ChatGPT

Session 4: Synthesis, Q&A, and Pathway to Continued Learning

In this concluding session, we tie together all the key concepts learned over the past days and set the stage for continued growth. The focus is on **synthesizing knowledge** across AI/ML techniques in Earth Observation (EO), ensuring any lingering questions are addressed, and empowering you with resources to keep learning [1]. By **recapping major techniques** in context (a form of spaced review that reinforces memory retention [2]) and engaging in open Q&A (an active learning approach, since effective learning is *active, not passive* [3]), this session solidifies your understanding. We also introduce avenues for **ongoing practice and community involvement**, aligning with The Math Academy Way's emphasis on dual-coding (combining verbal explanations with visuals [4]) and active, spaced repetition to combat the forgetting curve [2].

Module: Recap of Key AI/ML Techniques and Their Applications in Philippine DRR/CCA/NRM

Visual summary: Example of an AI-generated land cover map for Tuguegarao, Philippines, illustrating how machine learning classifies satellite imagery into meaningful categories (water, vegetation, built-up areas, etc.). Such outputs help monitor urban expansion and natural resources, demonstrating the real-world impact of the techniques covered in this training [5].

This module provides a synthesis of the **AI/ML methods** we covered – from traditional algorithms to deep learning – and reiterates their relevance to Disaster Risk Reduction (DRR), Climate Change Adaptation (CCA), and Natural Resource Management (NRM) in the Philippines [6]. We will revisit each technique with its real-world application, reinforcing how these tools solve specific problems in the Philippine context:

- **Random Forests (RF):** A classical ensemble learning method (decision tree-based) used for classification and regression tasks. In our context, RF demonstrated how *non-neural-network* models can classify EO data (e.g. land cover types from satellite imagery) with decent accuracy using smaller datasets or when interpretability is needed. For example, an RF model could distinguish land cover classes (forest, water, built-up, etc.) using Sentinel-derived features, supporting NRM efforts like national land cover mapping [6].

- **Convolutional Neural Networks (CNNs):** Deep learning models excellent at learning from images. We explored CNNs as the foundation for image classification tasks in EO – for instance, identifying whether a satellite image patch contains a certain land cover type or not. CNNs underpin more complex architectures (like U-Net and object detectors) and showed their utility in tasks like **land cover classification** and **urban feature recognition**, where learning hierarchical image features is crucial. In the Philippine setting, CNN-based classifiers can automatically recognize features such as *rice fields vs. urban areas* from optical imagery, aiding both CCA (by monitoring crops) and NRM (by mapping urbanization).

- **U-Net (Convolutional Segmentation Network):** A specialized CNN architecture for *semantic segmentation* (pixel-level classification). We applied U-Net to **flood mapping**, extracting water pixels from Sentinel-1 SAR images [7] [8]. This demonstrated how U-Net's encoder-decoder with skip connections precisely delineates flood extents on a per-pixel basis, an invaluable DRR application. In the case study of a Philippine typhoon (e.g. Typhoon Ulysses in Pampanga), the U-Net model converted SAR imagery into flood masks, helping identify inundated communities far faster than manual mapping [8]. The recap underlines how U-Net's design (learning both global context and fine details) is well-suited to mapping natural disasters for better emergency response.

- **Long Short-Term Memory (LSTM) Networks:** A type of Recurrent Neural Network (RNN) adept at sequence/time-series data. We covered LSTMs for **EO time-series analysis**, particularly for **drought monitoring** using vegetation index time series [9] [10]. In our Philippine case study (e.g. drought in Mindanao agricultural zones), LSTMs were used to model sequences of NDVI (Normalized Difference Vegetation Index) over months and years, capturing temporal patterns like seasonality or prolonged dips indicative of drought [11] [12]. This technique addresses CCA needs by forecasting or detecting drought stress on crops, informing early interventions. The recap emphasizes how LSTMs "remember" long-term dependencies (e.g. the cumulative effect of low rainfall) better than standard models, making them powerful for climate-related analysis where timing matters.

