sufficient for at least low-end MRGL. ...Gulf Coast... The disturbance across the northern Gulf will continue to slowlypropagate west- southwestward with an attendant surface lowremaining situated just south of the west-central Gulf coast.Current model guidance still keeps the feature far enough offshoreto preclude widespread impacts. However, the airmass surroundingthe disturbance will still be pretty robust with precipitable watervalues remaining very high (>2.3") for much of the immediatecoastal plain over TX back through the central Gulf coast. Bann Day 1 threat area: www.wpc.ncep.noaa.gov/qpf/94epoints.txt Page 3 WPC Day 2 Excessive Rainfall Outlook Risk of 1 to 6 hour rainfall exceeding flash flood guidance at a point Updated: 0824 UTC Fri Jul 25, 2025 Valid: 12 UTC Jul 26, 2025 - 12 UTC Jul 27, 2025 Forecast DiscussionExcessive Rainfall DiscussionNWS Weather Prediction Center College Park MD1148 AM EDT Fri Jul 25 2025Day 2Valid 12Z Sat Jul 26 2025 - 12Z Sun Jul 27 2025 ...THERE ARE MARGINAL RISK AREAS FOR EXCESSIVE RAINFALL OVERMULTIPLE REGIONS OF THE COUNTRY ON SATURDAY... ...Gulf Coast... The upper trough and associated surface low hugging the Gulf coast willremain situated across the western half of the Gulf with the mainarea of surface reflection likely coming ashore into TX during theperiod. Model solutions remain varied...but high precipitablewater and enough mid- and upper level forcing to continue producingdownpours across the central and western Gulf coast with anemphasis on the immediate coastal plain. ...Northern Plains... The next in a series of potent shortwave will eject northeast outof the northern High Plains resulting in another round of heavyprecip potential with more organized convective clusters migratingthrough the Dakotas. Isolated 2 to 3 inch rainfall maxima arepossible and embedded within broader areas of lesser rainfallamounts. The pattern is fairly progressive so see little reason tomove from the Marginal risk category. ...Northeastern California and Northwest Nevada... Almost a carbon copy of the prior period for convective impactslingering across the Northern Sierra up through northeastern CA andnorthwest OR. The upper pattern is pretty slow to breakdown withthe diffluent area in the longwave setup still situated overnorthern CA into NV. Instability is expected to be modest andslightly above normal moisture in the terrain will offer thecapability for some isolated flash flood concerns within anycomplex terrain and burn scar remnants in the above area. Bann Day 2 threat area: www.wpc.ncep.noaa.gov/qpf/98epoints.txt Page 4 WPC Day 3 Excessive Rainfall Outlook Risk of 1 to 6 hour rainfall exceeding flash flood guidance at a point Updated: 0825 UTC Fri Jul 25, 2025 Valid: 12 UTC Jul 27, 2025 - 12 UTC Jul 28, 2025 Forecast DiscussionExcessive Rainfall DiscussionNWS Weather Prediction Center College Park MD1148 AM EDT Fri Jul 25 2025Day 3Valid 12Z Sun Jul 27 2025 - 12Z Mon Jul 28 2025 ...THERE IS A SLIGHT RISK OF EXCESSIVE RAINFALL OVER PORTIONS OFTHE UPPER MIDWEST... ...The eastern Dakotas to northern Minnesota... Effects of ashortwave trough interacting with a surface front across the UpperMidwest will continue into Sunday as does uncertainty withplacement and timing of any convection capable of supporting heavyrainfall. There are some signals in the GFS and ECMWF for possibleMCS development while the NAM does generate some storms but wouldbe less concerning, Given the amount of rainfall recently acrossparts of northern Minnesota...will maintain the Slight risk indeference by the GFS/ECMWF for the time being. ...The Mid Atlantic to southern New England...Mid-level flow flattens over the Great Lakes and OhioValley...allowing embedded shortwave energy to start digging eastof there with corresponding height falls. The atmosphere will stillbe anomalously moist and capable of supporting convection withlocalized downpours that produce localized flooding. ...Southwest US...Deeper moisture that made its way across parts of the Gulf andinland across Mexico should start to be drawn northwest into partsof the Southwest United States...resulting in scattered late dayand evening convection across parts of New Mexico and a smallportion of Arizona. Bann Day 3 threat area: www.wpc.ncep.noaa.gov/qpf/99epoints.txtWPC Verification Forecast Products Quantitative Precipitation Forecasts How Threat Scores and Bias are Computed 24-Hourly QPF's Monthly Record Threat Scores Annual WPC