2.1 QPE IN NWS HYDROLOGIC APPLICATIONS: PRESENT AND FUTURE

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1. INTRODUCTION

On average, flooding kills more than 100 people a year in the U.S., more than any other single weather hazard, including tornadoes and hurricanes. The average flooding toll has increased in recent decades while deaths from tornadoes and hurricanes have dropped. Almost half of all flash-flood deaths are connected to stream crossings or highway travel. In many years, it is common for three-quarters of all U.S. disaster declarations to be due, at least in part, to flooding. The inclusion of quantitative precipitation estimation (QPE) and hydrological applications as a theme for the 33rd Conference on Radar Meteorology provides us an opportunity to advance QPE research and applications for hydrologic forecasting.

2. NWS OPERATIONS

The U.S. National Weather Service (NWS) is the Federal agency charged with providing flood and stream flow forecasts to the American public. With increased emphasis on drought and water resources, our role is expanding. We are leveraging our hydrologic and meteorological modeling capabilities, our data, our operational infrastructure, and our partnerships to provide additional information such as debris flow warnings, soil moisture forecasts, coastal and estuary inundation forecasts, and inflows to coastal ecosystems and fisheries.

NWS is a line office of the National Oceanic and Atmospheric Administration (NOAA), which in turn is part of the U.S Department of Commerce. NOAA itself consists of many elements including the Office of Oceanic and Atmospheric Research (OAR). NWS and OAR work together to advance the sciences that contribute to NWS products and services. In particular, the NWS Office of Hydrologic Development (OHD) and OAR's National Severe Storm Laboratory (NSSL) collaborate on the development of radar-based quantitative precipitation estimates (QPE).

As shown in Figure 1, NWS products and services are generally delivered through 124 Weather Forecast Offices (WFOs) located strategically across the country (Figure 2). Thirteen River Forecast Centers (RFCs) responsible for different river basins provide hydrologic "guidance" and some meteorological guidance related to hydrologic models to the WFOs while meteorological guidance is provided by the National Centers for

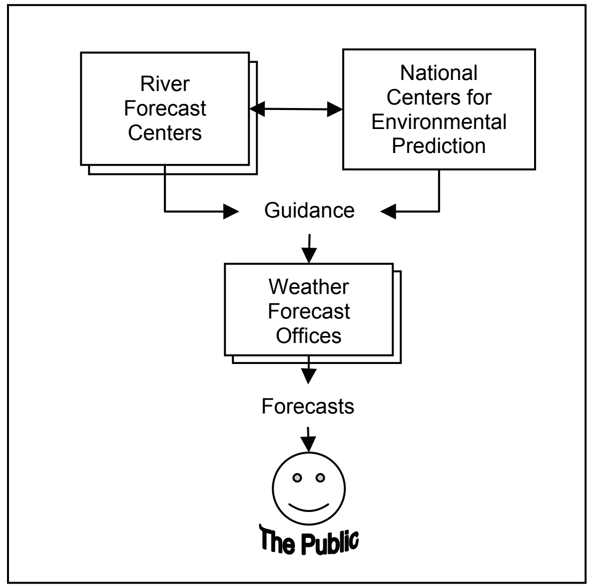

Figure 1. WFOs provide information to the public using guidance provided by RFCs and NCEP