- **Object Detection Models:** Algorithms (often deep learning-based, like YOLO or Faster R-CNN) that not only classify objects in an image but also localize them with bounding boxes. We examined object detection in the context of **urban monitoring**, such as detecting buildings or other features in high-resolution or Sentinel-2 imagery. The Philippine use-case highlighted was monitoring *informal settlement growth* or *urban change* – a topic relevant to both DRR (identifying vulnerable dense communities) and NRM (urban planning). For example, a model pre-trained on common objects was fine-tuned to detect rooftops/buildings in Metro Manila from satellite images, thereby automatically mapping urban expansion. In this recap, we connect how object detection complements pixel-level methods: rather than classifying every pixel, it zeroes in on distinct entities (houses, roads, ships, etc.), which is crucial for tasks like counting structures in flood-prone areas or assessing infrastructure exposure.

Each technique above addresses a piece of the bigger puzzle in EO for DRR/CCA/NRM. By revisiting them side by side, you can appreciate the **toolkit** you've gained: from **tabular data models** (like RF) to **imagery-based deep learning** (CNNs/U-Net), to **sequence models** (LSTMs), and **detection algorithms** – all of which have been applied to real Philippine scenarios. This integrated perspective reinforces how AI/ML can be chosen or combined to tackle complex environmental challenges. It's also a moment to reflect on *why* these methods matter: each provides faster, scalable, and sometimes more accurate insights than manual methods – whether it's mapping a flood in hours (not days) or monitoring crops over an entire growing season automatically.

Key Takeaways: By the end of this recap, ensure you can *articulate which AI/ML method is suited for which type of EO task* and *recall the Philippine case study example for each*. This not only cements your understanding (a form of retrieval practice) but also prepares you to explain these concepts to colleagues – a crucial skill in spreading capacity within your organization.

Module: Best Practices for AI/ML Model Training, Validation, and Deployment in EO

Visual summary: A simplified AI/ML workflow emphasizing a data-centric approach. Notice how after model evaluation, the process loops back to data improvement (dashed arrows), underscoring that enhancing data quality and diversity can be as important as tuning the model itself [13] *. Such iterative refinement – revisiting data preparation when validation metrics are subpar – leads to more robust models ready for real-world deployment.*

Building effective AI/ML solutions in Earth Observation is not just about choosing an algorithm – it's about **how** you develop, validate, and deploy that algorithm. This module distills **best practices** that we encourage you to follow in your projects, to ensure models that are reliable and usable beyond the lab setting [14] :

- **Data-Centric Model Development:** Focus on data quality and relevance as much as (or more than) model architecture. In EO, a well-curated dataset (with consistent georeferencing, quality labels, diverse examples across seasons/locations) often yields better results than an ultra-complex model trained on messy data. We discussed the importance of data preprocessing (e.g., cloud masking in optical imagery, speckle filtering in SAR, normalization) and dataset augmentation. The principle is: **improve the data to improve the model**. High-quality, representative data enables simpler models to perform well and prevents the "garbage in, garbage out" problem [13] . As Andrew Ng and others have noted, *"Data is extremely important in AI... obtaining high-quality data is critical"* [15] . In practice, this means investing time in labeling, cleaning, and balancing your dataset, and iterating on it when your model shows failure patterns (for example, if flood maps had systematic false alarms in forests, perhaps add more training samples or features for forest areas). A data-centric mindset also implies using domain knowledge – e.g., involving a hydrologist or agriculturist to ensure your input data and labels make sense – since EO data often has nuances (like seasonal changes or sensor artifacts) that experts can help handle.

- **Robust Validation Strategies:** When evaluating your models, go beyond a single metric or a single train/test split. Best practices include: using appropriate metrics for the task, performing cross-validation or testing on multiple study areas/times, and checking model performance on edge cases. In the training, we highlighted that **overall accuracy alone can be misleading** – especially for imbalanced EO data (e.g., "mostly no change" vs "some change" pixels). Instead, use metrics suited to the problem: for example, *Intersection-over-Union (IoU)* and *Dice coefficient* for segmentation maps, or *precision/recall and F1-score* for detection and classification tasks. These metrics give insight into different error types (false positives vs. false negatives) which is crucial in applications like flood detection (where missing a flooded area is a different kind of error than falsely marking a dry area as flooded). We also encourage *spatial and temporal validation*: e.g., train on one region and test on another to see if the model generalizes geographically, or train on one year's data and test on another year to check temporal robustness. **Validate on the ground when possible** – if field data or higher-quality reference is available, use it to corroborate your model outputs (as mentioned, the flood maps from AI ideally should be checked against ground reports [16] [17]). In summary, treat model validation as an ongoing *stress test* of how the model would perform in real deployments, and prefer rigorous testing over optimistic results.