Day-1 / Day-2 / Day-3 Threat Scoresand Observed Areal Coverage;Annual WPC Day-1 / Day-2 / Day-3 Bias Annual WPC vs. NWP Guidance Threat Scores1993-20241.00 inchDay 1ThreatPercent Improvement Over NWP Monthly WPC vs. NWP Guidance Threat Scores and BiasMarch 2024 to March 2025 Monthly WPC Threat Score and Bias Comparisons (.50", 1.00", 2.00")March 2024 to March 2025Day 1Day 2Day 3Threat BiasThreat BiasThreat Bias Monthly WPC Threat Score and Bias Comparisons (Day 1 / Day 2 / Day 3)March 2024 to March 2025.50 inch1.00 inch2.00 inchesThreat BiasThreat BiasThreat Bias NAM and GFS QPF Verification by Region Object-oriented Verification 6-Hourly QPF's MonthlyRecord Threat Scores Monthly WPC vs. NWP Guidance Threat ScoresUpdateMarch 2024 to March 2025 00-06 Hours.25 inch.50 inch Monthly WPC vs. NWP Guidance Threat ScoresDay 1March 2024 to March 2025 Monthly WPC vs. NWP Guidance Threat ScoresDay 2March 2024 to March 2025 Monthly WPC vs. NWP Guidance Threat ScoresDay 3March 2024 to March 2025 WPC vs. NWP Guidance - Threat ScoresOctober 2024 - March 2025 All 6-Hour Periods.25 inch.50 inch Days 4-5/6-7 QPF's Annual WPC Days 4-5/6-7 Threat Scoresand Observed Areal Coverage (2001-2024).50 inch1.00 inch2.00 inchesThreatThreatThreat Monthly WPC vs. NWP Guidance Threat Scores and BiasMarch 2024 to March 2025 Monthly WPC Threat Score and Bias Comparisons.50", 1.00", 2.00"March 2024 to March 2025Days 4-5ThreatBiasDays 6-7ThreatBias 5-Day Total QPF's Monthly WPC vs. NWP Guidance Threat Scores and BiasMarch 2024 to March 2025 Monthly WPC Threat Score and Bias Comparisons.50", 1.00", 2.00", 3.00", 4.00"March 2024 to March 2025 Medium-Range Forecasts Overview of data plotted on annual charts Minimum Temperatures Annual Mean Absolute Error (MAE) Charts (1972 - 2024) Monthly Performance Charts (March 2024 - March 2025)Year-to-Date Performance Chart (January - March 2025) Maximum Temperatures Annual Mean Absolute Error (MAE) Charts (1972 - 2024) Monthly Performance Charts (March 2024 - March 2025)Year-to-Date Performance Chart (January - March 2025) Probability of Precipitation (PoP) Monthly Performance Charts - 24-Hour PoP (March 2024 - March 2025) Year-to-Date Performance Chart - 24-Hour PoP (January - March 2025)Monthly Performance Charts - 12-Hour PoP (December 2018 - December 2019) WPC Gridded Medium-Range Forecasts How grids are verified Monthly Performance Charts (December 2019)Note:MAE = Mean Absolute Error Forecasts prepared by WPC meteorologists NBM/WPC/NDFD Minimum Temperature(Days 4-7) MAE Bias NBM/WPC/NDFD Maximum Temperature(Days 4-7) MAE Bias NBM/WPC/NDFD 12-Hour PoP(Days 4-7) Brier Score Products derived from forecasts prepared by WPC meteorologists NBM/WPC/NDFD Dew Point Temperature(valid every 6 hours from F90-F180) MAE Bias NBM/WPC/NDFD Wind Speed(valid every 6 hours from F90-F180) MAE Bias NBM/WPC/NDFD Wind Direction(valid every 6 hours from F90-F180) MAE Bias WPC/NDFD Cloud Cover(valid every 6 hours from F90-F180) MAE Bias Mean Sea Level Pressure (PMSL)WPC -vs- Guidance Anomaly Correlations Such powerful technologies as our ML can significantly advance both the accuracy and computing speed of global assemble forecasting models, a practice that was impossible only a few years ago. That makes the entire calculation fast and cost-effective, providing millions of customers with accurate forecasts promptly. Weather data should be open to anyone Not many types of data can affect business decisions and personal everyday plans on the same scale as weather data does. And that is not to mention the billions of dollars that businesses and governments are losing indeed due to extreme weather conditions that are beyond their control. However, most applications of accurate forecasts and history for businesses are more routine, yet more practical for daily analysis and decision-making. To name just a few, these include analysis of the impact of weather on customers demand for retailers, planning of safe routes for transport companies, accurate evaluation of customers cases for insurers, sensitive planning of energy consumption for householders, and timely watering of crops for farmers. Modern technologies make accurate weather data not only widely available, but also nearly free What seemed impossible just a few years ago, you can now do at lightning speed. Machine learning (ML), neural networks, big data, cloud spaces all of this is easily accessible for calculating hugely sophisticated forecasting models such as