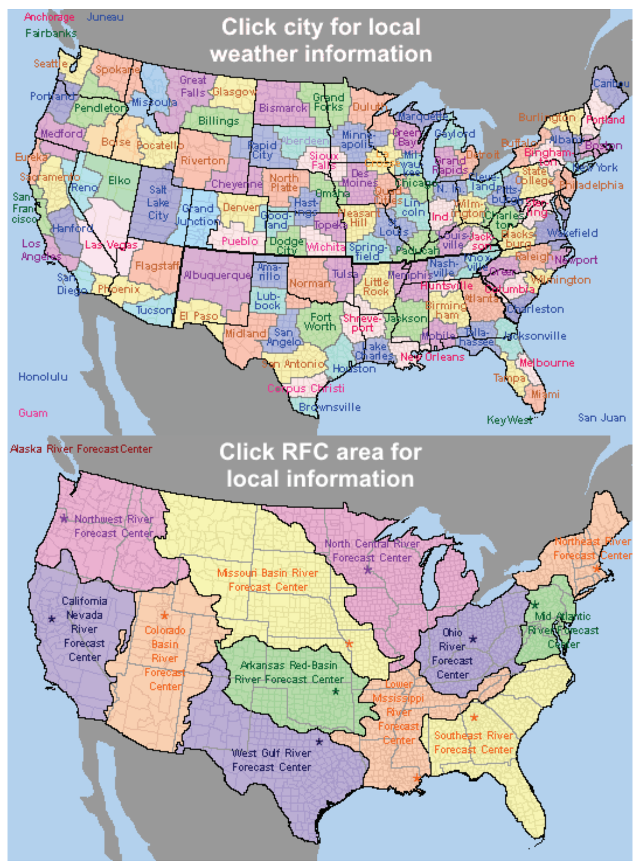

Figure 2. WFO and RFC areas of responsibility

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Environmental Prediction (NCEP). There are also cases where RFCs and NCEP deliver information directly to the public, bypassing the WFOs.

NWS products and services are provided without charge to the public. We work in partnership with the private weather industry to ensure distribution and availability. The private weather industry generates income by providing value-added services.

3. QPE AND HYDROLOGIC FORCING

Quantitative precipitation estimates are integral to all phases of NWS operations. While precipitation occurrence is an important weather element, knowledge of quantitative amounts is crucial to numerical computations in streamflow and flood forecasting, numerical weather prediction, and drought assessment. QPE is generally expressed in terms of point amounts, spatially continuous grids, and basin areal averages over different time scales of aggregation.

We use the term hydrologic "forcing" here to describe those hydrometeorological elements that determine the storage and time distribution of water and energy through the hydrologic cycle. In terms of hydrologic analysis and prediction, precipitation is a prime forcing that affects streamflow over many time scales, through direct runoff of rainfall, subsurface flow of water through soil layers, seasonal accumulation and melting of snow packs, and recharge of aquifers. QPE therefore is a vital input to hydrologic modeling.

3.1 NWS Operational QPE

The prime elements in producing QPE in NWS operations include rain gauge, radar, and satellite observations, combined through a series of manual and automated processes that further depend on human expertise. Human intervention is crucial in identifying suspect data from any of the original sources, and intelligently combining the input streams to make the best use of their respective strengths.

In general, the remote-sensor systems (radar and satellite) provide spatial detail and timing of precipitation. Rain gauge input is indispensable to the overall analysis process as a means of providing quantitative baseline through a range of meteorological conditions that often affect the quality of radar and satellite estimates greatly.

Prior to the deployment of the WSR-88D radar network and routine availability of digital reflectivity data, NWS hydrologic operations relied mostly on rain gauge reports, spatially interpolated to river basins. Rain gauges provide only point estimates of precipitation. The ability to extract reliable spatial information largely depends on the spatial density of rain gauges. With limited spatial density in most of the U.S., reliance on rain gauges essentially limited hydrologic modeling to larger, slow-reacting basins with lag times greater than 6 hours except in those places where high-density rain gauge networks existed.

The WSR-88D radar system needs to operate over a large range of hydroclimatologies, from the tropical summer conditions of the Southeast U.S., the Gulf Coast, Puerto Rico and Hawaii to the prolonged cool-season conditions of Alaska and the northern-tier states in winter. QPE must be reliable in a broad range of weather conditions from intense tropical cyclones, local-scale thunderstorms and broad frontal systems, and under conditions of rain, snow, sleet and hail.

Radar enables real-time estimation of the detailed spatial distribution of rainfall over large basins, and detection of localized heavy rain events. Currently, the grid size for such estimates ranges from ~4 km for most river forecasting applications to ~1 km for flash flood forecasting (Fulton et al., 1998). The availability of radar-based QPE has led to great improvements in flash flood warnings (Polger et al., 1994), and the development of distributed rainfall-runoff models (Smith et al., 2004).

Radar QPE is subject to various systematic and random errors, which can cause large differences between estimates from neighboring radar units, or between radar and co-located gauge estimates. Such errors can be mitigated by statistical corrections based on comparisons between contemporaneous gauge and radar estimates. This bias-correction procedure can be applied to all locations within the radar umbrella as a single multiplicative value (mean-field bias correction), or to sub-regions within the umbrella (local bias correction).