- **Considerations for Operational Deployment:** Taking an AI model from a notebook into the real world requires planning for reliability, efficiency, and maintenance. We discussed the pipeline of going from *proof-of-concept* to *operational use* [18]. Some best practices here include:

- *Model optimization:* Simplify architectures or compress models for faster inference if needed (important when running on limited hardware or large areas). For instance, a smaller U-Net might be chosen if it runs fast enough to produce flood maps within hours of a satellite pass.
- *Automation and integration:* Use workflows or APIs to integrate the model into existing systems. An example is deploying a drought prediction model as a scheduled service that automatically ingests new satellite data (possibly via Google Earth Engine or a cloud pipeline) and outputs alerts to stakeholders. We mentioned how tools like the **AI Processing Interface (AIPI)** from DOST-ASTI aim to make such integration easier – essentially providing an API to run AI models on EO data on-demand within a larger system.
- *Monitoring and updating:* Once deployed, monitor the model's predictions over time. If the environment changes (e.g., new types of crops are introduced, sensor characteristics change with a new satellite), you may need to retrain or update the model. Plan for this by versioning your models and retaining training data. **MLOps** principles – such as tracking data versions, model versions, and performance metrics – ensure that the model remains accurate and trustworthy over time.
- *Ethical and legal considerations:* Although not a heavy focus of our technical training, remember operational models might face concerns about data privacy (if using high-resolution imagery of communities), fairness, and transparency. A best practice is to document what your model does and doesn't do (its intended use), and who to contact if an issue is found in its output.

By adhering to these best practices – data-centric development, robust validation, and careful deployment – you increase the chance that your AI/ML project will deliver value in the field and not just produce a one-time demo. As a final check, whenever you build an EO ML model, ask yourself: **Would I trust this output for an important decision?** If not, iterate further (better data, better validation) until you can say yes with confidence.

Module: Introduction to the CopPhil Digital Space Campus

One of the goals of this training is to not only transfer knowledge now but also to enable **continuing education**. In this module, we introduce the **CopPhil Digital Space Campus**, an online platform where all the training materials and more will be available to you [19]. The Digital Space Campus is essentially a learning management system (LMS) set up under the Copernicus Capacity Support Program for the Philippines, designed for self-paced learning and collaboration.

What you'll find on the Digital Campus:

- **Training Materials Repository:** All the slide presentations, lecture notes, sample codes (Colab notebooks), and datasets from this 4-day course will be uploaded to the platform for your access [19]. This means if you want to revisit the **flood mapping exercise** or share the **land cover classification notebook** with a colleague, you can easily do so. The platform ensures those who couldn't attend live, or future participants, can also benefit from these materials, thereby **widening access** beyond just our session.

- **Structured Courses and Modules:** The Digital Campus hosts organized courses (under categories like Land Cover Monitoring, Forest Monitoring, etc., as we saw in the introduction) with content developed by CopPhil and PhilSA. Our AI/ML EO training will likely be listed as a course you can enroll in. Each module may contain explanatory text, videos (e.g., the welcome message from the EU Ambassador [20]), and quizzes or exercises. Think of it as an online textbook + classroom combined. You can progress through modules at your own pace, and even earn certificates or badges for completion if offered.

- **Continuous Updates:** Because the field of AI/ML in EO is rapidly evolving, the Digital Campus will serve as a living repository. New case studies, new Copernicus data updates, or improved code examples might be added over time. For instance, if next year a new Sentinel satellite is launched or a new algorithm (say a **Transformers-based model**) becomes relevant for, e.g., land cover mapping, the platform can include a lesson on it. By being connected to the Digital Campus, you'll automatically have a way to keep your skills up-to-date even after this training program ends.

- **Community Interaction:** Some LMS platforms (and we anticipate the CopPhil Campus as well) have forums or discussion boards. You are encouraged to use these to ask questions (e.g., "Has anyone applied the drought monitoring LSTM to a different province?" or "I encountered an error using the flood dataset – any advice?"). Trainers and peers can respond, creating a support network. There may also be announcements for upcoming events or opportunities (like scholarships, hackathons, webinars) posted on the platform [21]. Check in periodically so you don't miss out on these chances for further engagement.