Numerical Weather Prediction (NWP) or short-term forecasts that update rapidly. ML empowers the classic forecasting models When it comes to the computing and valuation of complex hydro-meteorological models, we rely on the most honourable agencies such as NOAA, Met Office, ECMWF, Environmental Canada. But we can enhance their models with our knowledge of data science and ML, given that most of the mathematics behind forecasting is well-known. For example, the forecasting algorithms for its extreme form, nowcast, have been in use since the 1950s radar data is open, and even free for some territories. Additionally, there are lots of specialised instruments for developers, such as Python libraries for the STEP (Short-term Ensemble Prediction System) computation. Plethora of open weather data to be fed the ML model Fortunately, global meteorological companies such as NOAA, the Met Office, Environment Canada and ECMWF share our belief that weather data should be open. They supply us with enormous data feeds, including data from radars, weather satellites and weather stations. They also provide a lot of more specialised products such as road alerts, road risks and marine weather. Weather data finds their way to developers with Openweather ML model Before weather data can find its way to businesses, it has to pass through the hands of developers, and they have to come to us. Our weather products are based on open data and open technologies. With our convolutional neural networks and ML technologies, we significantly enhance fundamental global forecast models with radar-based nowcasts, weather satellite data and the vast network of weather stations (82,000), rain gauges and other weather sensors. Developers access these vast amounts of data via our light-speed, elegant APIs. Openweather ML calculates weather data for any location, for any moment, in the past, now, and in the future With our APIs, you can get data for any location on the globe: minutely forecast for the two hours, hourly forecasts for one week, current weather, and history for the 46+ years back, with a vast range of meteorological parameters. All these remarkable products are available for free with up to 1 million calls per month. For those who are looking for a bigger service, we provide several paid subscriptions and a range of historical products. If you want to know how accurate our weather model is, please read our detailed report. For all requests, please contact us at info@openweathermap.org. Share copy and redistribute the material in any medium or format for any purpose, even commercially. Adapt remix, transform, and build upon the material for any purpose, even commercially. The licensor cannot revoke these freedoms as long as you follow the license terms. Attribution You must give appropriate credit , provide a link to the license, and indicate if changes were made . You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use. ShareAlike If you remix, transform, or build upon the material, you must distribute your contributions under the same license as the original. No additional restrictions You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits. You do not have to comply with the license for elements of the material in the public domain or where your use is permitted by an applicable exception or limitation . No warranties are given. The license may not give you all of the permissions necessary for your intended use. For example, other rights such as publicity, privacy, or moral rights may limit how you use the material. QuantitativePrecipitation Forecasts Day 1 Days 1-2 5- and7-day Totals Day 2 Days 1-3 Day 3 Days 4-5 andDays 6-7 Loop of All 6-hourly or 24-hourly Forecasts for Days 1-3 View 12-Hour QPFs for Days 1-3 WPC QPF Archive Extreme Precipitation Monitor Day 1 QPF[contours only] 18-24 hr.[contours only] 24-30 hr.