NWS operations are designed to produce products and services reliably with repeatability under tight time constraints on a 24x7 schedule, often under extreme circumstances of human and system stress, uncertainty and changing conditions. The operational process is quite different from the research and development process, which has markedly dissimilar time, reliability and repeatability requirements.

3.2 Injecting Forecaster Expertise

NWS produces QPE using a mix of automated and human processes. In highly time-constrained situations such as flash flooding, there is very little time available for human input to the production of QPE. Flash flood forecasting is the primary responsibility of WFOs and the processes used at WFOs are largely automated. However, QPE production at RFCs is geared towards situations that take longer to develop. This allows RFC QPE production to add human intelligence to the mix. The automated process at WFOs including the science algorithms is largely the same as that used at RFCs except that the RFC process includes many opportunities for review and intervention by forecasters. Furthermore, whereas the WFO process generally is focused on the coverage area of a single radar, the RFC process includes merging the data from multiple radars and covers hydrologic modeling at both large and small spatial and temporal scales. Because there is a varying time lag between rain gauge observation time and the time the data is available for use, RFC processes are able to use more rain gauge data than is available under the tight time constraints of the WFO processes. NCEP merges the QPE products from RFCs in an automated process to produce a product of national coverage suitable for use in numerical weather prediction.

The addition of forecaster expertise in the RFC QPE processes is a primary factor in distinguishing these products from those produced at WFOs. As a result, the user operations concept, design of the user interface, and system responsiveness are key to effectively infusing the forecaster expertise. The user operations concept and design of the user interface for QPE production have evolved through many iterations since the first fielding of the Stage II and Stage III processes in the early 1990s (Hudlow, 1988). For example, today's processes add techniques for quality control of precipitation gauge, radar and satellite data as well as temperature and freezing level information. We are also working on incorporating Terminal Doppler Weather Radar (TDWR) data and other radars. We are doing it in a fashion that makes them transparent in terms of user operations concept while recognizing differences in the basic sensor capabilities. Advice from operational forecasters has been critical to the changes in user operations concept and user interface.

The system of WSR-88D radars was designed to provide coverage of the majority of the U.S. However, limitations of the radar reduce its effectiveness for QPE where terrain and other features block the radar beam or cause the radar beam to overshoot the precipitating cloud. In such cases, gaps in radar coverage are filled by satellite-based estimates and/or rain gauge based estimates. The operational QPE processes provide forecasters with the ability to combine estimates from different sources, providing human intelligence and experience that adds to the quality of the final QPE products.

4. FUTURE DEVELOPMENTS

In coming years the NWS will begin to routinely use data from other radar systems, such as the TDWR maintained by the Federal Aviation Administration. This radar system covers many major metropolitan areas and promises to provide valuable supplemental information on precipitation. Operational use of TDWR base data has already begun, and algorithms have been prepared to create precipitation products from TDWR reflectivity (Istok et al., 2007). Likewise, we expect to utilize data from the evolving network designated Collaborative Adaptive Sensing of the Atmosphere (CASA). These small X-band radars are designed specifically as "gap fillers" for detection of small scale phenomena such as tornadoes and heavy rain (Brotzge et al., 2006).

NOAA plans to begin deploying dual-polarization radar capability in 2009. The current WSR-88D Transmits a horizontally polarized signal. The addition of a vertically polarized signal promises improvements in QPE. Today, OAR and NWS are developing the software to accommodate dual-polarization in preparation for deployment. The NSSL-proposed QPE algorithm continues to evolve (Ryzhkov, 2007) and the software architecture is being designed to accommodate this evolution. Figure 3 shows a comparison of results using version 2 of the dual-polarization QPE algorithm compared with a WSR-88D convective Z-R relationship.