In summary, the CopPhil Digital Space Campus is your **go-to hub for ongoing learning**. After Day 4, you will receive instructions (if not already provided) on how to create your account and navigate the platform. We highly recommend exploring it – perhaps start by downloading the materials of this course, and then look at other available courses (there are related ones on Land Cover, Forest, Crop monitoring, etc., which complement what you've learned here [22] [23]). The platform embodies the idea that learning doesn't stop when the live sessions end; instead, you have a springboard into *continuous, self-paced development*. This also means you can **share this resource with your colleagues**. If some team members could not join the training, direct them to the Digital Campus – they might be able to follow a substantial part of the course there and you can then collaborate locally to practice the skills.

(Pedagogical note: By making the materials available for self-study, we leverage the idea of spaced repetition – you can revisit lessons later to reinforce memory – and we encourage active learning – you might re-run notebooks or attempt exercises on your own, which helps transfer the knowledge from short-term to long-term memory [2]. The Digital Campus is a tool to facilitate this reflective practice.)

Module: Fostering a Community of Practice Among EO & AI/ML Practitioners

Learning is most effective when it continues beyond the classroom through a **community of practice**. This module discusses how you can connect with and contribute to the growing community of Earth observation and AI/ML professionals in the Philippines [24]. By engaging with peers, experts, and initiatives, you not only keep yourself updated but also find collaborators for your projects and support for challenges you encounter.

Why Community? According to educational research, collaborative learning and discussion reinforce understanding and help in solving novel problems, because you're exposed to diverse perspectives and can get help on specific issues. In the Philippines, there is a strong spirit of *bayanihan* (communal unity) – we see this mirrored in the tech sphere by groups eager to share knowledge and co-develop solutions. We want you to be aware of and plug into these networks:

- **SkAI-Pinas (Philippine Sky Artificial Intelligence Program):** This is a flagship program under DOST (Department of Science and Technology) that aims to democratize AI, particularly for remote sensing and other applications. Under SkAI-Pinas, notable initiatives include:
- **DIMER (Democratized Intelligent Model Exchange Repository):** Think of this as a *"model marketplace"* or repository where AI models can be shared, downloaded, and reused across the community [25]. For example, if a research group develops a great model for flood detection or rice crop identification, they can publish it on DIMER so that others can deploy it (rather than reinventing the wheel). This lowers barriers for organizations that need AI solutions but may not have resources to train models from scratch [25]. As a participant skilled in EO now, you might one day contribute a model to DIMER or pick up a model from there to jumpstart your project. It's essentially an AI knowledge-sharing platform – "a palengke for AI models" as one article described it [25].

- **AIPI (AI Processing Interface):** This is another component under SkAI-Pinas, focused on providing an interface or platform to deploy and run AI models on data easily. While DIMER is about model sharing, AIPI is about model *serving*. For instance, AIPI could allow you to input a satellite image and choose a model (say from DIMER) and get outputs (like a flood map) without worrying about the back-end computing – a valuable service if you don't have powerful hardware. Together, DIMER and AIPI aim to make AI accessible: DIMER provides the *brains* (models) and AIPI provides the *muscle* (computing power and interface), so even local government units or academic groups with limited resources can leverage state-of-the-art AI.

- **PhilSA and DOST-ASTI Programs:** The Philippine Space Agency (PhilSA) and DOST-ASTI are key players in the EO and AI space. Beyond SkAI-Pinas, **PhilSA** has initiatives like the **Space Data Dashboard / Space Information Infrastructure** where you can get satellite data relevant to the Philippines. Being aware of these will help you find local datasets (e.g., hazard maps, land cover maps from NAMRIA, climate data from PAGASA) that complement AI projects [26]. **DOST-ASTI** operates the **DATOS Project**, which is essentially a remote sensing and data science help desk for disaster risk reduction. DATOS has historically provided on-demand satellite image analysis during disasters. As someone trained in AI/ML, you could potentially collaborate with or learn from DATOS and similar initiatives, as they often integrate AI (they've experimented with flood detection, etc.). ASTI also hosts computing infrastructure – e.g., the Computing and Archiving Research Environment (COARE) – which might be available for researchers who need servers to run models. Engaging with ASTI's community (like attending their yearly conferences or joining their forums) could provide both mentorship opportunities and technical support.