[contours only] Scrollable Multi-Chart Series Excessive Rainfall Forecast + All Day 1 ForecastsAll Day 2 ForecastsExcessive Rainfall + All 6-Hourly Fcsts Days 1 and 224-Hourly Fcsts Days 1-3 + 48-Hour Fcst Days 4-5 and Days 6-7Interactive QPF Product Browser WPC 6-Hour Probabilistic QPFsExperimental Probabilistic Precipitation PortalWPC QPF is also available in the following formats: About These ProductsPrecipitation Verification How accurate are WPC precipitation forecasts?Computing precipitation forecast accuracy 24-Hour Observed Precipitation Charts (Valid 12Z-12Z) (introduced 10/1/2008)Latest24-Hour Precipitation Chart (original version) [printableversion] Probabilistic weather forecasting with machine learning Article Open access Published: 04 December 2024 Ilan Price orcid.org/0000-0003-4765-27031na1, Alvaro Sanchez-Gonzalez1na1, Ferran Alet1na1, Tom R. Andersson orcid.org/0000-0002-1556-99321na1, Andrew El-Kadi orcid.org/0009-0009-6510-08311, Dominic Masters orcid.org/0009-0000-6945-83251, Timo Ewalds orcid.org/0000-0002-9693-79861, Jacklynn Stott orcid.org/0009-0004-7859-33841, Shakir Mohamed1, Peter Battaglia orcid.org/0000-0003-3622-71111, Remi Lam orcid.org/0000-0003-4222-53581 & Matthew Willson orcid.org/0000-0002-8730-19271 Nature 637,8490 (2025)Cite this article 303k Accesses 98 Citations 1455 Altmetric Metrics Atmospheric dynamicsComputer scienceNatural hazards Weather forecasts are fundamentally uncertain, so predicting the range of probable weather scenarios is crucial for important decisions, from warning the public about hazardous weather to planning renewable energy use. Traditionally, weather forecasts have been based on numerical weather prediction (NWP)1, which relies on physics-based simulations of the atmosphere. Recent advances in machine learning (ML)-based weather prediction (MLWP) have produced ML-based models with less forecast error than single NWP simulations2,3. However, these advances have focused primarily on single, deterministic forecasts that fail to represent uncertainty and estimate risk. Overall, MLWP has remained less accurate and reliable than state-of-the-art NWP ensemble forecasts. Here we introduce GenCast, a probabilistic weather model with greater skill and speed than the top operational medium-range weather forecast in the world, ENS, the ensemble forecast of the European Centre for Medium-Range WeatherForecasts4. GenCast is an ML weather prediction method, trained on decades of reanalysis data. GenCast generates an ensemble of stochastic 15-day global forecasts, at 12-h steps and 0.25 latitudelongitude resolution, for more than 80 surface and atmospheric variables, in 8min. It has greater skill than ENS on 97.2% of 1,320 targets we evaluated and better predicts extreme weather, tropical cyclone tracks and wind power production. This work helps open the next chapter in operational weather forecasting, in which crucial weather-dependent decisions are made more accurately and efficiently. Article Open access 29 March 2025 Article Open access 22 April 2024 Article Open access 03 July 2025 Every day, people, governments and other organizations around the world rely on accurate weather forecasts to make many key decisionswhether to carry an umbrella, when to flee an approaching tropical cyclone, how to plan the use of renewable energy in a power grid, or how to prepare for a heatwave. But forecasts will always have some uncertainty, because we can only partially observe the current weather, and even our best weather models are imperfect. The highly non-linear physics of weather means that small initial uncertainties and errors can rapidly grow into large uncertainties about the future5. Making important decisions often requires knowing not just a single probable scenario but the range of possible scenarios and how likely they are to occur.Traditional weather forecasting is based on numerical weather prediction (NWP) algorithms, which approximately solve the equations that model atmospheric dynamics. Deterministic NWP methods map the current estimate of the weather to a forecast of how the future weather will unfold over time. To model the probability distribution of different future weather scenarios6,7, weather agencies increasingly rely on ensemble forecasts, which generate several NWP-based forecasts, each of which models a single possible scenario4,8,9,10,11. ENS of the European Centre for Medium-Range Weather Forecasting (ECMWF)4 is the state-of-the-art NWP-based ensemble forecast in the broader Integrated Forecast System ofthe ECMWF and will subsume their deterministic forecast, HRES, going forward12.ENS satisfies several key desiderata of a probabilistic weather model. First, its ensemble members represent sharp and spectrally realistic individual weather trajectories, as opposed to some summary statistic such as a conditional mean. Second, it produces skilful and calibrated marginal forecast distributions (forecasts of the weather at a given place and time), which is important for many day-to-day users of weather forecasts. Third, it