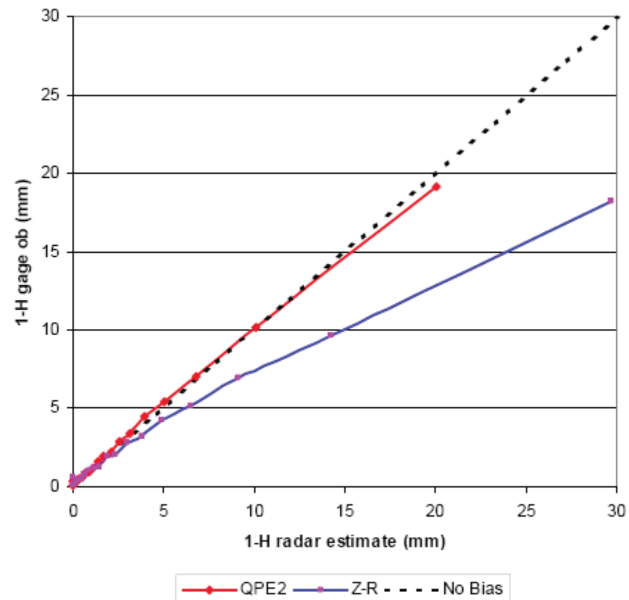

Figure 3. Conditionally-averaged 1-h rain gauge amount as a function of radar-estimated values, from 2002-2005 NSSL dataset. Rain gauge reports are from the Oklahoma mesonet, and ranges 25-230 km from the KOUN radar unit. Each plotted point on the trace represents approximately 250-350 gauge-radar pairs. (Kitzmiller et al., 2007)

One of the most important benefits from dual polarization is the ability to distinguish different types of hydrometeors and other targets. Figure 4 shows an example of removal of returns from biota using dual polarization data.

5. DEALING WITH ERROR

A major problem in hydrologic forecasting using QPE is that there are errors associated with the quantitative precipitation estimates. These errors derive from many different parts of the system, from the basic physics assumptions of the radars, the nature of the radars themselves, the techniques used to convert radar pulse echoes to rainfall estimates, the impact of other reflectors in the atmosphere such as ice, birds, dust and insects as well as the fundamental resolution limits of the radars. These errors are further compounded when combined with the errors associated with hydrologic modeling (Olsson, 2006). NWS is attempting to account

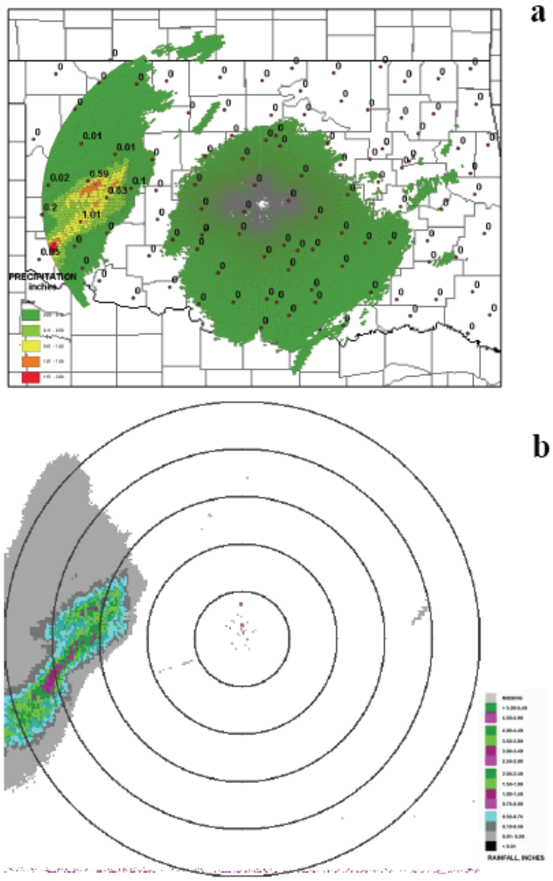

Figure 4. One-hour precipitation ending 0500 UTC, 13 May 2005, from (a) WSR-88D KTLX (OHP) and (b) KOUN “Synthetic” dual-polarization algorithm, incorporating Hydrometeor Classification Algorithm Version 1. Rain gauge reports in inches are shown in (a). Range rings in (b) are at 50-km intervals. (Kitzmiller et al., 2007)

for these errors through data assimilation techniques and probabilistic forecasts.

Data assimilation techniques allow us to apply the assumptions of consistency and integrity of the hydrometeorological system to constrain the possible realizations of elements of the system such as QPE and so reduce the error associated with those realizations.

Probabilistic forecasts (Figure 6) allow us to state forecasts in a way that associates an estimate of the error of a forecast with the estimate of the forecast itself. It is generally presented in probabilistic terms to provide users with a better appreciation of the meaning of the prediction. Both data assimilation and probabilistic forecast approaches require an objective understanding of the nature and distribution of errors at intermediate points in the analysis and forecast process, as well as an understanding of the way errors propagate through those processes.