- **Academic and Developer Communities:** The training today is a start, but you may consider joining groups like the GeoAI PH community (if one exists formally or informally), or even international communities like Radiant Earth's MLHub community or the ESA Phi-Lab forums, and so on. Many Filipino practitioners share knowledge on platforms like LinkedIn, Twitter (now X), and Facebook groups. For example, the group that organized this training might create a Slack or Facebook group for alumni – if so, joining that will allow you to continue asking questions and sharing progress on projects. Keep an eye out for local meetups or webinars hosted by universities (UP, Ateneo, etc. have

AI and remote sensing groups), NGOs, or international bodies (like UN, World Bank projects in the Philippines) – being active in these circles means you will hear about new funding opportunities or tools quickly.

- **Relevant National Initiatives:** Apart from SkAI-Pinas, note that the Philippines has a National AI Strategy and organizations like **AIPI** (Advanced Science and Technology Institute's AI Program Interface) and others pushing AI forward. The **Philippine Council for Industry, Energy, and Emerging Technology Research and Development (PCIEERD)** often funds AI for EO projects – their calls for proposals can be an avenue if you aim to start a project. Also, **DOST-PCARI**, **USAID STRIDE**, and other programs sometimes sponsor AI and geospatial capacity-building. We mention these because building a community often means knowing who the stakeholders are. By knowing, for example, that PhilSA and DOST co-chair many EO initiatives [27], you can align your work with national priorities and tap into those networks for support.

In essence, **fostering a community of practice** means **staying connected and contributing**. After this training, we encourage you to do a few concrete things: - Share your experience and new skills with your team or department. Maybe organize a brownbag session where you demonstrate the flood mapping or drought prediction you learned. Teaching others will reinforce your own knowledge and spark interest, growing the community from within your organization. - Join at least one mailing list or group (for instance, if there's a CopPhil or PhilSA newsletter, subscribe to it; if there's a Google Group for "Philippines GeoAI", join it). This keeps you in the loop. - If feasible, attend the next relevant conference or webinar. For example, the **Philippine Space Agency Conference** or **Data Science Philippines meetups** often have segments on remote sensing AI. - Consider contributing: It could be writing a blog post about your project for a wider audience, contributing code to an open-source project (maybe an EO data tool), or mentoring a junior colleague. By giving back to the community, you strengthen it.

Remember, **the community grows when knowledge is shared** – this training is an initiation, and you are now part of this network of practitioners who can collectively advance how AI and EO are used for the Philippines' sustainable development and disaster resilience.

(Pedagogical note: This aligns with the Math Academy Way philosophy that collaborative, socially-supported learning can enhance motivation and success. While deliberate practice is key, having a community provides accountability and shared problem-solving, which can improve both performance and enjoyment in learning.)

Open Q&A and Troubleshooting

After covering all modules, we will dedicate time to an **open Q&A session**. This is your chance to ask **any remaining questions** about the content from the past four days – whether it's a conceptual clarification (e.g., *"Why did we choose U-Net over another architecture for flood mapping?"*), a technical issue (*"I had trouble installing GeoPandas on my laptop – any advice?"*), or an application question (*"How might I apply LSTMs to our organization's data on rainfall?"*). No question is too basic or too advanced – this is a safe space to address uncertainties. We encourage you to take advantage of the collective knowledge present: the instructors and also your fellow participants who may share similar challenges.

The Q&A is also a time for **troubleshooting**. If you encountered errors in the hands-on exercises (perhaps a snippet of code didn't run, or you got an unexpected result in the classification task), you can bring it up so we can solve it together. Often, resolving these issues in a group setting is beneficial – it teaches general debugging skills and often the fixes are instructive for everyone (for example, learning that a `MemoryError` in Python means you need to use smaller batches or a crop of the image).

Why do we emphasize Q&A? Because *interactive problem solving* is where a lot of deeper learning happens. As highlighted by our pedagogical approach, **learning is most effective when active** [3]. By formulating a question or attempting to explain your point of confusion, you're actively engaging with the material. It also helps us identify if there are any common areas that need a bit more review. Perhaps multiple people will express difficulty understanding how **transformer models** might be applied in EO, or maybe there's curiosity about other data sources (like "Can we use Himawari-8 weather satellite data with these techniques?"). We'll address these as best as possible, given time.