captures the aspects of the joint spatiotemporal structure of the forecast distribution that are crucial for probabilistic modelling of large-scale phenomena such as cyclones and for applications such as forecasting distributed energy generation. Nonetheless, ENSalong with other NWP-based ensemble forecastsis still prone to errors, is slow to run and is time-consuming to engineer.Recent advances in machine learning (ML)-based weather prediction (MLWP) have been shown to provide greater accuracy and efficiency than NWP for non-probabilistic forecasts2,3,13,14,15,16,17,18. Rather than forecasting a single weather trajectory, or a distribution of trajectories, these methods have largely focused on forecasting the mean of the probable trajectories, with relatively little emphasis on quantifying the uncertainty associated with a forecast. They are typically trained to minimize the mean squared error (MSE) of their predictions and as a result tend to produce blurry forecasts, especially at longer lead times, rather than a specific realization of a possible weather state2. There have been limited attempts to use traditional initial condition perturbation methods to produce ensembles with MLWP-based forecasts3,15,18,19. However, these methods have not addressed the issue of blurringmeaning that their ensemble members do not represent realistic samples from the weather distributionand they have not rivalled operational ensemble forecasts such as ENS. An exception is NeuralGCM20, a hybrid NWPMLWP method, which combines the dynamical core of a traditional NWP with local ML-based parameterizations and shows competitive performance with operational ensemble forecasts. However, ensembles of this hybrid model have 1.4 spatial resolution, which is an order of magnitude coarser than operational NWP-based forecasts.This work presents GenCast, the first MLWP method, to our knowledge, that significantly outperforms the top operational ensemble NWP model, ENS. We demonstrate that GenCast generates ensembles of realistic individual weather trajectories, providing both better marginal and better joint forecast distributions than ENS.GenCast is a probabilistic weather model that generates global 15-day ensemble forecasts at 0.25 resolution, which are more accurate than the top operational ensemble system, ENS of ECMWF. Generating a single 15-day GenCast forecast takes about 8min on a Cloud TPUv5 device, and an ensemble of forecasts can be generated in parallel.GenCast models the conditional probability distribution P(Xt+1|Xt, Xt1) of the future weather state Xt+1 conditional on the current and previous weather states. A forecast trajectory X1:T of length T is modelled by conditioning on the initial and previous states, (X0, X1), and factoring the joint distribution over successive states,$$P({{\bf{X}}}^{1:T}| {{\bf{X}}}^{0},{{\bf{X}}}^{-1})=\mathop{\prod }\limits_{t=0}^{T-1}P({{\bf{X}}}^{t+1}| {{\bf{X}}}^{t},{{\bf{X}}}^{t-1})$$each of which is sampled autoregressively.The representation of the global weather state, X, consists of six surface variables and six atmospheric variables at 13 vertical pressure levels (Extended Data Table 1) on an equiangular 0.25 latitudelongitude grid. The forecast horizon is 15days, with 12h between successive steps t and t+1, so T=30. We train GenCast using analysis for X, which represents the best estimate of the weather state, inferred from observations.GenCast is implemented as a conditional diffusion model21,22,23, a generative ML method that can model the probability distribution of complex data and generate new samples. Diffusion models underpin many of the recent advances in modelling natural images, sounds and videos under the umbrella of generative AI24,25. Diffusion models work through a process of iterative refinement. A future atmospheric state, Xt+1, is produced by iteratively refining a candidate state initialized as pure noise, \({{\bf{Z}}}_{0}^{t+1}\), conditioned on the previous two atmospheric states (Xt, Xt1). The blue box in Fig. 1 shows how the first forecast step is generated from the initial conditions and how the full trajectory, X1:T, is generated autoregressively. Because each time step in a forecast is initialized with noise (\({{\bf{Z}}}_{0}^{t+1}\)), the process can be repeated with different noise samples to generate an ensemble of trajectories. SeeMethods for further details of the sampling process.Fig. 1: Schematic of how GenCast produces a forecast.The blue