It is insufficient to demonstrate improvements in QPE itself. QPE is, after all, only an uncertain estimate. The state-of-the-art in precipitation measurement is such that “true” QPE is seldom known. As such, improvements in QPE for hydrologic applications should be judged in terms of the purpose of those applications i.e., the outputs of the hydrologic modeling process such as flow, stage and soil moisture. If this were not the case, we would be unable to adequately judge whether investment in new techniques, systems and organizational processes produce their desired results (Welles et al., 2007).

OHD has a rich history in this regard, prompted largely by the transition from lumped to distributed modeling begun in the 1990’s following the nationwide deployment of the WSR-88D radar system. Early efforts evaluated the use of radar-based gridded precipitation estimates for lumped model applications. Johnson et al. (1997), Finnerty and Johnson, (1997), and Wang et al. (2000) compared mean areal values of precipitation from rain gauge networks to those derived from WSR-88D’s. They found time-varying biases in the radar-based precipitation estimates, which negatively impact hydrologic model simulations.

Recently, we have analyzed the impacts of enhanced radar QPE on distributed model streamflow simulations in Pennsylvania. Ding et al. (2005) noted improvement in hydrologic simulations provided by enhancements to the WSR-88D QPE from the Range Correction Algorithm (RCA) and the Convective Stratiform Separation Algorithm (CSSA).

As the NWS begins to use distributed hydrologic models for operational forecasting, it is critical to have high quality estimates of the precipitation forcing. A key concept is that of error propagation through a distributed model (e.g., Moreda et al., 2004; Sharif et al., 2002).

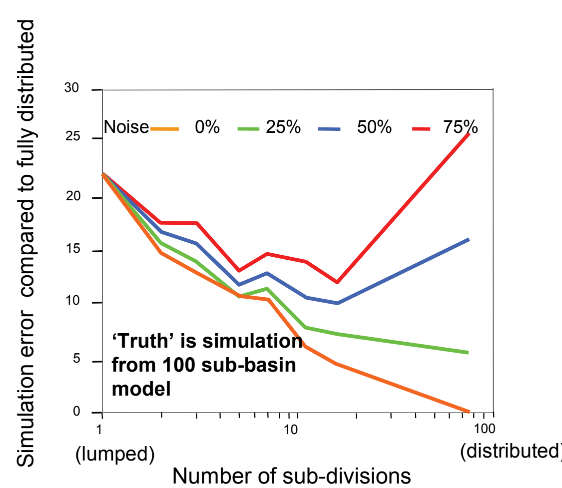

Figure 5. Effects of noise in WSR-88D precipitation data on modeling at various resolutions.