Troubleshooting topics might include: environment setup problems (some might ask "How do I set this up on my office computer outside of Colab?" leading to a discussion on installing Python and libraries, using QGIS, etc.), data access issues ("Is there a way to get Sentinel-1 data without internet if I'm in the field?" – prompting us to mention downloading in advance or using the CopPhil mirror site), or algorithm tuning questions ("I tried re-training the model with more epochs and it overfit – how do I handle that?" – leading to advice on early stopping or regularization).

We also encourage you to discuss **anticipated challenges** in applying these techniques at work. Maybe you foresee difficulty convincing your boss to adopt an AI approach, or you have limited GPU resources – bring that up. We might have suggestions (e.g., for hardware limitations, using cloud computing or lightweight models; for management buy-in, focusing on pilot projects that demonstrate value).

By the end of the Q&A, we hope every participant has clarity on the **"muddy points"** and feels confident to attempt these AI/ML methods on their own datasets. Additionally, through troubleshooting together, you gain insight into *how to approach problems when they arise* – a meta-skill as important as the content itself, since inevitably you will hit snags in real projects, but now you have strategies to debug and overcome them.

(Tip: Keep notes during this Q&A. Often the answers to others' questions will prove useful later. It might even be worth adding a FAQ section to the shared materials based on this discussion, which we can do on the Digital Campus forum or as an appendix in the notes.)

Feedback and Conclusion: Pathway to Continued Learning

Finally, we will conduct a **feedback session** to gather your input on this 4-day training. Your honest feedback is extremely valuable – it will help us improve future iterations of the course and identify what worked well and what can be better. We typically will ask you to fill out a short survey (online form) and/or share verbally one thing you liked and one suggestion for improvement. This practice not only helps the instructors but also encourages you to reflect on your own learning experience ("What did I gain? What could have been more helpful?"), which is a good learning habit.

More importantly, we want to close the training by **empowering you with concrete next steps** [1]. Training doesn't end at the last slide – it transitions into **application**. We will discuss and brainstorm how you can apply your newly acquired skills within your institutions. For example, if you work at a local government unit, perhaps your next step is to try using Sentinel-2 data to map something of interest in your area (like mangrove extents or urban growth). If you are in a research institute, maybe you can draft a proposal to secure funding for an AI project addressing a national issue (like landslide susceptibility mapping using AI). We encourage you to identify at least one **mini-project** you can embark on in the coming weeks. It could be as simple as re-running the flood mapping workflow on a different flood event, or as ambitious as starting a new initiative – but having a plan will help ensure the skills stay fresh and continue to grow.

We will also highlight how to **access further support and resources** after this training [1]. Aside from the Digital Campus and community networks discussed, there are many online courses and materials you can use to deepen specific skills: - For instance, if the session on LSTMs piqued your interest in deep learning, we can recommend free online courses (like Andrew Ng's Deep Learning specialization, or fast.ai lessons) to strengthen your foundations. - If you want to learn more about Google Earth Engine (since we touched on it for data access), there are tutorials and a whole community forum on it. - Documentation for libraries we used (GeoPandas, Rasterio, TensorFlow/PyTorch, etc.) are available and often have user-contributed examples specific to geospatial data.

We might compile a short list of **curated resources** (links or references) and share it on the Digital Campus – such as relevant GitHub repositories (e.g., for flood detection), papers or blogs for further reading (like the MDPI paper referenced in the flood exercise [16], or success stories of AI in Philippine context), and contacts of resource persons.

As we conclude, remember that the end of this training is really the **beginning of your journey** as part of the EO+AI practitioner community. You now have the foundational skills to innovate in your work – *keep practicing them*. The field will evolve, but the core understanding you've built (and the ability to learn new tools) will ensure you can adapt. We hope you feel encouraged to continue exploring and we, the instructors and organizers, are excited to see how you will use these skills. Please don't hesitate to reach out in the future – whether through the Digital Campus, email, or community forums – if you have questions or need collaboration.

Thank you for being an engaged and inquisitive group throughout these four days. We look forward to the **post-training success stories** – perhaps in a year, you might be the one presenting in a community webinar about how your AI model helped solve a problem in your locality! That kind of outcome is exactly what this program aims for: building local capacity so that **the next big advances** in applying AI for Earth Observation in the Philippines come from talents like you [28].

Let's keep the momentum going – *padayon!* (continue onwards).

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