box shows how, conditioning oninputs (X0, X1), an initial noise sample, \({{\bf{Z}}}_{0}^{1}\), is refined by the neural network refinement function, r (green box), which is parameterized by . The resulting \({{\bf{Z}}}_{1}^{1}\) is the first refined candidate state, and this process repeats N times. The final \({{\bf{Z}}}_{N}^{1}\) is then added as a residual to X0 to produce the weather state at the next time step, X1. This process then repeats autoregressively, T=30 times, conditioning on (Xt, Xt1) and using a new initial noise sample \({{\bf{Z}}}_{0}^{t}\) at each step to produce the full weather trajectory sample (for visual clarity, we illustrate the previous state in parentheses, (Xt1), below the current state, Xt, but note that it is not added to \({{\bf{Z}}}_{N}^{t}\) as a residual for predicting Xt+1). Each trajectory generated by independent \({{\bf{Z}}}_{0}^{1:T}\) noise samples represents a sample from, P(X1:T|X0, X1).At each stage of the iterative refinement process, GenCast makes use of a denoiser neural network, which is trained to remove noise artificially added to atmospheric states using the loss function described in the Methods. The architecture of the denoiser comprises an encoder, processor and decoder. The encoder component maps a noisy target state \({{\bf{Z}}}_{n}^{t+1}\), as well as the conditioning (Xt, Xt1), from the equiangular 0.25 latitudelongitude grid to an internal learned representation defined on a six-times-refined icosahedral mesh. The processor component is a graph transformer26 in which each node attends to its k-hop neighbourhood on the mesh. The decoder component maps from the internal mesh representation back to a denoised target state, defined on the grid.GenCast is trained on 40years of best-estimate analysis from 1979 to 2018, taken from the publicly available ERA5 (fifth generation ECMWF reanalysis) reanalysis dataset27. Reanalysis provides a reconstruction of past weather by computing analysis for historical dates and times. For simplicity, we refer to ERA5 reanalysis as analysis from here on. Full details of the GenCast architecture and training protocol are provided in the Methods. When evaluating GenCast, we initialize it with ERA5 analysis.As an illustrative example, Fig. 2bd,hj showcases GenCast forecast samples and Fig. 2nq provides an example of how they can be used in important downstream applications, such as predicting the paths of tropical cyclones. Typhoon Hagibisthe costliest tropical cyclone of 2019is shown as a representative case study. When initialized 7days before the landfall of Typhoon Hagibis, the predicted trajectories of GenCast exhibit high uncertainty, covering a wide range of possible scenarios. At shorter lead times, the uncertainty of GenCast about the path of the cyclone is lower, reflecting greater confidence about the landfall timing and location.Fig. 2: Visualization of forecasts and tropical cyclone tracks.a, The ERA5 analysis state27 for specific humidity at 700hPa, at validity time 06 UTC, 12 October 2019, shows Typhoon Hagibis near the centre of the frame, hours before making landfall in Japan. bd, Sample 1 (b), sample 2 (c) and sample 3 (d) GenCast forecast states, initialized one day earlier, show how the samples are sharp and very similar to one another. e, The GenCast ensemble mean, obtained by computing the mean of 50 sample states such as in bd, is somewhat blurry, showing how uncertainty results in a blurrier average state. f, Sample 1 forecast state from GenCast-Perturbed, initialized one day earlier as in be, is blurry, similar to a single-step ensemble mean. g, The spatial power spectrum of the states in a, b, e and f, in which the line colours match the frames of the panels, show how spectra of the GenCast samples closely match with that of ERA5, whereas the blurrier GenCast ensemble mean and GenCast-Perturbed states have less power at shorter wavelengths. hm, These subplots are analogous to bg, except the forecasts are initialized 15days earlier. The GenCast samples are still sharp (hj) and GenCast-Perturbed (l) is still equally blurry, whereas the GenCast ensemble mean (k) is even blurrier than at 1-day lead time. This is also reflected in the power spectrum (m). nq, The trajectory of Typhoon Hagibis based on ERA527 (in red) and the ensemble of tropical cyclone trajectories from GenCast (in blue) up to a validity time 4h before the cyclone made landfall in Japan. GenCast forecasts are shown at