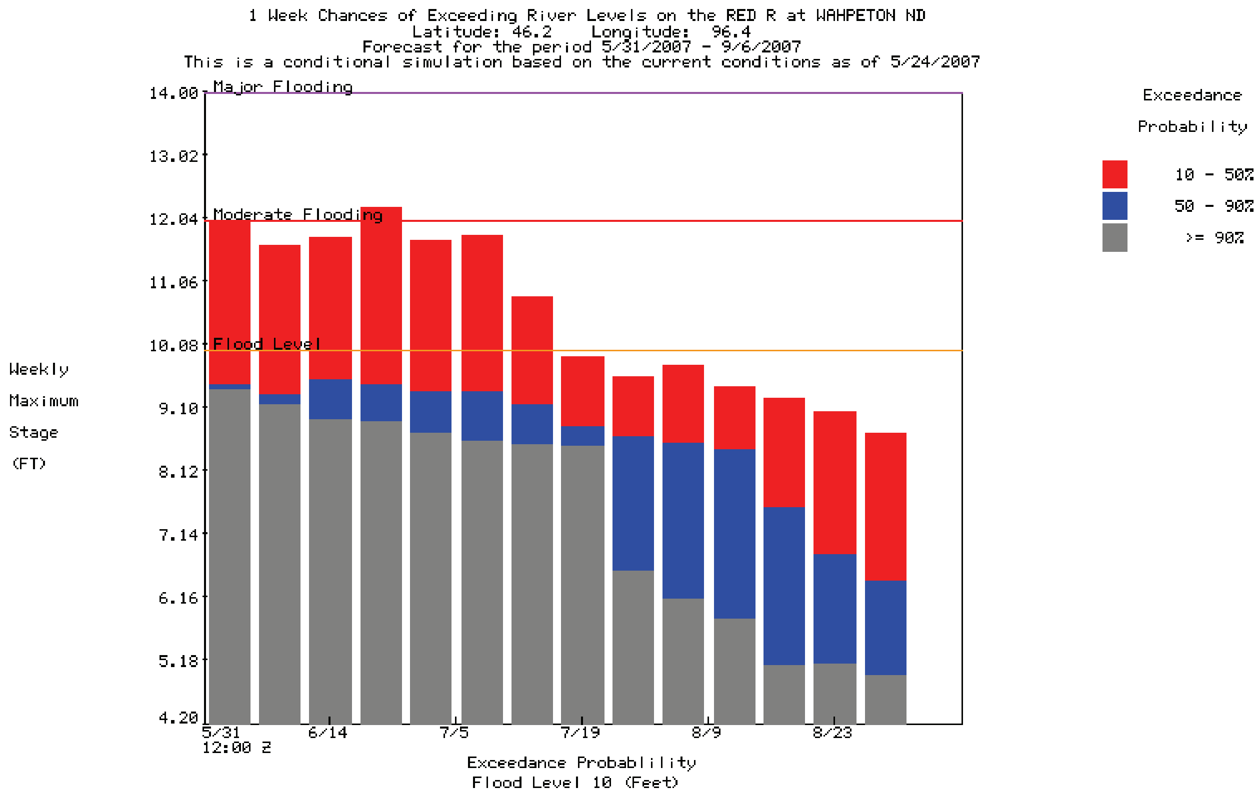

Figure 6. Sample probabilistic forecast showing chance of exceedance at one week intervals

Radar and radar-based QPE contain known errors (Young et al., 2000) which may be magnified (rather than averaged out) by the non-linearities and interactions among many computational elements in a distributed model. This concept is illustrated using a numerical experiment in which a hypothetical basin is disaggregated into a number of computational units of various sizes.

The effects of using erroneous data as forcing for the basins are shown in Figure 5 (Koren et al., 2003). The x-axis displays the level of basin disaggregation, with a lumped hydrologic model on the left and the finest resolution of a distributed model on the right. In the study, the finest resolution was 100 cells. The y- axis denotes the error between the simulations at any scale and the “truth” simulation. The “truth” simulation is generated by modeling the basin at the highest resolution. The “error” is the difference between the current simulation and the “truth” simulation.

Figure 5 shows that for the case of the assumed “perfect” radar QPE (i.e. no noise added), the lumped model generates a simulation having a large error. As the level of disaggregation increases, the simulations improve until finally, the error is reduced to zero as one would expect. From this, one could conclude that the finest level of basin disaggregation would lead to the best simulation.

However, a different picture emerges as we add noise to the radar data. Higher levels of noise lead to simulations that show less improvement compared to the “perfect” data case. At higher levels of noise, further basin disaggregation does not gain any simulation improvement. Finally, with a noise level of 75%, the simulations actually worsen as the level of disaggregation increases to say, 20 subdivisions. The 75% noise level simulation at the finest level of disaggregation is actually worse than the lumped case.

6. CONCLUDING REMARKS

QPE is arguably the most important input for operational hydrologic forecasting in NWS. With dramatically increased spatio-temporal sampling of precipitation information, radar QPE and radar-based multisensor QPE have revolutionized operational hydrology in NWS in the last 15 years. With increasing needs for expanded hydrologic products and services that include, beyond flood forecasting, water resources monitoring and prediction, operational hydrology needs more than ever accurate and uncertainty-quantified QPE that is unbiased over a very wide range of scale for flash flood to climate prediction. We expect that radar will continue to play a critical role in the NWS QPE processes.

While great progress has been made in operational radar and multisensor QPE in NWS in recent years, a number of long-standing issues still exist that need be addressed to support the expanded hydrology and water resources products and services. We believe that a “community-wide” and “integrated” approach (“Q2”, Vasiloff et al. 2007) is necessary for cost-effective research, development, and research-to-operations transition of the new and existing science and technology solutions.

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