lead times of 7days, 3days, 5days and 1day. The blue and red circles show cyclone locations at the validity time. At long lead times, the cyclone trajectories have a substantial spread, whereas for the shorter lead times, the predictive uncertainty collapses to a small range of trajectories. Typhoon Hagibis represents the 55th percentile of GenCasts ensemble mean position error among tropical cyclones in 2019.We compare GenCast to ENS, currentlythe best operational ensemble forecast, which we regridded from its (pre-June 2023) native 0.2 latitudelongitude resolution to 0.25. ENS contains 50 perturbed ensemble members, so we used 50-member GenCast ensembles to perform all evaluations. The public TIGGE archive28 only makes all 50 ENS ensemble members available for surface variables and for atmospheric variables at eight pressure levels in the troposphere. So these are the variables and levels we compare models on.We also develop a deterministic 12h step forecast model using the GenCast architecture, to serve as a strong ML baseline and an ablation of the role of diffusion. We used this model to generate ensemble forecasts (denoted as GenCast-Perturbed) by initializing it using ERA5 analysis perturbed by Gaussian Process noise; full details are in Supplementary Information sectionA.4.For a fair comparison of models, we evaluate each model against its corresponding best-estimate analysis, following established practice2,29. We thus evaluate the operational forecasts of ECMWF against HRES-fc030 (a dataset comprising the initial conditions used for the HRES deterministic forecast of ECMWF), and we evaluate ML models that were trained and initialized using ERA5, against ERA530.We use 2019 as our test period, and, following the protocol in ref.2, we initialize ML models using ERA5 at 06 UTC and 18 UTC, as these benefit from only 3h of look-ahead (with the exception of sea surface temperature, which in ERA5 is updated once per 24h). This ensures ML models are not afforded an unfair advantage by initializing from states with longer look-ahead windows.We follow a standard verification practice29 in evaluating ensemble forecasts using best-estimate analysis as ground truth. However, we note that this does not reward representing initial condition uncertainty. We also note that we evaluate the raw output of GenCast against that of ENS, following standard practice in the field. Both MLWP and NWP forecasts can be further improved by post-processing methods, and the relative impact of these methods on the two approaches is an interesting direction for future work.Figure 2 shows some of the forecast samples of GenCast for Typhoon Hagibis, shortly before it made landfall in Japan on 12 October 2019. Figure 2be,g,hk,m shows that GenCast forecasts are sharp and have spherical harmonic power spectra that closely match the ERA5 ground truth at both 1- and 15-day lead times. This reflects how the ensemble members of GenCast, like those of ENS, represent realistic samples of the weather. As expected, the GenCast ensemble mean is blurry, losing power at high frequencies (see also Supplementary Figs. B5 and B6). Forecasts by deterministic models trained to minimize forecast MSEincluding top deterministic MLWP models such as GraphCast2are blurred and closer to the ensemble mean2. Ensemble members generated by perturbing these deterministic models also blur. This is especially true for multi-step-trained models such as GraphCast, but it is also true (albeit to a lesser extent) for models such as GenCast-Perturbed (Fig. 2f,l), which are only trained to predict a one-step forecast-distribution mean.Many day-to-day users of weather forecasts rely on the spatiotemporal marginals of the forecast distributions, that is, the weather forecast for a given place and time. We evaluate the per-grid-cell marginals of GenCast and ENS in terms of overall forecast skill, calibration and performance on extreme weather prediction.Ensemble skillThe CRPS31 is a standard measure of the skill of a probabilistic forecast. It measures how well the marginal distributions of the forecast represent the ground truth, and it is minimized, in expectation, by a forecast whose marginals reflect true predictive uncertainty. See Supplementary Information sectionA.5.1 for the mathematical definition of CRPS. As shown in the scorecard of Fig. 3, the forecasts of GenCast are significantly more skilful (P

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